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Bond Insurance and Public Sector Employment

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Bond Insurance and Public Sector Employment*

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Abstract

This paper uses a unique data set of local governments' bond issuance, expenditure, and employment to study the impact of the monoline insurance industry's demise on local governments' operations. To show causality, I use an instrumental variable approach that exploits persistent insurance relationships and the cross-sectional variation in insurers' exposure to high-quality residential mortgage-backed securities. Governments associated with ailing insurers issued less debt, cut expenditures, and hired fewer workers. These effects are persistent. Partial equilibrium calculations show that affected governments' aggregate expenditures and employment levels in 2017 would have been 6% to 10% higher if bond insurance had remained available.

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1 Introduction

Prior to the Global Financial Crisis (GFC), more than 30% of municipal debt was issued with insurance. As such, several academic papers have attempted to explain the existence of bond insurance (Thakor, 1982; Nanda and Singh, 2004; Cornaggia et al., 2020). There is also a fairly large body work that tries to estimate the amount of yield savings that bond insurance provides to issuers (Braswell et al., 1982; Bland, 1987; Kidwell et al., 1987; Hsueh and Chandy, 1982; Quigley and Rubinfeld, 1991; Bergstresser and Shenai, 2010; Lai and Zhang, 2013; Bergstresser et al., 2015; Chun et al., 2018). However, to my knowledge, little work has been done to explore the real effects that the monoline insurance industry's demise had on local governments' operations. It is important to answer this question because local governments are the main providers of local public goods and impairments to their ability to perform this crucial function have significant implications for people's quality of life.

Why might the demise of monoline insurers affect local governments' operations? Local governments are opaque entities with substantial default risks (Schwert, 2017).[1] These entities are opaque because they are not required to disclose their financial positions in a regular manner (Baber and Gore, 2008) and, often times, do not have credit ratings. In a market with asymmetric information and substantial default risks, borrowers face credit rationing because profit-maximizing lenders cannot separate good risks from bad (Stiglitz and Weiss, 1981). In this equilibrium, borrowers cannot obtain funds by paying higher interest rates because potential lenders interpret the action as a signal that these borrowers are the "bad risk" type.

Bond insurance solves this credit rationing problem because it eliminates information asymmetry between investors and issuers by shifting the burden of information production onto insurers. Insured bonds are issued with the insurers' ratings because, when the issuer defaults, the insurers continue to pay the bonds' coupons and principals. To learn about an insured bond's default risk, potential investors only need to produce information on the bond's insurer. In cases where insurers have AAA ratings, information production is not worthwhile because there are very few states of the

[1] I use the term *opacity* in the sense of Dang et al. (2013), which is where it is costly for investors to produce information about each issuer's true default probability.

world where the insurer would also default. In cases where insurers have lower ratings, information production is less costly because insurers regularly disclose their financial positions and are closely monitored by major credit rating agencies. With little information asymmetry left, investors can allocate their capital more efficiently and opaque local governments can obtain necessary funding. Baber and Gore (2008) provide empirical evidence that supports this explanation.

This paper uses a unique data set that combines information on local governments' entity-level bond issuance, expenditure, and employment to study the impact of the monoline insurance industry's demise on the governments' operations. The first part of the paper uses the universe of municipal bond issuance between 1980 and 2006 to conduct descriptive analyses of municipal bond insurance usage and relationship prior to the GFC. This set of analyses serves two purposes: (1) document stylized facts about bond insurance usage that support the information view of bond insurance, which I outline above, and (2) provide empirical facts in which the identification strategy that I use in the second part of the paper relies on.

I use issuer characteristics such as smallness, lack of credit rating, and special district function as proxies for opacity. Compared to larger governments such as states and counties, small and special district government entities do not regularly report their financial positions, which makes their credit risks more difficult to study.[2] Unrated government entities do not enjoy the informational benefits from having a major credit agency continuously quantify their default risks. Using these proxies, I find that more-opaque issuers are more likely to issue insured bonds. In addition, using the percentage of municipal bonds issued with insurance as a measure of bond insurance usage intensity, I find that this percentage is larger for more-opaque issuers.[3] These stylized facts align with the information view of bond insurance, outlined above.

