Estimating the Feedback Among Credit Rating Agencies and its Impact on the Municipal Bond Market *

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Abstract

Local governments often seek credit ratings from multiple agencies for external financing. Rating shopping and catering, the incentives of the rating agencies, and the career incentives of the analysts issuing the ratings may render the ratings interdependent. This paper estimates the feedback among the credit ratings as well as the impact of the ratings on a bond's yield. To this end, we put forward a simultaneous equations model with three features. First, the model allows the bond's latent fundamental (i.e. credit worthiness) and observed characteristics to directly influence its ratings and yield. Second, the model allows each credit rating to influence the other ratings. Third, the model allows each credit rating to influence a bond's yield. To tackle the simultaneity and endogeneity in the model, we make use of higher order moments. We report simulation results that support our novel econometric framework. We report several important empirical findings. First, ceteris paribus, an agency increases its rating in response to another agency increasing its rating. Second, in full equilibrium, the feedback improves the overall quality of the ratings, measured by the reliability ratio. Third, a ceteris paribus increase in a credit rating decreases the bond yield, corroborating the literature's previous findings. Last, we document a separate substantive effect of the latent fundamental on the yield.

PRELIMINARY AND INCOMPLETE DRAFT.

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1 Introduction

In 2011, the Illinois Finance Authority issued non-callable revenue municipal bonds, in the amount of 25 million dollars, which were rated by S&P, Fitch, and Moody's. In 2020, the Illinois Finance Authority issued another non-callable revenue municipal bonds, in the amount of 67 million dollars. S&P assigned the issue a rating that is 4 notches above what it gave 9 years ago. Similarly, both Fitch and Moody's assigned the issue ratings that are 3 notches above what they assigned 9 years ago. The administration of the state of Illinois attributed the significant upgrades to the strong asset fundamental (Hinton, 2021a,b; NBC Chicago, 2021).

It is possible that the concurring ratings from three independent agencies merely reflect a common asset fundamental. Nevertheless, the previous literature suggests additional possibilities. A rating agency may learn from, and respond to, the actions of other agencies. This interdependence can occur due to e.g. rating shopping, rating catering, the reputation and credibility of the rating agencies, as well as the career incentives of the analysts issuing the ratings.[1].

While the literature addresses some of these aspects separately, a unified framework has been lacking. This paper puts forward a model that enables us to separate (1) the impact of the latent asset fundamental on the credit ratings and the bond's yield, (2) the feedback among the credit ratings, and (3) the effect of the ratings on a bond's yield. Among other things, this enables us to conduct a counterfactual analysis that studies how the feedback affects the quality of the ratings, measured by the rating's reliability ratio.

U.S. municipal bond markets are often viewed as opaque because the issuers of municipal bonds do not face the same disclosure requirements as public corporations (Aguilar, 2015). As a result, credit ratings play an important role in alleviating the information friction

[1]See Griffin et al. (2013); Becker and Milbourn (2011); Bruno et al. (2016); Cornaggia and Cornaggia (2013); Jiang et al. (2012); Flynn and Ghent (2018); He et al. (2012). See also the news articles Banerji (2019); Podkul and Banerji (2019)

(Butler, 2008). Indeed, the ratings can influence the local government's borrowing costs (Cornaggia et al., 2018) and the quality of public services (Adelino et al., 2017). And the ratings of municipal bonds have become increasingly relevant over the past two decades Baghai et al. (2020), after the collapse of the municipal bond insurance industry during the 2007-08 financial crisis (Thakor, 1982; Cornaggia et al., 2020b; Agrawal and Kim, 2022).

Municipal bonds are often rated by multiple agencies. Specifically, this market is dominated by three rating agencies: S&P, Moody's, and Fitch (Best, 2020). Between 2011 and 2020, 77% of 2.36 trillion dollars of municipal bonds issued were rated by two or three agencies. The ratings are highly correlated - the correlation between S&P's and Moody's is 0.86, that between S&P's and Fitch's is 0.91, and that between Moody's and Fitch's is 0.92.

To understand the genesis of these correlations, we develop a model that separates the effect of the latent bond fundamental on the ratings from the interdependence among the ratings. Further, the model also distinguishes between the effect of the latent bond fundamental and the effects of each credit rating on the yield.

In particular, we model an agency's credit rating as a linear function of the issue's unobserved fundamental, the ratings of the other agencies, and the bond's observed characteristics. We also include time and issuer fixed effects. The dependence of the ratings on the fundamental reflects several factors. First, a primary function of an agency's rating is to accurately measure the issue's unobserved fundamental. This can improve the reputation and credibiliy of the agency, and may lead to higher profitability (Bolton et al., 2012). But other incentives may be present. For instance, to further their careers, credit rating analysts may signal their skill by producing ratings that accurately reflect the unobserved fundamental (Kempf, 2020). Alternatively, they may inflate the rating of a client's issue to increase their chance of gaining employment with this client (see Cornaggia et al. (2016)).

A key feature of our model is that it allows (but does not require) an agency's rating to depend on the ratings of the other agencies. The feedback among the credit ratings reflect how agencies may learn form, and react to, each other. This can arise due to several factors such as the practices of "rating shopping" whereby clients may shop for the best rating and "rating catering" whereby agencies may inflate their ratings to attract clients and increase their revenues (Griffin et al., 2013).[2] In equilibrium, the ratings of all agencies are determined simultaneously as a function of the unobserved fundamental, capturing the net effects of these various forces.

As for the bond's price, we model this as a linear function of the issue's unobserved fundamental, the ratings of all agencies, and the bond's observed characteristics. This allows (but does not require) the ratings to directly impact the yield. As discussed in the literature, this may arise due to several mechanisms. For instance, retail and institutional investors may rely on credit ratings in their investment decisions (see e.g. Cornaggia et al. (2018, 2020a)). Moreover, certain institutional investors face regulations that are based on the ratings (see e.g. Kisgen and Strahan (2010); Ellul et al. (2011); Bongaerts et al. (2012); Manso (2013); Opp et al. (2013); Becker and Opp (2014); Chen et al. (2014); Becker and Ivashina (2015); Stanton and Wallace (2017); Painter (2020)). See also Parlour and Rajan (2020) who studies a model in which contracts between an investor and a manager may be contingent on credit ratings.

To estimate this paper's model, we must confront several econometric challenges. First the unobserved fundamental may drive the ratings and the yield and is likely correlated with the observed characteristics, rendering the basic regression estimates prone to omitted variable bias. Second, the potential feedback among the credit ratings renders these simultaneously determined and endogenous. Third, although the credit ratings may serve the role of proxies for the unobserved fundamental, they can directly impact the price, violating the proxy exclusion restriction (Chalak and Kim, 2021).

To address these challenges, we develop an econometric framework that relies on higher

[2] Cornaggia et al. (2021) suggests that rating catering may be less prevalent in the municipal bond markets than in other asset classes such as corporate bonds, due to the different fee disclosure requirements.

order moments to point identify the system coefficients. Estimators based on higher order moments have a long tradition in econometrics (see e.g. Reiersøl (1950), Erickson and Whited (2002), and Erickson et al. (2014)). These methods have been extensively used to address measurement errors in financial data (see e.g. Erickson and Whited (2000) and Erickson and Whited (2012)).[3] The literature typically assumes that the proxies (e.g. credit ratings) for the latent variables are excluded from the outcome (e.g. price) equation. Nevertheless, Chalak and Kim (2022) extend these methods to relax this proxy exclusion restriction. Here, we build on this result to accommodate a system with a single latent variable and multiple proxies that violate the proxy exclusion restriction and exhibit feedback.

Our econometric framework enjoys several advantages. First, it affords studying various effects within a unified framework. For example, we jointly estimate the interdependence among the ratings and the effects of the ratings on the yield. This leads to coherent estimates of various related quantities of interest and enables us to perform counterfactual analyses of e.g. the effect of shutting down the feedback among the agencies on the quality of the ratings. It also permits us to conduct overidentification tests of the validity of the overall structure. Second, prior studies have used natural experiments to estimate certain effects at particular time periods. For example, Becker and Milbourn (2011) finds that the material entry of the third rating agency (Fitch) into the market in 2000 decreased the quality of the ratings of the other agencies (S&P and Moody's). Further, Cornaggia et al. (2018) and Adelino et al. (2017) used Moody's 2010 scale recalibration to estimate the effect of ratings on yield. Nevertheless, these effects are not necessarily transportable to other contexts or time periods. Yet, several interesting developments and reforms took place in the recent years following the Dodd-Frank Act.(Rivlin and Soroushian, 2017) We use our framework to gain a better understanding of the role of ratings in the recent 2011-2020 time-frame. Third, since our econometric framework relies on higher order moments, it is particularly suitable for analyzing credit

[3] Here, we interpret the measurement error broadly as the discrepancy between the underlying economic variables and the observed measurements.

ratings, where the variables of interest follow skewed non-normal distributions. (Erickson et al., 2014). In particular, credit ratings are skewed and are suggested to be highly inflated (see e.g. Podkul and Banerji (2019)).

In a nutshell, we report four main results. First, we find that agencies increase their rating between 0.05 to 0.38 notches in response to a notch increase in the rating of another agency ceteris paribus. In equilibrium, this feedback amplifies the sensitivity of the ratings to changes in the unobserved fundamental. Second, we measure the quality of the ratings using the reliability ratio (the signal to total variance ratio). We find that the ratings of Moody's are most accurate, followed by Fitch and then S&P. Moreover, we find that the quality of the ratings decreases if we shut down the feedback among the ratings in the model or as the number of agencies issuing ratings increases.[4] Third, we find that a notch increase in S&P's (resp. Moody's) rating leads to a decrease of 8 basis points (resp. 2 basis points) in price even after we control for the unobserved fundamental and the observed characteristics.[5] Last, we document a separate substantial effect of the latent fundamental on the yield.

The remainder of this paper is organized as follows. Section 2 describes the institutional background and our model. Section 3 discusses our econometric framework and reports simulation results. Section 4 describes the data. Section 5 reports our empirical findings. Section 6 concludes.

[4] This holds when we compare the quality of ratings for issues that are rated only by S&P and Moody's to those that are rated by S&P, Moody's, and Fitch, and is qualitatively consistent with the findings of Becker and Milbourn (2011), who uses the entry of Fitch as a natural experiment to study how competition affects credit ratings.

[5] Our estimates of the effect of the ratings on yield corroborate the results in Cornaggia et al. (2018) based on Moody's 2010 scale re-calibration as a natural experiment.

2 Institutional Background and Framework

2.1 Credit Ratings for Municipal Bonds

We begin with a brief review of the process for issuing a credit rating in the municipal bond market (see e.g. Cash (2018) for more details). As summarized in S&P Gloal Ratings (2021) (see Figure 1), an issuer who decides to issue rated municipal bonds (or "munis" for short) must first submit a "rating request" to the rating agencies —S&P, Moody's, and/or Fitch. Upon meeting with the issuer's management to collect data, a team of analysts at the agency use their proprietary credit risk model to perform a credit analysis and propose a rating to a rating committee. The committee reviews the rating recommendation and updates it if needed. Last, the issuer is notified of the final rating, along with rationale for it, and the rating gets typically published.

During this process, the rating agencies may learn from or react to each other directly or indirectly. For example, in order to solicit better ratings, an issuer may strategically engage in a particular sequence with multiple rating agencies. Similarly, to increase market share, agencies may respond to the other agencies' rating. In both instances, a sequence of exchanges between the agencies unfolds. Unfortunately, researchers do not observe the exact sequence of these actions. Instead, only the equilibrium outcome is observed.

