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Differences of opinion and selection bias in the credit rating industry

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Abstract

Many regulations use private sector credit ratings to determine investment prohibitions and capital requirements for institutional portfolio investments. These regulations implicitly assume that different agencies have equivalent rating scales, despite the fact that some agencies assign systematically higher ratings than others. We assess the appropriateness of these regulatory practices by testing whether observed rating differences reflect different rating scales or simply result from sample selection bias. Our analysis reveals only limited evidence of selection bias. We also ask what types of firms are most likely to seek ratings from the agencies with higher rating scales. Our analysis uncovers no evidence that firms seek ratings from these agencies to clear specific regulatory hurdles or to reduce ex ante uncertainty about default risk.

Keywords: Credit ratings; Bond ratings; Split ratings; Selection bias; Credit risk; Prudential regulation

JEL classification: G11; G12; G20; G23

1. Introduction

Regulators, like investors, use private sector credit ratings to economize on the resources they devote to credit evaluation. In particular, financial regula-

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tors employ a variety of specific letter ratings as thresholds for determining capital charges and investment prohibitions on institutional portfolio holdings. These regulators generally treat the ratings of different rating agencies as equivalent, and when the agencies disagree, usually recognize the highest rating. These practices would be hard to rationalize if different agencies based their ratings on different cardinal scales.

In fact, the two leading agencies, Moody's Investor Service and Standard and Poor's (S&P), assign lower corporate bond ratings on an average than their main competitors. It is unclear, however, whether these differences in average ratings reflect differences in rating scales or the existence of sample selection bias. The latter possibility arises because Moody's and S&P automatically assign ratings to all corporate bonds issued in US public markets, whereas their competitors provide ratings only when requested by issuers. Their competitors' ratings may therefore be sought predominantly by firms that have reason to expect they can improve upon their ratings from Moody's and S&P.

Ultimately, the issue of whether observed ratings differences reflect different rating scales or sample selection bias is an empirical question. Are the default risks associated with a particular letter grade higher for some agencies than for others? Or, do some agencies assign higher average ratings because they provide ratings only upon request? Our study is the first to estimate the importance of sample selection bias in explaining observed rating differentials. Our findings indicate that sample selection bias does not explain the average rating differentials and the same letter grades used by different agencies correspond to different levels of default risk. We also estimate a model for the firm's decision to obtain a third rating and find that frequent and large debt issuers are the most likely to obtain additional ratings. However, we do not find evidence that firms obtain additional ratings to help clear specific regulatory hurdles or to resolve greater ex ante uncertainty about default risk.

In Section 2 of this article, we describe the current regulatory use of ratings and document differences in average ratings across agencies. We then develop in Section 3 a model of ratings differences that can account for the impact of sample selection bias. In Section 4, we introduce our data set, based on a sample of 1,137 corporations which had credit ratings assigned by Moody's and S&P at year-end 1993. We present and estimate a model of the firm's decision to obtain a third rating in Section 5. In Section 6, we proceed to test hypotheses concerning the importance of sample selection bias. Section 7 concludes with a discussion of the implications of our results.

2. The credit rating industry, ratings scales, and regulatory uses

Two rating agencies, Moody's and S&P, dominate the US credit rating industry. Moody's was the first to begin rating bonds in 1909, and the two companies that merged to form S&P started their rating operations in 1916 and 1922. Both agencies currently have a policy of rating all taxable corporate bonds publicly issued in the United States regardless of whether they have been asked by an issuer for a rating. [1] The vast majority of issuers pay both Moody's and S&P for their ratings despite no legal obligation to do so because this allows them to put their best case before the agencies in the context of a cooperative ratings process.

Two other US rating agencies also have a long history, but do not rate as many corporate bond issues as Moody's and S&P. Fitch Investors Service began rating bonds in 1924; Duff & Phelps Credit Rating Agency (DCR), which began rating a wide range of companies in 1982, has researched public utility companies since 1932. [2] For our sample of 1,137 firms rated at year-end 1993 by Moody's and S&P, 336 firms also had ratings from DCR, 155 firms had ratings from Fitch. The smaller market shares of the latter two agencies reflect not only less intrinsic demand for their ratings but also their longstanding policy of rating bonds only on the request of the issuer. [3]

The bond ratings of all four agencies are comparable in the sense that they attempt to measure the likelihood of the default or delayed payment of a security. However, although each agency's ranking of relative default risks is simple to understand, the correspondence between their rating letters and absolute of measures default risk has not been made explicit by the agencies. S&P, DCR, and Fitch all use the same basic set of rating symbols, but Moody's uses a slightly different system. Table 1 provides the standard correspondence drawn by both the regulatory and investment communities between Moody's ratings and those of the other agencies. [4]

The early regulatory uses of ratings drew only on the agency distinctions between investment-grade securities – or those rated BBB– by S&P (Baa3 by Moody's) and above – and speculative-grade securities – those rated BB+ by S&P (Ba1 by Moody's) and below. Regulations required that extra capital be held against speculative securities or they prohibited such investments altogether. Although the distinction between investment-grade and speculative-

[1] The same agencies usually rate municipal bonds, asset-backed securities, and foreign issues only on request, although Moody's frequently issues unsolicited ratings. Our study is not concerned with ratings for these categories of issuers.

[2] Although a number of other credit rating agencies with a narrower focus operate in the United States, DCR, Fitch, Moody's and S&P are the only agencies that rate US corporate obligations across a broad industry spectrum. For example, Thomson Bankwatch and IBCA (in the United States) exclusively rate financial institutions and A.M. Best provides ratings on insurance companies' claims-paying abilities.

[3] In other markets, such as those for asset-backed securities, DCR and Fitch have greater market share.

[4] See, for example, the mapping provided by the National Association of Insurance Commissioners' Securities Valuation Office (1993), 50–53.

Table 1
Long-term debt rating symbols

Interpretation	Moody's	DCR, Fitch, S&P
Investment-grade ratings		
Highest quality	Aaa	AAA
High quality	Aa1	AA+
	Aa2	AA
	Aa3	AA−
Strong payment capacity	A1	A+
	A2	A
	A3	A−
Adequate payment capacity	Baa1	BBB+
	Baa2	BBB
	Baa3	BBB−
Speculative-grade ratings		
Likely to fulfill obligations, ongoing uncertainty	Ba1	BB+
	Ba2	BB
	Ba3	BB−
High-risk obligations [a]	B1	B+
	B2	B
	B3	B−

[a] The agencies do assign ratings to securities below this level of risk (very near or actually in default); however, they use different categorization systems that are difficult to compare.

grade securities remains important, over time regulatory capital requirements, disclosure requirements, and investment prohibitions have increasingly been tied to other letter grades as well. The history of selected uses of ratings by regulators is summarized in Table 2.

