Municipal Bond Ratings and Citizens' Rights

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Abstract

Municipal bond ratings are designed to tell investors the likelihood that different municipal bonds will default, but they also are of interest to the public because they alter the cost of public infrastructure. Nevertheless, bond ratings are not regulated. This paper explores the possibility that municipal bond ratings involve behavior analogous to redlining, which is a type of discrimination against people who live in places with a high minority composition. Drawing on our civil rights laws, the paper develops a regulatory framework to balance societal objectives with a rating agency's legitimate objective to provide information about default probabilities. An application to the ratings of large cities' general obligation bonds finds evidence of redlining-type behavior. This analysis supports the need for the regulation of municipal bond ratings.

Introduction

Municipal bond ratings are designed to help investors manage risk by indicating the likelihood that a particular municipal bond will default. Bond ratings also have significant consequences for the public interest, largely because a low rating raises the cost of borrowing money for public capital projects. Despite this link to the public interest, however, bond ratings are not regulated. Only a few companies are formally recognized as bond-rating agencies, but no regulator examines the ratings themselves to determine whether they serve the public interest. This paper develops a regulatory framework to determine whether bond ratings reflect an appropriate balance between societal objectives and the legitimate objective of rating agencies to provide information about default probabilities.

The societal objectives addressed in this paper have to do with the fair treatment of citizens in different jurisdictions. Thanks to municipal bond ratings, citizens must pay more for infrastructure in some jurisdictions than in others. The question is whether this variation is entirely "legitimate," in the sense that it is based solely on factors that society deems acceptable, or is to some degree "unfair," in the sense that it is based on factors, such as the racial or ethnic composition of a jurisdiction, that businesses should not consider. This paper draws on the nation's civil rights laws to develop a regulatory framework for answering this question. This framework is designed to preserve the ability of ratings agencies to provide their services while helping to protect the rights of citizens affected by the rating process. This framework is implemented using data for general obligation (GO) bonds. The results indicate that regulation of bond rating agencies is needed to protect citizens' rights.

The paper begins with a discussion of bond rating schemes and the regulatory environment for bond rating agencies. The second section reviews evidence about the impact of bond ratings on the cost of municipal borrowing. The third section presents a conceptual framework, developed for mortgage lending, that highlights the key tradeoffs that arise when pricing something (a bond) on the basis of a predicted future outcome (a default). This framework, which shows several ways in which discrimination might arise, is modified to account for differences between mortgages and municipal bonds. The modified framework explains why bond rating schemes might involve behavior that is analogous to discrimination.

The fourth section presents tools that a regulatory agency could use to evaluate a bond rating scheme. These tools measure the various types of unfair outcomes identified in the conceptual framework, all of which involve deviations from schemes that provide legitimate predictions of bond default probabilities. These tools are applied to GO bonds in section five. Using data for large city bond ratings in 2000 and for a random sample of state GO bonds issued between 1982 and 1990, I estimated the extent to which existing rating schemes affect jurisdictions with different ethnic compositions. The final section contains conclusions and policy recommendations.

Bond Rating and the Regulation of Bond Rating Agencies

The three major agencies that rate municipal bonds—Fitch, Moody's, and Standard and Poor's (S&P)—use different methodologies, but they all say that their ratings indicate the likelihood that an investor will lose money because of default. Moody's, for example, says that "Municipal Ratings are opinions of the investment quality of issuers and issues in the US municipal and tax-exempt markets. As such, these ratings incorporate Moody's assessment of the default probability and loss severity of these issuers and issues."[1]

Ratings are based on factors that the rating agency believes are linked to the creditworthiness of the bond issue or issuer. Revenue bond issues, each of which is backed by its own revenue stream, receive their own rating, whereas GO bonds, which are backed by a government's full taxing power, receive the rating of the issuing government.[2] The factors emphasized by Moody's, again as expressed on Moody's website, are "economy, debt, finances, and administration/management strategies." Similar factors are considered by the other rating agencies.[3]

In principle, these agencies are regulated by the Securities and Exchange Commission (SEC). In practice, however, the only substantive regulation conducted by SEC has been the designation of these three agencies as National Recognized Statistical Rating Organizations (NRSROs). This designation was first made in 1975 (Cantor and Packer, 1994). Because of their long histories as rating agencies, Fitch, Moody's, and S&P were given this designation automatically. Since then, six other agencies have been given this designation, but most of these agencies have been eliminated by mergers, and there are now only five NRSROs. Fitch, Moody's, and S&P remain the only three NRSROs that rate municipal bonds in the United States.[4]

Although ratings themselves are not regulated, the regulators responsible for ensuring the safety and soundness of the nation's financial institutions often require the institutions that they supervise to focus on "investment-grade" bonds, which are bonds rated at least BBB (or Baa using Moody's symbols) by a NRSRO. Companies other than

NRSROs can still offer bond-rating services, but their ratings cannot be used to satisfy these regulations, so the market for their ratings is greatly limited.

The regulations linked to NRSRO ratings may prohibit the use of non-investment-grade (also called "speculative") bonds, impose stricter reporting requirements on financial institutions purchasing non-investment-grade bonds, or place lower weights on non-investment-grade bonds when evaluating the institution's portfolio. As explained by Cantor and Packer (1994, p. 5), "The reliance on ratings extends to virtually all financial regulators, including the public authorities that oversee banks, thrifts, insurance companies, securities firms, capital markets, mutual funds, and private pensions." For example, the Financial Institutions Recovery and Reform Act of 1989 prohibits savings and loan associations from investing in speculative bonds, either municipal or commercial (Cantor and Packer, 1994).

Over the last few years, an active debate took place concerning the regulation of the rating agencies, culminating in the passage of the Credit Rating Agency Reform Act of 2006 (CRARA). The focus of this debate and this legislation was on revising the NRSRO designation, which serves to some degree as a barrier to entry. As explained by White (2002, 2005), the combination of the NRSRO designation and the regulations concerning investment-grade bonds both limits entry and ensures a market for the services of bond rating agencies. Thus, White and others recommended loosening or even eliminating the NRSRO designation. The legislative response in CRARA was to allow firms to voluntarily register as NRSROs, with a limited role for the SEC.[5]

CRARA also declares that "neither the Commission nor any State (or political subdivision thereof) may regulate the substance of credit ratings or the procedures and methodologies by which any nationally recognized statistical rating organization determines credit ratings." The oversight role of the SEC, in other words, is limited to a focus on the capacity of an organization to provide ratings and cannot address the quality of the ratings themselves. One might think that regulation of ratings is unnecessary because an agency producing ratings that did not successfully predict default would not have credibility in the market place. However, "credibility in the market place" is not a legitimate standard for public policy. The central purpose of this paper is to develop societal standards for evaluating municipal bond ratings and to determine whether regulation is needed to ensure that these standards are met. This paper could be characterized, therefore, as an evaluation of the above provision in CRARA.

More specifically, this paper addresses the question: How could a regulator determine whether municipal bond ratings meet standards of fairness that are widely applied to other activities in our society? This question has not been addressed in the recent hearings on bond rating agencies; instead, it grows out of the finding of several studies (Moon and Stotsky, 1993, Loviscek and Crowley, 1990) that the racial or ethnic composition of a jurisdiction is a significant predictor of that jurisdiction's credit rating, controlling for other things. The Moon and Strotsky study found, for example, that in 1981 American cities with a higher proportion of non-whites in their population received lower GO bond ratings than other cities, controlling for a wide range of city characteristics. This country prohibits businesses from accounting for race or ethnicity in other settings, so the question is whether municipal bond ratings violate this prohibition. This paper provides a framework for answering this question based on our civil rights laws, along with some results for GO bonds.

