Municipal Bond Insurance Premium, Credit Rating, and Underlying Credit Risk

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This article explores the question of whether bond insurers are able to sufficiently evaluate the credit risk of insured bonds, the answer to which would determine the future of municipal bond insurance. A sample of insured municipal bonds is investigated to determine whether bond insurance premia can predict the future credit rating transition, the proxy for bond credit risk. The results show that municipal bond insurance premia, conditional on bond credit ratings and other explanatory variables, have explanatory power over credit rating downgrades but not over upgrades. As such, bond insurance premia convey extra information about the underlying credit risk of a bond issue than the original credit rating reveals. This research also provides evidence that the rating agencies might not be doing as a good job as they could potentially do.

INTRODUCTION

One practice of the municipal bond market that was hammered significantly in the subprime crisis is municipal bond insurance.[1] As of January 1, 2011, all seven municipal bond insurers that were rated triple A before the subprime crisis had been downgraded to below triple A ratings. During 2010, only Assured Guaranty Corp. (AGC) was able to write new business, with a market penetration rate of less than 10 percent that dropped from the over 50 percent in 2007.

Although bond insurers' default risk mainly comes from their guarantee for structured asset-backed securities (ABS) such as collateralized debt obligations (CDO), the market

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1. Dwight V. Denison, "What Happens When Municipal Bond Insurance Companies Lose Credit," *Municipal Finance Journal* 29, no. 4 (2009): 27–47; Paul Kwiatkoski, 2009. "Effects of the Credit Crisis on the U.S. Municipal Market: A Fragmented Market Wrestles with both the Demise of Bond Insurance and its Reliance upon Retail Investors," *Municipal Finance Journal* 29, no. 4 (Winter 2009): 23–35; G. Liu, *Essays on Municipal Bond Insurance. The Martin School of Public Administration and Policy* (Lexington, KY: University of Kentucky, 2009).

seems also concerned about insurers' major business of municipal bond insurance, as evidenced by its shrunk market penetration rate. It is uncertain at this point whether municipal bond insurance can survive and how it will develop. The future of municipal bond insurance can be affected by many factors. An essential one is whether the bond insurer is able to correctly evaluate the underlying credit risk of insured bonds.

Previous studies have argued that reducing information asymmetry through signaling effect is one reason for the existence of bond insurance.[2] To reduce information asymmetry, one necessary condition is that insurers invest in information production and collect valuable information about the bond default probability.[3] Studies have empirically examined the signaling effect of municipal bond insurance by investigating the costs and benefits of insured bonds.[4] No studies, however, have examined this necessary condition of whether insurers are able to correctly generate valuable information about bond credit risk.

Credit risk is unobserved. Credit ratings may be the most important instrument that helps to pierce this "fog" of asymmetric information.[5] However, as observed in the current subprime crisis, credit rating agencies failed to adequately reveal the credit risk of securities.[6] In theory, compared to credit rating agencies, bond insurers have more incentives to collect sufficient information and evaluate the underlying credit risk of the bonds they insure, because the credit risk that arises from insurance policy underwriting eventually affects insurers' own default risk and profitability. The role of bond credit rating agencies, on the other hand, may allow them to miss some information without directly suffering from the consequences.

This study aims to examine the relationship of bond insurance premia and the future credit migration of insured bonds, a proxy for their inherent credit risk. It investigates the explanatory power of bond insurance premia over future bond credit rating migration in California between 2001 and 2005. If bond insurance premia contain extra information about the underlying credit risk of bond issues, bond insurance provides an added value to

2. Anjan V. Thakor, "An Exploration of Competitive Signaling Equilibria with 'Third Party' Information Production: The Case of Debt Insurance," *Journal of Finance* 37 (1982): 717–739; David S. Kidwell, Eric H. Sorensen, and John M. Wachowicz, 1987, "Estimating the Signaling Benefits of Debt Insurance: The Case of Municipal Bonds," *Journal of Financial & Quantitative Analysis* 22, no. 3 (1987): 299; Jun Peng and Peter F. Brucato, "An Empirical Analysis of Market and Institutional Mechanisms for Alleviating Information Asymmetry in the Municipal Bond Market," *Journal of Economics and Finance* 28, no. 2 (2004): 226–238.

3. Thakor (1982).

4. L. Paul Hsueh and Y. Angela Liu, "The Effectiveness of Debt Insurance as a Valid Signal of Bond Quality," *Journal of Risk and Insurance* 57, no. 4 (1990): 691–700; Kidwell et al. (1987); Peng and Brucato (2004).

5. Lawrence J. White, 2001. The Credit Rating Industry: An Industrial Organization Analysis. NYU Center for Law and Business Research Paper No 01-001, 2001); available from SSRN: *http://ssrn.com/abstract=267083* or DOI:10.2139/ssrn.267083: accessed 24 June 2008.

6. John P. Hunt, "Credit Rating Agencies and the 'Worldwide Credit Crisis': The Limits of Reputation, the Insufficiency of Reform, and a Proposal for Improvement," *Columbia Business Law Review* 1 (2009): 109–209; John M. Griffin and Dragon Yongjun Tand, "Did Subjectivity Play a Role in CDO Credit Ratings?" McCombs Research Paper Series No. FIN-04-10 (Austin, TX: University of Texas, 2009).

the market and has the potential to provide signaling effects. Consequently, it has a reason to exist in the market.

I find that, conditional on bonds' current credit ratings, bond insurance premia have explanatory power over future bond credit rating downgrades but not over rating upgrades. Conditional on credit ratings and other observable information, bonds that pay higher insurance premia are more likely to be downgraded within two years following the bond issuance. However, the propensity of future credit upgrades is not associated with bond insurance premia, holding other observed factors constant. These findings suggest that insurance premia convey latent information that helps to predict at least future underlying credit rating downgrades, and insurers may be able to gauge the underlying credit risk of municipal bonds more sufficiently than bond credit ratings reveal. It also suggests that municipal bond insurance can potentially improve the quality of its credit rating.

While focusing on the relationships between municipal bond insurance premia and credit risk, this article is also the first attempt, to the best of the author's knowledge, to quantify the determinants of municipal bond insurance premia. The findings advance our understanding on how municipal bond insurance premia are determined. An additional contribution of this study is that it provides a more sophisticated method for studying credit rating transition. Standard & Poor's (S&P) yearly reports,[7] the only studies exploring the credit rating migration of municipal bonds, use a univariate method to analyze credit rating migrations and thus fail to reveal the ceteris paribus effect.

This article proceeds with the following outline. Section 2 provides relevant background about municipal bond insurance and bond credit ratings and relevant literatures. Section 3 elaborates on the conditions under which municipal bond insurance premia convey extra information beyond that revealed by credit ratings and public information, and develops empirical methods for the estimation. Section 4 introduces the data, followed by estimation results in Section 5. Section 6 provides a discussion of the findings, and the final section concludes with a brief discussion of the policy implication.

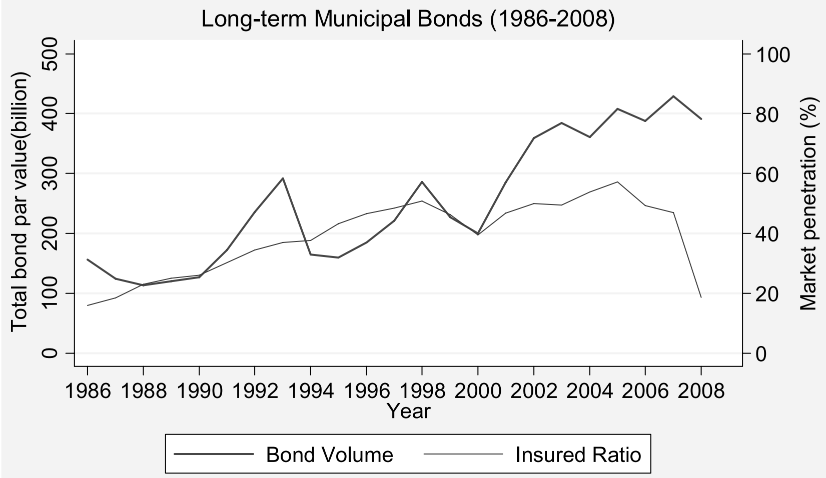
BACKGROUND KNOWLEDGE AND LITERATURE

Municipal Bond Insurance

The municipal bond insurance industry started in 1971. Charging a certain amount of insurance fees, a municipal bond insurer promises to assume the responsibility of paying the interest and principal when the insured issue defaults. With this financial guarantee,

7. Standard & Poor's, *U.S. Municipal Rating Transitions and Defaults, 1986–2003* (Research report) (New York: Standard and Poor's, 2004); Standard & Poor's, *U.S. Municipal Rating Transitions and Defaults, 1986–2005* (Research report) (New York: Standard and Poor's, 2005); Standard & Poor's, *U.S. Municipal Rating Transitions and Defaults, 1986–2006* (Research report) (New York: Standard and Poor's, 2006); Standard & Poor's, *Standard & Poor's Global Bond Insurance Book 2006* (Research report) (New York: Standard & Poor's, 2007a).

