Does competition improve ratings?

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Abstract

to be competed

1 Introduction

There is little doubt the financial strength ratings issued by the dominant insurance rating agencies can have a significant impact on the opinions of participants in the insurance marketplace and therefore on the functioning of the market itself. Yet surprisingly little is known about the incentives of the agencies, how well the ratings perform over time, and how one agency’s system performs relative to another’s. We know of only one study that has looked at the determinants of insurance company financial strength ratings across multiple rating agencies and they document significant differences across the various systems (Pottier and Sommer 1999). However, a shortcoming of the research is that the author’s do not have any reason to suspect why the rating should differ. The purpose of this paper is to both theoretically and empirically investigate the incentives a single rating agency has to produce ratings and then ask how those ratings are likely to change when another agency enters the market.

We begin by considering the ratings process itself. First, consider that the rating agencies themselves can be judged only in reference to the quality of the models and the data employed. Better formulated models with richer data should, one assumes, outperform more primitive models. But the choice of models might be constrained by modeling technology and the data limited to what is accessible. However, within these constraints, rating agencies can choose how much they wish to invest in model building, how much invest in data and how they will interpret the results. The question we address is whether these choices are affected by competition between agencies and how that competition impacts the ultimate ratings.

The information content of financial ratings is of great interest to many actors and an extensive empirical literature exists. Earlier empirical papers tended to look predict the ratings (e.g. from public information) though many later papers mainly sought to examine the accuracy
of rating, i.e., their ability to predict default. Other papers have asked whether ratings contain information that is not already impounded in the prices of financial instruments. The accuracy of rating is clearly of immense practical importance. Yet little attention has been given to understanding the economic mechanisms that determine rating accuracy. Is accuracy purely determined by the available data and computational capacity? Or is accuracy the result of economic choices and market forces?

We will develop a model of rating in which, first there is a single rating agency that acts as a monopolist. In this sense, the agency charges a fee to firms. Receiving a high rating can enhance the value of the firm, e.g., because it lowers the cost of debt and may permit the firm to access some customers that would otherwise be off limits. The monopolist rating agency is then able to price for its services to extract all rent. However, it can manipulate these rents by its choice of both the accuracy and stringency of the rating scheme. We will then introduce a second agency and address a duopoly in which firms compete on both stringency and accuracy. Like all oligopoly models, different equilibria are possible and, since we are unable to obtain a closed form, we will illustrate a Cournot solution. However, since our purpose is to understand the actual dynamics of new entry into the insurance rating market (the entry of Standard & Poor’s to compete with the incumbent A. M. Best), we will use the reaction functions to speculate on the temporal evolution of the market after entry. We will then see how the incumbent and entrant actual behaved in terms of their choices of accuracy and stringency.

Our model has some roots in Lizzeri, 1999 and De, Kale and Shahrur, 2003. Lizzeri first considers as monopoly rating agency and shows that maximize surplus by “certifying” firms according to whether they exceed a threshold. The monopoly agency can earn a large portion of the surplus in spite of the fact that this certification conveys relatively little information. However, if there is competition between rating agencies, there is a full information equilibrium in which intermediaries make no profits. This paper differs from ours in several respects the most important of which is that we look multiple ratings in which insurers competes in its joint choices of its costly investment in accuracy and in stringency. While different oligopoly equilibria are feasible, and are illustrated, we are mainly concerned with explaining the actual entry of new rating agencies into the insurance industry. Accordingly, our main interest is in the properties of the reaction functions.

De, Kale and Shahrur, 2003, look at the demand for ratings under different assumptions about rating accuracy. Customers are assumed to know the accuracy and they show equilibria in which all high quality and some low quality firms are rated according to a less than perfectly accurate standard. We differ in looking at both stringency and accuracy and in considering
the effects of new entry. The focus on stringency, as well as accuracy, echoes earlier empirical work on bond ratings (Blume, Lim and MacKinlay 1998) and insurance ratings (Doherty and Phillips, 2002) which showed that rating downgrades in the 1980’s and 1990’s could be explained by increasing stringency, as opposed to declines in credit quality. We are interested in whether this increased stringency in the insurance industry can be explained by the competitive effects of new entry.

We build a model that analyzes the behavior of the rating agency when it decides both stringency and precision of its advice. We consider a situation in which the insurance industry is composed of firms with heterogeneous insolvency risks. The rating agency possesses a technology to estimate the insolvency risk, but the precision of the estimate is costly for the agency. This information is valuable to risk averse customers. It may also be valuable to insurance companies who wish to signal high reliability, and, ultimately, increase the price a customer is ready to pay for a particular contract.

An agency also decides the stringency of its rating. Once estimates are obtained, the way they are aggregated in rating categories affects the expected probability of default in each category.

One of the key features of the model is that the insurance company is not obliged to obtain a rating. Therefore, precision and stringency decisions must take into account incentives of firms to participate in rating.

The objective of the model is to explain the recent started employed by S&P to enter insurance ratings traditionally dominated by a single company, AM Best.

The outline of the analysis is as follows. We start by considering the precision choice by a single agency. Then we study the incentives of an agency to pool heterogeneous estimates in different categories (stringency). Then we allow for the possibility of entry, and analyze which firms may have incentives to obtain a second opinion. In general these are the firms that either have been overestimated in terms of insolvency risk, or firms that have been pooled with less favorable risk types in the rating process. Therefore, the new entrant is general will be characterized by higher precision and also higher stringency of ratings. We also analyze how the presence of the "second opinion" competitor affects the accuracy and stringency strategy of the incumbent rating agency.

2 The model

We consider interaction among three groups of agents - a unit mass of insurance companies, monopolistic rating agencies and a unit mass of customers. A distinctive characteristic of each
insurance company is its insolvency risk. Customers are risk averse and are willing to pay for the insurance contract in accordance to the insolvency risk of the issuing company. Insurer cannot credibly communicate its insolvency risk. However, an intermediary possesses a technology that allows to estimate the risk. Also, it has the reputation to communicate its findings to customers.

We assume that there are three types of companies with insolvency risks $\theta_1 < \theta_2 < \theta_3$, and $\Pr(\theta_i) = \frac{1}{3}$. A company $\theta_1$ has the lowest probability to become insolvent, while a company with $\theta_3$ has the highest probability.

The rating agency has two decisions to make. First, it chooses the precision $\sigma$ of the estimate $r_i$, $i = 1, 2, 3$ of the insolvency risk, so that the resulting estimate coincides with the true value of insolvency risk with probability $\sigma$, that is,

$$\Pr(\theta_i | r_i) = \sigma,$$

$$\Pr(\theta_j | r_i) = \frac{1}{2}(1 - \sigma), \ j \neq i. \ (1)$$

We assume that the signal is informative, and $\sigma \geq \frac{1}{3}$. Precision is costly. The cost function is $\psi(\sigma)$, with $\psi(\frac{1}{3}) = 0$, $\psi(1) = \infty$, and $\psi' > 0$, $\psi'' > 0$.

Second, the agency decides the stringency of the rating schedule. We assume that an agency can assign an exogenously given number of categories, $K = 2$. Denote these two categories $A$ and $B$. Then, the stringency is endogenously determined by the partition of $\{r_1, r_2, r_3\}$ in two subintervals. An example of the rating system is illustrated on Figure 1. The company that is assigned rating $A$ has low risk, while the company with $B$ rating has high risk. We refer to the system with $A = \{r_1\}$, $B = \{r_2, r_3\}$ as more stringent and to the one with $A = \{r_1, r_2\}$ and $B = \{r_3\}$ as less stringent. Customers are aware of the rating system used by the agency, but they observe only the rating assigned to the company. They do not know the actual estimate of insolvency risk produced by the rating agency.

Obtaining ratings is voluntary for insurance companies. Thus the payoff of the rating agency is determined by the demand for ratings. Each company pays an exogenously given fee $t$ for
rating services. Then the payoff of the agency,

$$\pi_A = \delta(t - \psi(\sigma)),$$

where $\delta$ is the share of companies that decide to obtain ratings, $\delta \in \{0, \frac{1}{3}, \frac{2}{3}, 1\}$.

Customers are risk averse. Their valuation of the insurance contract depends on the estimate of the company’s insolvency risk and precision of the rating. For simplicity we consider a situation in which customers observe the rating agency’s choice of $\sigma$. The valuation of the contract of a company with insolvency risk $\theta_i$ is $v_i$, with $v_1 > v_2 > v_3 > 0$. Customers are risk averse, and the valuation of insurance contract from a company with rating $K$, $K = \{A, B, N\}$, where $N$ stands for no rating, depends on the expected insolvency risk and precision of information,

$$Ev(K) + \frac{1}{2}a(\sigma - \frac{1}{3})^2.$$

The first part is the expected valuation of the contract. The second part, with $a > 0$, is a measure of customers’ risk aversion.

The insurance company sets a price $p$ for the contract. A customer is willing to buy a contract if and only if

$$Ev(K) + a(\sigma - \frac{1}{3})^2 - p \geq 0.$$

Thus the price of the contract is

$$p = Ev(K) + a(\sigma - \frac{1}{3}).$$

A rating agency imposes a fee $t$ for the rating services\footnote{In accordance with the industry practice, the fee does not depend on the rating grade assigned to a company.}. Then the payoff of the insurance company is

$$\pi_I = Ev(K) + I_k(a(\sigma - \frac{1}{3})^2 - t),$$

where $I_k = \begin{cases} 1, \text{ if company is assigned a rating } k \in \{A, B\}, \\ 0, \text{ if company is not rated, } k = N. \end{cases}$

We study Bayesian Perfect equilibria of the game. Strategies of all players must be optimal given the beliefs about other’s players information. Beliefs must be consistent with the Bayes rule whenever possible.
3 Full disclosure benchmark

To highlight the nature of trade-offs that drive our results we first analyze a situation in which the estimate produced by the rating agency is disclosed to customers. In other words, we study a choice of precision under the rating schedule \( r_1 \), \( r_2 \), \( r_3 \).

An insurance company decides to obtain a rating only if the expected profit gained with rating is higher than the one without a rating. At the same time, the expected value of the contract without a rating depends on the composition of the pool of non-rated companies and customers' beliefs concerning the pool.

Suppose that the low risk company \( \theta_1 \) is not rated, and the other two are rated. Then if \( \theta_2 \) decides not to be rated, it obtains
\[
\frac{1}{2}v_1 + \frac{1}{2}v_2 > v_2,
\]
while if it is rated, its payoff is
\[
\mu(\theta_2 | r_j)v_2 + \mu(\theta_3 | r_j)v_3 - t + \frac{1}{2}a(\sigma - \frac{1}{3})^2 \leq v_2.
\]
Thus, in this case type \( \theta_2 \) also decides not to be rated. Note that type \( \theta_3 \) would also prefer not to be rated because it obtains higher expected payoff by pooling with better types. Therefore, it not possible to have an equilibrium in which a low risk company decides not to obtain a rating, while higher risk companies are rated.