At first glance, the logic of our civil rights laws may seem to have nothing to do with municipal bond ratings. After all, the primary purpose of these laws is to prohibit unfavorable treatment of individuals based solely on their membership in a legally protected class. In fact, however, several of these laws also protect individuals against unfavorable treatment based on the racial or ethnic characteristics of their residential location. The Fair Housing Act, for example, makes it illegal:[6]

> for profit, to induce or attempt to induce any person to sell or rent any dwelling by representations regarding the entry or prospective entry into the neighborhood of a person or persons of a particular race, color, religion, sex, handicap, familial status, or national origin**.**

This type of discrimination, which is called redlining, is also prohibited by the Equal Credit Opportunity Act.[7] A municipal bond rating that reflects the racial or ethnic composition of the issuing jurisdiction is analogous to a form of redlining. Like redlining in the housing or mortgage market, it would place the citizens of jurisdictions with certain racial or ethnic compositions at a disadvantage and therefore would violate societal standards that are widely accepted in other contexts. This article provides a framework to determine whether this type of municipal bond redlining occurs.

Becker (1971, 1993) argued that competition would eliminate prejudice-based discrimination under some conditions.[8] An application of this argument to the case of municipal bond ratings would suggest that the problem is a lack of competition, not potential redlining. If redlining does exist right now, this argument goes, it would be eliminated by the removal of barriers to entry into the municipal bond rating business, which was accomplished by CRARA.

In fact, however, many scholars have shown that competition will not eliminate all forms of unfavorable treatment based on race or ethnicity. Consider, for example, statistical discrimination, which is defined as the use of race or ethnicity to predict business-relevant variables that cannot be observed (Arrow, 1973; Phelps, 1972).[9] To the extent that race or ethnicity predicts information that is not otherwise available concerning an applicant for a job, mortgage, and so on, firms that use this prediction may have higher profits than other firms. Competition will not eliminate this type of behavior. Moreover, our society has decided, in the form of our civil rights laws, that firms may not make use of information on race or ethnicity, even if it is profitable to do so.

In the case of municipal bond ratings, the racial or ethnic composition of a city might be correlated with difficult-to-observe factors that influence the ability of a city to avoid defaulting on its bonds. If so, a bond rating agency might be able to increase the accuracy of its ratings, and hence its profits, by incorporating racial or ethnic composition into its bond ratings. This is not, of course, a claim that credit rating agencies actually behave in this manner. Nevertheless, this possibility is consistent with a statement made by a former president of S&P, Brenton W. Harries in a 1993 interview. The rating agencies take "demographic issues" into account, he said, because "this particular mix of population requires more welfare payments, more housing. They're more of a drain as opposed to being more of a contributor" (cited in Sinclair, 2005, p. 109).

It is worth emphasizing that the civil rights laws allow a business to base its decisions on relevant observable characteristic other than membership in a protected class. In making a loan-approval decision, for example, a lender is allowed to consider observable factors that predict default, such as past credit history. Similarly, a credit rating agency should be allowed to base its ratings on any observable factors that do not undermine widely held views of fairness. Civil rights laws, like laws protecting the health and safety or workers or environmental quality, are not designed to discourage innovation and competition, but instead are designed to make sure that competition takes place within the boundaries of fair treatment established by society. The objective of this paper is to devise a similar set of boundaries for bond ratings.

The Link between Bond Ratings and Borrowing Costs

Bond ratings would not matter, and would not be worth regulating, if they did not affect the behavior of people and institutions that invest in municipal bonds. Many scholarly studies have demonstrated, however, that bond ratings do matter. Before turning to our framework, I will briefly review some recent evidence on this point.[10] I focus on studies that have an extensive set of control variables and use the true interest cost (TIC) of a bond issue as the dependent variable.

Simonsen and Robbins (1996) examined TIC for 210 GO bonds issued by municipalities in Oregon in 1992 and 1993. They found that AA bonds had significantly lower TIC than unrated bonds and estimated the difference in TIC between Baa and AA bonds to be 0.40 percentage points. Their sample contained one uninsured AAA bond, so they were unable to determine the interest savings of an AAA rating without insurance. In a follow-up study, Simonsen, Robbins, and Helgerson (2001) examined 212 GO bonds issued by municipalities in Oregon between 1994 and 1997. The estimated difference in TIC between AA and Baa bonds is only half the size in this study as in the previous study, and the rating variables are no longer statistically significant. Because their study focused on the role of competitive bidding, Simonsen et al. did not ask why the ratings variables are not significant. One possibility is that their municipal population variable, which is highly significant, is so highly correlated with ratings in their sample that they cannot estimate a separate ratings effect. As they pointed out, “small municipalities, on average, have lower ratings than larger municipalities” (p. 711).

Robbins (2002) examined a sample of 148 bond sales by the state treasury and authorities of New Jersey. This study is characterized by extensive controls for bidding procedures, market conditions, and issue and issuer characteristics. Robbins found that TIC is about 0.9 percentage points lower for an uninsured AAA bond than for a Baa bond or a bond that is unrated. Insured AAA bonds are estimated to have even lower TIC, but the difference between insured and uninsured AAA bonds was not statistically significant.

Johnson and Kriz (2005) examined the determinants of TIC for 521 state GO bonds issued between 1990 and 1997. Their rating variable was defined to equal 0 for a rating of AAA, 1 for AA, 2 for A, 3 for BBB, and 4 for BB (which indicates that the bond is speculative). The coefficient of this variable was 0.062 and was highly significant statistically. This coefficient indicates that the difference in TIC between a bond rated AAA bond and a bond rated BB was (4)(.062) = 0.248 percentage points.

Overall, therefore, scholars have found clear evidence that higher ratings lead to lower interest costs, for both GO and other types of bonds. Interest rates for highly rated bonds have been in the 4 to 6 percent range in recent years, so these estimates imply that bonds with speculative ratings cost 10 to 20 percent more than bonds rated AAA.[11]

A Framework for Understanding Bond Rating Schemes

As explained earlier, bond rating schemes are designed to predict the probability that the issuing government will default on a particular bond issue.[12] This is a critical issue for an investor, of course, because a default implies that the investor will not receive the all principal and redemption payments specified in the bond contract, at least not on time. Presumably, a bond rating agency builds a rating scheme by evaluating the probability of default over a certain time period for bonds that have already been issued. In this section I explore the possible ways a bond rating scheme might be devised. In the following section, I show how a regulator could evaluate an existing bond rating scheme.