If bond insurance alleviates information asymmetry problems, then bond insurance relationships should be sticky and especially so for opaque issuers. This intuition highlights the relationship between an issuer's opacity and the cost of information production. If insurance relationships are

[2]Special district governments are small entities that have very specific functions and revenue sources. Examples are school districts, fire departments, public libraries, and local water authorities.

[3]The results are in line with the work by Gore et al. (2004), which shows that financial disclosure and bond insurance are substitutes. In addition, Gao et al. (2020) show that bond insurance mitigates the effects that newspaper closures have on municipalities' financing costs only prior to the GFC, which provides support for the information view of bond insurance because it highlights the relationship between information frictions and financing costs.

formed based on private information production, then these relationships should be persistent because the lemons problem induced by information asymmetry between insurees and potential insurers makes switching costly (Sharpe, 1990). Intuitively, switching costs should be higher for more-opaque governments because it is more costly for insurers to learn about their default risks. Using the same bond issuance data set, I show that insurance relationships are sticky. An issuer is more than twice as likely to use the same insurer twice than to choose an insurer at random. Furthermore, I find that persistence in insurance relationships is higher for special district and unrated issuers. The results from this set of analyses highlight the relationship between information frictions and bond insurance.

The second part of the paper studies the impact that the demise of bond insurers has on associated local governments. If local governments use bond insurance to access the municipal bond market, then it is intuitive to expect that the insurers' demise would have real effects on these governments' operations. To study these effects, I merge the aforementioned bond issuance data with data on local governments' expenditures and employment. This merged data set allows me to study the impact that loss of bond insurance has on local governments' ability to issue debt, spend, and hire workers.

The main challenge for this set of analyses lies in identifying the causal impact that loss of bond insurance has on local government outcomes. I use an identification strategy that relies on three ingredients – cross-sectional variation in bond insurers' health, persistent insurance relationships, and an instrumental variable. Cross-sectional variation in insurers' health allows me to compare outcomes of governments associated with ailing insurers to outcomes of governments related to healthy insurers. Persistent insurance relationships, documented in the first part of the paper, make it difficult for governments related to ailing insurers to switch insurers. This bind constrains associated governments' ability to issue new bonds and operate because their insurers cannot underwrite new insurance policies. To provide further support to this identifying assumption, I also show that switching costs are high during the GFC. Within the same insurer, governments that have a prior business relationship with the insurer are twice as likely to issue insured debt with the insurer's guarantee. This result holds when I condition on observable government characteristics and compare governments that are located in the same state and have similar financing needs.

The finding that local governments associated with ailing insurance companies had worse outcomes during the GFC alone is insufficient for me to conclude that loss of bond insurance had a direct effect on local government outcomes. The causal interpretation relies on a strong identifying assumption, which is that governments randomly match with insurers. It could be the case that riskier bond insurers choose to sell bond insurance to riskier municipalities, both of which are more likely to have worse outcomes during the GFC. I use an instrumental variable to relax the identifying assumption. I instrument for the variation in insurers' health with the cross-insurer variation in residential mortgage-backed securities (RMBS) insurance portfolio risk. I use the percentage of AAA rated RMBS in each insurer's RMBS insurance portfolio as a proxy for each insurer's exposure to troubles in the RMBS market. With the instrument, the identifying assumption becomes that there is random matching between governments and insurers with respect to RMBS insurance portfolio risk. This assumption is more plausible because very few people suspected that housing markets across the country would crash at the same time, which resulted in correlated defaults across many lowly rated mortgage bonds (Cheng et al., 2014).

Using the identification strategy outlined above, I find that, during the GFC, local governments associated with less healthy insurers were able to issue less insured debt and were unable to make up for this shortfall by issuing uninsured bonds. This result not only shows that insurers' health had a direct effect on local governments' ability to fund themselves, but lends support to the idea that local governments rely on bond insurance to access the municipal bond market. I also find that, for governments that were able to issue new insured bonds during the GFC, those that were associated with less healthy insurers saw their bond yield spreads increase by more.