Suppose now that none of the companies are rated, and \( \theta_1 \) decides to be rated. Then it increases its expected payoff by signalling to be low risk. In response, type \( \theta_2 \) is better off by obtaining a rating. Finally, type \( \theta_3 \) may decide either way, depending on the fee \( t \) and the precision of the signal. Hence, in equilibrium it must be that either all three types are rated, or type \( \theta_3 \) is the one that decides not to obtain a rating. Also, out-of-equilibrium, if a company \( \theta_i \), \( i = 1, 2 \) decides not to be rated, it will be considered by customers as type \( \theta_3 \).

The decision of \( \theta_3 \) whether to be rated depends on the precision of the technology employed by the rating agency. If the technology is poor, \( \theta_3 \) may benefit when it is mistaken for a better type. So \( \theta_3 \) decides to be rated when
\[
Ev(\theta_3) - t \geq v_3,
\]
where \( Ev(\theta_3) \) denoted the expected valuation of the contract offered by \( \theta_3 \) when it is rated.
When all types are rated, the expected values of contracts with estimates \( r_i, i = 1, 2, 3 \) are

\[
v(r_1) = \sigma v_1 + \frac{1}{2}(1 - \sigma)(v_2 + v_3),
\]

\[
v(r_2) = \sigma v_2 + \frac{1}{2}(1 - \sigma)(v_1 + v_3),
\]

\[
v(r_3) = \sigma v_3 + \frac{1}{2}(1 - \sigma)(v_1 + v_2).
\]

Then the expected valuation of \( \theta_3 \)'s contract when this type decides to be rated is

\[
Ev(\theta_3) = \frac{1}{2}(1 - \sigma) v(r_1) + \frac{1}{2}(1 - \sigma) v(r_2) + \sigma v(r_3) + \frac{1}{2}a(\sigma - \frac{1}{3})^2
\]

\[
= \left( \frac{1}{2}(1 - \sigma)^2 + \sigma^2 \right) v_3 + \left( \sigma(1 - \sigma) + \frac{1}{4}(1 - \sigma)^2 \right) (v_1 + v_2) + \frac{1}{2}a(\sigma - \frac{1}{3})^2.
\]

Similarly,

\[
Ev(\theta_1) = \left( \frac{1}{2}(1 - \sigma)^2 + \sigma^2 \right) v_1 + \left( \sigma(1 - \sigma) + \frac{1}{4}(1 - \sigma)^2 \right) (v_2 + v_3) + \frac{1}{2}a(\sigma - \frac{1}{3})^2,
\]

\[
Ev(\theta_2) = \left( \frac{1}{2}(1 - \sigma)^2 + \sigma^2 \right) v_2 + \left( \sigma(1 - \sigma) + \frac{1}{4}(1 - \sigma)^2 \right) (v_1 + v_3) + \frac{1}{2}a(\sigma - \frac{1}{3})^2.
\]

How does higher precision of estimates affect the incentives of the high risk company to be rated? Consider

\[
\frac{dEv(\theta_3)}{d\sigma} = (3\sigma - 1)(v_3 - \frac{1}{2}(v_1 + v_2)) + a(\sigma - \frac{1}{3}).
\]

The first term of this expression is negative because higher precision of the rating implies that the high risk type is less often mistaken for the low risk type. Consequently, it obtains expected valuation of its contract is lower. The second term is positive and it indicates that higher risk aversion of customers increases the price they are willing to pay for more precise information.

To characterize the equilibrium level of precision, we consider three cases when \( \rho = 1, \rho = \frac{2}{3}, \) and \( \rho = \frac{1}{3}. \)

**Case 1: Full coverage of the market.** In this case the optimal precision of the rating agency solves the problem

\[
\max t - \psi(\sigma)
\]

subject to

\[
PC_1 \quad Ev(\theta_1) - t \geq v_3,
\]

\[
PC_2 \quad Ev(\theta_2) - t \geq v_3,
\]

\[
PC_3 \quad Ev(\theta_3) - t \geq v_3.
\]

The participation constraints guarantee that all companies indeed choose to obtain ratings. Since \( Ev(\theta_1) \geq Ev(\theta_2) \geq Ev(\theta_3), \) the last constraint \( PC_3 \) implies the other two participation
Thus,
\[ t = Ev(\theta_3) - v_3, \]
and the expected profit of the rating agency is
\[
\left( \frac{1}{2} (1 - \sigma)^2 + \sigma^2 \right) v_3 + (\sigma(1 - \sigma) + \frac{1}{4} (1 - \sigma)^2) (v_1 + v_2) - v_3 - \frac{1}{2} a(\sigma - \frac{1}{3})^2 - \psi(\sigma).
\]
Thus the optimal precision is determined by the first order condition
\[
(3\sigma - 1)(v_3 - \frac{1}{2}(v_1 + v_2)) + a(\sigma - \frac{1}{3}) - \psi'(\sigma) \leq 0, \text{ satisfied as an equality when } \sigma > \frac{1}{3}.
\]

When customers do not value precision of information offered by the rating agency, \( a = 0 \), the optimal precision of the estimate is zero, \( \sigma = \frac{1}{3} \). Higher risk aversion implies higher optimal precision. It is interesting to compare this result with Lizzeri (1999). In his model the rating agency does not invest in precision and nonetheless manages to obtain full coverage of the market.

Our result may help to understand how such an outcome is possible. When customers do not value precision of information, full coverage of the market is obtained due to pooling effect: High risk companies are willing to obtain ratings because pooling with low risk companies increases the expected valuation of their contract. At the same time, low risk companies obtain ratings in order not to be considered as high risk companies by the customers. The structure of the equilibrium implies that the rating agency’s payoff is increasing with pooling, and therefore, it’s optimal precision level is zero. Therefore, to obtain positive precision in equilibrium, it must be the case that customers are willing to pay for precision. Higher values of \( a \) thus imply higher equilibrium level of precision.

**Case 2: Partial coverage.** Suppose now that type \( \theta_3 \) decides not to obtain a rating. Then a rating agency designs a system that satisfied the following participation constraints.

\[
PC_2 : \quad t \leq \sigma v_2 + \frac{1}{2}(1 - \sigma)(v_1 + v_3) - v_3 - \frac{1}{2}(\sigma - \frac{1}{3})^2;
\]
\[
NPC_3 : \quad t \geq \sigma v_3 + \frac{1}{2}(1 - \sigma)(v_1 + v_2) - v_3 - \frac{1}{2}(\sigma - \frac{1}{3})^2.
\]

The first constraint states that type \( \theta_2 \) is willing to be rated while the second constraint guarantees that type \( \theta_3 \) decides not to obtain a rating. The optimal precision of the rating agency is a solution to
\[
\left( \frac{2}{3}\sigma v_2 + \frac{1}{2}(1 - \sigma)(v_1 + v_3) - v_3 + \frac{1}{2}(\sigma - \frac{1}{3})^2 - \psi(\sigma) \right).
\]

The benefit of serving only two types is that a rating agency can extract a higher share of the surplus.

[to be completed]
4 Partial disclosure and optimal stringency

In this section we focus on the case where a monopoly rating agency provides full coverage of the market, and consider two alternative rating systems - more stringent and less stringent. Under more stringent system companies with risk estimate \( r_1 \) are assigned rating \( A \), while companies with estimate \( r_2 \) and \( r_3 \) are assigned rating \( B \). Under less stringent system, rating \( A \) is assigned under estimates \( r_1 \) and \( r_2 \), while \( B \) is assigned under \( r_3 \). We also show that partial disclosure is more profitable than full disclosure presented in the previous section.

4.1 Stringent rating system

Since companies with insolvency risks \( r_2 \) and \( r_3 \) are pooled together under this system, the expected values of contract for companies with ratings \( A \) and \( B \) are

\[
\begin{align*}
v(A) &= \sigma v_1 + \frac{1}{2}(1 - \sigma)(v_2 + v_3), \\
v(B) &= (\sigma + \frac{1}{2}(1 - \sigma))\frac{1}{2}(v_2 + v_3) + \frac{1}{2}(1 - \sigma)v_1.
\end{align*}
\]

The expected value of high risk company’s contract when it obtains a rating is

\[
v(\theta_3) = (\sigma + \frac{1}{2}(1 - \sigma))(\sigma + \frac{1}{2}(1 - \sigma))\frac{1}{2}(v_2 + v_3) + \frac{1}{2}(1 - \sigma)v_1 + \frac{1}{2}(1 - \sigma)(\sigma v_1 + \frac{1}{2}(1 - \sigma)(v_2 + v_3)).
\]

Thus it decides to be rated when

\[
t \leq v(\theta_3) - v_3 + \frac{1}{2}a(\sigma - \frac{1}{3})^2.
\]

Optimal precision of the rating agency solves

\[
\max_{\frac{1}{2} \leq \sigma \leq 1} \left( \sigma + \frac{1}{2}(1 - \sigma))(\sigma + \frac{1}{2}(1 - \sigma))\frac{1}{2}(v_2 + v_3) + \frac{1}{2}(1 - \sigma)v_1 + \frac{1}{2}(1 - \sigma)(\sigma v_1 + \frac{1}{2}(1 - \sigma)(v_2 + v_3)) - v_3 + \frac{1}{2}a(\sigma - \frac{1}{3})^2 - \psi(\sigma),
\]

resulting in \( \sigma \) that is implicitly defined by

\[
\frac{1}{2}(3\sigma - 1)(\frac{1}{2}(v_2 + v_3) - v_1) + a(\sigma - \frac{1}{3}) - \psi'(\sigma) = 0.
\]

It is straightforward to show that optimal precision is increasing in the degree of risk-aversion. Also it is decreasing in the diversity of companies in the industry.
4.2 Non-stringent rating system

Under less stringent system companies with estimates $r_1$ and $r_2$ are pooled together by the rating agency. When the rating agency covers all the market, the expected value of contracts that obtain ratings $A$ and $B$ are

$$v(A) = (\sigma + \frac{1}{2}(1 - \sigma)) \frac{1}{2}(v_1 + v_2) + \frac{1}{2}(1 - \sigma)v_3,$$

$$v(B) = \sigma v_3 + \frac{1}{2}(1 - \sigma)(v_2 + v_3).$$

Then, the expected value of the contract for a rated high risk company is

$$v(\theta_3) = (1 - \sigma)((\sigma + \frac{1}{2}(1 - \sigma)) \frac{1}{2}(v_1 + v_2) + \frac{1}{2}(1 - \sigma)v_3)$$

$$+ \sigma(\sigma v_3 + \frac{1}{2}(1 - \sigma)(v_2 + v_3)),$$

and it obtains a rating when

$$t \leq v(\theta_3) - v_3 + \frac{1}{2}a(\sigma - \frac{1}{3})^2.$$

Optimal level of precision under this system solves

$$\max_{\frac{1}{3} \leq \sigma \leq 1} (1 - \sigma)((\sigma + \frac{1}{2}(1 - \sigma)) \frac{1}{2}(v_1 + v_2) + \frac{1}{2}(1 - \sigma)v_3)$$

$$+ \sigma(\sigma v_3 + \frac{1}{2}(1 - \sigma)(v_2 + v_3)) - v_3 + \frac{1}{2}a(\sigma - \frac{1}{3})^2 - \psi(\sigma),$$

resulting in the level of precision $\sigma$ implicitly defined by

$$\frac{1}{2}(3\sigma - 1)(v_3 - \frac{1}{2}(v_1 + v_2)) + a(\sigma - \frac{1}{3}) - \psi'(\sigma) = 0.$$

Similarly to the results above, the optimal level of precision under this system is increasing in the degree of risk aversion and decreasing in the diversity of the market.