Since financial regulators adopted ratings-dependent rules, they have had to specify which agencies qualify for consideration under their regulations. The Securities and Exchange Commission (SEC) currently designates only Moody's, S&P, DCR, and Fitch as "nationally recognized statistical rating organizations" (NRSROs) for rating all US corporate bond issues; [5] the other regulators rely on the SEC's designations.

Most ratings-dependent regulations require that a bond issue carry only a single agency's rating. However, as issues almost always have more than one rating, regulators have developed methods for dealing with the inevitable differences of opinion across the rating agencies which frequently arise. The most common approach is to adopt an explicit rule, recognizing either the issue's highest or second-highest rating, regardless of the level of the other outstand-

[5] Ratings of financial institutions assigned by two other agencies, Thomson Bankwatch and IBCA, are also recognized as NRSRO ratings by the SEC.

Table 2
Selected uses of ratings in regulation

Year adopted	Rating-dependent regulation	Minimum rating	How many ratings?	Regulator/regulation
1931	Required banks to mark-to-market lower rated bonds	Baa/BBB	2	OCC and Federal Reserve examination rules
1936	Prohibited banks from purchasing "speculative securities"	Baa/BBB	Unspecified	OCC, FDIC, and Federal Reserve joint statement
1951	Imposed higher capital requirements on insurers' lower rated bonds	Various	N.A.	NAIC mandatory reserve requirement
1975	Imposed higher capital haircuts on broker/dealers' below-investment-grade bonds	Baa/BBB	2	SEC amendment to Rule 15c3-1; the uniform net capital rule
1982	Eased disclosure requirements for investment-grade bonds	Baa/BBB	1	SEC adoption of Integrated Disclosure System (Release #6383)
1984	Eased issuance of nonagency mortgage-backed securities (MBSs)	Aa/AA	1	Congressional promulgation of the Secondary Mortgage Market Enhancement Act of 1984
1987	Permitted margin lending against MBS and (later) foreign bonds	Aa/AA	1	Federal Reserve Regulation T
1989	Allowed pension funds to invest in high-rated asset-backed securities	A/A	1	Department of Labor relaxation of ERISA Restriction (PTE 89-88)
1989	Prohibited S & Ls from investing in below-investment-grade bonds	Baa/BBB	1	Congressional promulgation of the Financial Institution Recovery and Reform Act of 1989
1991	Required money market mutual funds to limit holdings of low-rated bonds	P1/A1 [a]	1 [b]	SEC amendment to Rule 2a-7 under the Investment Company Act of 1940
1992	Exempted issuers of certain asset-backed securities from registration as a mutual fund	Baa/BBB	1	SEC adoption of Rule 3a-7 under the Investment Company Act of 1940
1994 Proposal	Would impose varying capital charges on bank and S & L holdings of different tranches of asset-backed securities	Aaa & Baa/AAA & BBB	1	Federal Reserve, OCC, FDIC, OTS proposed rules on recourse and direct credit substitutes

[a] Highest ratings on short-term debt, generally implying an A long-term debt rating or better.
[b] If issue is rated by only one nationally recognized statistical rating organization, its rating is adequate; otherwise, two ratings are required.

Table 3
Rating differences between agencies

	Distribution of DCR's ratings relative to:		Distribution of Fitch's ratings relative to:	
	Moody's	Standard and Poor's	Moody's	Standard and Poor's
Percent rated higher	49.7	43.2	58.7	49.7
Percent rated same	39.6	44	35.5	43.2
Percent rated lower	10.7	12.8	5.8	7.1
Average difference in rating notches	0.60	0.46	0.74	0.56

Note: The table compares 363 firms rated jointly by Moody's, Standard and Poor's, and DCR, and 157 firms rated jointly by Moody's, S&P, and Fitch at year-end 1993.

ing ratings and the identity of the rating agency. Thus, regulators currently assume uniformity of cardinal rating scales across agencies.

There is, however, reason to doubt that rating scales are indeed uniform. Table 3 summarizes the average ratings differences observed in a large sample of credit ratings assigned at the end of 1993 by the Moody's, S&P, DCR, and Fitch. Consistent with previous studies (Beattie and Searle, 1992; Cantor and Packer, 1994), our sample reveals that DCR and Fitch give systematically higher ratings on jointly rated issues than Moody's and S&P. For instance, while DCR rates higher than Moody's 49.7% of the time, it rates lower than Moody's only 10.7% of the time, and on average rates 0.60 notches higher than Moody's. (A rating notch is, for example, the gap between an A and an A+rating.) Similar gaps can be seen in a comparison of Fitch and Moody's ratings and in a comparison of both DCR and Fitch and S&P's ratings on jointly rated issues.

From the point of view of regulatory practice, an agency with a higher average rating scale enables relatively more borrowers to meet minimum ratings cutoffs. However, the fact that an agency assigns higher average ratings on issues also rated by Moody's and S&P need not imply it has a higher rating scale, instead it may simply imply that firms rated severely by Moody's and S&P are more likely to seek a third rating. [6]

[6] In a letter to issuers in October 1995, Fitch Investors Service explained an intention to rate many issuers on a unsolicited basis as part of a strategy to "change the misperception that our ratings are higher than those of our competitors, which has resulted from our previous policy of only rating upon request of the issuer" (High Yield Report, 1995). To date, however, Fitch still rates almost exclusively on a solicited basis.

3. A model of ratings differences and the effects of sample selection bias

If all agencies rate all firms, then differences in the agencies' average ratings can be interpreted as differences in their rating scales. However, many firms do not receive ratings from DCR and Fitch. As a result, observed differences between the average ratings of these agencies and those of Moody's and S&P may reflect the effects of sample selection bias.