FIGURE 1
The Development of Municipal Bond Insurance Market



Note: The left-hand scale represents total municipal bond volume (unadjusted for inflation); the right-hand scale indicates the percent insured of total volume issued.

Source: Justice & Simon (2002); CDIAC (2002); Bond Buyer(19 Feb. 2002); Bond Buyer(9 Feb. 2004); Bond Buyer (25 Jan.2005); Bond Buyer (11 Feb.2008); Bond Buyer (2 Jan.2009)

the insured issue inherits the credit quality of its insurer and consequently may be able to attract more investors and enjoy a lower interest rate.

As illustrated in Figure 1, the industry grew significantly in the past two decades but shrank rapidly in recent years. Until late into 2007, it had been considered a promising industry, as suggested by its 49 percent market penetration and an insured par volume of more than 191 billion dollars in 2006.[8] Starting in the late 1990s, most municipal bond insurers, attracted by the high profit and the demand for diversification, rapidly ventured into the business of providing guarantees to ABS, including such structured securities as CDOs.

Unfortunately, structured finance is a field municipal bond insurers were much less familiar. The credit risk of these subprime mortgage-related securities was underestimated by most financial market participants and regulators, including credit raters, bond insurers, and many investment banks. Although on average the CDOs guaranteed by bond insurers were rated triple A or double A, these subprime mortgage-related securities have systematically defaulted or been downgraded as a consequence of the subprime crisis since August 2007.

The systematic defaults and credit downgrades of CDOs left their insurers at high risk and lead to the sweeping downgrade of insurers, although at the early stage of the subprime

8. Dakin Campbell, "For Insurers, 1st half is OK, but the 2nd Half? Don't Ask," *Bond Buyer,* February 11, 2008, p. 6A.

crisis credit rating agencies expected that "subprime exposure [was] unlikely to cause bond insurers major difficulties."[9] Since November 2007, credit rating agencies have started to downgrade insurers' credit ratings to below AAA. In 2010, only AGC was able to underwrite new insurance. Currently, it is hard to foresee what might be the future of the industry. The market is concerned about the credit risk of bond insurers and their capability of evaluating the underlying credit risk of the bonds they insure. At this point, limited empirical research has been done to answer these questions.

On the other hand, researchers have long explored the rationale underlying bond insurance, and attributed its former popularity to cost saving,[10] elimination of information asymmetry,[11] tax-based benefits,[12] and market segmentation reduction.[13] The studies that argue the elimination of information asymmetry is most closely related to the current study. Thakor[14] builds a theoretical model, in which municipal bond insurance can reduce the information asymmetry between issuers and investors by signaling the quality of municipal bonds. One of the necessary conditions of Thakor's model assumes that insurers invest on information producing and are informed about the credit quality of municipal bonds.

Regardless of the underlying reasons for issuers to purchase bond insurance, issuers have to pay insurance premia in exchange for insurers' unconditional and irrevocable financial guarantee. The insurance premium is determined through the underwriting process of bond insurance. Upon receiving the solicitation for insurance from the bond issuer or the bond underwriter, insurance companies analyze the financial situation of the issuer and the legal status of the bond issue based on both public and private information, a process similar to the credit rating process of bond rating agencies. To be sure, the credit rating of the issue is important information for pricing bond insurance premia. But not all insurers require bonds to be rated by a credit rating agency because they have the ability to evaluate the risk of a bond through their own underwriting process. Based on the default possibility and recovery rate in the event of a default, they will generate an internal risk rating that serves as the basis for future pricing. With the internal credit rating, the insurance companies decide whether or not to offer an insurance policy and, if a policy is offered, the price of the credit enhancement. Essentially the insurance underwriting process is an evaluation of the underlying credit risk, through which the bond insurer, with its experience to evaluate public information and its authority to access private financial information of the issue,

9. R. Green and D. Smith, *Subprime Exposure Is Unlikely to Cause Bond Insurers Major Difficulties* (New York: Standard & Poor's, 2007).

10. Robert L. Bland, "The Interest Cost Savings from Municipal Bond Insurance: The Implications for Privatization," *Journal of Policy Analysis and Management* 6, no. 2 (1987): 207–219; D.V. Denison, "An Empirical Examination of the Determinants of Insured Municipal Bond Issues," *Public Budgeting & Finance* 23, no. 1 (2003): 96–114.

11. Thakor (1982), Kidwell et al. (1987), Peng and Brucato (2004).

12. Vikram K. Nanda and Rajdeep Singh, "Bond Insurance: What Is Special about Munis?" *Journal of Finance* 59, no. 5 (2004): 2253–2279.

13. Dwight V. Denison, "Bond Insurance Utilization and Yield Spreads in the Municipal Bond Market," *Public Finance Review* 29, no. 5 (2001): 394–411; Denison (2003).

14. Thakor (1982).

may be able to find out valuable information about bond credit risk and reveal it through the insurance premium.

Partly due to unavailability of appropriate data, no publication has examined the determinants of municipal bond insurance premia, to the best of the author's knowledge. However, some studies have shed light on the average insurance cost, which seems to have decreased in the past 30 years. In their work examining the issue of whether bond insurance saves money for municipalities, Kidwell et al.[15] documented that between 1975 and 1980, one dollar par value insurance cost 10.0 basis points per year for Aa-rated and 12.7 basis points per year for Baa-rated general obligation (GO) issues. Smith and Harper[16] found that, in the early 1990s, insurance companies charged bonds issued in Florida at a premium of 6.6 basis points per year.

Credit Rating

Credit risk, the risk that obligors may default, is an important factor for determining the price of credit-risky instruments[17] and a critical subject of regulatory supervision and policy debate.[18] However, the true credit risk of a bond cannot be observed by market participants, calling for measurement systems, or tools capable of sufficiently revealing credit risk.[19] This challenge is more pronounced in the municipal bond market, which is characterized by significantly stronger information asymmetry between issuers and other market participants.[20]

The growth of the credit rating industry, which in 2006 provided ratings to debt issuance totaling over 8 trillion dollars, has echoed this demand. The credit rating of a municipal bond reflects the rating agency's current opinion on the creditworthiness of the obligor with respect to the bond.[21]

However, it is not a perfect measurement of credit risk. As an ordinal measure, a credit rating in nature cannot perfectly reflect default risk, which is continuous.[22] Moreover,

15. Kidwell et al. (1987).

16. Stephen D. Smith and Richard B. Harper, "Private Insurance of Public Debt: Another Look at the Costs and Benefits of Municipal Insurance," *Economic Review - Federal Reserve Bank of Atlanta* 78, no. 5 (1993): 27–38.

17. See, for example, Darrell Duffie and Kenneth J. Singleton, *Credit Risk: Pricing, Measurement, and Management* (Princeton, NJ: Princeton University Press, 2003); Frank J. Fabozzi, Dessa Fabozzi, and Sylvan Feldstein, *Municipal Bond Portfolio Management* (Burr Ridge, IL: Irwin Professional Pub, 1995).

18. Samuel Hanson and Til Schuermann, 2006. "Confidence Intervals for Probabilities of Default," *Journal of Banking & Finance* 30, no. 8 (2006): 2281–2301.

19. For a discussion of credit risk models and credit risk measures, refer to Duffie and Singleton (2003) and Michel Crouhy, Dan Galai and Robert Mark, "Prototype Risk Rating System," *Journal of Banking and Finance* 25, no. 1 (2001): 47–95.

20. Peng and Brucato (2004).

21. Standard & Poor's, *Public Finance Criteria* (Research report) (New York: Standard and Poor's, 2000).

22. S&P's and Moody's have both introduced plus and minus subcategories into each of the original letter categories, suggesting that the prior rating system might have disguised some credit risk differences for

the extra market power arising from the entry barrier to the credit rating industry may discourage bond raters to acquire valuable information about bond credit risk. Finally, given the nature of the current credit rating system, in which for instance, credit rating agencies are paid by issuers rather than by information consumers, credit rating agencies may lack strong incentives to accurately reveal risk information with credit ratings.

The creditworthiness of the bond is evaluated based on both public and private information available to the agency on the rating date. According to S&P,[23] three aspects are considered when determining bond credit ratings: the likelihood of default, the nature and provisions of the obligation, and the extent of losses in the event of a default. Since all three factors are also relevant in determining bond insurance premia, we can feasibly expect that bond insurance premia and bond credit ratings are highly correlated.