Suppose the agency observes a large sample of bonds with information about the characteristics of the bond and of the issuing government at the time the bond was issued. Let D stand for default (1 = default in the sample period; 0 = no observed default), B_i stand for the i-th bond characteristic, and G_j stand for the j-th characteristic of the issuing government and the jurisdiction it serves, including its tax base and other relevant financial and economic characteristics. Then the agency can build a rating scheme system by estimating the following regression, where α's and the β's are parameters to be estimated and ε is a random error term:[13]

$$D = \alpha_0 + \sum_i \alpha_i B_i + \sum_j \beta_j G_j + \varepsilon. \tag{1}$$

The rating problem applies to prospective bond issues for which the B's and the G's are observed but D is not. Using the estimated values of the coefficients, which I will refer to as "weights," and the actual values of the B's and the G's, the agency can obtain a predicted probability of default, $\hat{D}$, for any given prospective bond issue that is drawn from the same pool as the bond issues used to estimate equation (1). In symbols:

$$\hat{D} = \hat{\alpha}_0 + \sum_i \hat{\alpha}_i B_i + \sum_j \hat{\beta}_j G_j. \tag{2}$$

Because a higher probability of default is indicated by a lower rating, the agency then translates $\hat{D}$ into a rating through a monotonic, inverse function. Let R indicate the rating, which consists of a set of categories. Then

$$R = f\left(\hat{D}\right), \tag{3}$$

where f is a function that translates higher values of $\hat{D}$ into lower ratings.

Issuer Demographic Characteristics

Building on the framework for mortgage lending in Ross and Yinger (2002), two types of complexities can show up in a scheme for predicting bond defaults. The first complexity can arise when the demographic characteristics of the issuing jurisdiction, say M, are correlated with unobserved default determinants. To take one hypothetical example, suppose an issuer's minority composition is correlated with default because cities with a large minority population are less likely than other cities to obtain financial help from their state when they encounter fiscal difficulties.[14]

When a characteristic of this type exists, a rating agency can handle it in one of three ways, two of which are inappropriate, at least some of the time. The first way is to include the M variables in equation (1) and hence in the rating scheme based on it. To be more specific, the agency will estimate:

$$D = \alpha_0' + \sum_i \alpha_i' B_i + \sum_j \beta_j' G_j + \sum_n \gamma_n M_n + \varepsilon. \tag{4}$$

The predicted default from this equation is

$$\hat{D}_1 = \hat{\alpha}_0' + \sum_i \hat{\alpha}_i' B_i + \sum_j \hat{\beta}_j' G_j + \sum_n \hat{\gamma}_n M_n \tag{5}$$

and the associated bond rating scheme is

$$R_1 = f\left(\hat{D}_1\right). \tag{6}$$

If M is percent Hispanic, for example, then predicted default in equation (5), and hence the bond rating scheme in equation (6), includes the estimated coefficient for percent Hispanic in equation (4) multiplied by an issuer's actual percent Hispanic.

According to our civil rights laws, behavior that treats a customer differently based solely on his or her membership in a legally protected class is called disparate-treatment discrimination. As explained earlier, legally protected classes are defined both by the race or ethnicity of an individual and by the racial or ethnic composition of an individual's neighborhood. Discrimination based on the latter type of definition is called redlining.[15] Thus, use of the bond rating scheme in equation (6) is analogous to disparate-treatment redlining. Our earlier discussion also pointed out that discrimination can have different causes. Membership in a protected class may provide an economic agent with information that can affect profits. Acting on that information is called statistical discrimination.[16] Thus the bond-rating scheme in equation (6) is also analogous to a form of statistical discrimination.

The second way for a bond rating agency to deal with *M* is for it to estimate equation (4) but then to predict default by setting each *M* at its average value in the sample, $\bar{M}$, instead of at the value for each individual issuer. In this case,

$$\hat{D}_2 = \hat{\alpha}'_0 + \sum_i \hat{\alpha}'_i B_i + \sum_j \hat{\beta}'_j G_j + \sum_n \hat{\gamma}_n \bar{M}_n \tag{7}$$

and

$$R_2 = f\left(\hat{D}_2\right). \tag{8}$$

This approach eliminates the impact of demographic characteristics on bond ratings. It recognizes that observed defaults are influenced by *M* but does not consider the role of *M* in predicting default for a particular bond. Moreover, the estimated weights for the *B* and *G* variables accurately reflect their substantive impact on default. Thus, the bond rating scheme in equation (8) is analogous to non-discriminatory behavior.

The third way for a bond rating agency to handle *M* is to ignore it, that is, to build a rating scheme based on the estimation of equation (1) instead of equation (4). At first glance, this procedure appears to be a way of avoiding behavior that is analogous to redlining; after all, the rating scheme does not consider *M* at all. As shown by Ross and Yinger (2002) in the mortgage case, however, this approach is not as neutral as it appears.

In formal terms, this scheme is based on a predicted value from equation (1), or,

$$\hat{D}_3 = \hat{\alpha}_0 + \sum_i \hat{\alpha}_i B_i + \sum_j \hat{\beta}_j G_j . \tag{9}$$

and

$$R_3 = f\left(\hat{D}_3\right), \tag{10}$$

Because, by assumption, *M* would be statistically significant if it were included in equation (1), the estimated coefficients in equation (9) may be subject to omitted variable bias. To be specific, these coefficients reflect the impact of *M* on default and the correlation between *M* and the included variables. The standard formula for this bias with a single *M* variable indicates that the expected value of $\hat{\beta}_j$ is

$$E(\hat{\beta}_j) = \beta_j' + \gamma r_j , \tag{11}$$

where β_j' and γ are the true parameters from equation (4) and r_j is the correlation between G_j and *M*. A similar formula reveals the bias in the estimated α's. Under standard assumptions, the expected values of the estimated coefficients in equation (7) equal the underlying parameter values in equation (4), so we can compare the expected values of default in equations (4) and (9)—and hence the expected values of the bond rating schemes defined by equations (5) and (10). Specifically, Ross and Yinger show that:

$$E(D_3) = E(D_2) + \gamma\left(\sum_i r_i(B_i - \overline{B}_i) + \sum_j r_j(G_j - \overline{G}_j)\right) \tag{12}$$

Equation (12) shows that the weight on each variable in the default prediction scheme D_3 is adjusted by a factor that depends on the product of γ and the correlation between that variable and M. In other words, these weights are adjusted to reflect not only the substantive impact of the variable on the probability of default but also the ability of that variable to indirectly capture some of the impact of M, which is not considered directly. In the mortgage context, M indicates whether an applicant belongs to a legally protected class, and this type of behavior is called disparate-impact discrimination. This type of scheme changes the weights on some variables because they help identify minority applicants, not because they help predict defaults within a group. Our civil rights laws forbid this type of behavior. In the case of municipal bonds, the default prediction D_3 and associated rating scheme R_3 are analogous to disparate-impact discrimination, where the discrimination takes the form of redlining. Because M is not directly linked to default it is inappropriate, if not illegal, for any default prediction and associated rating scheme to consider it.

Approximations

The second type of complexity that can arise in developing a scheme to predict default comes from an agency's use of rules of thumb or other approximations. A variable with a significant estimated coefficient in equation (4) could be dropped, for example, or a variable with no significant impact on default could be given a non-zero weight. With any such approximation, the weights placed some or all of the *B*'s and the *G*'s do not correspond to the estimated coefficients from equation (4), which are, as is well known, the best possible predictors of the dependent variable.[17] Deviations from these estimated coefficients may place certain types of cities at a disadvantage for no legitimate reason. An agency could also consider an issuer characteristic that has no substantive connection to default, namely, *M*.