To captures the interdependence among the ratings, we use the following system of simultaneous equations in which each rating depends on the ratings of the other agencies and the unobserved fundamental:

$$\mathrm{R}_{S\&P} = \xi_{S\&P} \cdot \text{Fundamental} + \alpha_{SM} \cdot \mathrm{R}_{Moody's} + \alpha_{SF} \cdot \mathrm{R}_{Fitch} + \epsilon_{S\&P} \tag{1}$$

$$\mathrm{R}_{Moody's} = \xi_{Moody's} \cdot \text{Fundamental} + \alpha_{MS} \cdot \mathrm{R}_{S\&P} + \alpha_{MF} \cdot \mathrm{R}_{Fitch} + \epsilon_{Moody's} \tag{2}$$

$$\mathrm{R}_{Fitch} = \xi_{Fitch} \cdot \text{Fundamental} + \alpha_{FS} \cdot \mathrm{R}_{S\&P} + \alpha_{FM} \cdot \mathrm{R}_{Moody's} + \epsilon_{Fitch}. \tag{3}$$

Here, $\mathrm{R}_{S\&P}$, $\mathrm{R}_{Moody's}$, and R_{Fitch} denote the ratings issued by S&P, Moody's, and Fitch respectively for the same muni. Fundamental refers to the unobserved credit worthiness of this muni. $\epsilon_{S\&P}$, $\epsilon_{Moody's}$, and ϵ_{Fitch} are idiosyncratic rating innovations. We model $\mathrm{R}_{S\&P}$ as a linear function of three components: the unobserved Fundamental, Moody's rating $\mathrm{R}_{Moody's}$, R_{Fitch}, and the disturbance $\epsilon_{S\&P}$. $\mathrm{R}_{Moody's}$ and R_{Fitch} are determined analogously. The ratings may also depend on other observed issue characteristics as well as on issuer and time fixed effects. To ease the exposition, we leave these implicit. We discuss each of these terms in more detail in what follows.

First, consider the role of the unobserved (Fundamental) in, e.g., the first equation. The coefficient $\xi_{S\&P}$ controls the sensitivity of $\mathrm{R}_{S\&P}$ to variations in the unobserved fundamental ceteris paribus. For example, as reflected by the multistage review process described above, agencies have an incentive to issue accurate ratings in order to maintain a good reputation (see e.g. Bolton et al. (2012)). Similarly, to further their careers, analysts may signal their skill by issuing accurate ratings that reflect the issue's fundamental (see e.g. Kempf (2020)). On the other hand, issuers may hire analysts who review them favorably, and this "revolving doors" practice produces less accurate ratings (see e.g. Cornaggia et al. (2016)). In the absence of feedback, a perfectly accurate rating occurs when $R_{S\&P} = \xi_{S\&P} \cdot \mathrm{Fundamental}$.

Next, consider the rating variables such as ($\mathrm{R}_{Moody's}$) in the first equation. The coefficient (α_{SM}) encodes how S&P's rating $\mathrm{R}_{S\&P}$ responds to a ceteris paribus increase in Moody's rating $\mathrm{R}_{Moody's}$. It may be cost effective for S&P to "learn" from Moody's ratings, either directly or indirectly. In the limit, if $\xi_{S\&P} = 0$, $(\alpha_{SM}) = 1$, $(\alpha_{SF}) = 0$, and $\epsilon_{S\&P} = 0$ then S&P would simply "copy" Moody's. Further, issuer can shop for better rating and agencies can cater for a client since the muni issuer pays the rating fees. These "rating catering" (see e.g. Griffin et al. (2013)) and "rating shopping" (see e.g. Becker and Milbourn (2011);Bruno et al. (2016); Cornaggia and Cornaggia (2013); Jiang et al. (2012); Flynn and Ghent (2018); He et al. (2012)) practices may also lead to a positive α_{SM}.[6] Similar comments apply to the

[6] Recently, Cornaggia et al. (2021)) suggests that "rating catering" is less severe in the muni market.

coefficient α_{SF} attached to the Fitch rating.

As explained in Spatt and Sangiorgi (2017), credit rating agencies are viewed as rendering opinions, and their ratings are therefore likely to embody an idiosyncratic component. The disturbances, $\epsilon_{S\&P}$, $\epsilon_{Moody's}$, and ϵ_{Fitch} capture various such idiosyncrasies. They may also include general factors, such as the political views of the credit rating analysts (Kempf and Tsoutsoura, 2021), agency incentives[7], and other type of measurement errors.

2.2 Municipal Bond Price

In addition to estimating the feedback among the ratings, we also study the effect of the ratings and of the unobserved fundamental on the muni price. Credit ratings play an important role in alleviating the friction that arises due to the information asymmetry between issuers and investors. This friction is particularly severe for munis, compared to other assets, because municipalities are under no obligation to disclose their financial statements. Although the municipal bond insurance industry helped reduce the information asymmetry (Thakor, 1982), its role has significantly diminished after the municipal bond insurance industry collapsed during the financial crisis. Consequently, the role that credit ratings play in signaling quality has become even more important (Baghai et al., 2020).

Several papers argue that ratings have an impact on prices. The literature argues that this can be due to demand driven by rating-based regulation (Kisgen and Strahan, 2010; Ellul et al., 2011; Bongaerts et al., 2012; Manso, 2013; Opp et al., 2013; Becker and Opp, 2014; Chen et al., 2014; Becker and Ivashina, 2015; Stanton and Wallace, 2017; Painter, 2020) as well as to retail investors attempting to learn from credit ratings (Cornaggia et al., 2018, 2020a). See also Parlour and Rajan (2020) who study a model in which contracts between an investor and a manager may be contingent on credit ratings. As such, we model

[7]Some agencies may face a conflict of interests when assigning ratings. For example, unlike Moody's and Fitch, in addition to issuing ratings, S&P also decides on which companies to include in the S&P 500 index. This can incentivize S&P to issue better ratings to the indexed entities to increase S&P's overall profits (Cash, 2018; Li et al., 2021; Powell, 2021).

the price as follows:

$$\text{Price} = \delta \cdot \text{Fundamental} + \phi_S \cdot \text{R}_{S\&P} + \phi_M \cdot \text{R}_{Moody's} + \phi_F \cdot \text{R}_{Fitch} + \eta \tag{4}$$

Equation (4) allows the price to depend on the unobserved fundamental that appears in equations (1), (2), and (3). Further, it allows (but does not require) it to depend on all the issued ratings and on the observed characteristics which we continue to leave implicit. The pricing error η captures any remaining idiosyncratic factors.

3 Econometric Framework

3.1 Identification Challenges

Consistently estimating the parameters in equations (1), (2), (3), and (4) requires resolving several identification challenges. First, the latent Fundamental affects the ratings $\text{R}_{S\&P}$, $\text{R}_{Moody's}$, R_{Fitch} and the price Price. As such, we must account for the impact of this omitted variable. Second, we must account for the endogeneity that arises due to the potential simultaneity among the credit ratings $\text{R}_{S\&P}$, $\text{R}_{Moody's}$, R_{Fitch}. Third, although the credit ratings may serve the role of proxies for the unobserved fundamental, allowing $\phi_{S\&P}$, (ϕ_M), and (ϕ_F) to be nonzero violates the proxy exclusion restriction. This renders the measurement error "differential" and hinders the use of common methods (Chalak and Kim, 2021).[8]

To resolve these challenges, we develop an econometric framework that relies on higher order moments to point identify the system coefficients. Estimators based on higher order moments have a long tradition in econometrics (see e.g. Reiersøl (1950), Erickson and Whited (2002), and Erickson et al. (2014)) and have been extensively used to treat measurement errors in financial data (see e.g. Erickson and Whited (2000) and Erickson and Whited

[8] Allowing the proxy to directly enter the outcome equation is a leading setting for "differential" measurement error that "occurs when [$\text{R}_{S\&P}$] is not merely a mismeasured version of [U], but is a separate variable acting as a type of proxy for [U]" (see Carroll et al. (2006) and Chalak and Kim (2021)).

(2012)). These methods assume no feedback and that the proxy exclusion restriction holds. Here, we build on the result in Chalak and Kim (2022) that relax the proxy exclusion restriction and extend these to accommodate a system with a single latent variable and multiple proxies that violate the proxy exclusion restriction and exhibit feedback.

3.2 Data Generation Assumptions

To illustrate our econometric framework, we focus on the case of three ratings. The two-ratings case is similar. To ease the notation, we relabel the variables as follows:

$$\ddot{W}_1 = \xi_1 \ddot{U} + \alpha_{12} \ddot{W}_2 + \alpha_{13} \ddot{W}_3 + \gamma_1 X + \ddot{\epsilon}_1 \tag{5}$$

$$\ddot{W}_2 = \xi_2 \ddot{U} + \alpha_{21} \ddot{W}_1 + \alpha_{23} \ddot{W}_3 + \gamma_2 X + \ddot{\epsilon}_2 \tag{6}$$

$$\ddot{W}_3 = \xi_3 \ddot{U} + \alpha_{31} \ddot{W}_1 + \alpha_{32} \ddot{W}_2 + \gamma_3 X + \ddot{\epsilon}_3 \tag{7}$$

$$\ddot{Y} = \delta \ddot{U} + \phi_1 \ddot{W}_1 + \phi_2 \ddot{W}_2 + \phi_3 \ddot{W}_3 + \beta X + \ddot{\eta} \tag{8}$$

where $\ddot{Y}$ denotes the price, $\ddot{W}_1$, $\ddot{W}_2$, and $\ddot{W}_3$ denote the ratings, $\ddot{U}$ denotes the unobserved fundamental, and X denotes the observed covariates. Further, we assume that $(\ddot{\epsilon}_1, \ddot{\epsilon}_2, \ddot{\epsilon}_3, \ddot{\eta})$ and X are uncorrelated.

Assumption 1. *W_1, W_2, W_3, and Y are generated according to the linear equations (5), (6), (7), and (8), and X is uncorrelated with $(\ddot{\epsilon}_1, \ddot{\epsilon}_2, \ddot{\epsilon}_3, \ddot{\eta})$.*

Projecting both sides of these equations on X yields the residuals U, W_1, W_2, W_3, Y, $\tilde{\epsilon}_1$,

$\tilde{\epsilon}_2$, $\tilde{\epsilon}_3$, and η that satisfy the following system of equations:

$$W_1 = \xi_1 U + \alpha_{12} W_2 + \alpha_{13} W_3 + \tilde{\epsilon}_1 \tag{9}$$

$$W_2 = \xi_2 U + \alpha_{21} W_1 + \alpha_{23} W_3 + \tilde{\epsilon}_2 \tag{10}$$

$$W_3 = \xi_3 U + \alpha_{31} W_1 + \alpha_{32} W_2 + \tilde{\epsilon}_3 \tag{11}$$

$$Y = \delta U + \phi_1 W_1 + \phi_2 W_2 + \phi_3 W_3 + \eta \tag{12}$$

In what follows, we leave the covariates implicit and work directly with the above net-of-X system of equations. In equilibrium, we obtain the following reduced form equations for W_1, W_2, and W_3 along with the Y equation:

$$W_1 = \kappa_1 U + \epsilon_1 \tag{13}$$

$$W_2 = \kappa_2 U + \epsilon_2 \tag{14}$$

$$W_3 = \kappa_3 U + \epsilon_3 \tag{15}$$

$$\begin{aligned} Y &= \phi_1 W_1 + \phi_2 W_2 + \phi_3 W_3 + \delta U + \eta \\ &= (\delta + \sum_{l=1}^{3} \phi_l \kappa_l) U + \phi_1 \epsilon_1 + \phi_2 \epsilon_2 + \phi_3 \epsilon_3 + \eta \end{aligned} \tag{16}$$

where

$$\begin{bmatrix} \kappa_1 \\ \kappa_2 \\ \kappa_3 \end{bmatrix} = \alpha^{-1} \xi = \begin{bmatrix} 1 & -\alpha_{12} & -\alpha_{13} \\ -\alpha_{21} & 1 & -\alpha_{23} \\ -\alpha_{31} & -\alpha_{32} & 1 \end{bmatrix}^{-1} \begin{bmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \end{bmatrix}$$

and

$$\epsilon = \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \end{bmatrix} = \alpha^{-1}\tilde{\epsilon} = \begin{bmatrix} 1 & -\alpha_{12} & -\alpha_{13} \\ -\alpha_{21} & 1 & -\alpha_{23} \\ -\alpha_{31} & -\alpha_{32} & 1 \end{bmatrix}^{-1} \begin{bmatrix} \tilde{\epsilon}_1 \\ \tilde{\epsilon}_2 \\ \tilde{\epsilon}_3 \end{bmatrix} \tag{17}$$

For such an equilibrium to exist, we require that the matrix α is invertible. Otherwise, κ_1, κ_2, and κ_3 and ϵ are not well defined.