The following model makes the effects of sample selection bias amenable to empirical examination. Suppose rating agencies assign numerical ratings as follows:

$$r_{a,f} = \alpha_a + \mathbf{x}_f \boldsymbol{\beta}_a + \epsilon_{a,f}, \tag{1}$$

where $r_{a,f}$ is the rating assigned by agency a to company f, α_a a constant term that may vary across agencies, $\mathbf{x}_f$ a vector of observable information on company f, $\boldsymbol{\beta}_a$ a vector of coefficients summarizing agency a's rating technology, and $\epsilon_{a,f}$ the unobservable component of agency a's rating of firm f.

This final variable, $\epsilon_{a,f}$, is a random variable that reflects intangible factors inherent to the ratings process – public and private information on firm f not included in $\mathbf{x}_f$, and the agency's ratings technology that translates that information into ratings with error. The constant term α_a is defined so that the expectation of $\epsilon_{a,f}$ taken over the entire population of firms is zero.

Our primary equation of interest is the difference between the ratings of two agencies, m and o, assigned to the same firm, which is defined by

$$r_{\mathrm{m},f} - r_{\mathrm{o},f} = \alpha_{\mathrm{m}} - \alpha_{\mathrm{o}} + \mathbf{x}_f(\boldsymbol{\beta}_{\mathrm{m},f} - \boldsymbol{\beta}_{\mathrm{o},f}) + \epsilon_{\mathrm{m},f} - \epsilon_{\mathrm{o},f}, \tag{2}$$

where the subscripts m and o refer respectively to a "mandatory" agency, or one that publishes ratings on all issuers, and an "optional" agency, or one that only publishes upon request of the issuer. For ease of notation, we will rewrite Eq. (2) as

$$r_f = \alpha + \mathbf{x}_f \boldsymbol{\beta} + \epsilon_f, \tag{3}$$

where all variables and coefficients represent differences between agencies m and o and the agency subscripts have been suppressed. If both agencies rated the entire population of firms, then the mean of the observed rating differences would be an unbiased estimate of the difference in the agencies' cardinal ratings scales. However, we know that while the mandatory agency rates the entire population, P, of firms, the optional agency rates only a subsample, S, and thus we have data on r_f only for that subsample.

The hypothetical population regression of Eq. (3) may be written as

$$E[r_f \mid f \in P] = \alpha + E[\mathbf{x}_f \boldsymbol{\beta} \mid f \in P]. \tag{4}$$

The regression function for the subsample of the population with ratings from the optional agency is

$$E[r_f \mid f \in S] = \alpha + E[\mathbf{x}_f\boldsymbol{\beta} \mid f \in S] + E[\epsilon_f \mid f \in S]. \tag{5}$$

If the source of sample selection were purely random, the conditional expectation of ϵ_f in Eq. (5) would be zero and the conditional mean of $\mathbf{x}_f$ would equal its unconditional mean. Therefore, the mean of r_f for the subsample S would be an unbiased estimate of the population mean. If the sample selection is nonrandom, the sample mean of r_f may differ from the population mean simply because the mean of $\mathbf{x}_f$ differs between the sample and the population. Moreover, if sample selection is conditioned in part on ϵ_f, estimates of α and $\boldsymbol{\beta}$ in Eq. (3) will be biased. In particular, if $\boldsymbol{\beta}$ were zero, estimates of α would be biased upward if firms are more likely to obtain ratings from the optional agency when they have unusually high values of ϵ_f – that is, an exceptionally large positive difference between the optional firm's relative ratings ($\epsilon_{o,f}$) and the mandatory agency's relative ratings ($\epsilon_{m,f}$).

The existence of this sort of sample selection bias is a distinct possibility. A firm might know that the optional agency provides more favorable ratings treatment to firms in an industry with its specific characteristics. Alternatively, a firm might already know its rating from the mandatory agency before deciding whether to obtain a rating from the optional agency. Or a firm may be told its likely rating assignment by the optional agency before it is required to commit fully to the new agency's rating process.

Regardless of the source of sample selection, consistent estimates of α and $\boldsymbol{\beta}$ can be obtained with the two-step approach proposed by Heckman (1979). This approach utilizes information on the sample selection process in a first stage probit regression on the decision to obtain a third rating. If firm f's decision to obtain a rating from the optional agency is based on some exogenous characteristics $\mathbf{z}_f$ and a random variable η_f, which may be correlated with ϵ_f, then firm f's decision rule can be summarized by the following equation:

$$y_f = \mathbf{z}_f\boldsymbol{\gamma} + \eta_f \quad \text{for } f \in \mathbb{N}, \tag{6}$$

where y_f measures firm f's incentive to obtain a rating from the optional agency, $\boldsymbol{\gamma}$ a vector of parameters, $\mathbf{z}_f$ a vector of exogenous characteristics of firm f, and η_f a random error with mean zero, variance $\sigma_{\eta\eta}$ and covariance with ϵ, $\sigma_{\epsilon,\eta}$.

The variables that make up $\mathbf{z}_f$ include any observable factor that would influence the cost or benefit of obtaining a rating. Without loss of generality, we assume that the firm f obtains a rating from an optional agency if and only if $y_f > 0$. Hence, Eq. (5) can be rewritten as

$$\begin{aligned} E[r_f \mid f \in S] &= E[r_f \mid \eta_f > -\mathbf{z}_f\boldsymbol{\gamma}] \\ &= \alpha + E[\mathbf{x}_f\boldsymbol{\beta} \mid f \in S] + E[\epsilon_f \mid \eta_f > -\mathbf{z}_f\gamma]. \end{aligned} \tag{7}$$

If ϵ_f and η_f are jointly normally distributed, Eq. (7) can be rewritten as

$$E[r_f \mid \mathbf{z}_f, \eta_f > -\mathbf{z}_f\gamma] = \alpha + \mathbf{x}_f\boldsymbol{\beta} + (\rho/\sqrt{\sigma_{\epsilon\epsilon}})\lambda_f, \tag{8}$$

where ρ is the correlation between ϵ and η, and λ is the inverse Mills ratio, $\phi(v)/\Phi(-v)$, evaluated at $v = \mathbf{z}_f\boldsymbol{\gamma}/\sqrt{\sigma_{\eta\eta}}$.

The inverse Mills ratio is a measure of the extent to which a firm f appears in the sample of firms rated by agency j unexpectedly, based on their observed characteristics $\mathbf{z}_f$. Estimates of the inverse Mills ratio can be derived from a probit estimation of Eq. (6). Different specifications of this equation and an analysis of the resulting estimations are presented in Section 5.