A general way to write a default prediction and associated rating scheme that recognizes these possibilities is as follows:

$$\hat{D}_4 = \tilde{\alpha}_0 + \sum_i \tilde{\alpha}_i B_i + \sum_j \tilde{\beta}_j G_j + \sum_n \tilde{\gamma}_n M_n, \tag{13}$$

where the tilde (~) over a parameter indicates that it is based on a rule of thumb, a tradition, a guess, or a desire to treat certain types of cities differently—not on a statistical procedure—and

$$R_4 = f\left(\hat{D}_4\right), \tag{14}$$

This type of bond rating scheme obviously could include effects that are analogous to both disparate-treatment and disparate-impact discrimination. In addition, it could place inappropriate weights, that is, weights that do not accurately predict defaults, on *B* or *G* variables, even without the issues discussed in the previous section. This type of inaccurate weight, which is likely when weights are approximated instead of estimated, might place certain types of issuers at a disadvantage—for no substantive reason.

The Regulator's Problem: Evaluating a Bond Rating Scheme

This paper has been careful not to claim that municipal bond rating agencies actually practice discrimination. No current evidence about the behavior of these agencies has yet been presented, and the nations' civil rights laws, which define discrimination, were not written with these agencies in mind. Instead, this paper has developed a framework that can help to identify bond rating practices that are analogous to discrimination. Because of the widespread acceptance of the values built into our civil rights laws, existing regulatory agencies might want to let the public know whether this type of behavior exists. Moreover, elected official might want to pass a law outlawing this behavior and empower a regulatory agency to enforce it. As a result, this section addresses the question: How could a regulator determine whether a bond rating scheme violates the standards of fairness that are expressed by the nation's civil rights laws?

This section examines three tools that a regulator could use to evaluate a bond rating scheme based on its ability to predict default: regressions based only on information available at the time of issue, regressions that incorporate default information, and regressions based on predicted default. We will determine whether these tools could identify any of the troubling bond rating schemes described in the previous section. These schemes are troubling because they are influenced by the race or ethnicity of the issuing jurisdiction, which, according to widely held norms, should not be reflected in business decisions.[18] Thus, we will determine whether these tools can uncover the impact, if any, of race and ethnicity on a given agency's bond ratings.

Before proceeding, it is appropriate to ask whether a bond-rating scheme should be evaluated solely on its ability to predict default. From the point of view of an investor, after all, a rating may serve as more than just a default predictor. Relative demand for lower-rated bonds may decline, for example, during a downturn or after a major market shock, such as the New York City fiscal crisis of 1975 or the default of Orange County, California in 1994, thereby driving down the value of these bonds for people who hold them.[19] These possibilities give risk-averse investors an additional reason, beyond the probability of default, to take bond ratings into account.

A regulator should not evaluate a rating scheme, however, on its ability to predict these behavioral reactions. Indeed, it is circular to argue that a rating should be able to predict how investors respond to ratings. These behavioral reactions indicate that some investors alter the weight they place on a default prediction under some circumstances, but ultimately investors depend on the default prediction itself. As a result, these reactions do not alter the regulator's interest in determining whether that default prediction is consistent with our nation's fairness norms.

Regressions Based on Time-of-Issue Information

The first tool for evaluating a bond rating scheme is a regression of bond ratings on all the *B*, *G*, and *M* variables. This type of regression is similar to the analysis of loan approval by Munnell et al. (1996); to studies of wage discrimination, which are reviewed in Altonji and Blank (1999); and to studies of overages charged by lenders (Courchane and Nickerson, 1997; Crawford and Rosenblatt, 1999). The challenge in the case of bond ratings is that the dependent variable, the rating, is ordinal, not binary, as in Munnell et al. (1996) or cardinal as in the wage and overage studies. Fortunately, tools for studying ordinal outcomes, ordered logit and ordered probit, are readily available.

This tool requires data for a sample of bonds that were rated by a particular agency. These data must include the bond rating, *R*, bond characteristics, *B*, and issuer characteristics, *G* and *M*. Most of these characteristics are public information and are often provided by the issuer. Data on defaults are not required, but this tool builds on an expression for the *unobserved* default prediction by the rating agency, say D^*:

$$D^* = a_0 + \sum_i a_i B_i + \sum_j b_j G_j + \sum_n c_n M_n + \mu \tag{15}$$

where the *a*'s, the *b*'s, and the *c*'s are parameters to be estimated and μ is a random error term. This prediction then feeds into a rating scheme, the *f* in equation (3), which can be observed. The relationship between this rating scheme and the underlying bond and issuer characteristics can be estimated with the following equation, in which k=1 corresponds to the highest ranking, that is, to an AAA bond or its equivalent:

$$\begin{aligned} P\left(R=k \middle| B,G,M\right) &= P\left(\tau_k < D^* \le \tau_{k+1} \middle| B,G,M\right) \\ &= P\left(\tau_k < a_0 + \sum_i a_i B_i + \sum_j b_j G_j + \sum_n c_n M_n + \mu \le \tau_{k-1} \middle| B,G,M\right) \end{aligned} \tag{16}$$

In this expression, *c* indicates whether the bond rating scheme is directly influenced by *M*, and the τ's are boundaries that divide the values of D^* into ratings. These boundaries must be estimated. If the error term, ε, is assumed to follow the extreme value distribution, this equation describes an ordered logit model; if ε is assumed to follow a normal distribution, it describes an ordered probit model. These two models tend to yield similar results. See Greene (2003). Existing applications of this approach to municipal bond ratings include Moon and Stotsky (1993) and Ederington (1985).[20]

As explained by Ross and Yinger (2002), however, this approach has three flaws. First, the estimate of *c* is likely to be biased, upward or downward, if variables in *B* or *G* that are used by the rating agency are left out of the regulator's (or scholar's) regression. This problem is recognized by Moon and Stotsky (1993, p. 41), who write that their significant, negative estimate for *c* "suggests that the proportion of non-whites either captures characteristics of the community that depress the rating or affect Moody's perception of the community in an unfavorable way." Second, this approach cannot determine whether the factors included in the regression are the factors actually used by the agency. If a regression includes a particular *G* that is not actually used by the agency but that is correlated with one of the *M* variables, then the direct use of *M* could, to some degree, be hidden in the coefficient of this *G* variable. The best way for a researcher to minimize these two problems is to determine what variables the agencies actually use. This step may be eased by the fact that the bond ratings agencies provide lists of the variables that enter their bond rating schemes. Moreover, a regulator could interview a bond-rating agency to make sure that it had access to all the relevant variables.

Third, this approach is designed to capture the direct use of *M* in a bond rating scheme, which corresponds to disparate-treatment discrimination. Indirect use of *M*, which is analogous to disparate-impact discrimination, can be hidden in the weights placed on other explanatory variables, and this equation does not reveal whether the estimated weights accurately reflect the ability of an included variable to predict default.