These credit constraints lasted for more than 10 years after the GFC began. In particular, by 2017, governments associated with less healthy insurers were still lagging behind in bond issuance. This long-term effect result shows that the disappearance of bond insurance essentially locked some government entities out of the municipal bond market. I also find that the long-term effects are concentrated among special district governments, which highlights the role of opacity in preventing some local governments from issuing new debt.[4]

[4] Special district governments make up a nontrivial part of the state and local government sector. The 2007 Annual Survey of State and Local Government Finances shows that special district governments' expenditures account for 21% of the sector's total expenditure. This percentage increases to 43% if I exclude state governments.

The mechanisms that drive the long-run results may differ from those that drive the crisis-period results. The crisis-period results are driven by each government's associated insurers' inability to underwrite new insurance policy and high switching costs, which prevented affected governments from employing healthier insurers. On the other hand, the long-run results are likely driven by the fact that the municipal bond insurance industry has largely disappeared. In other words, the product that was the pre-GFC bond insurance was no longer available, which means that local governments that relied on bond insurance to raise new debt lost access to the municipal bond market. Post-GFC municipal bond insurance differs from its pre-GFC counterpart in at least two ways. First, no bond insurer obtained a AAA credit rating after the GFC, which means that the value of bond insurance was lower than what it used to be. Second, due to the GFC, investors may have lost trust in the product and so bond insurance is no longer an effective vehicle for local governments' access to the municipal bond market.

The last set of analyses explores how being associated with ailing insurers affected local governments' ability to spend and hire workers. I find that this group of governments experienced relatively lower wage expenditure, non-wage expenditures, and employment growth. In line with the financing results, I find that these negative effects lasted up to at least 2017. For this particular sample of special district governments, wage expenditures, non-wage expenditures, and employment levels in 2017 would have been 10%, 7%, and 6% higher, respectively, if the bond insurance industry had remained intact. These effects are economically meaningful. For context, the 2013 trough of state and local governments' aggregate employment level was 96% of its 2008 peak. The key implication from these findings is that, due to loss of bond insurance, local governments' ability to provide public goods was significantly impaired, both during and after the GFC.

The main contribution of this paper is to provide empirical evidence that the disappearance of bond insurance has real effects on local governments' operations and, hence, their ability to provide local public goods. This paper is directly related to the emerging literature on the real effects of financing frictions among local governments (Adelino et al., 2017; Dagostino, 2017; Yi, 2021). The key difference between this paper and the existing literature is its focus on municipal bond insurance, which was a key feature of the pre-GFC municipal bond market. More generally, this paper adds to the larger literature on real effects of financing frictions (Peek and Rosengren, 2000; Ashcraft, 2005; Gan, 2007; Almeida et al., 2009; Chodorow-Reich, 2013; Kim, 2021) by being the first to document the real effects of municipal bond insurance.

This paper also contributes to the literature on the value of bond insurance by providing suggestive evidence that the value of bond insurance lies in its ability to give local governments access to the municipal bond market (Braswell et al., 1982; Bland, 1987; Kidwell et al., 1987; Hsueh and Chandy, 1982; Quigley and Rubinfeld, 1991; Bergstresser and Shenai, 2010; Lai and Zhang, 2013; Bergstresser et al., 2015; Chun et al., 2018). In other words, the value of bond insurance lies in the quantity of debt that local governments can raise while using it.

In an independent and contemporaneous work, Agrawal and Kim (2021) uses a similar identification strategy to show that loss of bond insurance caused local governments to cut spending on water infrastructure, which leads to lower drinking water quality. The findings in Agrawal and Kim (2021) are important for our understanding of the water crisis that the United States faces and corroborate well with the real effects results in this paper. However, it is important to note that this article contributes to the literature beyond Agrawal and Kim (2021) by showing that the demise of the municipal bond insurance industry has large effects on local government spending and employment, which implies that the effect that this financing friction has on local governments' ability to provide public goods is much broader than just the drinking water crisis.