4.3 Optimal stringency

Denote $\pi(\sigma)$ and $\underline{\pi}(\sigma)$ the expected profit of the rating agency under these two systems. It can be easily shown that

$$\pi(\sigma) \geq \underline{\pi}(\sigma)$$

for all $\sigma \in [\frac{1}{3}, 1]$, and therefore, a stringent system is optimal.

\textbf{Proposition 1} Under monopoly, a stringent rating system is optimal.
There are two types of costs. First, providing precision is has direct cost $\psi(\sigma)$. Second, it has indirect costs of providing incentives to the high risk company to demand a rating. A high risk company benefit of a rating comes from the increased expected surplus of its contract when it is pooled with a better company. Under more stringent system a pooling is naturally obtained for any given level of precision, and as a result, providing incentives is less costly.

A stringent rating system is also optimal when an agency is free to disclose all information.

Remarkably, the optimal level of precision can be either higher or lower than under less stringent system, depending on the characteristics of the industry. When $v_2 > \frac{1}{2}(v_1 + v_3)$, more stringent system results is better precision that the less stringent one. However, when $v_2 < \frac{1}{2}(v_1 + v_3)$, less stringent system leads to better precision.

5 Entry of a second rating agency

In this section we study an equilibrium rating system when a second rating agency enters the market. We distinguish between short run and long run equilibria. In the short run, we consider a rating system of the incumbent rating agency as given, and study the optimal entry strategy of the second rating agency. In the long run, incumbent and entrant compete on the market simultaneously.

5.1 Short run equilibrium

Consider a situation when a firm that have obtained a rating from the incumbent rating agency is offered an opportunity to purchase a second rating. What is a potential market for the entrant? As we have argued above, there are three reasons why an insurance company may be willing to be rated. First, rating signals its insolvency risk. Second, rating may increase the expected value of its contract by pooling with better types. Third, information is valued by risk-averse customers. Obtaining a second rating increases the precision of information about the company’s insolvency risk. Thus it may not provide extra surplus to high risk companies due to pooling effect. At the same time, obtaining a second rating allows a low risk company to confirm its quality. The benefit is the highest for the company that has been mistaken for the high risk one by the incumbent rating agency. Hence the entrant’s target group is composed of low risk companies. The analysis presented below confirms this intuition.

Before evaluating the potential benefits of obtaining a second rating, let us discrbe entrant’s information technology. The information structure of the entrant’s signal is the same as the one of the incumbent defined by (1). Denote $\sigma_e$ the precision of the signal obtained by the entrant.
The cost of precision is $c\psi(\sigma_e)$, where $c > 0$ measures the efficiency of entrant’s technology compared to one of the incumbent. We assume that conditional on true insolvency risk of the insurance company, signals of the two rating agencies are independent. Entrant imposes a fee $t_e$ for the rating services. The profit of the entrant is

$$\rho_e(t_e - \psi(\sigma_e)),$$

where $\rho_e$ is entrants share of the market.

The decision to purchase a second rating depends on the surplus gained from receiving a second rating and the price of the rating. Consider a firm rated $R$ by the incumbent rating agency. Denote $v(R)$ the valuation of its contract by the customers. Obtaining a second rating results in expected valuation $E_e v(R, R_e)$. A company decides to obtain a second rating when its profits with two ratings is higher that with a single rating, that is,

$$E_e v(R, R_e) - t_e \geq v(R) - t,$$

or

$$E_e v(R, R_e) - v(R) \geq t_e.$$

The right hand side of the last condition is the extra benefit of the second rating. The left hand side is the cost of the second rating.

We study Bayesian equilibria of the game. The rating system of the entrant must be optimal given the incumbent’s rating system and insurance company’s decision to obtain a second rating. The company’s decision must be optimal given the rating system and evaluation of the rated contract by the customers.

Obtaining a second rating is not attractive to high risk companies.

**Proposition 2** There is no short-run equilibrium in which a second rating is obtained only by type $\theta_3$, or only by types $\theta_2$ and $\theta_3$.

The benefits of a second rating for low risk types depend on the rating system employed by the entrant. We consider different scenarios of rating systems below.

I. Only $\theta_1$ obtains a second rating.

Obtaining a second rating by $\theta_1$ reveals its insolvency risk to customers and guarantees the highest payoff $v_1$. Depending on the rating $A$ or $B$ assigned by the incumbent rating agency, there are two groups of companies with insolvency risk $\theta_1$. The marginal benefit of the company depends on the rating assigned by the incumbent rating agency. Thus to have all $\theta_1$ companies demanding ratings, two participation constraints must be satisfied.

- $PC_A : v_1 - (\sigma_e v_1 + \frac{1}{2}(1 - \sigma_e)(v_2 + v_3)) = (1 - \sigma_e)(v_1 - \frac{1}{2}(v_2 + v_3)) \geq t_e$,
- $PC_B : v_1 - ((\sigma_e + \frac{1}{2}(1 - \sigma_e))\frac{1}{2}(v_2 + v_3) + \frac{1}{2}(1-\sigma_e)v_1) = (\sigma_e + \frac{1}{2}(1 - \sigma_e))(v_1 - \frac{1}{2}(v_2 + v_3)) \geq t_e$. 

Naturally, the marginal benefit obtained by a company that obtained rating $B$ from the incumbent rating agency is higher than the marginal benefit of the company rated $A$ by the incumbent. This observation creates two possible strategies for the entrant: It may design a rating system that encourages all $\theta_1$ companies to obtain a second rating. In this case its fee is determined by $PC_A$. Alternatively, it may focus on companies that have obtained a low rating from the incumbent, and demand a higher fee.

I. All $\theta_1$ companies obtain a second rating. In this case the mass of companies covered by the entrant is $\rho_e = \frac{1}{3}$, and the profit of the entrant writes

$$\pi_e = \frac{1}{3}((1 - \sigma_e)(v_1 - \frac{1}{2}(v_2 + v_3)) + \frac{1}{2}a(\sigma_e - \frac{1}{3})^2 - cv'(\sigma_e)),$$

resulting in precision $\sigma_e$ implicitly defined by

$$-(v_1 - \frac{1}{2}(v_2 + v_3)) + a(\sigma_e - \frac{1}{3}) - cv'(\sigma_e)) = 0.$$

Note that for relatively low values of customers risk aversion $a$ providing imprecise rating can be optimal for the entrant rating agency. When all companies with low insolvency risk obtain a second rating, the self selection of companies is a signal about their quality.

This rating system creates strong incentives for the other insurance companies to obtain a second rating. Indeed, by doing so they are mistaken for the low risk company. Hence, this scenario cannot be part of equilibrium.

II. Types $\theta_1$ and $\theta_2$ obtain a second rating. The size of the market covered by the entrant depends on the precision of the incumbent rating agency, $\rho_e = \frac{1}{3}(1 - \sigma)$. The entrant gains profit

$$\pi_e = \frac{1}{3}(1 - \sigma)((\sigma_e + \frac{1}{2}(1 - \sigma_e))(v_1 - \frac{1}{2}(v_2 + v_3)) + \frac{1}{2}a(\sigma_e - \frac{1}{3})^2 - cv'(\sigma_e)).$$

The optimal precision under this system is implicitly defined by

$$\frac{1}{2}(v_1 - \frac{1}{2}(v_2 + v_3)) + a(\sigma_e - \frac{1}{3}) - cv'(\sigma_e)) = 0.$$

Precision of the information offered by the entrant is higher than in the previous case because the company’s marginal benefit of obtaining a rating is increasing in precision.

Given that precision of the entrant is sufficiently high, types $\theta_2$ and $\theta_3$ may not benefit by obtaining the second rating. Thus this entry strategy may be optimal.

II. Types $\theta_1$ and $\theta_2$ obtain a second rating.

Consider a possibility that $\theta_2$ also purchases a second rating. In this case the marginal benefit of the second rating depends on the stringency of the rating system of the entrant. We
consider two cases depending on whether companies with different estimates are assigned the same or different ratings.

II.1. \( \theta_1 \) and \( \theta_2 \) are assigned the same rating. Beliefs of customers concerning company’s insolvency risk depends on the rating and precision of the incumbent. Denote \( R_e \) the second rating. Since both types obtain the same rating, the rating of entrant only signals that a company can be one of two types. Then beliefs about the company with rating \( A \) from the incumbent are

\[
\Pr(\theta_1| A, R_e) = \frac{\frac{1}{3} \sigma}{\frac{1}{3} \sigma + \frac{2}{3} \sigma (1 - \sigma)} = \frac{2\sigma}{2\sigma + (1 - \sigma)},
\]
\[
\Pr(\theta_2| A, R_e) = \frac{1 - \sigma}{2\sigma + (1 - \sigma)}.
\]

Similarly, beliefs about a company with rating \( B \) from the incumbent are

\[
\Pr(\theta_1| B, R_e) = \frac{\frac{1}{2} \sigma}{\frac{1}{2} \sigma + \frac{1}{2} \sigma (1 - \sigma)} = \frac{1 - \sigma}{2\sigma + (1 - \sigma)},
\]
\[
\Pr(\theta_2| B, R_e) = \frac{2\sigma}{2\sigma + (1 - \sigma)}.
\]

The participation constraint of each type depends on the rating obtained from the incumbent.

\[
PC_A : \frac{2\sigma}{2\sigma + (1 - \sigma)} v_1 + \frac{1 - \sigma}{2\sigma + (1 - \sigma)} v_2 - (\sigma v_1 + \frac{1}{2} (1 - \sigma) (v_2 + v_3)) \geq t_e,
\]
\[
PC_B : \frac{1 - \sigma}{2\sigma + (1 - \sigma)} v_1 + \frac{2\sigma}{2\sigma + (1 - \sigma)} v_2 - ((\sigma + \frac{1}{2} (1 - \sigma)) \frac{1}{2} (v_2 + v_3) + \frac{1}{2} (1 - \sigma) v_1) \geq t_e
\]
[to be completed]