For bonds with a credit enhancement, the creditworthiness of their guarantor is factored into their enhanced ratings, as discussed previously. Upon issuers' requests, credit raters can also publish underlying ratings, in addition to the enhanced ratings, to reveal the stand-alone credit risk of the issues.[24] For example, S&P assigns an S&P underlying rating (SPUR) at the request of the issuer to reveal the stand-alone creditworthiness of an issue.

Since credit ratings are an important measure of credit risk and play an important role in pricing bonds and other credit-risky instruments,[25] their stability and migration has attracted the attention of both academic researchers and practitioners.[26] Most of them focus on corporate bonds, with the sole exception of S&P, which periodically publishes credit rating migration matrices for unenhanced municipal bonds and enhanced municipal bonds with an underlying credit rating.[27] S&P reports rating transition matrices by clusters and documents that the patterns of credit rating migration differ among issuers of different functional types. However, rating transition matrices are simply mean comparisons and are essentially a univariate approach. Therefore, analyses based on rating transition matrices

(footnote Continued)

bonds within the same rating category. With the current notch-level categories, further differentiation may still exist within the same rating category (K. Galil, "The Quality of Corporate Credit Rating: An Empirical Investigation," Working Paper (Tel Aviv, Israel: Tel-Aviv University, 2003).

23. Standard & Poors (2000).

24. Ibid.

25. J.P. Morgan, "Creditmetrics- Technical Document." (Unpublished Discussion paper. J.P. Morgan, 1997); Credit Suisse Financial Products, CreditRisk+: Technical manual. (Unpublished Discussion paper. CSFP, 1997); Pamela Nickell, William Perraudin, and Simone Varotto, "Stability of Rating Transitions," *Journal of Banking & Finance* 24, no. 1–2 (2000): 203–227; Duffie and Singleton (2003).

26. For example, Nickell et al. (2000); Douglas J. Lucas and John G. Lonski, "Changes in Corporate Credit Quality 1970–1990," *Journal of Fixed Income* 1, no. 4 (1992): 7–14; Lea V. Carty, and Jerome S. Fons, *Measuring Changes in Credit Quality', Moody's Special Report* (New York: Moody's Investors Service, 1993); Lea V. Carty, *Moody's Rating Migration and Credit Quality Correlation, 1920–1996* (New York: Moody's Investors Service, 1997).

27. Standard & Poor's (2004–2007a).

fail to reveal the ceteris paribus significance of conditional variables.[28] Recent studies[29] utilize pool ordered logit models to examine the credit rating migration of corporate bonds. Pool ordered logit models, however, may also lead to a biased estimation, as explained in the next section. Thus, more sophisticated methodologies are needed for a better understanding of the issue.

The literature on corporate bond rating transition, on the other hand, has provided some insights on the factors that may affect bond credit rating transitions. It has been documented that observed macroeconomic variables may have explanatory power over corporate credit rating transition.[30] It has also been found that the credit rating does not follow a Markove process.[31] In other words, the future credit rating transition is dependent on previous rating migrations.

THEORETICAL MODEL

This section first illustrates how credit raters and insurers' model and measure credit risk. Based on the illustration, I specify the conditions under which insurance premia convey extra information about bond credit risk, and then develop a model to empirically test our research questions.

The underlying default risk, $H_{i,t}$, of a municipal bond i at time t is unknown, and it is a function of $x_{i,t}$, the bond-specific information available at time t, and Y_t, the macroeconomic condition at time t. While both bond credit rating agencies and bond insurers have full access to macroeconomic information Y_t, they have only partial access to bond-specific information $x_{i,t}$, due to the information asymmetry. The respective information sets to which insurers and credit raters have access may differ from each other, as shown in Figure 2.

If a bond i is rated by a credit rating agency, we observe a category variable $G_{i,t}$ assigned to the bond at time t. $G_{i,t}$ is determined based on the bond credit risk, $\widehat{H^r}_{i,t}$ perceived by the credit rating agency. In turn, $\widehat{H^r}_{i,t}$ is predicted based on the bond-specific information and macroeonomic conditions; that is, $\hat{H}^r_{i,t} = h(x^r_{i,t}, Y_t)$, where $x^r_{i,t}$ is the bond-specific information that rating agencies can access at time t. As illustrated in Figure 2, $x^r_{i,t}$ is a subset of $x_{i,t}$, i.e., $x^r_{i,t} \subseteq x_{i,t}$. $\widehat{H^r}_{i,t}$ then is mapped to an ordinal variable $G_{i,t}$ with a scale

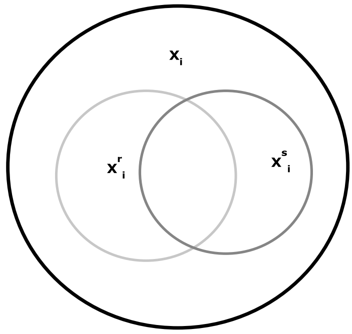
28. Nickell et al. (2000).

29. Ibid.; Jeffery D. Amato and Craig H. Furfine, "Are Credit Ratings Procyclical?" *Journal of Banking & Finance* 28, no. 11 (2004): 2641–2677.

30. Ibid.; Anil Bangia, Francis X. Diebold, Andre Kronimus, Christian Schagen, and Til Schuermann,"Ratings Migration and Business Cycle, with Application to Credit Portfolio Stress Testing," *Journal of Banking & Finance* 26, no. 2–3 (2002): 445–474; Yen-Ting Hu, Rudiger Kiesel, and William Perraudin, "The Estimation of Transition Matrices for Sovereign Credit Ratings," *Journal of Banking and Finance* 26, no. 7 (2002): 1383–1406.

31. See David Lando and Torben M. Skødeberg, "Analyzing Rating Transitions and Rating Drift with Continuous Observations," *Journal of Banking & Finance* 26, no. 2/3 (2002): 423–444, for a review.

FIGURE 2
An Illustration of the Relationships between x_i, $x^r{}_i$, and x_i^s



x_i: all bond-specific information available for bond *i* at time *t*

$x^r{}_i$: bond-specific information that can be accessed by the credit rater

$x^s{}_i$: bond-specific information that can be accessed by the insurer

from 1 to n.[32] The mapping follows the algorithm: $h^r_G < \hat{H}^r(G) \leq h^r_{G+1}$, where $G = 1, \ldots, n$, h^r_j is the upper boundary of the credit risk for a bond with rating G, $h^r_1 = -\infty$ and $h^r_{n+1} = \infty$, as illustrated in Figure 3.

To determine whether or not to offer an insurance policy and, if a guarantee is offered, the insurance premium, at time t insurers also evaluate the credit risk of bond i : $\hat{H}^s_{i,t} = h(x^s_{i,t}, Y_t)$,[33],[34] where $x^s_{i,t} \subseteq x_{i,t}$. The relationships between $x^s_{i,t}$, $x^r_{i,t}$, and $x_{i,t}$ are illustrated in Figure 2. $\widehat{H^s_{i,t}}$ may be measured as an ordinal variable[35] like credit rating or as a continuous variable. After $\widehat{H^s_{i,t}}$ is estimated, the bond's insurance premium, Ins_i, is determined based on $\widehat{H^s_{i,t}}$ and other publicly observed factors $z_{i,t}$: $Ins_i = f(\hat{H}^r_{i,t}, Z_{i,t})$. $z_{i,t}$ is a set of bond characteristics, issuer characteristics, and economic factors, and it has interceptions with $x^s_{i,t}$ and Y_t.

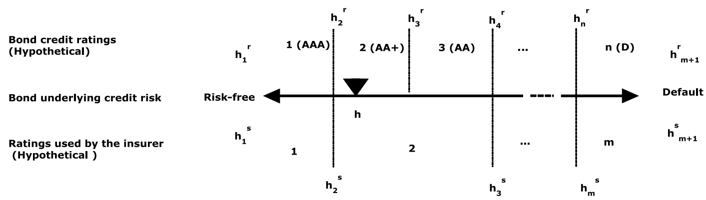
32. S&P's has ten rating categories as follows: AAA, AA, A, BBB, BB, B, CCC, CC, C, D, while Moody's has nine rating categories: AAA, Aa, A, Baa, Ba, B, Caa, Ca, C. Both rating agencies further split some of their rating categories into three notches.

33. It is assumed that the insurance premium is determined right after a bond's underlying credit rating is published. Thus credit rating G is known to the bond insurer when it underwrites the insurance policy, i.e., $G \in x^s_{i,t}$.

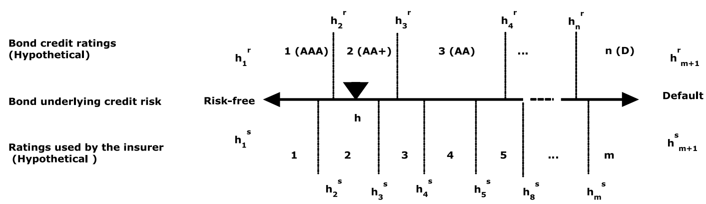
34. To simplify the illustration, it is assumed that, if given the same information set, bond rating agencies and insurers will predict the same value of credit risk. In other words, they have the same prediction function of credit risk.