Eq. (8) is then estimated using ordinary least-squares (OLS) regression. If estimates of Eq. (8) reveal a positive coefficient on λ, then $\rho > 0$, which implies that firms unexpectedly rated by the optional agency are more likely to have positive values of η_f. Using the least squares estimates of Eq. (8), the observed difference between the two agencies' average ratings can then be decomposed into the difference in the cardinal positioning of their rating scales $(\alpha + \boldsymbol{E}[\mathbf{x}_f\boldsymbol{\beta} \mid f \in P])$, the bias due to sample selection based on the "x's" $(\boldsymbol{E}[\mathbf{x}_f\boldsymbol{\beta} \mid f \in S] - \boldsymbol{E}[\mathbf{x}_f\boldsymbol{\beta} \mid f \in P])$, and other sources of sample selection,

$$(\rho/\sqrt{\sigma_{\epsilon\epsilon}}) * \boldsymbol{E}[\lambda_f \mid f \in S].$$

Having obtained estimates of α and $\boldsymbol{\beta}$, we can test the following two hypotheses:

H1: Sample selection does not cause the optional agency's average ratings to be biased relative to the ratings of the mandatory agency:

$$\boldsymbol{E}[r_f \mid f \in S] = \boldsymbol{E}[r_f \mid f \in P] = \alpha + E[\mathbf{x}_f\boldsymbol{\beta} \mid \mathrm{f} \in P].$$

H2: After accounting for sample selection bias, there is no difference between the mandatory and optional agencies' rating scales:

$$\boldsymbol{E}[r_f \mid f \in P] = \alpha + \boldsymbol{E}[\mathbf{x}_f\boldsymbol{\beta} \mid f \in P] = 0.$$

The alternative hypothesis to H1 is that sample selection bias does affect the average ratings differential; the alternative to H2 is that there are differences in rating scales even after accounting for sample selection bias.

The methodology outlined above follows much of the empirical literature on ratings by assuming that the ratings can be interpreted as cardinal variables. As a check on the robustness of our results to the weakening of this assumption, we also estimate an ordered multinomial probit estimation of Eq. (8), which assumes only that ratings signal a position relative to other ratings.

In particular, we divide the observed ratings differences r_f into three categories – the new agency rates higher, the same, or lower – and estimate the probabilities that ratings differences will fall into one of these categories. [7] These

[7] Note that we are treating rating *differences* as ordinal variables. One could in principle treat each agency's rating scale as an ordinal variable but that would require at least 16 parameter estimates for each agency.

estimates enable us to contrast the relative fractions observed directly in the data (subsample S) with those estimated for the population (sample P) when sample selection bias is taken into account. In this setup, H1 is the hypothesis that sample selection does not bias the ratio of the probability that the optional agency rates higher than the mandatory agency relative to the probability that it rates lower. Here, H2 is the hypothesis that, after adjusting for sample selection bias, the ratio of these probabilities is unity.

4. The data

The dependent variables in our regression analysis are long-term credit ratings assigned by Moody's, S&P, DCR, and Fitch to US corporations with public, taxable debt outstanding at year-end 1993. Our primary data source is *Credit Ratings International* (CRI), which tracks the ratings of all the major rating agencies on a quarterly basis. Our sample is drawn from this publication's first issue in 1994, which reports ratings assigned as of 31 December 1993.

Collecting a consistent data set for rating comparisons across agencies is difficult because individual firms often receive different ratings for different types of debt issues. CRI, however, presents agency ratings on a consistent basis since it reports only the ratings that agencies have assigned to each company's most representative long-term security, typically its long-term senior unsecured or senior subordinated debt. Because of possible misreporting by the rating agencies and typographical errors, we cross-checked CRI's ratings against alternative sources of information, including ratings given to us directly by Moody's and S&P for the purposes of this study and ratings published in the DCR *Rating Guide* and *Fitch Rating Book*. Discrepancies were resolved through these sources and direct contacts with the agencies themselves. Our source for other variables used in this study is 1993 data from COMPUSTAT, which records descriptive financial information and nonfinancial information (such as, industry and location) on a wide variety of companies. Altogether, we were able to obtain data on 1,137 COMPUSTAT companies rated jointly by Moody's and S&P. [8]

Rating differences between agencies are calculated by assigning numerical values to ratings [AAA (Aaa) = 1, AA+(Aa1) = 2, and so on] and subtracting

[8] We actually obtained data for 1,160 companies but dropped some outliers to clean the data of probable reporting errors. We employed the following filter: we ordered the firms according to the financial ratios used in subsequent analysis (leverage, coverage, and return on assets) and dropped the upper and lower half percent of the sample. Since there was considerable overlap in the sample outliers according to the different ratios, we dropped only 23 firms.

the associated numerical values from each other: the units of these differences are referred to as rating "notches." Since the agencies have different letter ranges in the C category, we truncated each agency's ratings from below B–(B3) = 16 to equal 17. Firms in default are not included in the sample.

Table 4 presents descriptive statistics for the data set. The proportion of firms rated by DCR and Fitch varies across different categories of firms. For example, DCR and Fitch are much more likely to rate utilities and financial firms than insurance or other industrial firms. Moreover, a firm is more likely to get a third rating if it is rated investment grade by Moody's and S&P, it has public debt outstanding for ten or more years, and it is relatively large. Table 4 also indicates that the average difference between the ratings of DCR and Fitch and those of Moody's and S&P differs across firm categories, although we see no systematic pattern in these differences.

5. Why do firms have third ratings?

To estimate the importance of sample selection bias, we must first empirically estimate a model of the firm's decision to obtain a third rating. [9] In addition to industry dummies, we include these explanatory variables:

Midwest headquarters. Since DCR is the only agency headquartered in Chicago rather than New York, it may have relative expertise in the analysis of firms from the Midwest. For this reason, we include in the DCR probits an indicator variable that equals 1 if the firm is headquartered in one of 12 Midwestern states.

Ten years of public debt. The amount of time that a firm has been active in the public bond market may be positively related to its likelihood of having a third rating. DCR and Fitch have had more opportunity to market themselves to firms that have been issuing public debt for some time. As a proxy for the length of time in the market, we include an indicator variable that takes on the value 1 if the firm had public debt outstanding for 10 or more years and takes on the value 0 otherwise. [10]

Long-term debt. While the average cost of obtaining a rating declines with the scale of issuance, [11] the major benefit of an additional rating – the potential

[9] Related papers by Hsueh and Kidwell (1988) and Moon and Stotsky (1993) find that rating level, size and location are important determinants of the likelihood of having ratings from Moody's and S&P.