II.2. Companies with different estimated are assigned different ratings. Suppose that the entrant assigns rating \( A \) to a company with an estimate \( r_1 \) and a rating \( B \) to a company with an estimate \( r_2 \). Beliefs of customers about the type of the company when it obtains rating \( R \) from the incumbent and \( R_e \) from the entrant are

\[
\Pr(\theta_1| A, A) = \frac{2\sigma \sigma_e}{2\sigma \sigma_e + (1 - \sigma)(1 - \sigma_e)},
\]
\[
\Pr(\theta_1| A, B) = \frac{2\sigma (1 - \sigma_e)}{2\sigma (1 - \sigma_e) + (1 - \sigma) \sigma_e},
\]
\[
\Pr(\theta_1| B, A) = \frac{(1 - \sigma) \sigma_e}{(1 - \sigma) \sigma_e + 2\sigma (1 - \sigma_e)},
\]
\[
\Pr(\theta_1| B, B) = \frac{(1 - \sigma)(1 - \sigma_e)}{(1 - \sigma)(1 - \sigma_e) + 2\sigma \sigma_e}.
\]

Beliefs about type \( \theta_2 \) can be derived from the condition that \( \Pr(\theta_2| R, R_e) = 1 - \Pr(\theta_1| R, R_e) \).
The participation constraints are as follows.

\[
PC_A(\theta_1) : \Pr(R_e = A| \theta_1)(\Pr(\theta_1| A, A)v_1 + \Pr(\theta_2| A, A)v_2) \\
+ \Pr(R_e = B| \theta_1)(\Pr(\theta_1| A, B)v_1 + \Pr(\theta_2| A, B)v_2) - (\sigma v_1 + \frac{1}{2}(1 - \sigma)(v_2 + v_3)) \geq t_e,
\]

\[
PC_B(\theta_1) : \Pr(R_e = A| \theta_1)(\Pr(\theta_1| B, A)v_1 + \Pr(\theta_2| B, A)v_2) \\
+ \Pr(R_e = B| \theta_1)(\Pr(\theta_1| B, B)v_1 + \Pr(\theta_2| B, B)v_2) \\
-((\sigma + \frac{1}{2}(1 - \sigma))\frac{1}{2}(v_2 + v_3) + \frac{1}{2}(1 - \sigma)v_1) \geq t_e,
\]

\[
PC_A(\theta_2) : \Pr(R_e = A| \theta_2)(\Pr(\theta_1| A, A)v_1 + \Pr(\theta_2| A, A)v_2) \\
+ \Pr(R_e = B| \theta_2)(\Pr(\theta_1| A, B)v_1 + \Pr(\theta_2| A, B)v_2) - (\sigma v_1 + \frac{1}{2}(1 - \sigma)(v_2 + v_3)) \geq t_e,
\]

\[
PC_B(\theta_2) : \Pr(R_e = A| \theta_2)(\Pr(\theta_1| B, A)v_1 + \Pr(\theta_2| B, A)v_2) \\
+ \Pr(R_e = B| \theta_2)(\Pr(\theta_1| B, B)v_1 + \Pr(\theta_2| B, B)v_2) -((\sigma + \frac{1}{2}(1 - \sigma))\frac{1}{2}(v_2 + v_3) + \frac{1}{2}(1 - \sigma)v_1) \geq t_e.
\]

The entrant may design a system that covers all companies \( \theta_1 \) and \( \theta_2 \) regardless the rating obtained from the incumbent rating agency. Alternatively, it may focus on particular groups of companies. [compare these alternatives.]

5.2 Long run equilibrium

In the long run, insurance companies have a possibility to purchase one or two ratings. In this case the rating systems of the entrant and the incumbent need to be considered simultaneously.

In line with the analysis presented above, the incentives to buy a second rating arise from the ability to signal high quality to the market and to increase the valuation that customers are ready to pay for the contract. Since second rating provide better information about the quality of the company, high risk companies have no incentives to demand a second rating.

[segmentation of the market, stringency of the incumbent and the entrant, impact on precision]

6 Empirical Analysis

In this section we empirically investigate the accuracy and stringency of the ratings assigned by two of the largest agencies that follow the property-liability insurance industry: the A.M Best Company and Standard & Poor’s. A.M. Best has covered the insurance industry for close to one hundred years. The company publishes ratings on virtually all insurers and, prior to the mid-1980’s, they were the only agency doing so. The monopoly position A.M. Best enjoyed, however, began to change in the mid-1980’s as new agencies began assigning ratings to insurers. The most aggressive firm to enter the market was Standard & Poor’s. S&P began publishing ratings on property-liability insurers in 1983, expanded their coverage to 100 firms in 1987, and
then significantly expanded coverage again in 1991 (Standard & Poor’s 1987; A.M. Best 1992). Today, S&P provides ratings on insurers that represent in excess of 80 percent of the assets of the industry – more than any other rating company except Weiss Research.

In this study we obtained data on all ratings assigned to property-liability insurers by A.M. Best from 1989-2000 and by Standard & Poor’s from 1992-2000. We use this information to investigate two primary research objectives. First, we are interested to empirically compare the stringency and accuracy of the ratings assigned by the incumbent firm (A.M Best) and by the new entrant into this market (S&P). How do S&P ratings compare to A.M. Best ratings? Are they more stringent or less stringent? Do they appear more accurate or less accurate? The second objective we have is to investigate how the accuracy and stringency of Best’s ratings changed over time in response to the increased competition they faced from S&P and other new entrants.

The benchmark we use to investigate these questions is the probability of default for each firm in our data set. The one-year probability of default is a reasonable benchmark since both agencies state the primary objective of their rating systems is to provide an opinion about the insurer’s ability to meet its contractual obligations to policyholders. We use these probabilities to estimate the stringency of the rating system by looking at either the median or mean probability of default for a given rating class. Presumably companies with lower probabilities of default should, on average, expect to receive higher ratings from each agency. More stringent ratings standards are said to exist when the average probability of default for insurers in a particular rating class is lower for one agency than the other.

The accuracy of the rating system will be measured by looking at the amount of dispersion of the estimated default probabilities conditional upon rating class. We use two measures of dispersion: First, the standard deviation of estimated probabilities for a particular rating class; and second, the difference between companies at the 90th percentile of the estimated probabilities for a particular rating class versus companies at the 10th percentile. Either measure of dispersion should give us an idea of the amount of noise in the rating category from each agency.

### 6.1 Estimating Default Probabilities: Methodology and Data

A variety of methods can be used to forecast the likelihood of bankruptcy for an insurance company. U.S. regulatory authorities use three univariate models to forecast bankruptcy. The Insurance Regulatory Information System (IRIS), the oldest system, utilizes a series of twelve audit ratios based upon financial statement data filed with the regulators. The newer Financial Analysis and Surveillance Tracking (FAST) system uses an expanded set of audit rations,
approximately thirty, where each ratio is given a corresponding score. Regulators multiple each individual ratio by its corresponding score and then sum over all ratios to produce a FAST score. Insurers with higher FAST scores are more likely to become financially distressed and are subject to greater regulatory scrutiny. The final regulatory system is the risk-based capital (RBC) system introduced in 1994. The risk based capital system defines a minimum amount of capital insurers must hold where the individual capital charges are a function of the riskiness of the assets and the businesses in which the insurer participates.

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

Unfortunately most, if not all of these models discussed can be considered static models as they are typically implemented using data that spans only one or just a few years of data. At a minimum, these static models are inadequate for the long-term panel data that we assembled for this study. In addition, recent research suggests that arbitrarily choosing when to observe each firm’s characteristics leads to unnecessary selection bias problems and reduced forecasting ability (Theodossiou 1993).

In this study we use the discrete-time hazard model suggested by Shumway (2001) to overcome the biases of the static models and to take advantage of our panel data. The hazard model approach has at least two primary advantages over the more traditional static models. First, hazard model allow for time-varying covariates that explicitly recognize the financial health of some firms may deteriorate over time even though the firm does not declare bankruptcy. Static models, on the other hand, only make comparisons between firms that are classified as healthy or not healthy at just one point in time and they therefore ignore firms that are at risk of bankruptcy even though they do not become bankrupt. Shumway shows ignoring this information creates a selection bias which leads to biased and inconsistent parameter estimates. Intuitively, hazard models correct this problem by allowing the researcher to extract useful information from the times series data on each individual firm. In addition, it can be shown that the parameter estimates from hazard models are unbiased and consistent.

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

Implementing the discrete-time hazard model is rather straightforward since it can be shown that the likelihood function of a discrete time hazard model is identical to the likelihood function for a multiperiod logit model. Thus, estimating the hazard model is equivalent to estimating the traditional static logistic model except the coding of the dependent variable is slightly different. The dependent variable for the hazard model, $y_{it}$, is a binary indicator set equal to 1 if firm $i$ is declared bankrupt in year $t+1$ and equals 0 otherwise. Thus, the dependent variable equals 0 for each year the firm does not exit the system. Otherwise, each bankrupt firm contributes only one failure observation, i.e., $y_{it} = 1$, in the last year the firm has data. Firms which survive the entire data period never receive a value of 1 and firms that become bankrupt no longer have observations after their last year of operation. Time varying covariates are easily incorporated by using each firm’s annual data.

The data to estimate the hazard model comes from the annual regulatory statements of all property-liability insurers maintained in electronic form by the National Association of Insurance Commissioners (NAIC). We include all firms that meet our data requirements (discussed below) over the years 1989-2000. As previously discussed, the dependent variable for the model, $y_{it}$, is a binary indicator set equal to 1 if firm $i$ is declared bankrupt in year $t+1$ and equals 0 otherwise. Consistent with the literature, we define the year of insolvency as the year that the first formal regulatory action is taken against a troubled insurer (e.g., Grace, Harrington and Klein 1998; Grace, Klein and Phillips 2005). We identify the year of first regulatory against insurers through a variety of sources including the NAIC’s Report on Receiverships for various years and the Status of Single-State and Multi-State Insolvencies (various years). We also obtained the list of insolvent insurers provided in a report by A.M. Best Company (A.M. Best, 2002), which lists all property-liability insurers that failed from 1969-2001. From these sources we identified 300 property-liability insurers that failed between 1990 and 2001.

The explanatory variables we use to estimate the hazard model are nineteen of the balance sheet and income statement ratios that make up the NAIC’s FAST solvency tracking system. We use the FAST variables for several reasons. First, the FAST system utilizes all of the same ratios used in the older solvency tracking system IRIS but includes several new variables that have been shown to have additional predictive power. Thus, the FAST ratios should provide more accurate bankruptcy probabilities than the IRIS system variables alone.

The second reason we use the FAST variables is due to research by Grace, Harrington and
Klein (1995) who test the FAST system plus a controls for firm size and organizational form against alternative specifications that include additional audit ratios. The authors conclude there were diminishing marginal returns to incorporating additional balance sheet and income statement ratios not already included in the FAST system plus the two control variables. Thus, short of adopting information from alternative modeling methodologies (e.g., simulation), the FAST system seems to capture as much predictive power as can be gleaned from financial statement ratios alone.