Assumption 2. *The matrix α is invertible.*

To point-identify the system coefficients, we employ the following additional assumptions. We assume that the idiosyncratic rating errors $\tilde{\epsilon}_1$, $\tilde{\epsilon}_2$, and $\tilde{\epsilon}_3$ are jointly independent.

Assumption 3. *The idiosyncratic rating disturbances ($\tilde{\epsilon}$) are jointly independent.*

Recall that S&P, Moody's, and Fitch are independent competitors who do not observe each other's idiosyncratic rating innovations. Note that the equilibrium rating disturbances ϵ_1, ϵ_2, ϵ_3 generally differ from the idiosyncratic rating errors $\tilde{\epsilon}_1$, $\tilde{\epsilon}_2$, and $\tilde{\epsilon}_3$ and depend on each other due to the feedback in the system of simultaneous equations for the ratings as shown in Equation (17).

Further, we assume that the unobservable fundamental, the idiosyncratic rating disturbances, and the pricing error are jointly independent.

Assumption 4. *The idiosyncratic rating disturbances $(\tilde{\epsilon}_1, \tilde{\epsilon}_2, \tilde{\epsilon}_3)$, the unobserved fundamental U, and the pricing error η are jointly independent.*

This is a specification condition that assumes that the latent variable and disturbances that are not observed by the market participants are not systematically related.

Using the above system of equations and Assumptions 1 , 2, and 3, we can express higher order moments involving Y, W_1, W_2, and W_3 as a function of the system coefficients and the moments involving the unobservables.

For our three ratings case, we include moments of order 2 or 3. Including moments of only order 2 implies an under-identified system where the number of unknowns is strictly larger than the number of equations. Including moments of order higher than 3 can help over-identify the system of equations, but this may also generate worse finite sample properties. Section 3.4 discusses an overidentification test for the overall validity of the assumptions that we employ.

More specifically, we include 29 moments in total. Among these, 10 are of order two: $(E(W_iY),\ E(W_iW_j),\ E(Y^2))$ for $i, j = 1, 2, 3$. The others are of order three: $(E(W_iY^2)$, $E(W_i^3)$, $E(W_iW_jY)$, $E(W_i^2W_j)$, $E(W_1W_2W_3))$ for $i, j = 1, 2, 3$. These moments are written as a function of 21 unknowns for $i, j = 1, 2, 3$ and $i \neq j$:

$$\phi_i, \delta, \alpha_{ij}, \xi_2, \xi_3, E(U^2), E(\tilde{\epsilon}_i^2), E(\eta^2), E(U^3), E(\tilde{\epsilon}_i^3)$$

For example, we express the moment $E(W_1W_3Y)$ as follows

$$E(W_1W_3Y) \quad = \quad \kappa_1\kappa_3 \sum_{l=1}^{3} E(U^3)(\phi_l\kappa_l + \delta/3) + \sum_{l=1}^{3} E(\epsilon_1\epsilon_3\epsilon_l)\phi_l$$

Stacking these equations yields a system of 29 moment equations in 21 unknowns. In case of two ratings, we obtain a system of 15 moment equations in 13 unknowns. We refer the interested reader to Section A for details.

It is well known that methods based on higher order moments require asymmetric distributions. Otherwise, the third moments are zero rendering the system underidentified (see Reiersøl (1950), Erickson and Whited (2002)). Thus, we require that the distribution of U be asymmetric.

Assumption 5. *The distribution of U is asymmetric, $E(U^3) \neq 0$.*

Examining the resulting system of moments reveals that these may exhibit multiple roots. In particular, properly interchanging the moments involving U and ϵ as well as their corresponding coefficients yields an observationally equivalent system of equations. As discussed in Chalak and Kim (2022), imposing sign restrictions on some of the coefficients can help distinguish these roots. We proceed accordingly here and impose the following assumptions to point identify the system coefficients.

First, we assume that sign of δ is known.

Assumption 6. *The sign of δ is negative, $\delta < 0$.*

Assuming that $\delta < 0$ is mild since this merely assumes that an increase in credit worthiness implies a lower bond yield.

Last, observe that one can generate an observationally equivalent system of equations by arbitrarily scaling U and then offsetting this by inversly scaling the system coefficients multiplying U. To pin down the scale of the unobserved fundamental, we set $\xi_1 = 1$. We further assume that $\xi_1 \geq 0$ and $\xi_2 \geq 0$ are nonnegative.

Assumption 7. *We have that $\xi_1 = 1$, $\xi_1 \geq 0$, and $\xi_2 \geq 0$.*

The normalization (or identification up to scale) $\xi_1 = 1$ is not specific to our framework. Rather, it is a generic and unavoidable feature of systems with latent variables. Thus, we interpret the magnitude of the coefficients relative to the unit of the sensitivity of W_1 to U. The assumption that ξ_1 and ξ_2 are nonnegative is mild, as it merely assumes that an increase in credit worthiness generates a (weakly) better rating ceteris paribus.

3.3 GMM Higher Order Moments Estimator

Collecting the moments, we can express these as a system of equations

$$E(g(Z, \theta^*)) = E(m(Z) - c(\theta^*)) = 0.$$

Here, Z is the vector of observables (W_1, W_2, W_3, Y) and $m(Z)$ is 29×1 vector that stacks 29 aformentioned moments. θ^* collects 21 uknowns that include the system "true" coefficients (e.g. ϕ_1) and higher order moments involving the unobservables (e.g. $E(U^2)$). We can therefore characterize θ^* as the solution to the following minimization problem

$$\min_{\theta \in \Theta} E(g(Z,\theta))' \Xi^* E(g(Z,\theta)).$$

where we set the positive definite weighting matrix Ξ^* to the optimal GMM weighting matrix:

$$\Xi^{*-1} = \mathbf{\Lambda}^* \equiv E[g(Z;\theta^*)g(Z;\theta^*)'] = Var[g(Z;\theta^*)].$$

Using an initial estimator $\hat{\Xi}$ for Ξ, we estimate θ^* by solving the sample analogue minimization problem:

$$\Omega = \min_{\theta \in \Theta} \left(\frac{1}{N} \sum_{i=1}^{N} g(Z,\theta) \right)' \hat{\Xi} \left(\frac{1}{N} \sum_{i=1}^{N} g(Z,\theta) \right), \tag{18}$$

and we iterate this procedure several steps to reach our final estimator $\hat{\theta}$. Under standard regularity (smoothness and rank) conditions, $\hat{\theta}$ is $\sqrt{N}$ consistent and asymptotically normally distributed:

$$\sqrt{n}(\hat{\theta} - \theta^*) \xrightarrow{d} N(0, (\mathbf{A}^*)^{-1}),$$

where

$$\mathbf{A}^* \equiv \mathbf{G}^{*\prime} \Xi^* \mathbf{G}^* \text{ and } \mathbf{G}^* \equiv E[\nabla_\theta g(Z,\theta^*)].$$

The asymptotic variance can then be estimated using the plug-in sample analogues or, alternatively, it can be bootstrapped.

3.4 Specification Test

We make use of the fact that the system of moment equations is overidentified to test the null hypothesis that the assumptions that we have imposed are jointly valid, using a standard

GMM overidentification test:

$$\mathrm{N} \cdot \Omega \tag{19}$$

where Ω is defined in Equation (18) and N is the sample size. Under the null of correct specification, this test statistic follows a χ^2 distribution asymptotically, with the degrees of freedom equal to the number of moments minus the number of unknowns.[9] Rejecting the null hypothesis implies that at least one of our assumptions fails. Otherwise, we do not have sufficient evidence against the specification of the model.

3.5 Rating Quality

An advantage of our econometric framework is that it allows estimating moments of the unobserved latent variable. This permits us to construct a measure of the quality of the ratings using the reliability ratio:

$$\mathrm{R}_j = \frac{Var(\kappa_j U)}{Var(\kappa_j U) + Var(\epsilon_j)} \tag{20}$$

Here, we continue to use the variables that are projected on the covariates. Thus, the above reliability ratio measures the quality of a rating net of the covariates. This is a measure of rating quality that is beyond what is easily observable by the market participants and the researcher. One can map this into an unconditional reliability ratio by accounting for the covariates and the fixed effects.[10]

[9] For instance, in the case of two (three) ratings, the degrees of freedom are $15 - 13 = 2$ $(29 - 21 = 8)$.

[10] There is one-to-one mapping between the unconditional reliability ratio and the ones that uses the variables after projecting on the covariates:

$$\mathrm{R}_j^* = R^2_{W_j,X} + (1 - R^2_{W_j,X}) \cdot R_j$$

where $R^2_{W_j,X}$ is R-square of regressing W_j on X. See for example, (Chalak and Kim, 2020)

3.6 Monte Carlo Simulations

This section reports simulations in the cases of two and three ratings.

3.6.1 Three Credit Rating Agencies

As in Erickson and Whited (2012), we calibrate our simulations following the sample that we use in the empirical analysis. For the case of three ratings (which corresponds to the subsample of issues that are rated by S&P, Moody, and Fitch), we generate a panel with 1,052 unique issuers and 10 time periods, where each issuer issues 31 muni's every time period. Following our assumptions, we generate data on the unobserved random variables, U, $\tilde{\epsilon}_1$, $\tilde{\epsilon}_2$, $\tilde{\epsilon}_3$, and η that follow jointly independent Gamma distributions:

$$U \sim \Gamma(1, 1) \qquad \tilde{\epsilon}_1 \sim \Gamma(1, 0.5) \qquad \tilde{\epsilon}_2 \sim \Gamma(1, 0.5) \qquad \tilde{\epsilon}_3 \sim \Gamma(1, 0.5) \qquad \eta \sim \Gamma(1, 1),$$

and we then demean these random variables. We generate data on the observables (Y , W_1, W_2, and W_3) according to the equations described above. We set $\xi_1 = 1, \xi_2 = 0.6, \xi_3 = 1.1, \alpha_{12} = 0.2, \alpha_{13} = 0.25, \alpha_{21} = 0.3, \alpha_{23} = 0.15, \alpha_{31} = 0.1, \alpha_{32} = 0.1$. Moreover, we set $\phi_1 = -0.1, \phi_2 = -0.15, \phi_3 = -0.3, \delta = -0.6$. We also include issuer and year fixed effects which we allow to be correlated with the unobservable fundamental, U.

To proceed with the GMM estimation, we use three initial points in the numerical optimization. We construct these points based on observed moments such as regression coefficients, instrumental variable estimates (see e.g. (Erickson et al., 2014)), second moments, and third moments. To speed up the running time, we set a wide range for the parameter values in the numerical optimization. The ranges are also based on observed moments. For example, the second moments for the rating innovations are positive and bounded by the second moments of the ratings. For each initial point, we use a five step iterated GMM estimator to obtain the estimate. We then pick the estimate that yields the smallest objective function value. We repeat the above steps over 1,000 simulations. The numerical optimization converges in 966 out of 1,000 simulations. One can possibly improve the numerical optimization convergence by increasing the number of GMM steps or the number of initial points.

We report the mean and standard deviation of our higher order estimator over the 966 simulation draws where the numerical optimization converged. Table 1 summarizes the results. As shown, the estimator performs very well across the 21 unknowns. For instance, the coefficient of the feedback from agency 2 to agency 1 converges to the true value 0.2 with a standard deviation of 0.004. The estimate for the third order moment $E(U^3)$ is 1.979 and has the largest standard deviation of 0.064 but falls well within one standard deviation of its true value, 2.