[10] We used an indicator variable rather than a continuous variable because we were able to obtain this information only as far back as 1983. There was little difference in the empirical results, however, when other indicator variables corresponding to different time periods were used.

[11] The direct fees charged by the agencies are about 2 or 3 basis points of principal for each year that a bond's rating is maintained; total fees per issuer, however, are subject to caps.

Table 4
Summary statistics for 1137 firms rated by Moody's and S&P (as of year-end 1993)

Firm categories	Number of firms	Percent rated by DCR	Observed ratings differential between DCR and...		Percent rated by Fitch	Observed ratings between differential Fitch and...	
			Moody's	S&P		Moody's	S&P
All firms	1137	29.6	0.60	0.46	13.6	0.74	0.56
Utilities	173	57.8	0.49	0.51	42.2	0.40	0.47
Banks & thrifts	92	46.7	0.47	0.49	26.1	1.13	0.92
Insurance	53	22.6	1.17	0.42	7.5	2.00	1.00
Other finance	63	47.6	0.90	0.43	39.7	1.08	0.64
Other industrial	756	20.0	0.60	0.44	3.8	0.79	0.38
Investment grade	695	40.3	0.52	0.40	20.4	0.68	0.56
Split rated	677	26.0	0.78	0.53	10.5	0.99	0.61
Ten or more years of public debt	646	44.7	0.59	0.44	21.4	0.66	0.54
Assets > $2.2 billion (median)	569	45.7	0.50	0.44	22.1	0.71	0.58
Long-term debt > $0.5 billion (median)	569	46.4	0.47	0.37	22.0	0.66	0.54

Note: The observed rating differential corresponds to the average difference in rating notches calculated for jointly rated firms only. For example, the difference between A and A+ corresponds to a one-unit rating differential. Positive numbers indicate that DCR or Fitch rate higher on average than Moody's or S&P. A firm is defined as investment grade if both ratings from Moody's and S&P are at least Baa3 (BBB-). A firm is defined as split-rated if it is assigned different ratings by Moody's and S&P.

to lower the market-required interest rate on new debt issues – should accrue in direct proportion to the amount of debt issued. Thus, we expect that firms with greater debt outstanding will be more likely to have third ratings.

Leverage, coverage, and profitability (ROA). Additional ratings may have a greater impact on the debt-issuing costs of firms that have greater intrinsic uncertainty regarding their credit risk, that is, firms about whom investors are more likely to have different opinions of their default risk. [12] Relatively high values of leverage and ROA and low values of coverage of fixed charges may be associated with greater firm uncertainty and therefore a higher probability of observing a third rating. The financial ratios are all constructed as deviations from industry means. [13]

Weighted average ratings. There is evidence that lower the average rating, greater the uncertainty about a firm's true credit risk, as there is much more cross-sectional variation in credit spreads and more disagreement among the agencies over bonds with low ratings than with high ratings (Cantor and Packer, 1994). For this reason, the probit's specification includes a weighted average of the firm's ratings from Moody's and S&P. Specifically, we weight the average ratings by the average credit spreads observed for bonds with those ratings over a twenty-year period as reported by Altman (1989). [14]

Absolute rating difference. We include a variable that measures the absolute difference, in rating notches, between the ratings assigned by Moody's and S&P to the same firm. This measure of uncertainty should be highly correlated with a firm's ex ante uncertainty and, hence, should be positively related to the probability of observing a third rating.

Interaction of uncertainty proxies with long-term debt. The expected effect of uncertainty (as measured by the weighted average rating and absolute rating difference) may be more important for large debt issuers. [15]

[12] Ramakrishnan and Thakor (1984) and Millon and Thakor (1985) discuss the theoretical role of credit rating agencies as information gatherers and processors. They conclude that credit rating agencies can reduce a firm's capital costs by certifying its value in a market characterized by informational asymmetries between purchasers and issuers.

[13] Since coverage ratios are reported only for the nonfinancial firms in COMPUSTAT, for financial firms we set coverage equal to a constant, which, given the presence of industry dummies, eliminated the effect of that variable for nonfinancial firms in the regression.

[14] We are grateful to a referee of this journal for suggesting this approach, as the agencies' ordinal ranking of risks does not represent a linear measure of default risk. Due to the construction of the ratings variable described above, lower ratings, which correspond to more uncertainty, are associated with higher numerical values.

[15] At the suggestion of a referee of this journal, we experimented with other interaction terms as well. In particular, we interacted the weighted average rating variable with the three financial ratios to see if leverage was a more important determinant of the decision to obtain a third rating for firms with low average ratings. The estimated coefficients (not reported) on these interaction terms were not significant. In addition, in place of the absolute rating difference, we tried split-rating dummies, with little impact on the results.

Regulatory variables. Debt issuers with Moody's and S&P ratings just below regulatory thresholds may have an added incentive to obtain third ratings to improve their chances of clearing those hurdles and thereby increase their investor base. [16] We include three indicator variables that proxy for such an incentive.

(i) *Commercial paper* (CP). This variable takes on the value 1 if the firm had commercial paper outstanding as reported on COMPUSTAT. We expect this variable to be positively related to the likelihood of a third rating since SEC regulations make mutual fund managers extremely sensitive to CP ratings. A firm obtaining a third CP rating is likely to obtain a third long-term bond rating as well.

(ii) *Marginally below investment grade.* This dummy takes on a value of 1 if the firm's ratings from Moody's and S&P are Ba1 and BB+, respectively. These firms are more likely than others to receive a third rating that would help put them over a critical regulatory hurdle.

(iii) *NAIC split.* This indicator variable equals 1 if the ratings of Moody's and S&P fall into different National Association of Insurance Commissioners (NAIC) quality categories. NAIC's Securities Valuation Office assigns each bond held by an insurance company to one of six quality categories, the first four of which correspond to A– (A3) and above, BBB– (Baa3), BB– (Ba3), and B– (B3), respectively. Capital charges rise as the quality category becomes lower. Because the Securities Valuation Office analysts may choose either the higher or lower rating when the agencies disagree, a third rating may be particularly valuable for firms with Moody's and S&P ratings that straddle two NAIC quality categories.