The variable we use to control for firm size equals the natural logarithm of the real assets of the firm where the price deflator we use is the Consumer Price Index. The organization form control variable is an indicator set equal to 1 if the insurer either belongs to a mutual or reciprocal group of insurers or is a single insurer that is either a mutual or a reciprocal. Otherwise the indicator variable is set equal to zero.

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

6.2 Estimating Default Probabilities: Summary Statistics and Regression Results

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

The results of the discrete-time hazard model are shown in Panel A of Table 2. Overall
the explanatory power of the model is reasonable as the pseudo R2 statistic is 26 percent. The results are consistent with many of the inferences that were discussed after reviewing the summary statistics shown in Table 1. The estimated beta coefficients suggest highly levered firms, rapidly growing firms, and firms that rely more heavily upon reinsurance to increase policyholder surplus are associated with higher failure rates. Larger firms and insurers that are part of mutual organizations are relatively safe. Finally, firms that have high cash outflows relative to inflows or who experience adverse reserve development are more likely to fail.

Looking at the estimated probabilities of default is another way to judge the reasonableness of the estimated hazard model. Summary statistics of the estimated one-year probabilities of default are shown in Panel B of Table 2. The average/median probability of default for the healthy firms is 0.8/0.2 percent while the average/median statistics for the firms in the year before they become bankrupt is 9.4/4.5 percent. Thus, the average probability of default for bankrupt firms is over 10 times larger than the average probability for healthy firms. Clearly the model does a reasonable job assigning high default probabilities to firms that ultimately fail and low probabilities to healthy firms.

6.3 Stringency and Accuracy Tests: A.M. Best vs. Standard & Poor’s

In this section we present statistics on the distribution of the ratings assigned by A.M. Best and S&P over the time period of this study. After presenting the general trends, we then compare and contrast the stringency and accuracy of the two rating systems.

In order to compare Best’s rating systems with S&P’s we need to define a mapping between the different symbols used by the two agencies. Unfortunately there is not a one-to-one mapping between two systems and prior research comparing insurance ratings across agencies have used different definitions. For this study we reviewed the verbal descriptions each agency ascribes to the individual ratings and decided to use the five rating categories shown in Table 3. Numerical values, also shown in the table, are assigned to each rating category to facilitate comparisons across agencies and over time.

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

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

One possible explanation for the difference of opinion regarding the average health of the industry across the agencies could be because the firms that A.M. Best tracked were, on average, of higher financial quality than the firms tracked by S&P. To consider this possibility, we calculated the average and median probability of default using the results from the hazard model for insurers tracked by A.M. Best and by S&P over the time period of this study. The results are shown in Table 5. Contrary to the hypothesis, the average and median probability of default statistics are always lower for S&P than they are for A.M. Best suggesting the firms tracked by S&P are typically of higher financial quality firms – not lower. The non-parametric Wilcoxon-Mann-Whitney test rejects the null hypothesis of equal medians for all nine years and the parametric t-test rejects the null hypothesis of equal means in seven out of nine years.

Since the financial quality of firms rated by S&P appears, on average, to be better than Bests, another possible explanation for the difference in opinion may be because S&P entered this market by employing higher standards. Before we can investigate this possibility, however, we first need to review how S&P entered this market.

Prior to 1991, S&P provided coverage to only a small number of property-liability insurers (approximately 100). However, in 1991, S&P dramatically expanded their coverage by introducing a new rating service they called “Insurance Solvency Review.” The primary enhancement in the new service was that S&P increased the number of firms it covered by offering a “qualified ratings” in addition to their traditional ratings. The methodology used to determine a qualified
rating for an insurer differed in at least three important ways from the traditional manner. First, qualified ratings were solely based upon publicly available data. Thus, unlike the traditional method, S&P analysts did not interview or speak to the management of an insurer prior to issuing the qualified rating. Second, individual insurers were not required to request the rating or to pay a fee to receive the qualified rating. Finally, the third important difference was that S&P had a policy that no insurer could receive above a BBB rating using the qualified method – regardless of the characteristics of the company. S&P ultimately relaxed this position following significant criticism from the industry and began to issue qualified ratings above BBB in 1994.

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

We know from Table 6 the average ratings issued by S&P differ significantly across the two rating methodologies. But do the firms differ? In addition, how did the standards S&P used to assign ratings differ from A.M Best? To answer these questions consider Table 7 which shows summary statistics regarding the default probabilities of firms rated by A.M Best’s and those rated by S&P’s on a qualified and unqualified basis.

First, consider the stringency of the standards employed across the three rating technologies. There is clearly a natural ordering within each rating technology: firms that received higher ratings had, on average, lower probabilities of default. For example, the average probability of default for firms rated by A.M. Best increases monotonically by rating category from a low of 0.25 percent for firms rated “Extremely Strong” to a high of 3.11 percent for firms that received the lowest rating “Marginal.” A similar pattern can be seen for S&P firms that received either a full or qualified rating. The results suggest that at least, on average, each of the three technologies required firms to be less likely to default in order to receive a higher rating.

Now consider the stringency across rating technologies. Figure 2 graphically displays the average probability of default of the firms over the time period of this study by rating category across each of the three rating technologies (the data can be seen in Table 7). It is easy to
see the stringency employed by A.M. Best and S&P are almost identical when S&P issued a full unqualified rating. This is particularly true in the higher rating categories (Extremely Strong, Strong, and Good) where the average probability of default for firms in the categories was almost identical. In stark contrast, however, is the case when S&P issued an unqualified rating. In this case we find the average probability of default was substantially lower in each rating category relative to Bests and S&P’s own full rating standards. For example, firms that received an adequate rating (BBB) from S&P on a qualified basis had an average probability of default equal to 0.22 percent. A firm with a default probability of 0.22 percent likely would have received either an Extremely Strong (AAA) or a Strong (AA) rating if S&P was using their full rating standards.

It is also interesting to consider the accuracy of the assignment of ratings across rating categories. Figure 3 displays the difference between the 90th and 10th percentile of the probability of default for firms in each rating category (the data can be seen in Table 7). The comparison across rating technologies is very similar to the conclusions that were drawn regarding stringency. S&P’s full rating system and A.M Best’s methodology had almost the same amount of noise in each rating category. The only exception to this general conclusion is the Marginal rating category where Best appears to have a wider range of default probabilities for firms in that category. This seems reasonable since Best rated many more insurers than did S&P and many of these are small insurers with lower financial quality (see Figure 2 where the average probability of default for insurers rated marginal by Best is also significantly higher than the average for insurers rated marginal by S&P). S&P’s qualified rating system, however, had significantly less noise than Bests or S&P’s full rating system.

There are two possible explanations for the results shown in Table 7. Clearly one possibility is that the standards S&P employed when they issued qualified ratings were much more stringent than those they used when the insurer paid a fee to receive a full rating. In addition, it suggests S&P very carefully choose insurers to issue a qualified rating to and then carefully placed those insurers in rating categories lower than what they would have received had they agreed to pay for a full rating methodology. Then, when the insurer agreed to pay a fee to receive a full rating, S&P would move some insurers into a more appropriate rating category or, in the language of our theoretical model, would misclassify some insurers which showed up as an increased amount of noise in the full rating system.

A second explanation for the results we show in Figures 2 and 3 is that it is possible, if not probable, that our econometric model does not fully capture all information that would be useful to determine the default probability of each insurer. More specifically, when a firm agrees to
pay for a full rating, S&P analysts presumably learn private information about the firm which is then factored into the ultimate ratings. Therefore, all we may be picking up is that we have an omitted variable problem since we only include publicly available information in our hazard model. Unfortunately, it is difficult to control for the information that S&P learns when they engage in conversations with the management of insurers when they decide to receive a full rating. Private information is, by its very nature, private.

One way to differentiate between the two explanations is to see how often S&P and A.M Best agree on the financial quality of firms they both review. In this case, the average financial quality of the firms included in the analysis is constant which allows us to avoid having to use the predicted probabilities from hazard model. In addition, in one case A.M. Best and S&P both gain private information and, in the other, only A.M Best has the private information.

Table 8 shows two frequency matrices where each matrix compares the ratings assigned to the firm when the firm is rated by both agencies. The cells of each matrix $c_{ij}$ display the number of firm-year observations that received rating $i$ from A.M Best and rating $j$ from S&P where $i,j \in \{\text{Extremely Strong, Strong, Good, Adequate, and Marginal}\}$. For example, over the time period 1992 – 2000, there were 281 firm-year observations where both agencies, A.M. Best and S&P using there full rating methodology, issued an Extremely Strong rating to the firm (see Panel A). Cells along the main diagonal of the matrices display cases where A.M Best and S&P issued the exact same rating. Cells along the two off-diagonals next to the main diagonal, coded in orange, are cases where A.M Best and S&P disagree slightly about the financial quality of the firm. For example, in the diagonal just below the main diagonal, A.M. Best was slightly more optimistic about the fortunes of the firm than was S&P as these firms received an A.M Best rating that is one category better than the rating they received from S&P. Cells coded in coded in green (blue), located in the lower (upper) triangles of each matrix represent cases where the S&P rating differed substantially from the A.M. Best rating. Cells in the lower (upper) triangle represent cases where S&P issued a rating that was significantly below (above) the rating issued by A.M Best.

Panel A of Table 8 compares the rating given by Best with the rating S&P issued when they used their full rating methodology. The results suggest A.M Best and S&P tended to agree in most cases about the financial health of the insurers they both oversaw over the time period. In 37 percent of the cases, Best and S&P agreed completely regarding the financial prospects of the insurers and they agreed to disagree only slightly on another 58 percent of the observations. It is also interesting to note that when S&P does diverge slightly from A.M. Best, they are more likely to issue a rating one category below the rating Best rather than one category above. There were
very few cases, only 4.7 percent of the observations, where S&P and Best’s completely disagreed about the financial health of the insurer. These results strengthen our earlier conclusion that, for the most part, A.M Best and S&P employed approximately the same standards when S&P issued a full rating.

Panel B tells a completely different story. The data in this matrix compares Best’s ratings with the rating S&P issued on a qualified basis. The results show S&P issued a rating that was at least two categories lower than A.M. Best in almost 60 percent observations (the comparable number in Panel A is only 4 percent). In addition, the percentage of cases where A.M. Best and S&P issued the same rating on a firm dropped from 37 percent in Panel to just 10.5 percent in Panel B. Clearly the standards S&P used to assign qualified ratings was significantly more stringent than the standards they used in their full rating methodology. In addition, the results lend significant credibility to the conclusion that S&P systematically chose insurers that would receive a qualified rating and then downgraded those insurers relative to what they would have received had they agree to pay to receive for a full unqualified rating.