3.6.2 Two Credit Rating Agencies

We also consider the case of two ratings. We have

$$W_1 = \xi_1 U + \alpha_{12} W_2 + \tilde{\epsilon}_1 \tag{21}$$

$$W_2 = \xi_2 U + \alpha_{21} W_1 + \tilde{\epsilon}_2 \tag{22}$$

$$Y = \delta U + \phi_1 W_1 + \phi_2 W_2 + \eta \tag{23}$$

In equilibrium, we obtain:

$$W_1 = \kappa_1 U + \epsilon_1 \tag{24}$$

$$W_2 = \kappa_2 U + \epsilon_2 \tag{25}$$

$$Y = (\phi_1 \kappa_1 + \phi_2 \kappa_2 + \delta) U + \phi_1 \epsilon_1 + \phi_2 \epsilon_2 + \eta \tag{26}$$

where κ_1, κ_2, ϵ_1, and ϵ_2 are given by

$$\kappa_1 = \frac{\alpha_{12}\xi_2 + \xi_1}{1 - \alpha_{12}\alpha_{21}} \qquad \kappa_2 = \frac{\alpha_{21}\xi_1 + \xi_2}{1 - \alpha_{12}\alpha_{21}}$$
$$\epsilon_1 = \frac{\alpha_{12}\tilde{\epsilon}_2 + \tilde{\epsilon}_1}{1 - \alpha_{12}\alpha_{21}} \qquad \epsilon_2 = \frac{\alpha_{21}\tilde{\epsilon}_1 + \tilde{\epsilon}_2}{1 - \alpha_{12}\alpha_{21}}$$

We construct our simulations in a way that mimics our sample on issues rated by S&P and Moody's. We generate a panel with 2,683 issuers and 10 time periods where each issuer issues 15 muni's every time period. Following our assumptions, we draw data on U, $\tilde{\epsilon}_1$, $\tilde{\epsilon}_2$, and η from jointly independent Gamma distributions:

$$U \sim \Gamma(1,1) \qquad \tilde{\epsilon}_1 \sim \Gamma(1,0.5) \qquad \tilde{\epsilon}_2 \sim \Gamma(1,0.5) \qquad \eta \sim \Gamma(1,1),$$

and we then demean these random variables. We generate data on the observables (Y , W_1, and W_2) according to Equations (21), (22), and (23) where we include issuer and year fixed effects that are correlated with U. Here too, we set $\xi_1 = 1, \xi_2 = 0.6, \alpha_{12} = 0.2, \alpha_{21} = 0.3$. Further, we set $\phi_1 = -0.1, \phi_2 = -0.15, \delta = -0.4$.

Similar to the three rating case, we use three initial points (based on the observed moments) for our five step iterated GMM estimator. Note, however, that the dimension of the vector of unknowns here is 13 whereas it was 21 in the case of three ratings. We use 1,000 simulation draws. The numerical optimization performs slightly better in the two rating case than the three rating case. The optimization converges in all 1,000 simulation draws.

We report the mean and standard deviation of our higher order estimator over 1,000 simulations. In each simulation, Table 2 summarizes the results. The estimators performs very well across all the 13 unknowns. For instance, the coefficient of the feedback from agency 1 to agency 2 converges to the true value 0.3, with standard deviation of 0.013. The estimate for the third order moment $E(U^3)$ is 1.959, and has the largest standard deviation 0.049, but is well within one standard deviation of its true value, 2.

4 Data

4.1 Sources

We use four main data sources: Municipal Securities Rulemaking Board (MSRB), Refinitiv Eikon, Bloomberg, and S&P Capital IQ. We obtain data on price (e.g. yield) from MSRB. We obtain data on the ratings of Moody's and Fitch as well as on issue characteristics from Eikon. The data on risk free rates is from Bloomberg. Last, we obtain data on S&P ratings from S&P Capital IQ.

As documented in the literature (Chun et al., 2019; Cornaggia et al., 2020b,a; Bergstresser et al., 2010), when muni bonds are insured, their price depends on the insurer's credit rating. To focus on the feedback among the issue's ratings, we restrict our sample to uninsured municipal bonds. We also focus our analysis on the primary muni market. This helps us study the direct impact of ratings on the borrowing cost of municipalities and to set aside matters, such as liquidity, that are more relevant in the secondary market.

Our data extends from 2011 to 2020. This therefore excludes the 2008 financial crisis and Moody's scale re-calibration in 2010. As shown in Figure 2, the fraction of bonds that are rated have fluctuated over time, and all three credit rating agencies reached a stable and large market share by year 2011. In particular, a large fraction of muni issues were rated by multiple agencies after 2011. For instance, among 45,828 primary issues in 2009, only 2,148 were rated by more than one agency. In contrast, among 46,306 primary issues in 2011, 19,969 received multiple ratings.

There is a total of 579,614 issues in our sample, issued by 22,443 unique government issuers. Among these issuers, there are 4 levels of government: states, counties, cities, and others. The data cover 50 US states, Washington D.C., and 5 US territories (American Samoa, Guam, Northern Mariana Islands, Puerto Rico, and U.S. Virgin Islands). Overall, the sample covers 2.36 trillion dollars of bonds that were issued between 2011 and 2020, ranging from 25,000 dollars at the 1st percentile to 50.5 million dollars at the 99th percentile.

4.2 Outcome and Control Variables

We closely follow Cornaggia et al. (2018) in constructing the outcome variables and controls. We consider 5 measures of the bond price. We begin by considering a muni's raw yield. We then use a spread measure by subtracting the risk free rate from the raw yield. For this, we construct the risk free rates from treasuries in four different ways. First, we set the risk free rate such that the treasuries' maturity matches the corresponding muni's duration. We construct a muni's duration in two ways: with or without accounting for the issue's callability. We label the former "duration1" and the latter "duration2." Accordingly, we label the spread constructed using duration1 (duration2) by "spread1" ("spread2"). For the last two measures, we account for a muni's tax exemption status. In contrast to treasuries, muni's are tax-exempt, and a number of papers (e.g. Green (1993); Longstaff (2011); Babina et al. (2021)) discuss the importance of accounting for this aspect. As such, in constructing the spread, we subtract the after-tax risk-free rate from a muni's raw yield. We label the spread measures corresponding to duration1 (duration2) by "spread1AfterTax" ("spread2AfterTax").

We consider several covariates. Specifically, our covariates include a muni's par value and duration (see Green (1993)). We also include an indicator "negotiated" to account for whether a muni was issued through a negotiated process or competitively (see Garrett et al. (2020)). We control for the number of bonds outstanding to account for the liquidity of the bond issuer. In addition, we control for the coupon rate, whether the bond is callable, and whether it is a general obligation bond. Last, we include year and issuer fixed effects to account for year-specific common changes, such as the federal tax rates, and issuer-specific time-invariant characteristics. For example, Gao and Murphy (2019) shows that borrowing costs depend on whether a state allows filing for bankruptcy under chapter 9. Accounting for issuer fixed effects helps capture such features.

4.3 Descriptive Statistics

Table 3 reports descriptive statistics for the whole sample. This focuses on the uninsured bonds, and includes both rated and unrated issues. The average raw yield is 2.329% and the average spreads range from 0.425% to 1.175%. The average par value is 2.6 million dollars. 42.8% of the bonds are callable, 46.2% of the bonds are negotiated, and 49.5% of the bonds are general obligation bonds. The bond durations are 6 to 8 years on average. Importantly, the ratings of the three agencies have heavy tails - they are negatively skewed and have a large kurtosis compared to a normal distribution. As discussed above, this facilitates the use of higher order moments estimators.

Table 4 also reports summary statistics for two subsamples of bonds that are rated. The first subsample (shown in the second column) includes uninsured bonds that are rated by all three agencies. The summary statistics for this subsample is similar to the whole sample in several dimensions. The average raw yield is 2.335% and the average spreads range from 0.381% to 1.164%. 43.3% of bonds are callable. The average durations are 6 to 8 years. All three ratings are negatively skewed and have heavy tails. The average ratings in this subsample are similar to those of the full sample. The subsample differs from the full sample in certain characteristics. The fractions of negotiated and general bonds are 52.3% and 41.4% respectively. The par value is 3.6 million dollars on average. This underscores the importance of accounting for these controls. The second subsample (shown in the first column) includes the uninsured bonds that are rated only by S&P and Moody's. This subsample is similar to the first one along several dimensions and differs from it mainly in that its par-value is 6.4 million dollars.

5 Empirical Findings

This section reports the empirical findings. As discussed above, there are three major credit rating agencies. In the data, a particular muni issue may not be rated or it may receive a rating from one or more of the credit rating agencies. To study the feedback among the credit rating agencies, we begin our analysis in Section 5.1 by discussing the estimates of the credit ratings and price equations as well as the ratings quality for the issues that are rated by all three credit rating agencies: S&P, Moody's, and Fitch. Section 5.2 studies a counterfactual analysis that studies the effects of shutting down the feedback among the ratings. Last, Section 5.3 discusses additional analyses. First, we report results for the issues that are rated only by S&P and Moody's and contrasts these with the three-CRAs results. Second, we relate the results to those that examine the impact of the entry of Fitch to the market. Third, we split the issues based on a proxy for information accessibility and report the results from this subsample analysis. Last, we relate our results to earlier work that is based on Moody's recalibration natural experiment.

5.1 Main Estimates

We begin by discussing the estimates for the issues that are rated by all three credit rating agencies: S&P, Moody's, and Fitch. Tables 5 reports the estimates, with bootstrapped standard errors. In each column, we consider the 5 measures of price discussed earlier. Column (1) reports the results when price is measured using the raw yield, Y. The price measures spread1 and spread2 in columns (2) and (3) account for the risk free rate. Last, to account for a muni's tax exemption status, column (4) and (5) measure price using spread1AfterTax and spread2AfterTax.

For all the specifications, we report in the last rows of Table 5 the p-values for the GMM overidentification test. For the first column, we can reject the model's assumptions at the the 1% level. This may in part because the price measure fails to account for a muni's callability and tax-exemption status (Green, 1993; Longstaff, 2011; Cornaggia et al., 2018; Babina et al., 2021). For the other 4 columns, we cannot reject the imposed assumptions at the 1%, although the p-value are not very large. Overall, we obtain similar qualitative conclusions across the different price measures. We discuss these in what follows.

5.1.1 Credit Rating Equations

First, consider the effects of the unobserved fundamental on the ratings encoded in the (ξ's). In most cases, the fundamental has a positive and significant effect on the credit ratings. Recall that we normalize the coefficient $\xi_1 = 1$ in the equation for S&P's rating. The coefficient ξ_2 in the equation for Moody's rating is around 1.44 and the coefficient ξ_3 in the Fitch equation is around 1.41. In both cases, these estimates are at least 40% larger than the normalized coefficient for S&P, $\xi_1 = 1$, suggesting that the ratings of Moody's and Fitch appear more responsive than S&P's rating to changes in the unobserved fundamental, ceteris paribus.

Moreover, we find that the ratings of the firms are indeed interdependent. In most cases, we report positive and significant estimates of the α's, suggesting that firms react to each other. S&P increases its rating by nearly 0.22 notches in response to a one notch increase by Moody's ceteris paribus. S&P's reacts to Fitch positively yet this coefficient is statistically insignificant. Moody's increases its rating by 0.34 notches in response to an increase of one notch by S&P and by 0.05 notches in response to an increase of one notch by Fitch, ceteris paribus. Lastly, Fitch increases its rating by 0.38 notches in response to an increase of one notch by S&P and increases its rating by 0.05 notches in response to an increase of one notch by Moody's.

5.1.2 Ratings Quality

We estimate the rating quality using the net of the covariates reliability ratio in Equation (20). As summarized in Table (5) Panel A, the net of the covariates reliability ratios for S&P is 25%, that for Moody's is 53%, and that for Fitch is 54%. This corresponds to an unconditional reliability ratio of 93%, 96.1%, and 96.4% for S&P, Moody's, and Fitch after accounting for the covariates and fixed effects. Thus, shows that all three rating agencies reported different imperfect ratings.