Regressions that Incorporate Default Information

The second type of evaluation tool for a bond rating scheme draws on a technique in the literature on pricing discrimination, such as the study of wage discrimination by Hellerstein, Newmark, and Troske (1999).[21] This tool requires information on the default history for a sample of bonds rated by a given agency, along with information on the bond and issuer characteristics observed at the time the bonds were issued and rated. This tool asks whether defaults depend on any issuer characteristics, either *G* or *M*, once ratings have been controlled for. If so, then the ratings do not systematically capture default probabilities and put some issuers at a disadvantage. If any *M* characteristics are significant, this type of disadvantage violates widely held norms.[22]

One way to describe bond ratings, that is, the output of a bond rating scheme, is through a series of binary variables, R^1 through R^n, where $R^k = 1$ if a bond is placed in the

k-th rating category. As before, the first rating category corresponds to an AAA rating or its equivalent. This approach is to estimate the following regression[23]

$$D = d_0 + \sum_k d_k R^k + \sum_j b_j G_j + \sum_n c_n M_n + \mu, \tag{17}$$

where the d's, the b's, and c are coefficients to be estimated and μ is a random error. A negative and significant c coefficient indicates that issuing jurisdictions with relatively large minority populations are less likely to default than their ratings would indicate, and therefore indicates that the ratings place these jurisdictions at a disadvantage by misstating their default probabilities.[24]

Regressions Based on Predicted Default

A problem arises with equation (17) when it is applied to a market in which prices or ratings are set based on *predicted* performance, namely, that it cannot measure the extent to which prices/ratings reflect characteristics that have no direct impact on default but are correlated with characteristics that do. This condition applies to municipal bond markets, in which defaults are observed only after a rating has been issued.

Consider the default prediction given by equation (9) and the associated bond rating scheme in equation (10). As explained earlier, this bond rating scheme makes use of weights that systematically capture the relationship between M and default that arises because M is correlated with unobserved determinants of default. If it is deemed inappropriate for a bond rating agency to include M directly in its bond rating scheme, then it should be deemed equally inappropriate for the agency to include M indirectly through "biased" weights on other issuer characteristics—even if this helps the agency predict default. Moreover, when this type of behavior does occur, the resulting inappropriate ratings accurately predict default and there may be nothing left over for the

M variable entered separately to capture. In this case, the estimated c's in equation (17) will not be statistically significant even though *M* inappropriately affects ratings.

This problem can be addressed by combining equations (15) and (16). Default is observed, so equation (15) can be estimated and a predicted value for D^*, labeled $\hat{D}^{**}$, can be obtained for every observation. Following the logic of equation (7), this predicted value should be based on the average value of the *M* characteristics in the sample, not on the values of the *M* characteristics for each observation. This step ensures that $\hat{D}^{**}$ is not based on any inappropriate variables. Instead, $\hat{D}^{**}$ summarizes the legitimate role of *B* and *G* in predicting default, and the ratings equation can now be written:

$$P\left(R = k \middle| \hat{D}^{**}, G, M\right) = P\left(\tau_k < d'\hat{D}^{**} + \sum_j b_j{}' G_j + \sum_m c_n' M_n + \mu' \leq \tau_{k-1} \middle| \hat{D}^{**}, M\right) \quad (18)$$

A statistically significant c' (b') coefficient indicates that the associated *M* (*G*) variable inappropriately influences the bond rating scheme either directly or indirectly.

Summary

The three methods presented here would allow a regulator to provide evidence on the extent to which municipal bond ratings reflect the racial or ethnic composition of the issuing jurisdiction after accounting for factors that can legitimately be used to predict default. The most precise estimates are provided by the third method, which requires the most information. These methods can be implemented without any information on a bond rating agency's actual bond-rating scheme, which is rightly presumed to be proprietary. Instead, they require information about bond issues and issuers. The information required for the first scheme is widely available and has appeared in scholarly publications. The information on default required by the second and third schemes is not widely available, however, and would have to be collected by the regulator (or provided by the bond rating agencies).

A Comment on Timing

The regulatory schemes discussed here are designed to evaluate forecasts made at time t about events in period (t+1) based on information from period (t-1). These schemes ask, in other words, whether the forecasts made at time t were reasonable given previous experience. One might also ask, however, whether bond ratings can predict future defaults even if they failed to predict defaults in the past. After all, the purpose of a rating is to provide investors with information about possible future events, not about bonds that have already matured.

This possibility can be addressed by giving rating agencies the right of appeal. If a rating agency implements a rating scheme that deviates from the best prediction based on previous experience, then it should have the right to demonstrate that it has a legitimate reason for this deviation. In this setting, the agency has a heavy burden of proof; unless they have a crystal ball, bond ratings agencies and regulators alike must base their rating schemes on information from previous periods. Nevertheless, if a rating agency uses methods not based entirely on past experience, then it should have an opportunity to prove that these methods are reasonable or improve its predictions. As discussed in the conclusions, the civil rights framework on which I draw provides a mechanism for this and other types of appeal.

The Special Case of General Obligation Bonds

One striking feature of the municipal bond market is that GO bonds rarely default. A recent study of GO bonds from 1970 to 2000 (Moody's Investors Service, 2002, p. 1), for example, concluded that “No Moody's-rated issuer defaulted on any of these securities during the sample period.” Another study (S&P, 2000, p. 1) examines monetary default, which it defines as “the failure of an issuer or borrower to pay principal or interest when due.” This identifies 14 general obligation monetary defaults during the 1990s (Table 1, p. 29). Except in the case of Orange County, CA, which defaulted on three short-term note deals in 1995, the amounts involved in these defaults were small. The Orange County case involved $800 million of notes, but this amount is still a tiny fraction of the municipal bond market.

Regulatory Approaches

Thus, the probability of default on a GO bond is so low that a default almost never occurs.[25] This fact poses a challenge for a regulator, because equation (15) cannot be estimated if defaults are never (or even rarely) observed. In this setting, neither a regulator nor an investor can verify that the implicit default predictions in a given rating scheme are accurate.

Before proceeding, it is worth pausing over the question of why an investor might care about default predictions that cannot be verified. One possibility is that investors simply trust the ratings agencies, perhaps because of their success in predicting defaults for non-GO bonds. This may not be the whole story, however, because the current regulatory environment gives institutional investors, which make up a growing share of the market for municipal bonds (Hildreth and Zorn, 2005), an incentive to care about a bond’s rating even if it does not predict default. As White (2002) puts it:

> A change in the rating of a bond (say, a downgrade) may cause the bond to cross a regulatory threshold (e.g. “investment grade”) and thereby change how the regulated financial firms (e.g. banks, insurance companies, pension funds) treat the bond (e.g. how much capital they must hold, or even whether they can continue to

> hold the bond)…. Thus, the new information that the change in a rating brings to the financial markets may be only about the change in the bond's regulatory status rather than any new information about the likelihood of default.

Moreover, investors in municipal bonds face market risk as well as default risk, that is, they face the possibility that the relative value of their asset will change under certain circumstances. As discussed earlier, for example, the value of bonds with high ratings appears to have increased relative to bonds with low ratings right after the New York City fiscal crisis of the 1970s. If an investor believes that other investors might respond in this way, then he has an incentive to consider a bond's rating in making his own investment decisions.[26]

A regulator can respond to its inability to verify GO default predictions using one of four approaches. The first approach is to follow the apparent lead of investors and to assume that GO ratings are accurate default predictors that do not violate societal objectives. This assumption is legally required at the moment, thanks to CRARA, but it is not very appealing. As shown earlier, even practices that appear to be neutral can result in a bond-rating scheme that involves behavior analogous to redlining.

Second, a regulator can collect data on B, G, and M and use an approach like the one in Moon and Stotsky (1993) to estimate equation (16). As explained earlier, however, this approach cannot uncover behavior analogous to disparate-impact discrimination and provides an accurate estimate of the analog to disparate-treatment discrimination only if the exact variables used by the bond rating agency are known. Moreover, this approach is particularly unappealing in the case of GO bonds, because the rarity of defaults implies that the rating agencies themselves cannot derive a rating scheme using statistical procedures. Instead, they must use judgments and rules of thumb, which might not be accurate and which might involve the analog to disparate-impact discrimination.