6.4 A.M. Best’s Reaction to S&P’s Entry

Did Best react to S&P’s entry into this market? It will be difficult to find direct evidence Best reacted to the strategies S&P employed to enter the market for property-liability insurer ratings. However, there is evidence Best did change their standards as competition for ratings increased. For example, in previous research Doherty and Phillips (2002) used an ordered probit model to study the determinants of Best’s ratings and report a significant and negative relationship between Best’s ratings and time after controlling for the financial quality of the firm. Specifically, holding firm quality constant, the authors showed an insurer could expect a 0.75 drop in rating category in the year 1999 relative to the standard that would have been applied in 1988.

We find similar results in this research. Table 9 – Panel A shows the median probability of default of the firms rated by A.M. Best by rating category over the years 1989-2000. In Panel B we show the ratio of the median probability of firms by rating category relative to the median probability of default for all insurers rated by A.M. Best in that year. We divide by the median default probability in each year because recent theoretical and empirical work suggests rating agencies have incentives to adjust their standards relative to the location of the distribution of credit quality in the industry/economy. For example, Prakash (2005) uses data on corporate bond ratings and shows there is a direct relationship between the quarterly change in the probability of default for the median firm in the economy and quarterly change in the standards he estimates for a firm from Standard & Poor’s. Nayak (2001) argues rating agencies
follow standards that are relative to the financial condition of firms in the economy. Specifically, he finds evidence ratings agencies determine ratings not by looking at the characteristics of the firm itself but instead by looking at the firm’s audit ratios and position relative to the median firm in that industry. Finally, the theoretical model presented earlier in this paper argues a rating agency will adjust the threshold (parameter a) as a function of the location of the distribution of the credit quality of the firms, E(X).

The results in Panel A suggest there was no significant time in the median probability of default for firms assigned to any particular rating category except the lowest rated firms. However, in Panel B we find evidence of a significant negative relationship between the median probabilities of default for firms in the Good and Strong categories relative to the median probability of default for all rated firms. For example, the average ratio of the median default probability for firms in the Strong category relative to the median for all rated firms over the years 1989-1991 was 1.0. This ratio dropped to be an average 0.75 for the last three years of this study. Thus, for at least the Strong and Good categories, we find evidence consistent with Best increasing stringency for firms to achieve either “Good” and “Strong” ratings - results consistent with earlier reported by Doherty and Phillips (2002).
Appendix

Proof of Proposition 2. Suppose that there is an equilibrium in which type $\theta_3$ is the only type that obtains a second rating. In such an equilibrium observing a second rating is correctly interpreted by customers that a company has high insolvency risk. Therefore, regardless the structure of entrant’s rating system, the payoff of $\theta_3$ equals to $v_3$. At the same time, type $\theta_3$ can guarantee the payoff of $v_3$ without obtaining any rating. Thus, this is not an equilibrium.

Suppose that there is an equilibrium in which types $\theta_2$ and $\theta_3$ obtain a second rating, and type $\theta_1$ does not obtain a second rating. By deviating and not obtaining a second rating, type $\theta_2$ increases its payoff: First, it does not incur a positive cost of a second rating $t_e$. Second, it is interpreted by customers as either type $\theta_1$ or type $\theta_2$, which increases the valuation of its contract. □
Figure 2
Average Probability of Default by Rating Category
A.M. Best vs. Standard & Poor's Full Rating vs. Standard & Poor's Qualified Rating
Figure 3

Difference between the 90\textsuperscript{th} and 10\textsuperscript{th} Percentile Probability of Default by Rating Category

A.M. Best vs. Standard & Poor's Full Rating vs. Standard & Poor's Qualified Rating
Figure 4

Adequate
Good
Strong
Extremely Strong

Ratio: Median Pr(Defaul) for Firms in Rating Category I over Median Pr(Defaul) All Rated Firms

Year


1.500
2.000
2.500
3.000

0.000
0.500
1.000
1.500
2.000
2.500
3.000

y = -0.010x + 1.843
R² = 0.028

y = -0.019x + 1.260
R² = 0.425

y = -0.027x + 1.023
R² = 0.615

y = 0.008x + 0.544
R² = 0.157
Table 1: FAST Ratio and Control Variable Summary Statistics: Solvent versus Insolvent Insurers 1989 - 2000

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

<table>
<thead>
<tr>
<th>Variable</th>
<th>Solvent Insurers</th>
<th>Insolvent Insurers</th>
<th>Test Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\mu_{sol}$</td>
<td>$\sigma_{sol}$</td>
<td>$\mu_{ins}$</td>
</tr>
<tr>
<td>Kenney Ratio: NPW to Policyholder Surplus</td>
<td>1.13</td>
<td>0.85</td>
<td>1.87</td>
</tr>
<tr>
<td>Reserves to Policyholder Surplus</td>
<td>1.03</td>
<td>0.94</td>
<td>1.64</td>
</tr>
<tr>
<td>1 Yr. Growth in NPW (%)</td>
<td>11.87</td>
<td>41.62</td>
<td>11.69</td>
</tr>
<tr>
<td>1 Yr. Growth in GPW (%)</td>
<td>11.94</td>
<td>37.63</td>
<td>11.06</td>
</tr>
<tr>
<td>Surplus Aid to Policyholder Surplus</td>
<td>2.05</td>
<td>4.34</td>
<td>6.07</td>
</tr>
<tr>
<td>Investment Yield (%)</td>
<td>5.71</td>
<td>1.38</td>
<td>5.41</td>
</tr>
<tr>
<td>1 Yr. Growth in Policyholder Surplus (%)</td>
<td>8.82</td>
<td>16.30</td>
<td>-8.50</td>
</tr>
<tr>
<td>Two-year Reserve Development to Policyholder Surplus (%)</td>
<td>-2.73</td>
<td>10.80</td>
<td>4.00</td>
</tr>
<tr>
<td>Gross Expenses to GPW</td>
<td>0.58</td>
<td>0.76</td>
<td>0.55</td>
</tr>
<tr>
<td>1 yr. Change in Gross Expenses (%)</td>
<td>0.05</td>
<td>0.47</td>
<td>0.09</td>
</tr>
<tr>
<td>1 yr. Change in Liquid Assets (%)</td>
<td>1.17</td>
<td>2.66</td>
<td>0.37</td>
</tr>
<tr>
<td>Investments in Affiliates to Policyholder Surplus</td>
<td>0.58</td>
<td>1.32</td>
<td>0.94</td>
</tr>
<tr>
<td>Receiv's. from Affiliates to Policyholder Surplus</td>
<td>0.02</td>
<td>0.04</td>
<td>0.04</td>
</tr>
<tr>
<td>Misc. Recoverables to Policyholder Surplus</td>
<td>0.03</td>
<td>0.05</td>
<td>0.07</td>
</tr>
<tr>
<td>Non-investment Grade Bonds to Policyholder Surplus</td>
<td>0.65</td>
<td>2.37</td>
<td>0.68</td>
</tr>
<tr>
<td>Other Invested Assets to Policyholder Surplus</td>
<td>0.01</td>
<td>0.03</td>
<td>0.02</td>
</tr>
<tr>
<td>Dummy = 1 if insurer has a large single agent</td>
<td>0.12</td>
<td>0.33</td>
<td>0.22</td>
</tr>
<tr>
<td>Dummy = 1 if insurer has a large single agent they control</td>
<td>0.08</td>
<td>0.28</td>
<td>0.12</td>
</tr>
<tr>
<td>Losses, Exp's, Div's and Taxes Paid to Premiums Collected</td>
<td>1.29</td>
<td>0.73</td>
<td>1.59</td>
</tr>
<tr>
<td>Total Assets (000000's in 2000 $)</td>
<td>433.65</td>
<td>2215.43</td>
<td>100.76</td>
</tr>
<tr>
<td>Indicator = 1 if insurer is part of a mutual group</td>
<td>0.26</td>
<td>0.44</td>
<td>0.08</td>
</tr>
</tbody>
</table>
Table 2: Hazard Model Regression Results

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

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient Estimate</th>
<th>Standard Error</th>
<th>$\chi^2$ Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-0.7577</td>
<td>1.1653</td>
<td>0.4228</td>
</tr>
<tr>
<td>Kenney Ratio: NPW to Policyholder Surplus</td>
<td>0.0047</td>
<td>0.0015</td>
<td>10.3304 ***</td>
</tr>
<tr>
<td>Reserves to Policyholder Surplus</td>
<td>189.3000</td>
<td>121.0000</td>
<td>2.4455</td>
</tr>
<tr>
<td>1 Yr. Growth in NPW (%)</td>
<td>0.0055</td>
<td>0.0026</td>
<td>4.3943 **</td>
</tr>
<tr>
<td>1 Yr. Growth in GPW (%)</td>
<td>0.5068</td>
<td>0.2575</td>
<td>3.8733 **</td>
</tr>
<tr>
<td>Surplus Aid to Policyholder Surplus</td>
<td>0.0415</td>
<td>0.0128</td>
<td>10.5759 ***</td>
</tr>
<tr>
<td>Investment Yield (%)</td>
<td>-0.0117</td>
<td>0.0646</td>
<td>0.0328</td>
</tr>
<tr>
<td>1 Yr. Growth in Policyholder Surplus (%)</td>
<td>-0.0390</td>
<td>0.0063</td>
<td>38.6798 ***</td>
</tr>
<tr>
<td>Two-year Reserve Development to Policyholder Surplus (%)</td>
<td>0.0311</td>
<td>0.0086</td>
<td>13.0963 ***</td>
</tr>
<tr>
<td>Gross Expenses to GPW</td>
<td>0.2654</td>
<td>0.1796</td>
<td>2.1834</td>
</tr>
<tr>
<td>1 yr. Change in Gross Expenses (%)</td>
<td>-0.1195</td>
<td>0.1961</td>
<td>0.3714</td>
</tr>
<tr>
<td>1 yr. Change in Liquid Assets (%)</td>
<td>-0.0462</td>
<td>0.0517</td>
<td>0.7956</td>
</tr>
<tr>
<td>Investments in Affiliates to Policyholder Surplus</td>
<td>0.0000</td>
<td>0.0000</td>
<td>10.9740 ***</td>
</tr>
<tr>
<td>Receiv's. from Affiliates to Policyholder Surplus</td>
<td>3.3208</td>
<td>1.6962</td>
<td>3.8327 *</td>
</tr>
<tr>
<td>Misc. Recoverables to Policyholder Surplus</td>
<td>2.1060</td>
<td>1.2641</td>
<td>2.7755 *</td>
</tr>
<tr>
<td>Non-investment Grade Bonds to Policyholder Surplus</td>
<td>0.0556</td>
<td>0.0317</td>
<td>3.0818 *</td>
</tr>
<tr>
<td>Other Invested Assets to Policyholder Surplus</td>
<td>6.7624</td>
<td>2.2026</td>
<td>9.4257 ***</td>
</tr>
<tr>
<td>Dummy = 1 if insurer has a large single agent</td>
<td>0.6341</td>
<td>0.2205</td>
<td>8.2740 ***</td>
</tr>
<tr>
<td>Dummy = 1 if insurer has a large single agent they control</td>
<td>-0.3205</td>
<td>0.2870</td>
<td>1.2477</td>
</tr>
<tr>
<td>Losses, Exp's, Div's and Taxes Paid to Premiums Collected</td>
<td>0.6960</td>
<td>0.1589</td>
<td>19.1885 ***</td>
</tr>
<tr>
<td>Ln(Total Assets in $2000)</td>
<td>-0.4707</td>
<td>0.0665</td>
<td>50.0860 ***</td>
</tr>
<tr>
<td>Indicator = 1 if insurer is part of a mutual group</td>
<td>-0.8337</td>
<td>0.2709</td>
<td>9.4694 ***</td>
</tr>
<tr>
<td>Log Likelihood Function Value</td>
<td>-908.617</td>
<td>-806.547</td>
<td>-11.4154</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>25.86%</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

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

The pseudo $R^2$ equals 1 minus the ratio of the log 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.