35. $h^s_G < \hat{H}^s(G^s_i) \leq h^s_{G+1,}$ where $G = 1, \ldots m$, $\hat{H}^s(G^s)$ is the credit risk of a bond with a rating G^s by the insurer and $h^s_1 = -\infty$ and $h^s_{m+1} = \infty$.

FIGURE 3
An Illustration of the Relationships between Bond Underlying Credit Risk, Bond Credit Ratings, and Ratings Used by the Insurer



Example 1: Rating categories used by the insurer are completely nested in those used by the credit rating agency



Example 2: Rating categories used by the insurer are not nested in those used by the credit rating agency

Note: in this illustration, bond credit ratings have a hypothetical scale from 1 ton, with 1 representing the risk-free rating (e.g. the AAA rating from S&P) and n representing the most risky rating(e.g. the D rating from S&P). These ratings are assigned based on category boundaries denoted as h_j^r, where j=1,..., n. Likewise, ratings used by the insurer have a hypothetical scale from 1 tom, with 1 presenting the risk-free rating and m representing the most risky rating. Ratings used by the insurer are defined based on category boundaries denoted as h_j^s, where j=1,..., m. The categories of neither bond credit ratings nor ratings used by the insurer are necessary to be evenly distributed along the bondunderlying credit risk.

Conditions Under Which Insurance Premia Contain Extra Information

Based on above discussion, *Ins* contains extra information, if (1) the bond-specific information that raters access is not a subset of the bond-specific information that insurers access, i.e., $x_{i,t}^s \not\subset x_{i,t}^r$; or (2) insurers' rating categories and cut points used to define categories are not pure subsets of those used by credit raters, i.e., $\{h_j^s\} \not\subset \{h_j^r\}$.[36]

Figure 2 exemplifies the first condition. Since the credit rating is published before the insurance premium is determined, the bond insurer knows at least as much bond-specific information as the credit rating reveals. If the insurer has access to some information other than $x_{i,t}^r$, then the insurance premium will convey extra information about the credit risk.

The upper panel of Figure 3 shows an example in which the rating categories used by the insurer are completely nested in those used by the credit rating agency. In this scenario, if the credit rating agency and the insurer have the same prediction on the value of the underlying credit risk, e.g., *h* as shown in Figure 1, then bond insurance premia are unable to reveal extra information. However, if rating categories used by the insurer are not nested in those used by the credit rating agency, then bond insurance premia may convey extra information even if condition 1 is not satisfied. The lower panel of Figure 3 demonstrates such an example. Assuming that both the credit rating agency and the insurer reach the

36. A continuous measure of $\widehat{H_{i,t}^s}$ can be viewed as one with an infinite number of categories and cut points.

same prediction value h for the credit risk of a bond, then the observed credit rating only tells us that the credit risk of the bond lies within the interval between h_2^r and h_3^r. However, with the information from bond insurance premia, I can narrow the credit risk down to a smaller rage between h_2^r and h_3^s, as shown in Example 2 of Figure 3.

EMPIRICAL MODEL

To empirically test our research question, the following null hypothesis is specified: the bond insurance premium, conditional on the current credit rating and other explanatory variables, provides no extra information about the inherent default risk of a bond, i.e.:

$$pdf(H_{i,t}|G_{i,t}, x_{i,t}, Y_t, Ins_i) \equiv pdf(H_{i,t}|G_{i,t}, x_{i,t}, Y_t) \quad (1)$$

The most direct way to test this hypothesis is to examine the explanatory power of bond insurance premia on bond defaults, because the bond default probability is the most precise measure of $H_{i,t}$. However, the rarity of municipal bond defaults[37] and the relatively short sample period make this approach infeasible. To circumvent this data limitation, I use future rating transition as a proxy for$H_{i,t}$. Conditional on the current rating, future rating transition is a good measure of bond default risk, as it has been found to be closely related to bond defaults.[38] Furthermore, a default can be viewed as an ultimate and extreme negative rating migration.[39]

I define $M_{i,t}$, the rating migration for a bond i from t to $t + 1$, as shown below:

$$M_{i,t} = \begin{cases} 1 & \text{if} \quad \text{bond } i \text{ was downgraded during the period } t \text{ to } t+1 \\ 2 & \text{if} \quad \text{bond } i \text{ had no credit rating change during the period } t \text{ to } t+1 \\ 3 & \text{if} \quad \text{bond } i \text{ was upgraded during the period } t \text{ to } t+1 \end{cases} \quad (2)$$

Thus, instead of testing equation (1), we test whether insurance premia, conditional on current credit ratings and other explanatory variables, have an explanatory power over future credit rating migration. In other words, we test the following equation:

$$pdf(M_{i,t}|G_{i,t}, x_{i,t}, Y_{t+1}, Ins_i) \equiv pdf(M_{i,t}|G_{i,t}, x_{i,t}, Y_{t+1}) \quad (3)$$

37. In 2006, for example, only one S&P-rated municipal issue defaulted: the Massachusetts Port Authority special facilities bonds issued for a Delta Air Lines Inc. project (S&P, 2007b). There is no bond in our sample that defaulted during the sample period.

38. Standard and Poor's (2007b).

39. Edward I. Altman, *Rating Migration of Corporate Bonds: Comparative Results and Investor/Lender Implications* (New York: University-Salomon Center-Leonard N. Stern School of Business, 1996).

where Y_{t+1} is the vector of observed macroeconomic variables at period $t + 1$. It has been argued that observed macroeconomic variables can explain credit rating transition to some extent.[40] The current credit rating $G_{i,t}$ is also included as a control variable.

Notice that the bond-specific information at period $t + 1$ is not included in equation (1) or equation (3), as it is assumed that conditional on future macroeconomic conditions, new bond-specific information that occurred between periods t and $t + 1$ is random. That is, $m(\Delta x_{i,t+1} | Y_{t+1}) = 0$, where $\Delta x_{i,t+1}$ represents the new information appearing between the issue date t and next time period $t + 1$. This assumption is made based on the belief that if all information available in the current period has been incorporated, then new bond-specific information only emerges randomly and all systematic bond-specific information is caused by macroeconomic conditions. With this assumption, $M_{i,t}$ does not depend on $x_{i,t+1}$ after $x_{i,t}$ is controlled for, since $m(x_{i,t+1} | Y_{t+1}) = x_{i,t}$.

Parallel Lines Assumption Violated

Most previous studies using multivariate analysis to examine the determinants of credit rating migrations of corporate bonds have used ordered logit or probit models.[41] In these standard ordered proportional models, coefficients are identical across dependent variable categories, except for the constant term. In other words, the slopes for different categories are the same. However, this assumption may be violated, as the impacts of one or more independent variables may affect bond rating downgrades and upgrades differently. For example, insurance premia may have different explanatory powers over downgrades and upgrades. More recent studies[42] have also utilized multinomial regression to investigate credit rating changes. While multinomial regressions produce unbiased results, they are less efficient in that they lose some useful information by treating credit rating changes as a nominal rather than an ordinal variable.

The violation of the parallel slopes assumption is confirmed by Wald tests, which suggest that coefficients are not identical across different groups of credit rating migration for our sample. Thus, the assumption of parallel slopes has been violated, and a pooled ordered logistic or probit model will generate a biased estimation. To overcome this problem, the present study introduces a partial proportional ordered logit model, which allows

40. Nickell et al. (2000); Bangia et al. (2002); Hu et al. (2002); Alexander J. McNeil and Jonathan P. Wendin, "Bayesian Inference for Generalized Linear Mixed Models of Portfolio Credit Risk," *Journal of Empirical Finance* 14, no. 2 (2007): 131–149.

41. For example, see Nickell et al. (2000), Amato and Furfine (2004). Rating transition matrices, which are in essence univariate analyses, are also widely used in the study of corporate bond credit rating changes. Two techniques to estimate rating transition matrices have been developed: cohort- and duration-based approaches. Interested readers may refer to Hanson and Schuermann (2006), for a detailed discussion and comparison of these two methods.