Table 5 reports representative specifications of the probit regression for both DCR and Fitch. [17] In the DCR probit, the estimated coefficient on the Midwest dummy has the expected positive sign and is statistically significant. In both the DCR and Fitch probits, the ten years of public issuance variable is positively related to the decision to obtain a third rating. Moreover, in both probits, the coefficient on long-term debt is positive as expected, although at a level of statistical significance in only the DCR regression.

The coefficients on the three financial ratios are similar in both the DCR and the Fitch probits. The probability of a third rating increases with coverage but decreases with leverage and profitability. These results are contrary to what

[16] West (1973) and Carey et al. (1993) show that spreads for BB(Ba)-rated borrowers rose following the adoption of regulations that reduced bank and insurance company purchases of below-investment-grade securities. For further discussion of the regulatory incentive to obtain third ratings, see Cantor and Packer (1994, 1996b).

[17] The second-stage results were insensitive to the inclusion of all but a few variables in the first-stage probit. Alternative specifications are reported in Cantor and Packer (1996a). Other estimates are available from the authors on request.

one might expect if uncertainty were negatively related to coverage and positively related to leverage. [18]

The other evidence is mixed over whether uncertainty about default risk drives the demand for third ratings. In both the DCR and Fitch probits, the estimated coefficients on weighted average ratings are negative, contrary to our expectations. The estimated coefficient on the interaction between average rating and long-term debt, however, is positive, suggesting that large debtors with low ratings are more likely to get third ratings. One interpretation of this result is that the below-investment-grade market may be a sophisticated institutional investor market that does not rely intensively on ratings. Very large below-investment-grade issuers, however, have to reach a broader investor pool, and the high level of uncertainty surrounding their default risk may lead issuers to demand additional ratings.

Our other measure of ex ante uncertainty, the absolute rating difference, is positively related to the probability of obtaining a third rating, although the relationship is statistically significant only for DCR. Contrary to our expectation, the interaction coefficients suggest that rating differences are less important in influencing the likelihood of a third rating when the debtor is large. By contrast, none of the estimated coefficients on our proxies for a regulatory demand for ratings is statistically significant. This finding is robust to other specifications, not reported, in which the regulatory demand proxies are added to the rest of the specification one at a time or are interacted with other explanatory variables.

In sum, the results suggest that firms are more likely to obtain a third rating if they are large and experienced issuers in the market. On balance, the probits do not provide firm evidence that the resolution of ex ante uncertainty drives the decision to obtain third ratings. Moreover, there is no evidence that firms seek third ratings specifically to help meet regulatory requirements.

6. Sample selection bias and ratings differences

We now analyze the differences between the ratings assigned by the optional agencies and Moody's and S&P. We regress the observed differences against a variety of possible determinants of relative ratings while controlling for selection bias based on the results of Section 5. We also run ordered-probit regressions in the second stage, in which the dependent variable represents the qualitative differences in ratings (higher, same or lower). Both sets of second

[18] The positive relationship between coverage and the probability of obtaining a Fitch rating is perhaps less surprising since that agency stresses that it places greater weight on cash flow coverage than other agencies (Fitch Research, 1994).

Table 5
Probit regressions predicting which firms obtain third ratings

	Dependent variable: Does the firm have a rating from DCR?	Dependent variable: Does the firm have a rating from Fitch?
Midwest headquarters [b]	0.27*	–
	(0.11) [a]	
Ten years of public debt [b]	0.72*	0.58*
	(0.13)	(0.18)
Long-term debt [c]	0.30*	0.12
	(0.07)	(0.09)
Leverage [c]	−1.43*	−0.77
	(0.36)	(0.46)
Coverage [c]	0.030	0.037*
	(0.016)	(0.019)
Profitability (ROA) [c]	−2.29	−4.96*
	(1.40)	(2.03)
Weighted average rating [c]	−0.007*	−0.010*
	0.003	(0.004)
Weighted average rating	0.0011*	0.0010*
*long-term debt	0.0004	(0.0006)
Absolute rating difference [c]	0.50*	0.24
	(0.17)	(0.30)
Absolute rating difference [c]	−0.10*	−0.06
*long-term debt	(0.03)	(0.04)
Commercial paper rating [b]	−0.02	−0.06
	(0.13)	(0.15)
Marginally below	−0.31	0.51
investment grade [b]	(0.42)	(0.48)
NAIC split [b]	0.15	0.08
	(0.14)	(0.19)
Sample size	1137	1137
Number with third rating	336	155
Log likelihood	−488.1	−297.79

[a] Standard errors are in parentheses. Asterisks indicate significance at 95% confidence levels.

[b] The following variables are 0/1 dummies which take on the value 1 as follows:

(a) Midwest headquarters – if company headquarters located in one of the twelve Midwestern states (as defined by the Census Bureau).

(b) Ten years of public debt – if company has issued public debt securities for ten years or more.

(c) Commercial paper rating – if company has a commercial paper rating.

(d) Marginally below investment grade – if Moody's and S&P rate Ba1 and BB+, respectively.

(e) NAIC split – if Moody's and S&P have assigned different ratings which fall into two different broad risk categories as defined by the National Association of Insurance Commissioners.

[c] Other variables are defined as follows (financial data are as of 1993):

(a) Long-term debt is the log of long-term debt outstanding.

(b) Leverage is [long-term debt +current liabilities + (8 times rent)]/assets, all at book value.

(c) Coverage is (net income + interest + rent)/(interest + rent).

(d) Profitability is net income/assets.

(e) Weighted average rating is the product of the numerical equivalent of the average of Moody's and S&P's ratings times the average spread over Treasuries associated with that rating. (Lower quality ratings are associated with higher numbers on the numerical rating scale.)

stage regressions of the determinants of rating differences are then used to test the hypotheses laid out in Section 3.