A third approach is to assume that the probability of default for GO bonds actually is zero, at least to a reasonable approximation. This assumption implies that, in the case of GO bonds, equation (18) can be estimated without a predicted default probability because this probability always equals zero. (Equivalently, it implies that equation (18) is not subject to bias from the omission of *B* and *G*, because these variables have no role in predicting an event that almost never occurs.) Instead, an ordered logit or probit analysis of bond ratings as a function of an issuer's *M* characteristics directly reveals whether any of these characteristics have an illegitimate impact on bond ratings.

The weakness of this approach, of course, is that the probability of default may not be zero, even if defaults are not actually observed. Moreover, the default probabilities upon which the bond ratings agencies base their ratings may be accurate, even if this claim cannot be tested. In effect, this approach puts the burden of proof on the rating agencies to show that their GO ratings are linked to default.

A fourth approach, which avoids the strong assumptions of the first three, builds on the observation that, within a rating category, a regulator can observe the maximum probability of default consistent with observed outcomes. It is therefore possible to control for this maximum probability of default in estimating equation (18). More specifically, this approach is based on the assumption that the probability of default, *P*, is the same for all the bonds within a given ratings class, *r*. Thus, the probability of zero defaults for *N* GO bond issues in class *r* is given by the binomial distribution: $\Pr(D_r = 0 \mid P_r, N) = (1 - P_r)^N$. (This formula can easily be adjusted to handle the case of a few observed defaults.) Now to find the maximum probability consistent with zero defaults at a 1 percent confidence level, we set the left side of this equation equal to 0.01 and solve for P_r. The result: $P_r^{\max} = 1 - (0.01)^{1/N}$. These maximum probabilities can be included in equation (18) as a control for the underlying default probabilities.

These maximum probabilities are not, of course, the same as actual probabilities, but they are the closest possible estimates of these probabilities when equation (15) cannot be estimated. Following the logic of anti-discrimination law, which is discussed below, a finding analogous to discrimination using this approach can be said to establish a presumption that this behavior exists, but a rating agency should always be given an opportunity to present evidence that this presumption is not correct.

This paper focuses on the impact on ratings of *M*. Because they are less likely to engage key societal values, the economic and financial characteristics in *G* are not considered (except to the extent that they are reflected in estimated default probabilities). We estimate this impact using the third and fourth approaches described above. These approaches do not indicate whether an observed association between ratings and *M* arises because the rating scheme directly considers racial or ethnic composition or because other factors in the rating scheme that do not help to predict default are correlated with racial or ethnic composition. Both of these effects are analogous to discrimination, however; the first is analogous to disparate-treatment redlining and the second to disparate-impact redlining.

Data

I collected two types of data to examine GO ratings. The first data set consists of large city bond ratings and city ethnic characteristics. A city's bond rating is its rating for

GO bonds.[27] The second consists of a random sample of 51 state GO bond issues taken from the *Bond Buyer* for the 1982-1990 period. These data are part of a larger data set collected for Lovely and Wasylenko (1992).[28] No city or state in my samples experienced a GO default during the sample period (or thereafter).

Variable definitions are provided in Table 1. Several of the ethnic categories are available only in one of the two data sets because of changes in the Census categories. The city data are described in Table 2. The ratings for each rating agency were translated into numerical form with a 1 being the highest rating. In a few cases, always involving relatively low ratings, ratings categories were combined to ensure that no category had fewer than four observations. As shown in Table 2, this procedure results in seven categories for Standard and Poor's ratings, nine categories for Moody's ratings, and five categories for Fitch ratings. The maximum possible default probabilities fall between 0.18 and 0.79.

Results

The ordered logit results for the city ratings are presented in Table 3. The columns labeled "model 1" correspond to the third approach described earlier; the columns labeled "model 2" correspond to the fourth.

The results for model 1 indicate that all three ratings agencies use rating systems that place at a disadvantage cities in which a large share of the population is African American. This result is highly significant statistically in every case. In addition, I these results indicate that both S&P and Moody's ratings disfavor cities with large concentrations of Hispanics ($p = 0.077$ and 0.014, respectively) and cities with large concentrations of people who say they have two or more races in their background (p =

0.050 and 0.074, respectively). In short, this model indicates that the ratings schemes used by these two agencies include components that are analogous to redlining.

Model 2 adds the control for the maximum probability of default that is consistent, at the 1 percent confidence level, with the number of defaults that have been observed. In every case, this control variable is statistically significant with the expected sign. Adding this control lowers the sign and significance of the minority composition variable in some cases. The Hispanic variable in the S&P regression and the two-race variable in the Moody's regression are no longer significant. Moreover, the significance of the two-race variable drops from 5 to 10 percent in the Moody's regression. Nevertheless, the coefficient of percent African American remains significant at the 5 percent level for all three ratings agencies, and the coefficient of percent Hispanic remains significant at the 5 percent level in the Moody's regression. Controlling for the maximum probability of default does not alter the conclusion that these GO bond ratings involve some behavior analogous to redlining. To some degree, in other words, existing bond ratings are boosted by city characteristics that do not predict default but are negatively correlated with the share of the city's population that is black or Hispanic.

The data set for state GO bonds is described in Table 4. The bond ratings translate into numerical categories 1 (the highest ratings) to 5 (the lowest rating). The maximum probabilities of default fall between 0.20 and 0.61. The ordered logit results for this data set are presented in Table 5.[29] Using Model 1, I find that states with relatively high concentrations of African Americans, which are all southern states, are favored by the Moody's ratings. This is, of course, the opposite of our result for cities. These results suggest, in other words, that Moody's state ratings in the 1980s included the analog of reverse redlining. One possible explanation for this result is that southern states, which have large black populations, tend to use fiscal practices that lead to favorable ratings even though they do not help predict default. Adding a control for the maximum probability of default does not alter this conclusion. Although the underlying data are not current, these results suggest that the link between *M* and bond ratings may not be the same under all circumstances.

Conclusions and Policy Recommendations

This paper shows that the municipal bond ratings agencies might act in a manner that is analogous to redlining, which is discrimination against people who live in places with a certain racial or ethnic composition. I also present some evidence that this type of behavior exists in city GO bond ratings. Although it does not violate existing civil rights laws, this type of behavior certainly violates the societal norms that these laws express.

With the current regulatory arrangements, no institution is given the authority to determine whether this type of behavior exists. Indeed, CRARA makes it illegal for SEC to regulate bond ratings. This is troubling because the rating agencies cannot be expected to regulate themselves. In fact, this behavior may be profitable so that the agencies will resist steps to ban it, and the introduction of more competition into the bond rating industry (which is beneficial for other reasons) cannot be expected to make it go away.

This analysis leads directly to the conclusion that more regulation of municipal bond rating agencies is needed. The CRARA provision that proscribes the regulation of bond ratings should be repealed and replaced with authority for SEC to evaluate ratings. Moreover, regulation of these agencies should be supported by new legislation prohibiting the use of a jurisdiction’s racial or ethnic composition in a bond rating, either directly or indirectly. This regulation need not be intrusive and it certainly need not undermine the valuable service these agencies provide. Indeed, none of the methods presented in this paper undermine a rating agency's fundamental business interests or require a regulator to have access to the agency's proprietary rating scheme. Instead, these methods only require that bond rating agencies meet societal fairness standards and provide regulators with the data on which their ratings are based.