2 Institutional Details

2.1 Municipal Bond Insurance

Bond insurance is an insurance policy that bond issuers buy from specialized insurance companies, often called monolines. For most policies, the issuer pays an upfront fee to the insurance company. On average, premium payments amount to approximately 1 percent of the total principal (Joffe, 2017) and could range from 0.5 to 2.5 percent (Thakor, 1982). The insurer then provides insurance for the bond in the event of default. If the issuer defaults on its obligation, the insurance company continues to pay interest and principal as scheduled and the bond continues to trade. The bond assumes the insurance company's credit rating instead of the issuer's. The insurance policy stays with the bond until the bond matures or is called.

Investors can also purchase secondary market insurance on uninsured bonds. The policy is usually written on a portion of the total par outstanding because a single investor is unlikely to hold the entirety of a bond issue. The insurance premium is prorated proportionately to the percentage of par outstanding and the premium is paid in full at the time of trade. The trade refers to the event in which the bond receives its secondary market insurance, which could happen in two ways. The first option is the investor delivers the bonds to the insurer's custodian bank and wires the insurance premium to the insurer. Then, the custodian bank will deliver the insured bond back to the investor in the form of a custodial receipt that has a new CUSIP. The second option is the investor sells the uninsured bond to a broker with the understanding that the investor will buy back the insured bond (with a new CUSIP) at the same price plus the insurance premium. The broker performs the same steps as in the first option. Once insured, the bond trades under a new CUSIP and has the same properties as a bond that was insured at issuance (Build America Mutual, 2021).[5]

Municipal bond insurance began with the founding of American Municipal Bond Assurance Corp. (AMBAC) in 1971 and grew in popularity after the Washington Public Power Supply System (WPPSS) defaulted on $2.25 billion worth of revenue bonds in 1983. Figure 1 plots municipal bond issuance and bond insurance activity between 1980 and 2017. In 1980, only about 2% of newly issued municipal bonds were insured. By 2007, approximately half of newly issued municipal bonds were insured. Between 1980 and 2007, 32.2% of all municipal bonds, measured by inflation-adjusted face value, were issued with insurance. During the GFC, seven out of nine active bond insurers stopped writing new insurance policies due to losses from their asset-backed securities (ABS) and collateralized debt obligation (CDO) insurance businesses. Insurers were unable to underwrite new policies because of two reasons. First, losses from their ABS and CDO insurance businesses decreased the level of their regulatory capital to the point that they could not underwrite new policies. Second, a low capital buffer caused their financial enhancement ratings to decline, which

[5] The existence of secondary market insurance does not affect the subsequent analyses because this paper focuses on primary market activities.

made their “credit wrapping” product less appealing. In 2016, three bond insurers remained active in the market – Assured Guaranty, Build America Mutual, and National Public Finance Guarantee. Other companies were bought by one of the survivors or remained inactive because their financial enhancement ratings were too low.

The business of municipal bond insurance never recovered after the GFC. Figure 1 shows that, in the post-GFC era, less than 5% of newly issued municipal bonds were insured. There are several potential reasons why the business never recovered. First, a low-rates environment means that yield is in short supply. Investors are willing to take on more risk to receive higher yields. Furthermore, when yields are low, the savings from bond insurance is also less attractive to issuers. Second, due to the events that unfolded during the GFC, investors lost confidence in bond insurance companies. Lastly, new credit rating scales have dramatically inflated municipal bond issuers' ratings, which makes bond insurance relatively less useful (Northern Trust Asset Management, 2014).