Theory and previous empirical research provide only limited guidance as to the selection of appropriate variables to explain rating differences beyond a simple constant term (controlling for potential differences in average rating scales) and the inverse Mills ratio (controlling for sample selection bias not accounted for by other included variables). While many papers have demonstrated that industry dummies and financial variables help predict an agency's *ratings* (for a survey, see Ederington and Yawitz, 1987), other research comparing Moody's and S&P ratings (Ederington, 1986) suggests that these same variables are unlikely to explain *ratings differences.*

We consider three models. The first simply regresses rating differences on a constant and the inverse Mills ratio obtained from the probit regressions. Our second model adds industry dummies to the ratings difference equation. This modification is important if the third agency rates firms in a particular industry conservatively or less conservatively than firms in other industries *and* if the third agency has a disproportionately small or large market share in that industry. Similarly, it may be important to incorporate certain financial variables in the regression if third agencies place different weights on specific variables and rate a disproportionate share of firms with high or low realizations of these variables. Our third model therefore includes four financial variable regressors – leverage, coverage, profitability, and log of assets.

In Table 6, all three models are estimated to explain the ratings differences between DCR and both Moody's and S&P. In five of the six regressions, the coefficient on the inverse Mills ratio is positive and, in four cases, significant at the 1 percent level. With regard to the industry dummies and financial variables, the reported *F*-statistics imply that both sets of variables add significant explanatory power to the DCR/Moody's ratings difference equations but not to the DCR/S&P equations. Hence, the coefficients in columns (c) and (d) in Table 6 reflect the preferred DCR/Moody's and DCR/S&P specifications, respectively.

Regressions similar to those in Table 6 are presented in Table 7, but here we examine factors underlying the differences between Fitch's ratings and those of Moody's and S&P. Looking first at the coefficient on the inverse Mills ratio, we find evidence of sample selection bias in the Fitch/Moody's regression and but none in the Fitch/S&P equations. In the Fitch/Moody's equations, the estimated coefficient is consistently positive and significant at the 1 percent level. In the Fitch/S&P regressions, the coefficient on the inverse Mills ratio changes sign

(f) Absolute rating difference measures the absolute value of the rating notch differential between the ratings from Moody's and S&P.

(g) Included in the probits are two interaction variables: weighted average rating and absolute rating difference are both interacted with long-term debt.

Table 6
OLS regressions for DCR using industry dummies, financial variables, and the inverse Mills ratio

	Dependent variable: Ratings notch difference between DCR and Moody's			Dependent variable: Ratings notch difference between DCR and S&P		
	(a)	(b)	(c)	(d)	(e)	(f)
Constant	0.27*	0.11	2.99*	0.27*	0.03	1.12
	(0.11)	(0.17)	(0.87)	(0.11)	(0.17)	(0.89)
Banks	–	0.08	0.22	–	0.23	0.27
		(0.19)	(0.21)		(0.18)	(0.21)
Insurance	–	0.51	0.67*	–	−0.07	−0.04
		(0.30)	(0.34)		(0.31)	(0.35)
Other finance	–	0.47*	0.58*	–	0.14	0.22
		(0.21)	(0.27)		(0.21)	(0.27)
Utilities	–	0.13	−0.27	–	0.27	0.15
		(0.15)	(0.20)		(0.15)	(0.21)
Leverage	–	–	−0.50	–	–	−0.28
			(0.45)			(0.46)
Coverage	–	–	0.003	–	–	0.01
			(0.02)			(0.02)
Profitability (ROA)	–	–	−0.63	–	–	−1.19
			(1.70)			(1.75)
Log of assets	–	–	−0.25*	–	–	−0.09
			(0.08)			(0.08)
Inverse Mills ratio	0.40*	0.45*	−0.11	0.24*	0.38*	0.19
	(0.12)	(0.14)	(0.23)	(0.12)	(0.14)	(0.23)
Adjusted R-squared	0.03	0.04	0.06	0.009	0.008	0.004
Model selection						
F-Statistics for significance of entire model	11.52*	3.80*	3.55*	4.08*	1.57	1.16
F-Statistics for significance of variables not in (a), (d)		1.84	2.50*	–	0.94	0.79
F-Statistics for significane of variables not in (b), (e)	–	–	3.10*	–	–	0.65

Note: See Table 5.

and is never significantly different from zero. According to the F-tests, including industry dummies adds significant explanatory power to the Fitch/Moody's equation, though not to the Fitch/S&P equation. The addition of financial variables does not improve the fit in either equation. Hence, the coefficients in columns (b) and (d) in Table 7 reflect the preferred Fitch/Moody's and Fitch/S&P specifications, respectively.

We also estimated, but do not report, the second-stage model of rating differences as trinomial, ordered probits. In these models, the dependent variable is a qualitative variable that represents one of three possible outcomes: the third agency rates higher, the same, or lower than Moody's or S&P. The right-hand side variables are the same as in Tables 6 and 7. While this ap-

Table 7
OLS regressions for Fitch using industry dummies, financial variables, and the inverse Mills ratio

	Dependent variable: Ratings notch difference between Fitch and Moody's			Dependent variable: Ratings notch difference between Fitch and S&P		
	(a)	(b)	(c)	(d)	(e)	(f)
Constant	0.30*	0.11	−0.97	0.60*	0.56	−0.40
	(0.16)	(0.39)	(1.39)	(0.16)	(0.41)	(1.50)
Banks	–	0.59*	0.71*	–	0.47	0.48
		(0.27)	(0.30)		(0.28)	(0.32)
Insurance	–	1.04*	1.16*	–	0.67	0.57
		(0.46)	(0.47)		(0.48)	(0.51)
Other finance	–	0.67*	0.76	–	0.16	0.60
		(0.31)	(0.46)		(0.32)	(0.49)
Utilities	–	−0.02	0.44	–	−0.01	0.41
		(0.27)	(0.47)		(0.29)	(0.50)
Leverage	–	–	0.38	–	–	−0.47
			(0.63)			(0.67)
Coverage	–	–	0.04	–	–	0.03
			(0.02)			(0.02)
Profitability (ROA)	–	–	−8.47*	–	–	−3.75
			(3.15)			(3.39)
Assets	–	–	0.06	–	–	0.07
			(0.09)			(0.10)
Inverse Mills ratio	0.41*	0.38*	0.62*	−0.04	−0.10	0.15
	(0.13)	(0.20)	(0.33)	(0.13)	(0.21)	(0.35)
Adjusted R-squared	0.05	0.16	0.18	−0.006	0.01	0.06
Model selection						
F-Statistics for significance of entire model	9.50*	6.74*	4.79*	0.09	1.45	1.07
F-Statistics for significance of variables not in (a), (d)	–	5.76*	4.01*	–	1.79	1.20
F-Statistics for significance of variables not in (b), (e)	–	–	2.10	–	–	0.62

Note: See Table 5.

proach is more general than least-squares in some respects, it reduces the weight given to large rating differences, putting all differences of the same direction into a single category. [19] Qualitatively, the results are the same as in the least square regressions – that is, the coefficients all had the same signs and similar significance levels, and the preferred specifications included the same variables for each pair of rating agencies being compared.