Any regulation of bond rating agencies must recognize the agencies' right of appeal. Existing civil rights laws provide an excellent framework for this issue. If a regulator finds evidence consistent with discrimination, then it is said to have established a prima facie case that discrimination exists. The alleged discriminator is then given the chance to show that the business practices in question are based on legitimate business factors, usually called "business necessity."[30] Suppose, for example, that a regulator's analysis of revenue bonds ratings came to the same conclusion as the study of GO bonds by Moon and Stotsky (1993). This finding would establish a prima facie case that these revenue bond ratings involve behavior analogous to redlining against cities with relatively high non-white populations. The rating agencies should then be given the opportunity to show that the percent-non-white variable is not significant when variables they consider (but the regulator did not) are added to the regression.

Rating agencies also should be allowed to respond if regulators find evidence equivalent to redlining using tools that include default information. In this case, however, the rating agencies cannot overturn a prima facie case for redlining-type behavior without providing two kinds of evidence. First, the rating agency must, as above, that the evidence for redlining-type behavior disappears when the statistical analysis is altered to conform more closely to the agency's actual practices. Second, the rating agency must show that these methodological changes do not result in poorer predictions of bond default.[31] This second requirement arises because the standard civil rights framework does not allow a firm to use a policy with a disparate impact on a legally protected class if there exists an alternative policy that achieves the firm's objectives without this impact. The regulator's regression provides just such a policy unless the agency can show that their approach does a better job predicting default.

According to this framework, the results in the previous section build a prima facie case for the existence of redlining-type behavior in city GO bond ratings. In a regulatory context, each bond rating agency should be allowed to respond to this evidence. If it could show that the apparent correlation between its ratings and race or ethnicity was due to a flaw in the regulator's analysis, then it would not be required to alter its rating scheme. If it could not uncover a flaw in the regulator's analysis, then they would have to revert to a scheme based on the regulator's regression or to some other scheme that passed the regulator's test.

The municipal bond rating agencies are important actors in the provision of state and local public services. Their rating decisions have a significant impact on variation in the cost of infrastructure across jurisdictions. Despite their cost implications, however, and despite evidence that they sometimes place jurisdictions with relative high minority populations at a disadvantage, these ratings are not examined by any regulatory agency. This situation cries out for reforms that balance the legitimate business purposes of ratings with the public's right to have ratings that conform to basic societal norms. The framework provided in this paper shows how these reforms could be designed.

Endnotes

[1] http://www.moodys.com/cust/default.asp.

[2] Strictly speaking, this sentence applies to GO unlimited tax bonds. Some GO bonds are "limited" tax bonds, that is, the tax pledge by which they are secured includes a limit on rate or amount. Limited and unlimited GO tax bonds may receive different ratings.

[3] A large literature uses statistical procedures to predict municipal bond ratings. See, for example, Ammar, et al. (2001), Moon and Stotsky (1993), Loviscek and Crowley (1990).

[4] The other two NRSROs are A.M. Best Company, Incorporated and Dominion Bond Rating Service Limited. See Nazareth (2005). The former specializes in insurance company bonds and the latter is a general-purpose rating company that has rates some municipal bonds in Canada. Both companies are relatively small.

[5] More specifically, CRARA requires SEC to "grant registration unless the applicant does not have adequate financial and managerial resources to consistently produce credit ratings with integrity and to comply materially with the procedures and methodologies disclosed in its application." This quotation is from the summary of CRARA on the Library of Congress website. The text of the bill is also on this site. See http://thomas.loc.gov/cgi-bin/bdquery/z?d109:s.03850.

[6] The Fair Housing Act can be found at http://www.usdoj.gov/crt/housing/title8.htm.

[7] An overview of ECOA on the Federal Trade Commission website, for example, says that "when deciding to give you credit, a creditor may not … consider the race of the people in the neighborhood where you want to buy, refinance or improve a house with borrowed money" (http://www.ftc.gov/bcp/conline/pubs/credit/ecoa.htm). ECOA can be found at: http://www.usdoj.gov/crt/housing/documents/ecoafulltext_5-1-06.htm.

[8] According to Becker (1993, p. 388), the impact of competition on discrimination in labor markets "depends not only on the distribution of tastes for discrimination among potential employers, but also on the nature of firm production functions."

[9] The reasons competition might not eliminate discrimination are reviewed in Ross and Yinger (2002, Chapter 7).

[10] I review statistical evidence. Another type of evidence comes from the histories of cities in a period of fiscal distress. For evidence of this type for Detroit, New York, and Philadelphia, see Sinclair (2005) and Hackworth (2002).

[11] An index of municipal bond interest rates prepared by S&P is posted by the Council of Economic Advisers at http://www.gpoaccess.gov/indicators/index.html.

[12] A bond rating also might be designed to indicate the expected magnitude of an investor's loss if a default occurs. I return to this issue in footnotes 25 and 31.

[13] This section draws on Ross and Yinger (2002).

[14] If some states can be observed refusing to help high-minority cities, then these states, not the bond-rating agencies should be held responsible for discrimination.

[15] Evidence of redlining in mortgage markets is uncovered by Ross and Tootell (2004).

[16] For evidence of statistical discrimination in other markets, see Altonji and Pierret (2001) and Ondrich, Ross and Yinger (2003).

[17] Strictly speaking, coefficients estimated by ordinary least squares are the best linear predictors, but the point here can easily be generalized to nonlinear models.

[18] The focus in this paper is on race and ethnicity, but lawmakers and regulators might also be concerned about other characteristics of the issuing jurisdiction, such as the

average age, gender-mix, or religious affiliations of its population. These other characteristics are also addressed in many civil rights laws.

[19] See, for example, Benson et al. (1981) and Halstead et al. (2004).

[20] Moon and Stotsky (1993) also estimated a model that incorporates a city's decision to obtain a rating. Ederington (1985) did not include any *M* variables.

[21] Hellerstein et al. find that the relative wages of female workers are lower than expected based on their relative productivity, which is a sign of discrimination. Other examples include Ayres and Waldfogle (1994) on bail charges, Szymanski (2000) on English soccer teams, and Conlin and Emerson (2006) on NFL teams.

[22] This approach differs from the so-called default literature in mortgage lending, which follows Becker's (1993)view that discrimination in loan approval constitutes a higher hurdle for minority applicants and therefore should result in higher performance for minority than for white mortgages. This approach is implemented by Berkovec at al. (1994, 1998) and criticized by Galster (1996) and Ross (1996). Ross and Yinger (2002) show how problems with this approach can be avoided by combining loan-approval and loan-performance information.

[23] Bond characteristics, the *B* variables, could also be included in this regression.

[24] Significant values for the *b* coefficients indicate that ratings also place other types of jurisdictions at a disadvantage, in the sense that their rating is lower than justified based on their default probability. This type of behavior by rating agencies is beyond the scope of this paper, but regulators or lawmakers might be concerned about it.

[25] The severity of loss upon default is also irrelevant here because no loss will ever occur.