42. Miles Livingston, Andy Naranjo, and Lei Zhou, "Split Bond Ratings and Rating Migration," *Journal of Banking and Finance* 32, no. 8 (2008): 1613–1624.

coefficients to change across dependent variable groups.[43] The following model is used to test equation (3):

$$\begin{aligned} &p(M_i > j|G_{i,t}, x_{i,t}, Y_{t+1}, Ins_i) \\ &\quad = g(\alpha_j + G_{i,t}\beta_{1j} + x_{i,t}\beta_{2j} + Y_{t+1}\beta_{3j} + Ins_i\beta_{4j}) \\ &\qquad \text{where } j = 1, 2 \end{aligned} \tag{4}$$

where $g(\cdot)$ is the distribution function, and α_j is the unknown cut point (or threshold parameters) for group $M_i > j$. The t in $M_{i,t}$ is suppressed, as all observations in our empirical study will have the same migration period, two years following the issue date. Since logistic distribution is assumed for $g(\cdot)$ in later estimation, we have:

$$\begin{aligned} &p(M_i > j|G_{i,t}, x_{i,t}, y_{t+1}, Ins_i) \\ &\quad = \frac{\exp(\alpha_j + G_{i,t}\beta_{1j} + x_{i,t}\beta_{2j} + Y_{t+1}\beta_{3j} + Ins_i\beta_{4j})}{1 + \exp(\alpha_j + G_{i,t}\beta_{1j} + x_{i,t}\beta_{2j} + Y_{t+1}\beta_{3j} + Ins_i\beta_{4j})} \\ &\qquad \text{where } j = 1, 2 \end{aligned} \tag{5}$$

There are two differences between this partial proportional ordered logit model and the traditional ordered logit model. First, equation (5) allows coefficients to change across j. Second, the values of the dependent variables are combined into groups. Specifically, the estimation becomes two binary logistic regressions. The first regression compares the group combining $M = 2$ and $M = 3$ against the group $M = 1$. And the second regression compares the group $M = 3$ against the group combining $M = 1$ and $M = 2$.

The Presence of Multicollinearity

To test whether insurance premia have an explanatory power over credit rating changes, a direct approach is to regress credit rating changes on insurance premium. However, insurance premium is a function of other variables, $x^r_{i,t}$, Y_{t+1}, and $G_{i,t}$ that may also have an explanatory power on credit rating changes. Using a direct regression approach would not be able to determine whether the association between of insurance premia and bond credit rating changes is caused by the credit risk or factors that determine insurance premia. For instance, the principal amount determines insurance premia and may also affect credit rating changes. A significant coefficient of insurance premia may simply show the relationship between principal amount and credit rating changes. Since the functional form of the relationship between insurance premia and bond issue principal amount is unknown, I need to include the polynomial functional forms of bond principal amount to remove the effects from principal amount. The consequence is that I may introduce multicollinearity.

43. J. Scott Long and Jeremy Freese, *Regression Models for Categorical Dependent Variables Using Stata* (College Station, TX: Stata Press, 2006); Richard Williams, "Generalized Ordered Logit/Partial Proportional Odds Models for Ordinal Dependent Variables," *The Stata Journal* 6, no. 1 (2006): 58–62.

With the presence of multicollinearity, the significance of estimators cannot be correctly evaluated, leading to false conclusions. To solve this problem, I use a two-stage approach, and separate potential factors that may have an association with bond credit rating changes from insurance premia in the first stage.

$$Ins = f\left(\hat{H}^{s}_{i,t}, z_{i,t}\right) = f\left(h\left(x^{s}_{i,t}, Y_{t}, G_{i,t}\right), z_{i,t}\right) \tag{6}$$

In the second stage, residuals from the first stage, the unexplained part of insurance premia that represents the unobserved information, are used to predict future credit rating migration. In addition to preventing the multicollinearity problem, this two-stage approach also provides valuable information about the factors determining insurance price.

Since the exact functional form of equation (6) is unknown, I include polynomial forms for nondummy variables and use a Ramsey test[44] to examine the correctness of the model specification. Equation (7) demonstrates the form of the regression function of bond insurance premia in the first stage:

$$Ins = \alpha + \sum_{i=1} \left(\beta_{i1} I_i + \beta_{i2} I_i^2 + \beta_{i3} I_i^3 + \cdots\right) + u \tag{7}$$

where I_i are independent variables, including $x^{s}_{i,t}$, Y_{t+2}, and $G_{i,t}$; α is the constant term; and β_i are coefficients. u is the error term, capturing the unobserved effects that are not explained by the independent variables in equation (7). In the second stage, I substitute $\hat{\mu}$ for *Ins* to estimate equation (5). Section 4 will discuss the exact variables to be included into equations (6) and (7).

DATA AND SAMPLING METHOD

To examine the aforementioned research questions, issue data of California municipal bonds are attained from the California State Treasurer's Office, with credit rating migration data extracted from S&P's RatingsIquery[45] and some complementary data from the SDC platinum.[46] Bonds are included into the sample if they were issued between January 1, 2001 and December 31, 2005, with at least one year to maturity, and insured by one of the

44. James Bernard Ramsey, "Tests for Specification Errors in Classical Least-Squares Regression Analysis," *Journal of the Royal Statistical Society* 31, no. 2 (1969): 250–271.

45. *Source:* (Standard and Poor's underlying ratings), RatingsIquery, a Standard and Poor's product, accessed May, 2008.

46. *Source:* (TIC and other characteristics of Municipal bond issues), SDC Platinum, a Thomson Financial product, accessed March 2007.

five largest bond insurers.[47] Bonds with no SPURs at issue date are excluded.[48] A total of 1,771 bonds survive the above selection criteria. However, of this total, 1,051 issues have unreported values of insurance premium, resulting in a final sample of 720 issues.[49] The three types of data included in the examination are discussed below.

Rating Migration

With the sample discussed above, I track from RatingsIquery the rating history of bond issues and extract all bond rating transitions that occurred within two years following the issue date.[50] A two-year horizon, rather than a one-year horizon, is examined, because in the sample only 2.5 percent of ratings experienced at least a rating change within one year, providing insufficient variation for our investigation.[51] I adopt the notch level, rather than the letter level, of bond underlying credit ratings, because notch-level credit ratings provide more detailed information about the credit risk perceived by credit raters. Rating transition is coded as an ordinal variable. Value 1 is assigned to bonds that were downgraded within two years following their issuance, value 3 to bonds that experienced rating upgrades within the two years following their issuance, and value 2 to bonds that kept the same credit ratings at the end of year 2. If a bond issue experienced multiple credit rating changes within the two years, only the first credit change is considered, since issuers' response to previous rating changes may generate bond-specific new information. The introduction of new information violates our assumption specified in Section 3 that there exists no bond-specific new information during the period between t and $t + 1$.

47. These five primary municipal bond insurance companies are all rated with AAA, including Ambac, Financial Guaranty Insurance Company (FGIC), Financial Security Assurance Inc (FSA), Municipal Bond Investors Assurance Corp (MBIA) and XCLA.

48. Since all bonds in our sample were insured by an AAA-rated insurance company in the sample period, they automatically inherit an AAA rating from their insurers, but they may also have underlying ratings that represent their stand-alone trustworthiness.

49. It is highly possible that the selection of our sample is nonrandom, since those with relatively higher insurance premia than other comparable bonds are more likely to choose not to disclose the value of their insurance premia. If the unmeasured factors that affect the selection are also associated with credit rating migration, then the nonrandomness leads to a biased estimation of the relationship between the insurance premium and credit rating migration. Fortunately, it is testable. To test the presence of potential selection bias, I conduct an ordered logistic regression to investigate whether the missing value of insurance premia is correlated with bond credit rating migration. The result suggests that the credit rating migration is independent of the publication of insurance premia conditional on variables included in equations (5) and (7). Thus, missing insurance premia would not cause a selection bias for the estimation of the association between insurance premia and bond credit rating migration.

50. For the sake of simplicity, this study assumes that bond rating dates are the same as bond issue dates. In reality, bond rating dates are generally a bit earlier than bond issue dates, but they are close enough to be considered the same.

51. As a robust test, I also examine the three-year transition using the same methodology. The results are similar, suggesting that the findings of this study are robust to the selection of time horizon of credit rating transition.

Table 1 presents the two-year SPUR transition matrix for our sample. Each cell represents the frequency distribution of SPURs two years following the issue date (given on the top of the matrix) for bonds with the original SPURs on the issue date (given along the left-hand side of the matrix). All bonds in our sample have an investment grade rating (BBB− or above) on the issue date and two years later. No bond in the sample has the highest SUPR AAA. This is not unexpected, as purchasing an insurance policy would not be considered beneficial for an issue already with the highest credit rating. There are more upgrades than downgrades for our sample. As shown in Table 1, about 2.92 percent of new bond issues were downgraded, while 4.44 percent were upgraded within two years following the issue date. Bonds rated with AA+ and BBB in our sample experienced no rating migration. But, on average, bonds with lower ratings at issuance tend to have a larger rating volatility. For bonds with BBB− and BBB ratings, only 33.3 and 87.5 percent, respectively, were able to remain unchanged after two years, while 100 percent of bonds originally rated AA+ and 95.3 percent of bonds rated AA remained in the same rating categories.

Our sample's transition rates are larger than reported by S&P,[52] as S&P reports letter level, rather than notch level, rating transitions. If grouped into letter level, our rating transitions are in fact significantly smaller than those[53] documented by S&P.[54] One important reason for this difference is that the sample of S&P[55] includes uninsured bonds, which generally are more likely to experience credit rating changes.