<table>
<thead>
<tr>
<th>Firm Type</th>
<th>Num</th>
<th>Ave.</th>
<th>Median</th>
<th>Standard Deviation</th>
<th>1st Percentile</th>
<th>99th Percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Solvent</td>
<td>24,062</td>
<td>0.81%</td>
<td>0.20%</td>
<td>2.46%</td>
<td>0.01%</td>
<td>11.08%</td>
</tr>
<tr>
<td>Insolvent</td>
<td>214</td>
<td>9.35%</td>
<td>4.46%</td>
<td>12.78%</td>
<td>0.09%</td>
<td>66.45%</td>
</tr>
</tbody>
</table>

The pseudo $R^2$ 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).
<table>
<thead>
<tr>
<th>Number</th>
<th>Description</th>
<th>A.M. Best</th>
<th>S&amp;P</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>Extremely Strong</td>
<td>A++,A+</td>
<td>AAA</td>
</tr>
<tr>
<td>3</td>
<td>Strong</td>
<td>A</td>
<td>AA</td>
</tr>
<tr>
<td>2</td>
<td>Good</td>
<td>A-</td>
<td>A</td>
</tr>
<tr>
<td>1</td>
<td>Adequate</td>
<td>B++,B+</td>
<td>BBB</td>
</tr>
<tr>
<td>0</td>
<td>Marginal</td>
<td>B and below</td>
<td>BB and below</td>
</tr>
</tbody>
</table>
Table 4
Number of Companies Rated and Average Rating
A.M. Best vs. Standard & Poor's 1989 - 2000

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

<table>
<thead>
<tr>
<th>Year</th>
<th>NAIC</th>
<th>A.M. Best</th>
<th>S&amp;P</th>
<th>Total Assets ($ billions)</th>
<th>NAIC</th>
<th>A.M. Best</th>
<th>S&amp;P</th>
<th>Average Rating</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1989</td>
<td>1903</td>
<td>1110 (58.3%)</td>
<td></td>
<td>534.6</td>
<td>491.6 (91.9%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1990</td>
<td>1897</td>
<td>1175 (61.9%)</td>
<td></td>
<td>566.5</td>
<td>511.6 (90.3%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1991</td>
<td>1968</td>
<td>1261 (64.1%)</td>
<td></td>
<td>615.2</td>
<td>565.1 (91.9%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1992</td>
<td>2012</td>
<td>1352 (67.2%)</td>
<td>360 (17.9%)</td>
<td>659.3</td>
<td>597.5 (90.6%)</td>
<td>218.9 (33.2%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1993</td>
<td>2061</td>
<td>1437 (69.7%)</td>
<td>349 (16.9%)</td>
<td>698.2</td>
<td>635.8 (91.1%)</td>
<td>164.5 (23.6%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1994</td>
<td>2065</td>
<td>1515 (73.4%)</td>
<td>391 (18.9%)</td>
<td>729.3</td>
<td>668.7 (91.7%)</td>
<td>177.9 (24.4%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1995</td>
<td>2084</td>
<td>1551 (74.4%)</td>
<td>393 (18.9%)</td>
<td>783.9</td>
<td>724.0 (92.4%)</td>
<td>200.0 (25.5%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1996</td>
<td>2100</td>
<td>1577 (75.1%)</td>
<td>572 (27.2%)</td>
<td>830.2</td>
<td>774.0 (93.2%)</td>
<td>554.6 (66.8%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1997</td>
<td>2096</td>
<td>1598 (76.2%)</td>
<td>568 (27.1%)</td>
<td>911.0</td>
<td>860.9 (94.5%)</td>
<td>612.9 (67.3%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1998</td>
<td>2096</td>
<td>1620 (77.3%)</td>
<td>587 (28.0%)</td>
<td>949.4</td>
<td>897.5 (94.5%)</td>
<td>644.1 (67.8%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1999</td>
<td>2042</td>
<td>1620 (79.3%)</td>
<td>583 (28.6%)</td>
<td>953.0</td>
<td>903.1 (94.8%)</td>
<td>655.7 (68.8%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2000</td>
<td>1952</td>
<td>1570 (80.4%)</td>
<td>590 (30.2%)</td>
<td>938.5</td>
<td>888.2 (94.6%)</td>
<td>645.4 (68.8%)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* - S&P provided ratings on property-liability insurers over the years 1989-1991. We were unable to locate this data in electronic format.
Table 5
Summary Statistics One-Year Probability of Default

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

<table>
<thead>
<tr>
<th>Year</th>
<th>Num</th>
<th>A.M. Best Mean</th>
<th>A.M. Best Median</th>
<th>Std. Dev.</th>
<th>Standard &amp; Poor's Num</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>T-Test</th>
<th>Non-Par.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1989</td>
<td>1110</td>
<td>0.40%</td>
<td>0.14%</td>
<td>1.39%</td>
<td>360</td>
<td>0.37%</td>
<td>0.11%</td>
<td>1.07%</td>
<td>3.050</td>
<td>4.427</td>
</tr>
<tr>
<td>1990</td>
<td>1175</td>
<td>0.60%</td>
<td>0.27%</td>
<td>1.25%</td>
<td>349</td>
<td>0.34%</td>
<td>0.09%</td>
<td>0.82%</td>
<td>1.767</td>
<td>4.027</td>
</tr>
<tr>
<td>1991</td>
<td>1261</td>
<td>0.50%</td>
<td>0.14%</td>
<td>1.80%</td>
<td>393</td>
<td>0.24%</td>
<td>0.06%</td>
<td>0.89%</td>
<td>2.604</td>
<td>5.744</td>
</tr>
<tr>
<td>1992</td>
<td>1352</td>
<td>0.64%</td>
<td>0.15%</td>
<td>2.55%</td>
<td>391</td>
<td>0.41%</td>
<td>0.10%</td>
<td>1.57%</td>
<td>0.601</td>
<td>4.953</td>
</tr>
<tr>
<td>1993</td>
<td>1437</td>
<td>0.47%</td>
<td>0.12%</td>
<td>2.15%</td>
<td>393</td>
<td>0.24%</td>
<td>0.06%</td>
<td>0.89%</td>
<td>2.604</td>
<td>5.744</td>
</tr>
<tr>
<td>1994</td>
<td>1515</td>
<td>0.46%</td>
<td>0.14%</td>
<td>1.18%</td>
<td>572</td>
<td>0.41%</td>
<td>0.14%</td>
<td>0.88%</td>
<td>4.988</td>
<td>5.028</td>
</tr>
<tr>
<td>1995</td>
<td>1577</td>
<td>0.88%</td>
<td>0.19%</td>
<td>3.44%</td>
<td>568</td>
<td>0.32%</td>
<td>0.11%</td>
<td>1.35%</td>
<td>2.771</td>
<td>4.767</td>
</tr>
<tr>
<td>1996</td>
<td>1598</td>
<td>0.52%</td>
<td>0.15%</td>
<td>1.72%</td>
<td>568</td>
<td>0.28%</td>
<td>0.12%</td>
<td>0.48%</td>
<td>5.421</td>
<td>5.108</td>
</tr>
<tr>
<td>1997</td>
<td>1620</td>
<td>0.69%</td>
<td>0.16%</td>
<td>2.91%</td>
<td>587</td>
<td>0.45%</td>
<td>0.16%</td>
<td>1.49%</td>
<td>3.935</td>
<td>3.898</td>
</tr>
<tr>
<td>1998</td>
<td>1620</td>
<td>0.80%</td>
<td>0.20%</td>
<td>2.55%</td>
<td>583</td>
<td>0.36%</td>
<td>0.17%</td>
<td>0.78%</td>
<td>5.129</td>
<td>3.548</td>
</tr>
</tbody>
</table>

Test Statistics
$H_0: \mu_{A.M.\text{Best}} = \mu_{S&P}$

<table>
<thead>
<tr>
<th>T-Test</th>
<th>Non-Par.</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.050</td>
<td>4.427</td>
</tr>
<tr>
<td>1.767</td>
<td>4.027</td>
</tr>
<tr>
<td>2.604</td>
<td>5.744</td>
</tr>
<tr>
<td>0.601</td>
<td>4.953</td>
</tr>
<tr>
<td>2.771</td>
<td>4.767</td>
</tr>
<tr>
<td>5.421</td>
<td>5.108</td>
</tr>
<tr>
<td>3.935</td>
<td>3.898</td>
</tr>
<tr>
<td>5.129</td>
<td>3.548</td>
</tr>
</tbody>
</table>

A.M. Best Mean vs. Standard & Poor's Mean and Median for each year from 1989 to 2000.
### Table 6

**Standard & Poor’s Qualified vs. Full Ratings: 1992 - 2000**

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

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

*** - significant at the 1 percent level

---

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

![Bar chart showing the number of firms with unqualified and qualified ratings by year from 1992 to 2000.](image)
Table 7
Stringency and Accuracy of A.M. Bests vs. Standard and Poor’s Ratings