5.1.3 Price Equations

We find that both the ratings and the fundamental have separate sizable effects on the price. Ceteris paribus, better ratings imply a lower price (a lower borrowing cost), and a better fundamental implies a lower price. These effects are captured by the estimates for ϕ's and δ reported in Table 5 Panel C.

The estimates for ϕ_1 suggest that a one notch increase in S&P's rating leads to a decrease of 8 basis points in price. Similarly, for most price measures, the estimates for ϕ_2 suggest that a one notch increase in Moody's rating leads to a decrease of nearly 2 basis points in price. The estimates for the effects of the ratings for Fitch (ϕ_3) are all negative, albeit less precisely measured. Further, the fundamental affect price negatively and significantly. Specifically, recall that we had normalized $\xi_1 = 1$, in effect anchoring the scale of the fundamental to that of the S&P rating. Our estimates of δ suggests that, on this scale, a unit increase in the fundamental leads to a decrease of nearly 1.4 basis points in the price.

5.2 Counterfactual Analysis

We use our framework to perform counterfactual analyses. Specifically, we study the consequences of shutting down the feedback among the credit ratings. That is, we report counterfactual estimates that would obtain when we set all the α's equal to 0. We study the impact of this thought experiment on the sensitivity of the ratings to the fundamental.

5.2.1 Credit Rating Equations

As shown in Equations (13), (14), (15), and (16), in equilibrium, the sensitivity of the ratings to changes in the fundamental is captured by the κ coefficients. To shut down the feedback mechanism, we consider the thought experiment whereby we set the α coefficients to 0. In this case, the κ coefficients reduce to the ξ coefficients. In what follows, we compare the κ's and ξ estimates.

We find that, in equilibrium, the feedback amplifies the dependence of the ratings on the fundamentals. For instance, in the subsample with three ratings, we find that the dependence of the S&P, Moody's, and Fitch ratings on the fundamental increases by nearly 55%, 43% and 49% respectively.

5.2.2 Ratings Quality

We also study the impact that the feedback has on the quality of the ratings. We report the counterfactual estimates that would obtain when we set all the α's equal to 0. In the absence of feedback, we slightly update Equation (20), as discussed above, by replacing κ with ξ. The updated reliability ratio is given by

$$\mathrm{R}_j^* = \frac{Var(\xi_j U)}{Var(\xi_j U) + Var(\epsilon_j)}$$

We then calculate this measure using our estimates for ξ's, α's, $Var(U)$, and $Var(\tilde{\epsilon})$'s, reported in Table (5) Panel C. The counterfactual rating qualities are summarized in Table (5) Panel B. We find that the feedback improves the quality of the ratings. We find that the rating qualities for S&P increases from 15% to 25%. In the same sample, the rating qualities for Moody's increase from 46% to 53% and the rating qualities for Fitch increase from 46% to 54%. Interestingly, the lower the quality of the rating is (e.g. S&P), the larger the improvement in quality is. This illustrates how the low-quality ratings benefit from the feedback.

5.3 Additional Analysis

5.3.1 Two CRA: S&P and Moody's

We replicate the above analysis using the issues that are rated only by the two major agencies: S&P and Moody's. We report the results in Table 6.

Similar to the three CRA case, we use five different price measures. Here too, we can reject the specification using the raw yield measure of price at the 1% level. The effect of the unobserved fundamental on the ratings is encoded in the (ξ's). Similar to the three-CRA's results, the fundamental has a positive and significant effect on the credit ratings. Moody's ξ_2's point estimate ranges from 1.5 to 1.9. In both cases, Fitch's dependence on the unobserved fundamental is at least 50% as large as S&P's normalized $\xi_1 = 1$.

Here too, we find that the ratings of the firms are interdependent. In most cases, we estimate positive and significant α's, suggesting that the ratings react to one another. S&P increases its rating by nearly 0.26 to 0.39 notches in response to an increase of one notch by Moody's, ceteris paribus. Similarly, Moody's increases its rating by nearly 0.06 to 0.08 notches in response to a one notch increase by S&P, ceteris paribus.

As summarized in Panel A, S&P's rating quality is much lower than Moody's. In addition, the counterfactual analysis reveals that the feedback improves the rating qualities, and the improvement is larger for low-quality ratings.

We note that issuers can choose which credit rating agencies to approach to rate their muni issues, and whether to publicize these ratings (Banerji, 2019). Thus, we only observe the ratings that the issuers chose to reveal. This process can generate a sample selection bias. To address this, we consider the subsample of issues rated by S&P and Moody's and impute the missing Fitch rating as follows:

$$\min(\text{S\&P's Rating}, \text{Moody's Rating}) - 1$$

This imputation is based on the assumption that the issuers choose not to publicize Fitch's rating because their rating was worse than the ratings of S&P and Moody's. We then deploy our estimator on the imputed sample with three ratings. As shown in Panel C, quality of the ratings does not change substantially. We leave a more detailed econometric analysis of sample selection to other work.

5.3.2 Entry of Fitch

Prior to Fitch entering the market materially in year 2000, corporate bonds were rated predominantly by S&P and Moody's. Becker and Milbourn (2011) finds that the entry of the third rating agency into the market led the quality of the ratings of the other agencies (S&P and Moody's) to deteriorate. A thorough analysis of the impact of entry into the rating market is beyond the scope of this paper. Nevertheless, we use our results to examine whether an increase in the number of rating agencies leads to a similar pattern in the municipal bonds market (see e.g. White et al. (2014)).

To study this pattern, one possibility is to conduct a counterfactual analysis in which one sets Fitch's α (α_{13} and α_{23}) in Equation (9), (10), and (11) to zero and study how the the resulting changes in rating qualities. This analysis would effectively shut down the impact of the Fitch ratings in the market but would not account for any industry-wide impact that results from Fitch's participation in the market. For instance, the participation of Fitch may influence how S&P relies on the fundamental (U) and on Moody's rating and alter how ratings affect prices. Instead, to proxy how firm entry affects the quality of the ratings, we compare the results for issues that are rated only by S&P and Moody's (using estimates reported in Table 6) to those that are rated by S&P, Moody's and Fitch (using the estimates reported in Table 5). Based on these estimates, when the Fitch rating are available, S&P's rating quality (measured by the net of controls reliability ratio) decreases from 45% to 25% and that of Moody's decreases from 89% to 53%. This echos the findings in Becker and Milbourn (2011). We note that the distribution of the observed characteristics also differs across the two ratings and three ratings subsamples. As a result, the unconditional reliability ratio for S&P increases from 90.3% to 93% when going from the two ratings to the three ratings subsample, whereas that for Moody's decreases from 98.6% to 96.1%.

5.3.3 Subsample Analysis: Rating Quality

In this section, we classfy issues based on a proxy for information accessibility and replicate our analysis using the resulting two subsamples. If data on issues are more readily available, the agencies may be able to generate higher quality ratings ceteris paribus. Thus, we examine whether the rating qualities are indeed improved in the subsample where market participants have better access to information.

To construct a proxy for information accessibility, we make use of the U.S. Securites and Exchange Commission (SEC) Rule 15c2-12. This rule stipulates that municipal issuers must provide certain information to the Municipal Securites Rulemaking Board (MSRB) about the securities on an ongoing basis[11]. However, this rule only applies to issues that are exceed 1 million dollars - issues less than 1 million dollars are exempt from SEC Rule 15c2-12. Accordingly, we split our sample in two folds based on whether the issue's size exceeds 1 million dollars.

We then replicate our results using each subsample. Table 7 reports the resulting estimates of the quality of the ratings. As shown in Panel A, for both the two ratings and three ratings cases, the rating quality is larger for larger issues. This corroborates the hypothesis that ratings improve as information becomes more available. Further, here too, we observe that the net of the covariates reliability ratio is lower in the three ratings case than in the

[11] See http://www.msrb.org/msrb1/pdfs/secrule15c2-12.pdf for more details

two ratings case. As before, the counterfactual analysis in Panel B finds that the feedback improves the quality of the ratings.

5.3.4 Moody's Recalibration Event

In year 2010, Moody's recalibrated the scale of their ratings for municipal bond issues. Cornaggia et al. (2018) argues that Moody's recalibration was unrelated to the asset fundamentals, and used this exogenous change to estimate the effect of their ratings on price. They find that a one notch increase in Moody's rating leads to 11-14 basis points decrease in a muni's price.

We use our model to capture the effect of a one notch increase in Moody's rating on price ceteris paribus, as encoded in the ϕ coefficient on Moody's rating in the price equation. This direct effect of a rating shuts down any feedback among the rating agencies. Across the four subsamples, we find significant estimates for this effect at 8 basis points (see Table 6's ϕ_2 estimate).

We also use our model to estimate the effect of an exogenous shock to Moody's rating on price while allowing for feedback among the agencies. For example, consider the S&P-Moody's subsample in Equations (24), (25), and (26) (where the S&P and Moody's ratings are indexed by 1 and 2 respectively). To capture the effect of an exogenous shock to Moody's rating, consider a unit increase in $\tilde{\epsilon}_2$. When allowing for feedback, in equilibrium, this shock leads $_1$ to increase by $\frac{\alpha_{12}}{1-\alpha_{12}\alpha_{21}}$ and $_2$ to increase by $\frac{1}{1-\alpha_{12}\alpha_{21}}$. In turn, this leads to an increase of $\frac{\alpha_{12}\phi_1}{1-\alpha_{12}\alpha_{21}} + \frac{\phi_2}{1-\alpha_{12}\alpha_{21}}$ in the price (Y). When we focus on S&P-Moody's subsample and use the estimates from Table 6, the effect of a one notch increase in Moody's ratings is 9.2 basis points with standard error at 2.2 basis points. For the S&P-Moody's-Fitch subsample, using the estimates from Table 5, the effect of a one notch increase in Moody's rating is 4.6 basis points with standard error at 1.1 basis point. Taken together, our results corroborate the results from the literature that document a positive effect of ratings on price in the muni market.

6 Conclusion

This paper studies the interdependence among the ratings of credit agencies in the municipal bond market as well as the impact that the ratings have on the price of bonds. We put forward an econometric model capable of accounting for the impact of the unobserved asset fundamental on the ratings and the bond price, the feedback among the credit ratings of agencies, and the direct impact that the ratings may have on the price of a bond. As such, our model captures in a unified framework various features of the municipal bond market that have been discussed in the theoretical and empirical literature. To address the econometric challenges due to the unobserved asset fundamental and the simultaneity of the ratings, we develop a novel estimator that relies on higher order moments. We find that agencies react positively to increases in the ratings of the other agencies, with estimates ranging from 0.05 to 0.38 notches in response to an increase of one notch by another agency. Second, we find that the feedback among the ratings improves the quality of the ratings measured by the reliability ratio. Last, we show that the ratings have a sizable direct impact on prices, with an increase of one notch in S&P's (Moody's) rating leading to a decrease of 8 basis points (2 basis points) in price, and we document a separate sizable effect of the unobserved fundamental on the bond's price.