[19] We also experimented with a multinomial ordered-probit model in which the number of values that the dependent variable could take on covered the full range of observed ratings differences. These results were also broadly the same as those presented in Tables 6 and 7.

Table 8
Hypotheses tests: is there no selection bias and are rating scales equal?

	DCR relative to Moody's [a]	DCR relative to S&P [b]	Fitch relative to Moody's [c]	Fitch relative to S&P [d]
OLS results				
(a) Mean rating difference in sample	0.60	0.46	0.74	0.56
(b) Mean rating difference corrected for bias	0.94	0.27	0.24	0.60
H1: (b) = (a)				
F-statistic	1.45	3.06	2.24	0.69
p-value	0.23	0.08	0.14	0.41
H2: (b) = 0				
F-statistic	10.90*	5.73*	0.54	14.36*
p-value	0.01	0.02	0.46	0.02
Ordered-probit results				
(c) Prob(higher)/Prob(lower) in sample	4.64	3.38	10.12	7.00
(d) Prob(higher)/Prob(lower) corrected for bias	11.75	2.79	3.52	12.14
H1′:(d) = (c)				
Chi-squared statistic	1.00	0.36	0.04	0.86
p-value	0.32	0.55	0.99	0.35
H2′:(d) = 1				
Chi-squared statistic	8.44*	10.65*	0.0003	19.28*
p-value	0.04	0.01	0.99	0.01

Note: * indicate significance at 95% confidence levels.
[a] Based on specification (c) in Table 6.
[b] Based on specification (d) in Table 6.
[c] Based on specification (b) in Table 7.
[d] Based on specification (d) in Table 7.

Our second-stage regressions allow us to conduct the central hypothesis tests laid out in Section 3. Table 8 reports the results of those tests, which were run using both the OLS regressions and the trinomial, ordered-probit regressions in the second stage. The upper panel of Table 8 presents the results based on the best least-squares models of rating differences reported in Tables 6 and 7. The first row reports observed (uncorrected) mean ratings differences between Moody's and S&P and the optional agencies. These differences, which were previously presented in Table 4, indicate that the optional rating agencies rate between 0.46 and 0.74 of a ratings notch higher than Moody's and S&P.

What is the effect of sample selection bias? The second row in Table 8 reports the mean rating difference corrected for both observed and unobserved sources of sample selection as estimated in the best specifications of Table 7. In two (DCR/S&P and Fitch/Moody's) of the four pair-wise comparisons presented in the top panel of Table 8, selectivity-corrected rating differences are lower by around 0.2–0.5 of a ratings notch, relative to the observed ratings differences. The F-statistics and associated p-values reported in the third and fourth rows of the panel, however, indicate that one cannot reject the hypothesis that there is no sample selection bias (H1) in all four pair-wise comparisons.

On the other hand, as indicated by the F-statistics and p-values in the fifth and sixth rows of the panel, the hypothesis that the optional rating agency has the same rating scale as the mandatory rating agency (H2) is strongly rejected in three of the four cases; the p-values range between 0.01 and 0.02 in these three cases. Thus, there appears to be statistically significant differences in the cardinal rating scales of the optional and mandatory rating agencies. Only in the Fitch/Moody's case were we unable to reject the hypothesis that the two agencies share the same scales. This result is clearly attributable to the small sample size and low power of the test since the observed ratings difference is the largest for this pair (0.74 rating notches), and we were unable to reject the hypothesis of no sample selection bias for this pair of agencies in the previous test.

The lower panel of Table 8 reports similar tests for the absence of selectivity bias and equivalence of rating scales, only here the second-stage regressions are based on the trinomial probits described above. In this case, we measure the difference in absolute scales by the ratio of the probability that the optional rating agency rated higher than the mandatory agency over the probability that the optional agency rated lower. The first row of the panel indicates, depending on which of the two agencies were being compared, that the optional agencies were between three and ten times more likely to rate higher as compared to lower than the mandatory agency. In the second row, we again see that a correction for sample selection bias leads to a decrease in this ratio, for only two (DCR/S&P and Fitch/Moody's) of the four pair-wise comparisons.

As reported in the third and fourth rows of the second panel, the tests and associated p-values cannot reject the hypothesis that there is no sample selection bias (H1) in any of the four pair-wise comparisons. This result directly parallels that reported in the top panel. Similarly, as indicated by the statistics in the fifth and sixth rows, in three out of four cases we can reject the hypothesis that the rating scales of the mandatory and optional agencies are identical, with the only exception being the test statistics generated by the Fitch/Moody's comparison.

The tests based on the more qualitative measures of ratings differences therefore result in exactly the same patterns of acceptance and rejection as the tests based on the quantitative measure of rating differentials. We cannot reject the hypothesis that there is no selection bias in any model and, except for a relatively low power test of one pair-wise comparison, our tests indicate that the optional agencies have higher rating scales than Moody's and S&P.

7. Conclusion

Many researchers have documented that third, or optional, agencies on average assign higher ratings than Moody's and S&P. This pattern may result because the default risks associated with the particular letter grades of third agencies are higher, or because their policy of rating only on request induces sample selection bias. Our study is the first to estimate the empirical importance of such bias. Our results suggest that observed differences in average ratings reflect differences in rating scales. They also call into question financial industry regulations that assume equivalence of rating scales. If these results are confirmed by other studies, they should prove useful in the ongoing efforts of the Securities and Exchange Commission (1994) to improve its methods of incorporating ratings into its regulations.

We also explored why firms choose to obtain additional ratings. We found that firms are more likely to obtain a third rating if they are large and experienced issuers in the capital market. However, there is little evidence that third agencies are employed either to resolve ex ante uncertainty or to clear regulatory hurdles. While the rating scales of third agencies may be higher than others, there is little evidence that the decisions of issuers to use them are influenced by that factor. Our results suggest that more research would be useful in clarifying the role of the rating agencies in capital markets.

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