Bond Insurance Premium and Bond Characteristics

As shown in Table 2, bond insurance premia decrease as bond credit ratings increase. While, on average, bonds rated with AA pay 1.89 basis points per dollar par value every year, bonds rated BBB+, or below have to pay quadruple this amount. On average, bonds in our sample pay 3.72 basis points insurance premium, which is about 44 percent lower than the 6.6 basis points found for bonds insured in the early 1990s.[56]

Table 3 summarizes the characteristics of bonds in our sample. The traditional four largest insurers (Ambac, FGIC, FSA, and MBIA) have similar market shares in the California market, each accounting for about 20 percent of newly insured issues. XCLA has a relatively small market share of 7 percent. In the sample, the three largest categories of bond issues by issue purpose are K-12 school, higher education, and redevelopment, which account for 39, 13, and 17 percent, respectively. The distribution of bond issues by issue purpose implies that the sample may be nonrandom. However, as discussed in footnote 14, there is evidence that the nonrandomness of our sample does not lead to a bias for our focal estimator.

52. Standard & Poor's (2004–2007a).

53. In S&P reports, about 5 percent of investment grade bonds have at least one credit rating change during the two-year period following the issue date.

54. Standard & Poor's (2004–2007a).

55. Ibid.

56. Smith and Harper (1993).

TABLE 1
Two-Year Transition Matrix (%)

	Rating two years later											
Rating at issuance	AAA	AA+	AA	AA−	A+	A	A−	BBB+	BBB	BBB−	Upgrade	Downgrade	Number of observations
AAA	0	0	0	0	0	0	0	0	0	0	0	0	0
AA+	0	100	0	0	0	0	0	0	0	0	0	0	6
AA	0	3.13	95.31	1.56	0	0	0	0	0	0	3.13	1.56	64
AA−	0	1.3	3.87	90.97	3.23	0.65	0	0.65	0	0	5.07	4.53	155
A+	0	0	0	0	99.17	0	0	0.83	0	0	0	0.83	120
A	0	0	0	0	1.8	91.02	4.19	0	0	2.99	1.8	7.18	167
A−	0	0	0	0	1.3	6.49	91.56	0.65	0	0	7.79	0.65	154
BBB+	0	0	0	0	0	0	12.5	87.5	0	0	12.5	0	40
BBB	0	0	0	0	0	0	0	0	100	0	0	0	11
BBB−	0	0	0	0	0	0	33.33	0	33.33	33.33	66.67	0	3

TABLE 2
Insurance Premium by S&P Underlying Credit Ratings

	Insurance premium (bps per dollar per year)		
SPURs	**Mean**	**Standard deviation**	***N***
AA+	0.91	0.77	6
AA	1.89	1.19	64
AA−	2.10	2.11	155
A+	2.38	2.31	120
A	3.76	2.86	167
A−	5.59	4.04	154
BBB+ and below	8.31	4.72	54
Total	3.72	3.54	720

Fifty-two percent of the issues in our sample are GO bonds. The majority are tax exempt, with the exception of 7 percent subject to federal income tax and 1 percent subject to Alternative Minimum Tax (AMT). About 42 percent of bonds are issued to refund previously issued bonds. Eighty percent are sold through negotiation, and 86 percent include a call option.

As discussed earlier, macroeconomic information between t and $t + 1$ may affect bond credit rating migration. The findings of previous research, while inconclusive, suggest that credit ratings may be more volatile when the economy is on the peak of a business cycle.[57] To account for this influence, two variables are included. One is the average quarterly GDP growth rates for the two-year period following the issue date. I expect GDP growth rates to be negatively related to credit rating downgrade, because bond issues are less likely to default in a better economy. Another macroeconomic variable included is the mean of the Treasury rate in the two years following the bond issue date. The Treasury rate reflects the market yield on U.S. Treasury securities at 10-year constant maturity, quoted on an investment basis. This is used to reflect the credit market situation. The U.S. Treasury rate is higher in a tighter credit market, in which borrowers find it more difficult to get credit and have to pay higher financing costs. In such a market, the bond issue is more likely to be downgraded. Thus, a negative relationship is expected between the Treasury rate and credit rating migration. Our sample has a mean value of average quarterly GDP growth rate of 2.78 percent and a mean value of average Treasury rate of 4.44 percent.

ESTIMATION RESULTS

This section reports the findings, with the first-stage regression results presented in Table 4 and the second-stage regression results in Table 6. One drawback in the partial proportional

57. Nickell et al. (2000).

TABLE 3
Variables Definition and Descriptive Statistics

Variable	**Definition**	**Mean**	**Standard deviation**
Panel A: Variables in the first stage			
Insurance fee	Amount of insurance fee ($)	437,377	2,086,850
	Per dollar per year (basis points)	3.72	3.54
Issue amount	Principal amount (in million $)	5,5.32	154.67
Years to maturity	Years to maturity	22.63	6.39
BBI20	Bond buyer 20 index	4.68	0.32
Yield spread	Yield spread between AAA-rated and BBB-rated bonds (bps)	64	10
Issuer experience	Number of bonds issued by the issuer during the past three years prior to the issue date	3.45	14.18
GO bond	Dummy variable = 1; if a bond is a general obligation issue	52%	
Callable	Dummy variable = 1; if a bond is callable	86%	
Refunding	Dummy variable = 1; if a bond is refunding bond	42%	
Competitive sale	Dummy variable = 1; if the bond is sold in a competitive way	20%	
Taxable	Dummy variable = 1; if the interest income from a bond is subject to federal income tax	7%	
AMT	Dummy variable = 1; if the interest income from a bond is subject to Alternative Minimum Tax	1%	
Issuer dummy variables			
Ambac	Dummy variable = 1; if insurer is Ambac	21%	
FGIC	Dummy variable = 1; if insurer is Financial Guaranty Insurance Company	22%	
FSA	Dummy variable = 1; if insurer is Financial Security Assurance Inc	21%	
MB IAC	Dummy variable = 1; if insurer is Municipal Bond Investors Assurance Corp	29%	
XCLA	Dummy variable = 1; if insurer is XL Capital Assurance	7%	
Rating dummy variables			
AA+	= 1 if the S&P underlying rating of the bond was AA+ at issuance	1%	
AA	= 1 if the S&P underlying rating of the bond was AA at issuance	9%	
AA−	= 1 if the S&P underlying rating of the bond was AA− at issuance	22%	

TABLE 3 (Continued)

Variable	Definition	Mean	Standard deviation
A	= 1 if the S&P underlying rating of the bond was A+ at issuance	17%	
A+	= 1 if the S&P underlying rating of the bond was A at issuance	23%	
A−	= 1 if the S&P underlying rating of the bond was A− at issuance	21%	
BBB+ or lower	= 1 if the S&P underlying rating of the bond was BBB+ or lower at issuance	8%	
Panel B: Variables in the second stage			
Rating migration	= 1 if the bond was downgraded by S&P within the next two years following the issue date	3%	
	= 2 if the bond had no S&P rating transition within the next two years following the issue date	93%	
	= 3 if the bond was upgraded by S&P within the next two years following the issue day	4%	
Residual from first stage	Residues predicted from the first stage	-3.97×10^{-9}	0.44
GDP growth rate	The mean of quarterly GDP growth rates in the two years following the issue date (%)	2.78	0.56
Treasury rate	The mean of market yields on U.S. Treasury securities at 10-year constant maturity (quoted on investment basis) in the two years following the issue date (%)	4.44	0.20
Issue purpose			
K-12 school	Dummy variable = 1; if the use of bond proceeds is for functions related with K-12 school	39%	
Higher education	Dummy variable = 1; if the use of bond proceeds is for functions related with higher education	13%	
Redevelopment	Dummy variable = 1; if the use of bond proceeds is for functions related with redevelopment	17%	
Other purposes	Dummy variable = 1; if the bond is issued for any purposes other than K-12 school, higher education, and redevelopment	31%	

Note: Variables shared in both stages—including issuer experience, yield spread, issue amount, years to maturity, refunding, taxable, and credit rating dummies—are defined and measured in the same way.

ordered logistic regression is the difficulty in interpreting its statistical results, which, as explained later, have to be read in quite a different way from the regular ordinal logistic regression.

The First Stage

To determine the polynomial form of numerical variables used in the first stage, I first conduct preliminary tests. For instance, the effect of principal amount is modeled as a polynomial of degree eight, because most coefficients of the polynomial lose significance when the effect is modeled as a polynomial of degree nine, although they are highly significant when the marginal effect is considered a polynomial of degree eight. The final model is tested with the Ramsey test, the result of which suggests that the model is not mis-specified ($F(3, 686) = 1.67$). To control for the insurer-specific and yearly fixed characteristics, the model also includes a set of insurer dummy variables and year dummy variables.