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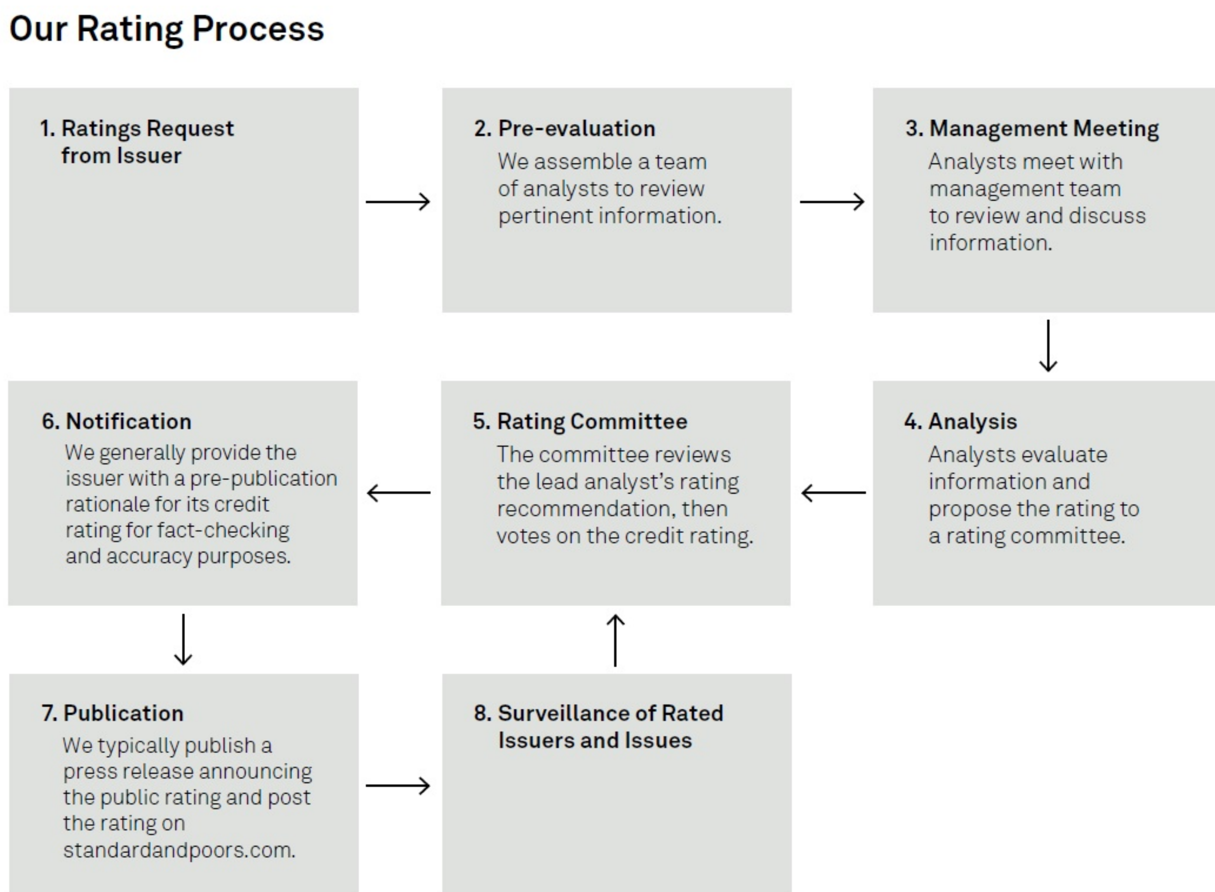

Figure 1: Credit Rating Agencies' Rating Process

Source: S&P Gloal Ratings (2021). This diagram describes how the rating process works. A municipal issuer who decides to issue rated municipal bonds must first submit a "rating request" to one or more rating agencies (typically S&P, Moody's, and/or Fitch). Upon meeting with the issuer's management to collect data, a team of analysts at the agency use their proprietary credit risk model to perform a credit analysis and propose a rating to a rating committee. The committee reviews the rating recommendation and, if needed, updates it. Last, the issuer is notified of the final rating, along with rationale for it, and the ratings gets typically publicized. This diagram is obtained from S&P Gloal Ratings (2021). However, both Moody's and Fitch follow the same general rating process as depicted above.

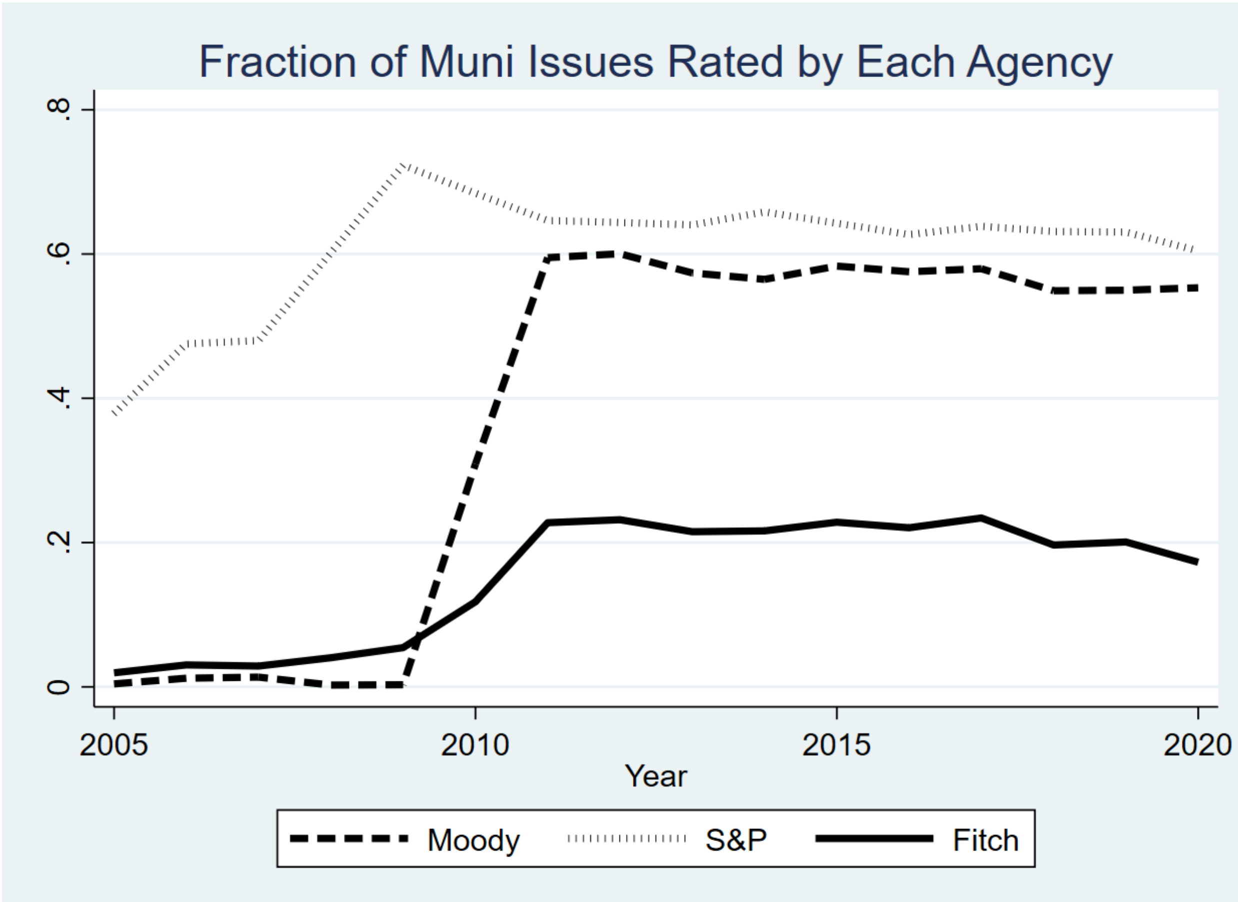

Figure 2: Fraction of Municipal Bond Issues that are Rated by Each Credit Rating Agency

This graph illustrates the fraction of municipal bond issues rated by each credit rating agency. For S&P, the fraction increased roughly from 40% at year 2005 to 60% at year 2020. For Moody's, the fraction increased from near 0% at year 2005 to roughly 55% at year 2020. For Fitch, the fraction has increased roughly from nearly 0% at year 2005 to 20% at year 2020. The three fractions do not need to sum up to 1 because some issues are rated by multiple rating agencies. In our empirical analysis, we focus on the 2011-2020 time period during which the market share of all three agencies have stabilized.

Table 1: Simulation Results: The Case of Three Ratings

This table summarizes the simulation results using our high order moment estimator. The results are based on 1,000 simulations. In each simulation, we draw a balanced panel data set with 1,052 unique issuers and 10 time periods, where each issuer issues 31 muni's every time period. We draw 13 random variables, U, ϵ_1, ϵ_2, ϵ_3, η, issuer fixed effects (IFE_1, IFE_2, IFE_3, IFE_y), and time fixed effects (TFE_1, TFE_2, TFE_3, TFE_y) based on a Gamma distribution and allow the issuer fixed effects to be correlated with U. These random variables are drawn to satisfy all the assumptions we impose. We then use these random variables to generate data on (Y , W_1, W_2, and W_3) as follows

$$\begin{aligned} W_1 &= \xi_1 U + \alpha_{12} W_2 + \alpha_{13} W_3 + IFE_1 + TFE_1 \tilde{\epsilon}_1 \\ W_2 &= \xi_2 U + \alpha_{21} W_1 + \alpha_{23} W_3 + IFE_2 + TFE_2 + \tilde{\epsilon}_2 \\ W_3 &= \xi_3 U + \alpha_{31} W_1 + \alpha_{32} W_2 + IFE_3 + TFE_3 + \tilde{\epsilon}_3 \\ Y &= \delta U + \phi_1 W_1 + \phi_2 W_2 + \phi_3 W_3 + IFE_y + TFE_y + \eta \end{aligned}$$

The first column "True values" summarizes the true parameter values. The second column "Estimates" summarizes the mean of the estimates in the first row and the standard deviations in the second row, across 966 simulations.

	True values	Estimates		True values	Estimates
ϕ_1	-0.100	-0.100 (0.005)	ξ_2	0.600	0.600 (0.007)
ϕ_2	-0.150	-0.151 (0.004)	ξ_3	1.100	1.099 (0.011)
ϕ_3	-0.300	-0.300 (0.005)	$E(U^2)$	1.000	0.997 (0.021)
δ	-0.200	-0.200 (0.004)	$E((\tilde{\epsilon}_1)^2)$	0.250	0.249 (0.003)
α_{12}	0.200	0.200 (0.004)	$E((\tilde{\epsilon}_2)^2)$	0.250	0.249 (0.002)
α_{13}	0.250	0.250 (0.006)	$E((\tilde{\epsilon}_3)^2)$	0.250	0.249 (0.003)
α_{21}	0.300	0.300 (0.003)	$E(\eta^2)$	1.000	0.996 (0.005)
α_{23}	0.150	0.150 (0.004)	$E(U^3)$	2.000	1.979 (0.064)
α_{31}	0.100	0.099 (0.006)	$E((\tilde{\epsilon}_1)^3)$	0.250	0.248 (0.005)
α_{32}	0.100	0.100 (0.004)	$E((\tilde{\epsilon}_2)^3)$	0.250	0.247 (0.004)
			$E((\tilde{\epsilon}_3)^3)$	0.250	0.248 (0.005)

Table 2: Simulation Results: The Case of Two Ratings

This table summarizes the simulation results using our high order moment estimator. The results are based on 1,000 simulations. In each simulation, we draw a balanced panel data set with 2,683 issuers and 10 time periods, where each issuer issues 15 muni's every time period. We draw 10 random variables, U, ϵ_1, ϵ_2, ϵ_3, η, issuer fixed effects (IFE_1, IFE_2, IFE_3, IFE_y), and time fixed effects (TFE_1, TFE_2, TFE_3, TFE_y) based on a Gamma distribution and allow the issuer fixed effects to be correlated with U. These random variables are drawn to satisfy all the assumptions we impose. We then use these random variables to generate data on (Y , W_1, and W_2) as follows

$$\begin{aligned} W_1 &= \xi_1 U + \alpha_{12} W_2 + IFE_1 + TFE_1 + \tilde{\epsilon}_1 \\ W_2 &= \xi_2 U + \alpha_{21} W_1 + IFE_2 + TFE_2 + \tilde{\epsilon}_2 \\ Y &= \delta U + \phi_1 W_1 + \phi_2 W_2 + IFE_y + TFE_y + \eta \end{aligned}$$

The first column "True values" summarizes the true parameter values. The second column "Estimates" summarizes the mean of the estimates in the first row and the standard deviations in the second row, across 1,000 simulations.