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

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

<table>
<thead>
<tr>
<th>Rating</th>
<th>Num</th>
<th>μ</th>
<th>σ</th>
<th>10th</th>
<th>Median</th>
<th>90th</th>
<th>90th - 10th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extremely Strong</td>
<td>339</td>
<td>0.16%</td>
<td>0.22%</td>
<td>0.01%</td>
<td>0.09%</td>
<td>0.33%</td>
<td>0.32%</td>
</tr>
<tr>
<td>Strong</td>
<td>697</td>
<td>0.36%</td>
<td>1.40%</td>
<td>0.03%</td>
<td>0.13%</td>
<td>0.61%</td>
<td>0.58%</td>
</tr>
<tr>
<td>Good</td>
<td>515</td>
<td>0.51%</td>
<td>0.72%</td>
<td>0.06%</td>
<td>0.29%</td>
<td>1.16%</td>
<td>1.10%</td>
</tr>
<tr>
<td>Adequate</td>
<td>69</td>
<td>0.51%</td>
<td>0.93%</td>
<td>0.04%</td>
<td>0.22%</td>
<td>1.15%</td>
<td>1.11%</td>
</tr>
<tr>
<td>Marginal</td>
<td>6</td>
<td>1.11%</td>
<td>1.94%</td>
<td>0.01%</td>
<td>0.43%</td>
<td>5.03%</td>
<td>5.02%</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Rating</th>
<th>Num</th>
<th>μ</th>
<th>σ</th>
<th>10th</th>
<th>Median</th>
<th>90th</th>
<th>90th - 10th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extremely Strong</td>
<td>9</td>
<td>0.01%</td>
<td>0.02%</td>
<td>0.00%</td>
<td>0.01%</td>
<td>0.06%</td>
<td>0.06%</td>
</tr>
<tr>
<td>Strong</td>
<td>92</td>
<td>0.05%</td>
<td>0.06%</td>
<td>0.01%</td>
<td>0.02%</td>
<td>0.13%</td>
<td>0.12%</td>
</tr>
<tr>
<td>Good</td>
<td>673</td>
<td>0.15%</td>
<td>0.46%</td>
<td>0.02%</td>
<td>0.06%</td>
<td>0.26%</td>
<td>0.24%</td>
</tr>
<tr>
<td>Adequate</td>
<td>1131</td>
<td>0.22%</td>
<td>0.45%</td>
<td>0.02%</td>
<td>0.09%</td>
<td>0.44%</td>
<td>0.42%</td>
</tr>
<tr>
<td>Marginal</td>
<td>862</td>
<td>0.70%</td>
<td>1.84%</td>
<td>0.03%</td>
<td>0.20%</td>
<td>1.62%</td>
<td>1.58%</td>
</tr>
</tbody>
</table>

Panel C: A.M. Best Ratings

<table>
<thead>
<tr>
<th>Rating</th>
<th>Num</th>
<th>μ</th>
<th>σ</th>
<th>10th</th>
<th>Median</th>
<th>90th</th>
<th>90th - 10th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extremely Strong</td>
<td>4790</td>
<td>0.25%</td>
<td>0.74%</td>
<td>0.02%</td>
<td>0.10%</td>
<td>0.48%</td>
<td>0.46%</td>
</tr>
<tr>
<td>Strong</td>
<td>4593</td>
<td>0.31%</td>
<td>0.90%</td>
<td>0.03%</td>
<td>0.13%</td>
<td>0.64%</td>
<td>0.61%</td>
</tr>
<tr>
<td>Good</td>
<td>4067</td>
<td>0.43%</td>
<td>1.06%</td>
<td>0.04%</td>
<td>0.18%</td>
<td>0.91%</td>
<td>0.88%</td>
</tr>
<tr>
<td>Adequate</td>
<td>2683</td>
<td>0.77%</td>
<td>2.16%</td>
<td>0.06%</td>
<td>0.28%</td>
<td>1.66%</td>
<td>1.60%</td>
</tr>
<tr>
<td>Marginal</td>
<td>1253</td>
<td>3.11%</td>
<td>6.61%</td>
<td>0.12%</td>
<td>0.89%</td>
<td>7.91%</td>
<td>7.79%</td>
</tr>
</tbody>
</table>
Table 8

Table compares the ratings assigned by A.M Best and S&P for insurers that receive a rating from both firms. The data in Panel A includes all firms over the years 1992 - 2000 that receive a rating from A.M Best and a full rating from S&P. The data in Panel B includes all firms over the years 1992 - 2000 that receive a rating from A.M Best and a qualified 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 $i,j \in \{\text{Extremely Strong, Strong, Good, Adequate, Marginal}\}$.

### Panel A

<table>
<thead>
<tr>
<th>A.M. Best Rating</th>
<th>S&amp;P Full Rating</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>Extremely Strong</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Marginal</td>
<td>Adequate</td>
<td>Good</td>
<td>Strong</td>
<td>Strong</td>
<td></td>
</tr>
<tr>
<td>Marginal</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Adequate</td>
<td>3</td>
<td>5</td>
<td>9</td>
<td>4</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Good</td>
<td>0</td>
<td>51</td>
<td>147</td>
<td>29</td>
<td>6</td>
<td>0</td>
</tr>
<tr>
<td>Strong</td>
<td>0</td>
<td>4</td>
<td>280</td>
<td>118</td>
<td>9</td>
<td>0</td>
</tr>
<tr>
<td>Extremely Strong</td>
<td>0</td>
<td>0</td>
<td>56</td>
<td>490</td>
<td>281</td>
<td></td>
</tr>
</tbody>
</table>

Total number of firm-year observations: 1493

- S&P and A.M. Best agree: 36.97%
- S&P and A.M. Best almost agree: 58.34%
- S&P rates significantly higher than A.M. Best: 0.67%
- S&P rates significantly lower than A.M. Best: 4.02%

### Panel B

<table>
<thead>
<tr>
<th>A.M. Best</th>
<th>S&amp;P Qualified Rating</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>Extremely Strong</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Marginal</td>
<td>Adequate</td>
<td>Good</td>
<td>Strong</td>
<td>Strong</td>
<td></td>
</tr>
<tr>
<td>Marginal</td>
<td>69</td>
<td>26</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Adequate</td>
<td>175</td>
<td>100</td>
<td>11</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Good</td>
<td>154</td>
<td>236</td>
<td>84</td>
<td>2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Strong</td>
<td>198</td>
<td>413</td>
<td>291</td>
<td>8</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Extremely Strong</td>
<td>140</td>
<td>317</td>
<td>265</td>
<td>78</td>
<td>9</td>
<td></td>
</tr>
</tbody>
</table>

Total number of firm-year observations: 2576

- S&P and A.M. Best agree: 10.48%
- S&P and A.M. Best almost agree: 31.79%
- S&P rates significantly higher than A.M. Best: 0.00%
- S&P rates significantly lower than A.M. Best: 57.73%
Table 9
Median Probability of Default for Firms Rated By A.M. Best by Rating Category: 1989 - 2000

Table displays the median probability of default for all insurers rated by A.M. Best by rating category. Panel A shows the median probability of default and Panel B shows the median probability for the individual rating category divided by the median probability of default for all firms that received a rating from A.M. Best. The table also displays the estimated beta coefficient $\beta$ for the following time series regression:

$$\text{Med}_i = \alpha + \beta t + \epsilon_i$$

where $\text{Med}_i$ is the median probability of default for firms in rating category $i$ in year $t$. The p-value is the probability associated with rejecting the null hypothesis $H_0: \beta = 0$.

### Panel A

<table>
<thead>
<tr>
<th>Year</th>
<th>Marginal</th>
<th>Adequate</th>
<th>Good</th>
<th>Strong</th>
<th>Extremely Strong</th>
<th>All Firms</th>
</tr>
</thead>
<tbody>
<tr>
<td>1989</td>
<td>0.568</td>
<td>0.242</td>
<td>0.175</td>
<td>0.158</td>
<td>0.087</td>
<td>0.145</td>
</tr>
<tr>
<td>1990</td>
<td>1.066</td>
<td>0.494</td>
<td>0.307</td>
<td>0.288</td>
<td>0.167</td>
<td>0.266</td>
</tr>
<tr>
<td>1991</td>
<td>0.834</td>
<td>0.277</td>
<td>0.182</td>
<td>0.118</td>
<td>0.074</td>
<td>0.143</td>
</tr>
<tr>
<td>1992</td>
<td>0.862</td>
<td>0.244</td>
<td>0.199</td>
<td>0.119</td>
<td>0.093</td>
<td>0.153</td>
</tr>
<tr>
<td>1993</td>
<td>0.914</td>
<td>0.184</td>
<td>0.152</td>
<td>0.108</td>
<td>0.073</td>
<td>0.122</td>
</tr>
<tr>
<td>1994</td>
<td>0.646</td>
<td>0.314</td>
<td>0.152</td>
<td>0.121</td>
<td>0.074</td>
<td>0.139</td>
</tr>
<tr>
<td>1995</td>
<td>0.559</td>
<td>0.178</td>
<td>0.111</td>
<td>0.079</td>
<td>0.045</td>
<td>0.099</td>
</tr>
<tr>
<td>1996</td>
<td>1.011</td>
<td>0.387</td>
<td>0.188</td>
<td>0.149</td>
<td>0.114</td>
<td>0.189</td>
</tr>
<tr>
<td>1997</td>
<td>0.786</td>
<td>0.250</td>
<td>0.147</td>
<td>0.117</td>
<td>0.090</td>
<td>0.148</td>
</tr>
<tr>
<td>1998</td>
<td>1.094</td>
<td>0.280</td>
<td>0.182</td>
<td>0.118</td>
<td>0.118</td>
<td>0.163</td>
</tr>
<tr>
<td>1999</td>
<td>1.657</td>
<td>0.346</td>
<td>0.224</td>
<td>0.161</td>
<td>0.118</td>
<td>0.196</td>
</tr>
<tr>
<td>2000</td>
<td>1.112</td>
<td>0.301</td>
<td>0.212</td>
<td>0.141</td>
<td>0.145</td>
<td>0.204</td>
</tr>
</tbody>
</table>

| $\beta$ | 0.0452  | -0.0006 | -0.0019 | -0.0044 | 0.0021 | 0.0011 |
| p-value  | 0.069   | 0.942   | 0.673   | 0.334   | 0.495  | 0.274  |

### Panel B

<table>
<thead>
<tr>
<th>Year</th>
<th>Marginal</th>
<th>Adequate</th>
<th>Good</th>
<th>Strong</th>
<th>Extremely Strong</th>
</tr>
</thead>
<tbody>
<tr>
<td>1989</td>
<td>3.928</td>
<td>1.674</td>
<td>1.210</td>
<td>1.094</td>
<td>0.604</td>
</tr>
<tr>
<td>1990</td>
<td>4.006</td>
<td>1.855</td>
<td>1.151</td>
<td>1.081</td>
<td>0.627</td>
</tr>
<tr>
<td>1991</td>
<td>5.846</td>
<td>1.943</td>
<td>1.273</td>
<td>0.827</td>
<td>0.517</td>
</tr>
<tr>
<td>1992</td>
<td>5.637</td>
<td>1.596</td>
<td>1.302</td>
<td>0.781</td>
<td>0.605</td>
</tr>
<tr>
<td>1993</td>
<td>7.470</td>
<td>1.499</td>
<td>1.244</td>
<td>0.882</td>
<td>0.594</td>
</tr>
<tr>
<td>1994</td>
<td>4.646</td>
<td>2.261</td>
<td>1.089</td>
<td>0.872</td>
<td>0.530</td>
</tr>
<tr>
<td>1995</td>
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| $\beta$ | 0.195  | -0.010 | -0.019 | -0.027 | 0.008 |
| p-value  | 0.076  | 0.605  | 0.022  | 0.003  | 0.202 |