With an R^2 of about 0.9, insurance premia are well explained by our model. Most explanatory variables are signed as expected, although some of them are statistically insignificant. Ceteris paribus, issues with a better rating, a shorter maturity, and a smaller principal amount are charged with a lower insurance fee. GO bonds enjoy a significantly lower insurance premium. Insurance premia are also found to be positively related to the market interest rate and the yield spread between AAA- and BBB-rated bonds, but neither relationship is statistically significant. Call option, refunding, and issuer experience are also statistically insignificant.

Sections 2 and 3 pointed out that the credit rating is an important factor to consider when insurers evaluate bond credit risk and can influence insurance premia. This hypothesis is supported by the findings of stage 1. Ceteris paribus, the higher the credit rating, the lower the insurance premium that a bond has to pay. On average, holding everything else constant, bonds rated with A− are able to pay about 30 percent ($1 \times 10^{-0.351}$) less than bonds in the rating group of BBB and subcategories, while bonds rated AA+ pay 83 percent ($1 \times 10^{-1.75}$) less.

Residuals from this regression are predicted for use in the second stage. Since the predicted residuals are independent of the variables included in stage 1, they represent the latent information that is conveyed by insurance premia and that fail to be explained by the explanatory variables in this stage. There is a possibility that the residuals from the first stage are simply random noise. If that is the case, they would not be significant in explaining the bond rating changes in the second stage.

The Second Stage

The second-stage regresses credit rating migrations on $\hat{\mu}$. The coefficient of $\hat{\mu}$ represents the association between insurance premia and credit rating migrations conditional on factors

TABLE 4
Results of the First-stage Regression

Coefficient (N = 720)	ln (insurance fee)
Issue amount	7.555e-02***
	(0.003)
(Issue amount)ˆ2	−6.826e-04***
	(.00004)
(Issue amount)ˆ3	2.779e-06***
	(2.54e-07)
(Issue amount)ˆ4	−4.544e-09***
	(5.22e-10)
(Issue amount)ˆ5	dropped
(Issue amount)ˆ6	7.981e-15***
	(1.21e-15)
(Issue amount)ˆ7	−7.424e-18***
	(1.21e-18)
(Issue amount)ˆ8	1.76e-21***
	(2.96e-22)
Years to maturity	0.053**
	(0.017)
(Years to maturity)ˆ2	−.0005
	(.0004)
Callable dummy	−0.090
	(0.058)
Issuer experience	7.882e-04
	(0.001)
Yield spread	1.842
	(1.882)
Yield spreadˆ2	−1.348
	(1.396)
BBI20	0.112
	(0.089)
Refunding bond	0.006
	(0.039)
GO bond	−1.048***
	(0.047)
Credit rating dummies	
AA+	−1.750***
	(0.196)
AA	−0.841***
	(0.094)
AA-	−0.806***
	(0.080)

TABLE 4 (Continued)

Coefficient (N = 720)	ln (insurance fee)
A+	-0.753^{***}
	(0.079)
A	-0.537^{***}
	(0.073)
A-	-0.351^{***}
	(0.072)
Constant	9.043^{***}
	(0.837)
R-squared	0.8980
Adj. R-squared	0.894
Yearly fixed effect	√
Insurer fixed effect	√

Note: 1. Standard errors in parentheses;
2. *** $p<0.001$, ** $p<0.01$, * $p<0.05$;
3. Reference group: BBB+ and below.

included into either the first- or the second-stage regression. If the coefficient is significant, then insurance premia convey extra information—in addition to the effect controlled for in equation (5) and equation (7)—which helps to predict the underlying credit risk of insured bonds.

As discussed in Section 3, I use a partial proportional ordered logit model in the second stage. However, for the purpose of comparison, a pooled ordered logit model is also examined and presented in the last column of Table 6. The coefficient of the residual from the first stage is signed negative and significant at a 90 percent confidence level, suggesting that conditional on credit rating and other explanatory variables, higher insurance premia are associated with a higher propensity of being downgraded and a lower propensity of being upgraded in the future.

The findings seem to support the hypothesis that insurance premia convey latent information for predicting credit risk. However, this conclusion is based on the assumption that the odd ratio is independent of rating transition categories, and coefficients across categories are not significantly different. As discussed earlier, this assumption may be violated, leading to a biased estimation. To assure that the parallel lines assumption holds, Wald tests are used to determine whether coefficients in any implied binary regressions are statistically different, both globally and individually for each coefficient. And the results, as presented in Table 5, suggest that for the entire model, coefficients are different across credit rating categories. Furthermore, the residual from the first stage, the variable of our interest, fails the Wald test, although other coefficients are not statistically different across categories at the 95 percent confidence level.

After establishing that differences exist for coefficients across dependent variable categories, our use of partial proportional ordered logit model is justified. Recalling from the discussion in Section 3, the partial proportional order logit model regroups dependent variables into binary groups, and it also relaxes the constraint of equal impacts across categories for coefficients that fail the test for parallel slopes assumption. Two binary regressions are conducted, one with dependent variable expressed in two categories: credit rating migration = 2 or 3 versus migration = 1 and the other with credit rating migration = 3 versus migration = 1 or 2 . Stata user-written procedure gologit2[58] is used to perform the model estimation.

The results for the partial proportional ordered logit regression are presented in the first two columns of Table 6. The estimation contains two binary regressions. The first regression compares upgrades and unchanged to the reference group of downgrades, and the second regression compares upgrades to the reference group of downgrades and unchanged. As shown in the table, some, but not all, coefficients have the same values for different categories. The gologit2 procedure adopts a stepwise approach to determine that variables are to be constrained for equal coefficients. While the procedure generates an estimation in which the entire model passes the global likelihood ratio (LR) test for equal coefficients, variables that are constrained may differ from those that fail the Wald tests for individual coefficients presented in Table 5, since different approaches are used.

Five variables are freed from the constraint of parallel slopes, including the residual from the first stage, GO bond, GDP growth rate, refunding bond, and the AA− dummy variable. As shown in Table 6, in the partial proportional logistic model, these five variables may have different coefficients in signs, significance, and/or magnitude for different credit rating change categories. They may also significantly differ from those estimated by the pooled ordered logit model. For instance, the ordered logit model generates a statistically insignificant coefficient for GO bond, suggesting that the probability of credit rating changes is not significantly different between GO bond and non-GO bond. Yet, the partial proportional logistic model suggests that GO bond has a significantly lower probability of being upgraded, but no statistically different odd of being downgraded. On the other hand, the restricted estimators from these two different models are quite similar. The coefficients have similar significance and the same sign in both models, and only differ in their magnitudes.

Our main variable of interest, the residual from the first-stage regression, has a negative and highly significant coefficient in the binary regression of $M = 2$ or 3 versus $M = 1$ (called regression 1 hereafter) and a positive but insignificant coefficient in the binary regression of $M = 3$ versus $M = 1$ or 2 (called regression 2 hereafter). Since the residual from the first-stage represents the latent information from insurance premia, a significant negative coefficient for regression 1 suggests that ceteris paribus, a higher insurance premium is associated with a higher probability of being downgraded (or a lower probability of staying unchanged or being upgraded). The insignificance in regression 2 suggests that insurance premia contain no latent information for determining bond credit upgrades. In other words,

58. Williams (2006).

TABLE 5
Wald Tests of Identical Coefficients across Categories

	χ^2	$P > \chi^2$
Residual from first stage	9.09	0.003***
GO bond	2.71	0.100*
GDP growth rate	1.28	0.257
Treasury rate	0.05	0.827
Refunding bond	3.51	0.061*
Issuer experience	0.12	0.733
Yield spread	0.29	0.592
Issue amount	2.10	0.147
Years to maturity	0.34	0.557
Taxable	0.00	0.99
K-12 school	2.01	0.156
Higher education	1.92	0.166
Redevelopment	3.2	0.074*
AA+	0.00	0.998
AA	0.00	0.992
AA−	0.00	0.990
A+	0.00	0.999
A	0.00	0.991
A−	0.00	0.991
All	39.78	0.003***

Note: $^{***}P < 0.001$; $^{**}P < 0.01$; $^{*}P < 0.05$.

insurance premia can predict bond credit rating downgrades but not upgrades. This result is only partially consistent with the finding from the pooled ordered logit regression.

To further test the extra explanatory power of insurance premia on credit rating migration, I conduct the LR chi-squared test that compares contrast between the model that includes the residuals of insurance premia from the first stage and the model that does not include the variable. The result ($\chi^2 = 17.35$, P-value $= 0.0003$) implies the model with the variable of the residuals from insurance premia provides a significantly higher explanatory power, compared to the model without.