	True values	Estimates
ϕ_1	-0.100	-0.100
		(0.007)
ϕ_2	-0.150	-0.150
		(0.003)
δ	-0.200	-0.200
		(0.005)
α_{12}	0.200	0.200
		(0.008)
α_{21}	0.300	0.300
		(0.013)
ξ_2	0.600	0.600
		(0.014)
$E(U^2)$	1.000	0.993
		(0.020)
$E((\tilde{\epsilon}_1)^2)$	0.250	0.249
		(0.009)
$E((\tilde{\epsilon}_2)^2)$	0.250	0.248
		(0.003)
$E(\eta^2)$	1.000	0.993
		(0.004)
$E(U^3)$	2.000	1.959
		(0.049)
$E((\tilde{\epsilon}_1)^3)$	0.250	0.245
		(0.012)
$E((\tilde{\epsilon}_2)^3)$	0.250	0.245
		(0.005)

Table 3: Full Sample Descriptive Statistics

This table reports summary statistics for the full sample. This focuses on uninsured bonds that are either rated or unrated. Our data extends from 2011 to 2020. There is a total of 579,614 issues in our sample, issued by 22,443 unique government issuers. Among these issuers, there are 4 levels of government: states, counties, cities, and others. The data cover 50 US states, Washington D.C., and 5 US territories (American Samoa, Guam, Northern Mariana Islands, Puerto Rico, and U.S. Virgin Islands). Overall, the sample covers 2.36 trillion dollars of bonds that were issued between 2011 and 2020, ranging from 25,000 dollars at the 1st percentile to 50.5 million dollars at the 99th percentile. Please see Table A1 for variable definitions.

	N	Mean	SD	Skewness	Kurtosis
Outcome variabls					
Yield (%)	579,614	2.329	1.097	0.773	4.870
spread1	579,614	0.425	0.708	1.854	13.17
spread2	579,614	0.553	0.814	1.566	9.424
spread1aftertax	579,614	1.091	0.770	1.726	10.58
spread2aftertax	579,614	1.175	0.851	1.536	8.404
Controls					
S&P Rating	370,071	19.59	1.938	-1.042	4.623
Moody's Rating	332,792	18.84	1.696	-1.188	5.560
Fitch Rating	126,515	17.86	2.071	-1.215	4.586
Coupon rate (%)	579,614	3.562	1.264	-0.270	2.553
Log(Par value)	579,614	0.951	0.893	1.595	5.834
Dummy: Callability	579,614	0.428	0.495	0.290	1.084
Dummy: Negotiated	579,614	0.462	0.499	0.153	1.023
Duration1	579,614	7.552	4.192	0.497	3.050
Duration2	579,614	6.059	2.639	0.339	6.234
Dummy: General Obligation	579,614	0.495	0.500	0.0184	1.000
Log(Outstanding bonds)	579,614	3.528	1.158	0.605	3.436

Table 4: Subsample Descriptive Statistics

This table summarizes statistics for bonds that are rated. The first column "S&P and Moody's" describes uninsured bonds that are rated only by S&P and Moody's. The second column describes insured bonds that are rated by all three CRA's: S&P, Moody's, and Fitch. Please see Table A1 for definition of variables.

	S&P and Moody's				S&P; Moody's; Fitch			
	Mean	SD	Skew	Kurt	Mean	SD	Skew	Kurt
Outcome variabls								
Yield (%)	2.350	1.044	0.396	3.516	2.335	1.037	0.215	2.782
spread1	0.378	0.600	0.846	6.168	0.381	0.600	0.727	4.814
spread2	0.520	0.730	0.853	4.772	0.533	0.737	0.763	3.989
spread1aftertax	1.068	0.681	0.913	5.248	1.065	0.681	0.711	3.810
spread2aftertax	1.161	0.777	0.897	4.438	1.164	0.783	0.741	3.474
Controls								
S&P Rating	19.91	1.708	-1.082	5.067	20.02	1.844	-0.954	3.681
Moody's Rating	18.98	1.667	-1.327	6.075	18.93	1.782	-1.034	4.408
Fitch Rating					18.06	1.833	-1.027	3.849
Coupon rate (%)	3.847	1.225	-0.765	2.868	4.192	1.071	-1.125	3.484
Log(Par value)	1.267	0.869	1.205	4.763	1.855	1.094	0.656	3.090
Dummy: Callability	0.433	0.496	0.269	1.072	0.440	0.496	0.241	1.058
Dummy: Negotiated	0.523	0.499	-0.0919	1.008	0.484	0.500	0.0654	1.004
Duration1	8.009	4.307	0.513	3.407	8.059	4.142	0.298	2.553
Duration2	6.402	2.627	0.549	9.995	6.498	2.546	0.0246	5.550
Dummy: G.O.	0.414	0.493	0.350	1.123	0.372	0.483	0.531	1.282
Log(Out bonds)	3.441	1.116	0.668	3.752	3.533	1.118	0.556	3.359
N	113,419				72,796			

Table 5: Estimates using the subsample with S&P, Moody's and Fitch

This table summarizes estimates based on bond issues that are rated by S&P, Moody's, and Fitch. Subscripts 1, 2 , and 3 correspond to S&P, Moody's, and Fitch respectively. In all columns, we account for issuer fixed effects and year fixed effects. We measure Y using the raw yield, Spread1, Spread2, Spread1AfterTax, and Spread2AfterTax in columns (1) through (5) respectively. Bootstrapped standard errors appear in parentheses. Panel A reports estimates for the ratings' quality, measured by the reliability ratio. Panel B reports estimates for the ratings' qualiy after shutting down the feedback among the ratings (i.e. setting all α's equal to 0). Panel C reports estimates for all the system coefficient. The last row reports the p-value for the GMM overidentification test using $\mathcal{X}^2$ with 8(= 29 − 21) degree of freedoms.

	(1)	(2)	(3)	(4)	(5)
Panel A: Rating Quality Estimates					
S&P	0.249	0.253	0.253	0.251	0.251
	(0.039)	(0.040)	(0.039)	(0.039)	(0.039)
Moody's	0.529	0.532	0.532	0.531	0.531
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
Fitch	0.542	0.545	0.546	0.544	0.544
	(0.033)	(0.033)	(0.032)	(0.033)	(0.033)
Panel B: Counterfactual Rating Quality Estimates					
S&P	0.148	0.149	0.149	0.149	0.149
	0.015	0.015	0.014	0.015	0.015
Moody's	0.462	0.465	0.465	0.464	0.463
	0.041	0.043	0.043	0.042	0.043
Fitch	0.453	0.455	0.455	0.454	0.455
	0.033	0.034	0.033	0.034	0.034
Panel C: Sytem Coefficients Estimates					
ϕ_1	-0.087	-0.075	-0.074	-0.080	-0.080
	(0.008)	(0.012)	(0.011)	(0.010)	(0.010)
ϕ_2	-0.012	-0.028	-0.028	-0.024	-0.024
	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
ϕ_3	-0.004	-0.012	-0.012	-0.006	-0.006
	(0.001)	(0.008)	(0.007)	(0.004)	(0.005)
δ	-0.013	-0.014	-0.014	-0.014	-0.014
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α_{12}	0.219	0.222	0.222	0.221	0.221
	(0.059)	(0.057)	(0.060)	(0.060)	(0.057)
α_{13}	0.047	0.047	0.047	0.047	0.047
	(0.036)	(0.035)	(0.042)	(0.036)	(0.035)
α_{21}	0.343	0.337	0.337	0.339	0.339
	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)

α_{23}	0.046	0.047	0.047	0.046	0.046
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
α_{31}	0.386	0.383	0.383	0.385	0.384
	(0.029)	(0.030)	(0.031)	(0.029)	(0.030)
α_{32}	0.047	0.047	0.047	0.047	0.047
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ξ_2	1.437	1.444	1.443	1.441	1.441
	(0.098)	(0.098)	(0.102)	(0.098)	(0.098)
ξ_3	1.408	1.408	1.408	1.408	1.408
	(0.080)	(0.081)	(0.082)	(0.081)	(0.081)
$E(U^2)$	0.034	0.034	0.034	0.034	0.034
	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
$E((\tilde{\epsilon}_1)^2)$	0.196	0.195	0.195	0.195	0.195
	(0.015)	(0.015)	(0.014)	(0.015)	(0.015)
$E((\tilde{\epsilon}_2)^2)$	0.082	0.082	0.082	0.082	0.082
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$E((\tilde{\epsilon}_3)^2)$	0.081	0.081	0.081	0.081	0.081
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$E(\eta^2)$	0.210	0.101	0.113	0.107	0.123
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
$E(U^3)$	-0.011	-0.011	-0.011	-0.011	-0.011
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$E((\tilde{\epsilon}_1)^3)$	-0.007	-0.007	-0.007	-0.007	-0.007
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$E((\tilde{\epsilon}_2)^3)$	-0.009	-0.009	-0.009	-0.009	-0.009
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$E((\tilde{\epsilon}_3)^3)$	0.004	0.004	0.004	0.004	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
N	72,796	72,796	72,796	72,796	72,796
Issuer Fixed Effects	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES
GMM test (p-value)	0.001	0.02	0.02	0.01	0.01

Table 6: Estimates using the subsample with S&P and Moody's

This table summarizes estimates based on bond issues that are rated by S&P and Moody's. Subscripts 1 and 2 correspond to S&P and Moody's respectively. In all columns, we account for issuer fixed effects and year fixed effects. We measure Y using the raw yield, Spread1, Spread2, Spread1AfterTax, and Spread2AfterTax in columns (1) through (5) respectively. Bootstrapped standard errors appear in parentheses. Panel A reports estimates for the ratings' quality, measured by the reliability ratio. Panel B reports estimates for the ratings' qualiy after shutting down the feedback among the ratings (i.e. setting all α's equal to 0). Panel C shows estimates for the ratings' quality after imputing Fitch's rating to account for any potential sample selection bias. Panel D shows estimates for all the system coefficients. The last row reports the p-value for the GMM overidentification test using $\mathcal{X}^2$ with $2(= 15 - 13)$ degree of freedoms.

	(1)	(2)	(3)	(4)	(5)
Panel A: Rating Quality Estimates					
S&P	0.452	0.458	0.456	0.455	0.452
	(0.030)	(0.014)	(0.014)	(0.015)	(0.017)
Moody's	0.835	0.901	0.897	0.893	0.888
	(0.068)	(0.021)	(0.025)	(0.027)	(0.032)
Panel B: Counterfactual Rating Quality Estimates					
S&P	0.219	0.297	0.296	0.294	0.293
	0.043	0.040	0.042	0.042	0.044
Moody's	0.829	0.896	0.892	0.888	0.883
	0.073	0.023	0.027	0.029	0.035
Panel C: Rating Quality After Imputing Fitch's Missing Rating					
S&P	0.380	0.385	0.384	0.384	0.383
	(0.027)	(0.026)	(0.026)	(0.026)	(0.026)
Moody's	0.813	0.825	0.824	0.823	0.822
	(0.076)	(0.075)	(0.076)	(0.076)	(0.078)
Fitch*	0.459	0.467	0.466	0.465	0.464
(Imputed)	(0.044)	(0.044)	(0.045)	(0.044)	(0.045)
Panel D: System Coefficients Estimates					
ϕ_1	-0.017	-0.034	-0.029	-0.028	-0.024
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
ϕ_2	-0.013	-0.080	-0.082	-0.083	-0.084
	(0.026)	(0.010)	(0.015)	(0.017)	(0.021)
δ	-0.098	-0.008	-0.008	-0.008	-0.009
	(0.044)	(0.006)	(0.019)	(0.023)	(0.031)
α_{12}	0.388	0.262	0.262	0.264	0.263
	(0.062)	(0.049)	(0.054)	(0.056)	(0.058)
α_{21}	0.062	0.067	0.069	0.071	0.075
	(0.031)	(0.010)	(0.011)	(0.013)	(0.015)