[26] A related argument is that investors may recognize a scheme that gave a lower rating to high-*M* cities than to low-*M* cities with the same default probability and accept lower interest rates from the high-*M* cities—thereby offsetting (but not justifying!) the redlining in the rating scheme. This argument is internally inconsistent; investors with enough information to correct a rating scheme do not rely on ratings in the first place (as studies reviewed earlier show that they do).

[27] These data were downloaded from the Census website (www.census.gov). The bond data are in the *Statistical Abstract of the United States* and the data on ethnic composition are in the *City County Data Book*.

[28] I am grateful to Mary Lovely for providing these data. See Lovely and Wasylenko (1992) for a description of the sampling procedure. I added state ethnic composition data from the Census web site to the original data set.

[29] None of these state bond issues were insured. If they were, a control for bond insurance would be appropriate because a rating provides different information for insured and uninsured bonds. See Robbins (2002) and Simonsen and Robbins (1996).

[30] Ross and Yinger (2002) provide a detailed examination of this framework as applied to discrimination in mortgage lending.

[31] Alternatively, the rating agencies could overturn the prima facie case for discrimination by showing that their methods predict the severity of loss upon default or that they predict default in the rated bonds even if they do not predict default in previous bonds.

Table 1. Variable Definitions

Variable	Definition
s&p	City rating in 2000 by Standard and Poor’s
moodys	City rating in 2000 by Moody’s
fitch	City rating in 2000 by Fitch
state	State GO bond rating, 1982-1990, by Moody’s
pblack	Percentage of the population that is African American
pasian	Percentage of the population that is Asian
ptwora	Percentage of the population with ancestors from two or more races
phispa	Percentage of the population that is Hispanic
pnativ	Percentage of the population that is Native American
pother	Percentage of the population from another race
probmax	Maximum probability of default consistent with number of defaults in a rating category (at a 1% confidence level)

Table 2. Description of Data for City Ratings, 2000

Variable	Obs.	Mean/(Std. Dev.)	Min	Max
s&p	62	3.5323	1	7
		(1.7341)		
moodys	68	4.1471	1	9
		(2.2478)		
fitch	33	2.7576	1	5
		(1.2508)		
pblack	76	25.5697	1.6	81.6
		(19.5867)		
pasian	76	5.9132	0.7	55.9
		(8.2491)		
ptwora	76	3.3763	0.8	14.9
		(1.9586)		
phispa	76	18.3066	1.2	76.6
		(18.3593)		
probmax (Fitch)	33	0.4666	0.3	0.8
		(0.1829)		
probmax (S&P)	62	0.3839	0.2	0.7
		(0.1603)		
probmax (Moody's)	68	0.4220	0.2	0.7
		(0.1860)		

Table 3. Results for Standard and Poor's, Fitch and Moody's City Ratings, 2000

Ordered logit estimates	**Standard and Poor's**		**Fitch**		**Moody's**	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
	Coef./(St.Er.)	Coef./(St.Er.)	Coef./(St.Er.)	Coef./(St.Er.)	Coef./(St.Er.)	Coef./(St.Er.)
phispa	0.0299	0.0274	0.0148	0.01811	0.0388	0.0349
	(0.0169)	(0.0168)	(0.0260)	(0.0267)	(0.0158)	(0.0155)
pblack	0.0689**	0.0614	0.0504	0.0513	0.0785	0.0599
	(0.0166)	(0.0168)	(0.0248)	(0.0249)	(0.0160)	(0.0164)
pasian	-0.0447	-0.0463	0.0432	0.0557	-0.0413	-0.0276
	(0.0591)	(0.0630)	(0.0729)	(0.0749)	(0.0578)	(0.0561)
ptwora	0.5441*	0.5098	0.0489	0.0088	0.4546	0.3564
	(0.2772)	(0.2923)	(0.3318)	(0.3375)	(0.2541)	(0.2476)
Probmax		4.5534		2.1086		7.1232
		(1.7011)		(1.7650)		(1.8182)
Ancillary Parameters						
_cut1	1.4240	2.6351	0.6574	1.6518	1.7115	3.3666
	(0.9587)	(1.1182)	(1.3409)	(1.5900)	(0.9069)	(1.0260)
_cut2	2.5608	3.6429	1.5083	2.4567	2.2091	3.7868
	(0.9574)	(1.0933)	(1.3635)	(1.5898)	(0.9036)	(1.0125)
_cut3	4.4143	5.6008	3.7233	4.7596	3.8410	5.4194
	(1.0546)	(1.2031)	(1.5508)	(1.8162)	(0.9637)	(1.0598)
_cut4	5.1578	6.5966	4.4514	5.5878	4.8128	6.7578
	(1.1022)	(1.3113)	(1.6068)	(1.9197)	(1.0207)	(1.770)
_cut5	5.9070	7.5560			5.5518	7.9780
	(1.1585)	(1.4173)			(1.0665)	(1.3230)
_cut6	6.6097	8.3555			6.0012	8.6875
	(1.2205)	(1.4933)			(1.099)	(1.4057)
_cut7					6.6570	9.5468
					(1.1719)	(1.5064)
_cut8					7.6401	10.7003
					(1.2910)	(1.6363)
Summary Statistics						
Log Likelihood	-100.7807	-97.0774	-45.0836	-44.3661	-123.2646	-113.9578
Number of obs.	62	62	33	33	68	68
LR $chi^2(4)$	20.04	27.45	5.69	7.12	27.52	46.14
Prob > chi^2	0.0005	0.0000	0.2236	0.2115	0.0000	0.0000
Pseudo R^2	0.0904	0.1239	0.0594	0.0743	0.1004	0.1684

* = Significant at 5% level

** = Significant at 1% level

Table 4. Description of State GO Bond Data, 1982-1990

Variable	Obs.	Mean/ Std. Dev.	Min.	Max.
state	51	2.5686 (1.3001)	1	5.00
pblack	51	11.8037 (9.4082)	0.23	35.48
pnativ	51	0.5345 (0.7937)	0.1	4.96
pasian	51	2.5302 (8.4353)	0.34	60.76
pother	51	2.0231 (2.5299)	0.1	10.64
phispa	51	4.5380 (5.0819)	0.6	20.52
probmax	51	0.3361 (0.1743)	0.21	0.60

Table 5. Results for State GO Bonds, 1982-1990

Ordered logit estimates

Variable	Model 1 Coef./(St. Er.)	Model 2 Coef./(St. Er.)
pblack	-0.0815*	-0.8923*
	(0.0349)	(0.0388)
pnativ	-0.3040	-0.5676
	(0.2990)	(0.3441)
pasian	-0.0033	0.0084
	(0.0279)	(0.0295)
pother	-0.1603	-0.3196
	(0.3010)	(0.3201)
phispa	0.1278	0.2502
	(0.1496)	(0.1607)
probmax		7.2337**
		(2.0123)
Ancillary Parameters		
_cut1	-1.6393	0.4877
	(0.6310)	(0.8686)
_cut2	-1.1100	1.0486
	(0.6007)	(0.8507)
_cut3	0.7714	3.3348
	(0.6178)	(0.9982)
_cut4	1.5584	4.4884
	(0.6877)	(1.1515)
Summary Statistics		
Log Likelihood	-68.2423	-60.6388
Number of obs.	51	51
LR $chi^2(4)$	7.73	22.93
Prob > chi^2	0.1720	0.0008
Pseudo R^2	0.0536	0.1590

*   = Significant at 5% level
** = Significant at 1% level

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