The refunding bond dummy variable has a significant positive coefficient in regression 1 but an insignificant coefficient in regression 2, implying that refunding bonds are less likely to be downgraded but show no propensity to be upgraded. The opposite holds true for GO bonds. GO bonds are more likely to be upgraded but show no correlation to bond credit downgrades.

Neither average GDP growth rate nor average Treasury rate within the two years following the bond issue date has a statistically significant coefficient. This result is unexpected, as it suggests that bond credit changes are not affected by macroeconomic conditions. One

TABLE 6
Results of Stage 2

Coefficient	Partial proportional odds		Ordered logit
(*N* = 720)	*M* = 2,3 (Downgrades against others)	*M* = 3 (Others against upgrades)	*M* = 1,2,3
Reference group	Downgrades	Downgrades and Nonmigrates	
Residual from first stage	−2.262***	0.418	−0.651*
	(0.674)	(0.481)	(0.378)
GO bond	0.927	−2.466***	−1.085
	(0.781)	(0.742)	(0.680)
GDP growth rate	0.533	−0.764	−0.363
	(0.570)	(0.562)	(0.533)
Refunding bond	2.537***	0.698	1.324***
	(0.839)	(0.454)	(0.370)
Treasury rate	0.759		1.090
	(1.736)		(1.481)
Issuer experience	−0.007		−0.008
	(0.010)		(0.005)
Yield spread	−2.494		−2.789*
	(1.543)		(1.468)
Issue amount	0.004**		0.006***
	(0.002)		(0.002)
Years to maturity	0.0211		0.0225
	(0.0273)		(0.0296)
Taxable	0.505		0.707
	(0.522)		(0.533)
Issue purpose*			
K-12 school	1.495**		2.048***
	(0.646)		(0.717)
Higher education	1.632**		2.119**
	(0.747)		(0.967)
Redevelopment	0.716		1.160**
	(0.452)		(0.570)
Credit rating dummies*			
AA+	−0.434		−0.00446
	(2.667)		(0.652)
AA	−0.692		−1.168
	(0.908)		(0.738)
A+	−1.487*		−1.607***
	(0.863)		(0.527)
A	−1.935***		−2.392***
	(0.719)		(0.631)

TABLE 6 (Continued)

Coefficient	**Partial proportional odds**			**Ordered logit**
($N = 720$)	**$M = 2,3$ (Downgrades against others)**		**$M = 3$ (Others against upgrades)**	**$M = 1,2,3$**
Reference group	**Downgrades**		**Downgrades and Nonmigrates**	
A−		0.0132		−0.226
		(0.567)		(0.581)
AA−	−3.190***		−0.211	−1.734**
	(0.943)		(0.836)	(0.808)
Constant	−0.410		−4.229	
	(10.18)		(10.33)	
α_1				−0.397
α_2				7.886
LR χ^2		131.2		68.80
Pseudo R^2		0.29		0.20

Note: 1. Standard errors in parentheses; 2. $^{***}P < 0.001$, $^{**}P < 0.01$, $^{*}P < 0.05$; 3. Reference group for credit rating dummy variables: BBB+ and below; 4. Reference group for issue purpose: other purposes.

explanation is that rating agencies rate through the (business) cycle.[59] Credit raters focus on the long-run risk that is not influenced by the short-run variation in economic conditions. As such, bond rating changes do not follow business cycles, and short-term macroeconomic conditions have no impact on municipal bond long-term credit ratings.

The coefficient of issue amount is found to be positive and statistically significant, indicating that bonds with larger principals are more likely to remain unchanged or be upgraded (less likely to be downgraded). The positive signs of the three major category variables by issue purpose imply that compared to bonds for other purposes, school bonds, higher education bonds and bonds for redevelopment have a higher probability of being upgraded, and a lower probability of being downgraded. Compared to the reference group (bonds rated with BBB−), bonds rated with A+ or A are less likely to be upgraded and more likely to be downgraded. Bonds with an AA+ rating are more likely to be downgraded but have no propensity of being upgraded.

DISCUSSIONS

Municipal bond insurance premia are highly significant in forecasting future credit rating downgrades but not in predicting rating upgrades. One may wonder why this is the case.

59. Standard & Poor's, *Corporate Rating Criteria* (White book) (New York: Standard and Poor's, 2002), 14.

Recall that in Section 3 I pointed out that the potential latent information may originate from two sources: insurers' capability of collecting valuable private information and their different measuring systems of credit risk than those used by credit raters. If the explanatory power arises from the latter, it is more likely that the insurance premia have similar explanatory power over both upgrades and downgrades, since downgrades and upgrades are more likely to be symmetric in this case.

The explanatory power of insurance premia may also stem from insurers' access to extra information. This explanation seems more plausible. In this case, insurers are more knowledgeable about bonds' credit risk than are credit raters, because, for instance, they have more incentive to collect valuable credit risk information. With this advantage, bond insurers can bargain for a higher insurance fee for bonds overrated by credit rating agencies, based on the private information that they collect. On the other hand, they have no incentive to charge underrated bonds less. Instead, using its credit rating as the benchmark, they are able to charge an underrated bond the same premium as what they charge those correctly rated. As such, insurance premia convey extra information about the credit risk of overrated bonds but not of underrated bonds. Consequently, insurance premia are able to explain credit rating downgrades, but not upgrades.

The bond insurance premium, conditional on other observed information, can be viewed as the bond insurer's private rating on the bond's credit risk. The presence of the latent information that fails to be explained by the credit rating and other information suggests that there exists a disagreement between the bond credit rating and the private rating by the insurer. This disagreement may be due either to their access to different information or to their use of different risk measurement systems. If the former case is true, then insurers have a more accurate prediction of bond credit risk, and the true credit risk is more likely to be closer to the insurer's internal rating than to the credit rating. If the latter case is true, the inherent credit risk should lie on the borderline between the rating agency's rating and the insurer's private credit rating. In either case, the insurance premia provide complementary information about the bond's credit risk to help forecast future credit rating downgrades.

This study also sheds light on the quality of credit ratings, which has recently been challenged by both academic researchers and practitioners. If credit ratings have perfectly captured all information available at the rating date, then no current information can systematically predict future credit rating changes (or defaults). The present study finds that some public information available at the rating date has explanatory power over future credit rating transition. For example, bonds with a larger principal amount are associated with a higher propensity to be upgraded. Refunding bonds are less likely to be downgraded, but they show no different propensity for future credit rating upgrades. These bond characteristics, as well as insurance premia, are available on the rating date, suggesting that credit raters have not fully taken into account the information available on the rating date. Thus, credit ratings can be improved based on current information.

CONCLUSION

The performance of municipal bond insurers on structure finance has also significantly affected their main business of providing insurance to municipal bonds. The penetration rate of bond insurance on the municipal bond market has shrunk substantively. One main concern of investors, issuers, and policy makers is whether the bond insurer has the capability of sufficiently evaluating the underlying credit risk of bonds that request insurance.

Our research investigates the California municipal bond market and finds that we should not obliterate insurers' capability of collecting valuable information and revealing it through insurance premia. Municipal bond insurance premia, conditional on bond credit ratings and other explanatory variables, have explanatory power over the underlying credit risk of municipal bonds, as measured by their underlying credit rating transition. As such, municipal bond insurance does provide an added market value. Investors could count on bond insurers, as least during our sample period, to research new issues. However, this research by no means suggests that insurers have perfect knowledge of the credit risk of their portfolios. I only imply that insurance premia add valuable information in predicting credit risk.

As the ongoing subprime turmoil unfolds, it has been realized that credit risks in the financial market have been substantially underestimated, and credit ratings assigned to financial instruments by credit rating agencies have failed to sufficiently reveal the credit risks of financial products.[60] As such, depending on credit ratings alone for gauging credit risk is not as reliable as people expected. Our research provides evidence that the rating agencies might not be doing as a good job as they could potentially do, perhaps because the oligopolistic structure of their market allows them to miss something without directly suffering the consequences.

I cannot dismiss another explanation for our results. Both issuer and insurers may notice the negative perspectives of bond issues with potential downgrade risk. Yet, insurers are more likely to incorporate this potential risk into the premiums at an early time, as insurance premia will not be altered once they have been determined. Rating agencies have the opportunity to adjust the credit ratings later when the potential risk becomes more certain. Yet, this possibility is not in conflict with our argument that insurers may be able to gauge the underlying credit risk of municipal bonds more sufficiently than bond credit ratings reveal.

Since our sample period, the insurance market landscape has changed substantively. As a result, our conclusions based on prior data may not be generalized to the current or future insurance market. On the other hand, the changes may in fact strengthen our conclusion. After the insurer credit crisis, insurers have more incentives to sufficiently evaluate the credit risk of the bonds that request guarantee. Thus, they may spend more effort and develop better models to assess the underlying credit risk of bonds to be insured.

60. Hunt (2009), Griffin and Tand (2009).