ξ_2	1.918	1.596	1.592	1.592	1.584
	(0.152)	(0.155)	(0.160)	(0.164)	(0.170)
$E(U^2)$	0.074	0.114	0.114	0.113	0.112
	(0.022)	(0.022)	(0.023)	(0.023)	(0.024)
$E((\tilde{\epsilon}_1)^2)$	0.263	0.269	0.270	0.270	0.271
	(0.009)	(0.006)	(0.006)	(0.006)	(0.007)
$E((\tilde{\epsilon}_2)^2)$	0.056	0.034	0.035	0.036	0.037
	(0.020)	(0.007)	(0.008)	(0.009)	(0.011)
$E(\eta^2)$	0.193	0.102	0.110	0.103	0.116
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
$E(U^3)$	-0.029	-0.053	-0.054	-0.053	-0.053
	(0.014)	(0.017)	(0.018)	(0.018)	(0.018)
$E((\tilde{\epsilon}_1)^3)$	-0.002	-0.006	-0.006	-0.005	-0.005
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
$E((\tilde{\epsilon}_2)^3)$	-0.030	-0.011	-0.011	-0.012	-0.011
	(0.014)	(0.005)	(0.006)	(0.007)	(0.008)
N	113,419	113,419	113,419	113,419	113,419
Issuer Fixed Effects	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES
GMM test (p-value)	0.005	0.02	0.01	0.02	0.01

Table 7: Subsample Analysis: Small vs. Large

This table summarizes the quality of ratings, measured by the reliability ratio, for different subsample of bond issues. We create two subsamples based on a proxy for information accessibility. The proxy is motivated by U.S. Securities and Exchange Commission (SEC) Rule 15c2-12 which enforces disclosure requirements for municipal bond issues with size larger than 1 million dollars. Accordingly, we construct "Large" ("Small") sample based on whether the size of an issue is above (below) 1 million dollars. Panel A shows estimates for the ratings' quality. Panel B shows estimates for the ratings' quality after shutting down the feedback among the ratings (i.e. setting all α's equal to 0)

	S&P-Moody's		S&P, Moody's, and Fitch	
	Small	Large	Small	Large
Panel A. Estimates				
S&P rating quality	0.144	0.492	0.109	0.250
	(0.046)	(0.010)	(0.079)	(0.049)
Moody's rating quality	0.293	0.853	0.275	0.507
	(0.108)	(0.078)	(0.108)	(0.046)
Fitch rating quality			0.209	0.565
			(0.091)	(0.043)
Panel B. Counterfactual				
S&P rating quality	0.119	0.255	0.091	0.149
	(0.040)	(0.041)	(0.081)	(0.020)
Moody's rating quality	0.226	0.846	0.152	0.433
	(0.104)	(0.082)	(0.113)	(0.050)
Fitch rating quality			0.126	0.488
			(0.084)	(0.043)
N	33,002	80,417	10,624	62,172

A Math Appendix

A.1 Two Credit Rating Agencies

We consider moments of order at most 3. We show that this yields a system of $p = 2+3+1+3+2+4 = 15$ equations involving $p^* = 2+1+2+1+1+2+1+1+2 = 13$ unknowns

$$\underset{p^*\times 1}{\theta^*} \equiv (\underset{2\times 1}{\phi}, \underset{1\times 1}{\delta}, \underset{2\times 1}{\alpha}, \underset{1\times 1}{\xi}, \underset{1\times 1}{E(U^2)}, \underset{2\times 1}{E(\tilde{\epsilon}_j^2)}, \underset{1\times 1}{E(\eta^2)}, \underset{1\times 1}{E(U^3)}, \underset{2\times 1}{E(\tilde{\epsilon}_j^3)}).$$

The $p = 15$ equations are defined as follows:

$$E(W_jY) \;= \kappa_j \textstyle\sum_{l=1}^{2} E(U^2)(\phi_l\kappa_l + \delta/2) + \sum_{l=1}^{J} E(\epsilon_j\epsilon_l)\phi_l \quad \text{for } j = 1,2 \tag{27}$$

$$E(W_jW_h) \;=\; \kappa_j\kappa_h E(U^2) + E(\epsilon_j\epsilon_h) \quad \text{for } j \le h = 1,2 \text{ (total 3 eqns)} \tag{28}$$

$$E(Y^2) \;=\; \sum_{j=1}^{2}\sum_{h=1}^{2}(\phi_j\kappa_j + \delta/2)E(U^2)(\phi_h\kappa_h + \delta/2) + \sum_{j=1}^{2}\sum_{h=1}^{2}\phi_j E(\epsilon_j\epsilon_h)\phi_h + E(\eta^2) \tag{29}$$

$$E(W_jW_hY) \;=\; \kappa_j\kappa_h \sum_{l=1}^{2} E(U^3)(\phi_l\kappa_l + \delta/2) + \sum_{l=1}^{2} E(\epsilon_j\epsilon_h\epsilon_l)\phi_l \quad \text{for } j \le h \tag{30}$$

$$E(W_jY^2) \;=\; \kappa_j \sum_{h=1}^{2}\sum_{l=1}^{2}(\phi_h\kappa_h + \delta/2)E(U^3)(\phi_l\kappa_l + \delta/2) + \sum_{h=1}^{2}\sum_{l=1}^{2}\phi_h E(\epsilon_j\epsilon_h\epsilon_l)\phi_l \tag{31}$$

$$E(W_jW_hW_l) \;=\; \kappa_j\kappa_h\kappa_l E(U^3) + E(\epsilon_j\epsilon_h\epsilon_l) \quad \text{for } j \le h \le l \text{ (total 4 eqs)} \tag{32}$$

we omit the moment $E(Y^3)$ since this adds the moment $E(\eta^3)$ which is not of direct interest here.

A.2 Three Credit Rating Agencies

Now, we set

$$\begin{bmatrix}\epsilon_1\\ \epsilon_2\\ \epsilon_3\end{bmatrix} = A \begin{bmatrix}\tilde{\epsilon}_1\\ \tilde{\epsilon}_2\\ \tilde{\epsilon}_3\end{bmatrix}$$

Then, ϵ's second moments can be written as

$$E[A\tilde{\epsilon} \otimes A\tilde{\epsilon}] = (A \otimes A)E[(\tilde{\epsilon} \otimes \tilde{\epsilon})]$$

ϵ's third moments can be written as

$$E[A\tilde{\epsilon} \otimes A\tilde{\epsilon} \otimes A\tilde{\epsilon}] = (A \otimes A \otimes A)E[(\tilde{\epsilon} \otimes \tilde{\epsilon} \otimes \tilde{\epsilon})]$$

We consider moments of order at most 3. We show that this yields a system of $p = 3+6+1+6+3+10 = 29$ equations involving $p^* = 3+1+6+2+1+3+1+1+3 = 21$ unknowns

$$\underset{p^*\times 1}{\theta^*} \equiv (\underset{3\times 1}{\phi}, \underset{1\times 1}{\delta}, \underset{6\times 1}{\alpha}, \underset{2\times 1}{\xi}, \underset{1\times 1}{E(U^2)}, \underset{3\times 1}{E(\tilde{\epsilon}_j^2)}, \underset{1\times 1}{E(\eta^2)}, \underset{1\times 1}{E(U^3)}, \underset{3\times 1}{E(\tilde{\epsilon}_j^3)}).$$

The $p = 29$ equations are defined as follows:

$$E(W_jY) = \kappa_j \sum_{l=1}^{3} E(U^2)(\phi_l\kappa_l + \delta/3) + \sum_{l=1}^{3} E(\epsilon_j\epsilon_l)\phi_l \quad \text{for } j = 1,2,3 \tag{33}$$

$$E(W_jW_h) = \kappa_j\kappa_h E(U^2) + E(\epsilon_j\epsilon_h) \quad \text{for } j \leq h = 1,2,3 \text{ (total 6 eqns)} \tag{34}$$

$$E(Y^2) = \sum_{j=1}^{3}\sum_{h=1}^{3}(\phi_j\kappa_j + \delta/3)E(U^2)(\phi_h\kappa_h + \delta/3) + \sum_{j=1}^{3}\sum_{h=1}^{3}\phi_j E(\epsilon_j\epsilon_h)\phi_h + E(\eta^2) \tag{35}$$

$$E(W_jW_hY) = \kappa_j\kappa_h \sum_{l=1}^{3} E(U^3)(\phi_l\kappa_l + \delta/3) + \sum_{l=1}^{3} E(\epsilon_j\epsilon_h\epsilon_l)\phi_l \quad \text{for } j \leq h = 1,2,3 \tag{36}$$

$$E(W_jY^2) = \kappa_j \sum_{h=1}^{3}\sum_{l=1}^{3}(\phi_h\kappa_h + \delta/3)E(U^3)(\phi_l\kappa_l + \delta/3) + \sum_{h=1}^{3}\sum_{l=1}^{3}\phi_h E(\epsilon_j\epsilon_h\epsilon_l)\phi_l \tag{37}$$

$$E(W_jW_hW_l) = \kappa_j\kappa_h\kappa_l E(U^3) + E(\epsilon_j\epsilon_h\epsilon_l) \quad \text{for } j \leq h \leq l \text{ (total 10 eqs)} \tag{38}$$

we omit the moment $E(Y^3)$ since this adds the moment $E(\eta^3)$ which is not of direct interest here.

B Additional Tables and Figures

Table A1: Variable Definitions

Column	Description	Source/Code
Yield	Offering yield in percentages	MSRB
S&P rating	S&P rating on issuance. Converted to numeric numbers. "AAA" to 22, "AA+" to 21 through "C" to 2 and "D" to 1	S&P CapitalIQ
Moody's rating	Moody's rating on issuance. Converted to numeric numbers. "Aaa" to 21, "Aa1" to 20 through "Ca" to 2 and "C" to 1	Eikon
Fitch rating	Fitch rating on issuance. Converted to numeric numbers. "AAA" to 20, "AA+" to 19 through "DD" to 2 and "D" to 1	Eikon
Risk free rate	We select the two STRIPS with the closest durations (one above and one below) and linearly interpolate to determine the risk free rate. See Cornaggia et al. (2018) pg15-16 for the details	Bloomberg: Generic Treasury coupon STRIPS rate for 1, 2, 3, 4, 5, 6, 7, 8, 10, 15, 20, and 30 maturity years
Coupon rate	Stated interest rate on this tranch.	Eikon: TR.MUNICouponRate
Par value	Principal amount of the new security issued in million dollars,	Eikon: TR.FiFaceIssuedTotal
Dummy: Callability	An indicator variable taking a value of one if a bond is callable and zero if not.	Eikon: TR.FIIsCallable: Y/N flag indicating whether the bond is callable.
Dummy: Negotiated	An indicator variable taking a value of one if a bond was issued through a negotiated process and zero if the bond was issued through a competitive process.	Eikon: TR.FIOfferingType: Code representing the nature of the registration

Duration1	A bond's duration, measured in years, calculated using the bond's time to maturity regardless of whether the bond is callable. Constructed using 4 variables	Eikon: 1. Yield described above 2. TR.FIIssueDate (Date of issuance of the asset (for example, the date of initial settlement)) 3. TR.FIMaturityDate (Date the asset pays the remaining total principal amount to the holder in a redemption transaction. For an extendible security, the maturity date will change on each extend date from the current extend date to the next extend date) 4. TR.FICouponFrequency (Code representing the frequency of coupon payments for the asset)
Duration2	A bond's duration, measured in years, calculated using the bond's call date if the bond is callable and the bond's time to maturity if the bond is not callable	Eikon: 1. Yield described above 2. TR.FIIssueDate (Date of issuance of the asset (for example, the date of initial settlement)) 3. TR.FIMaturityDate (Date the asset pays the remaining total principal amount to the holder in a redemption transaction. For an extendible security, the maturity date will change on each extend date from the current extend date to the next extend date) 4. TR.FICouponFrequency (Code representing the frequency of coupon payments for the asset) 5. TR.FINextCallDate (Next date the issuer can call the bond before maturity. If the bond is callable now, the next call date is the date on which the call price changes)
Dummy: General Obligation	An indicator variable taking a value of one if a bond is a general obligation bond and zero if a bond is a revenue bond or other type	Eikon: TR.FiDebtServiceLongDescription (debt service long dscerption)
Outstanding bonds	The number of other bonds outstanding for the issuer at the time of issuance. This was manually constructed based on data from Eikon	

Bond insurance	The name of commercial insurance company that writes insurance contract which provides payment to bondholders in the event of issuers' default	Eikon: TR.MUNIBondInsuranceDesc