2.2 Local Government Finances

The main results in the second part of this paper rely on the assumption that local government financing depends heavily on municipal bonds. This subsection provides background information that supports this assumption. State and local governments are financed by tax revenue, service revenue, intergovernmental transfers, and debt. A crucial question is how important is debt as a source of financing for these governments? I use data from the Census Bureau's Annual Survey of State and Local Government Finances (ASSLGF) to answer this question. For each government-year that appears in the survey, the data set reports the amount of long-term debt that was issued and retired. A measure of how much a local government relies on long-term debt to finance its operations is the ratio of long-term debt that it issued in year t and its total expenditure in the same year, averaged across all years. The average of this ratio across all government entities that issued at least some long-term debt between 1980 and 2007 is 13.4%, which suggests that, on average, state and local governments finance 13.4% of their annual expenditure with long-term debt.

The cross-government average ratio of *net* long-term debt issued in year t and total expenditure in the same year is 2.9%.[6] This quantity suggests that the average local government is financing 2.9% of its total annual expenditure with *new* long-term debt and the majority of long-term debt issuance activity serves to replace or roll over old debt. This analysis implies that a substantial drop in these governments' ability to issue new long-term debt would significantly affect their ability to spend.

A natural follow-up question is how often does the average state and local government issue new long-term debt? To answer this question, I construct a sample of state and local governments from the ASSLGF with the requirement that each government appears in the survey for every single year between 1980 and 2007 and issued at least some long-term bond during that time window. Next, I compute the probability of long-term debt issuance, which is the number of years that the government issued some long-term debt divided by 28. I find that the average government in this sample has a long-term debt issuance probability of 39.8%, which implies that the average government issues at least some long-term debt once every 2.5 years.

Long-term municipal debt is composed of bank and municipal bond debt. An important question is how important is municipal bond debt relative to bank debt? I use statistics from SIFMA (2021) and Ivanov and Zimmermann (2019) to address this question. By the end of 2006, the total amount of municipal bonds outstanding was \$3.3 trillion, while the total amount of municipal bank loans outstanding was approximately \$40 billion or just about 1% of the total amount of municipal bonds outstanding. The same statistics for 2020 are \$3.95 trillion, \$200 billion, and 5%, respectively. Although municipal bank loans have experienced a substantial growth between 2007 and 2020, bank debt is a relatively minor source of funding for state and local governments, both before and after the GFC. This short analysis makes two points. First, any impairment to local governments' ability to issue municipal bonds is likely to have real effects on their ability to function because the market for municipal bank debt is not large enough to serve as an alternative source of funding. Second, if local governments are able to use bank loans as substitutes for insured bonds, then the results presented below could be interpreted as a lower bound of the effect that loss of bond insurance has on local governments' operations.

[6] Net long-term debt issuance is defined as the difference between the amount of new long-term debt issued in year t minus the amount of long-term debt that was retired in the same year.

3 Data

This paper uses data from several sources. The first main data set is SDC Platinum, which contains information on issuers and municipal bond issuances. From this data source, I download all municipal bond issuance between 1980 and 2017. Each observation of the downloaded data is a bond deal issued by a state or local government entity, which can contain one or more individual bonds. For each observation, I observe issuer and bond deal characteristics at the time of issuance. Issuer characteristics include issuer name, issuer state, issuer type (e.g., state, county, city, or special district government), and credit rating at time of issuance. Bond deal characteristics include issue amount, maturity date, coupon rate, taxable status, call option, sinking fund provision, bank qualification status, and insurance status.[7] For each deal that was issued with insurance, the data set provides the insurer's name and the amount of debt that is insured. I supplement issuance data from SDC Platinum with bond-level data from Thomson Reuters EIKON.

The second main data set is the Census Bureau's Annual Survey of State and Local Government Finances (ASSLGF). This data set contains information on each government's revenue sources, expenditure items, and debt issuance. I downloaded this data for all years between 1980 and 2017. This data set has several important features. First, since the data set comes from a survey, it does not contain data for all state and local government entities. Second, each data item is either reported by the government entity or imputed by the Census Bureau. Therefore, the analyses that follow only use reported data.[8] Third, the data set's coverage is more comprehensive in years ending in 2 and 7 (e.g., 2002 and 2007), which forces me to mostly rely on data from these years. Lastly, government entities have different fiscal year-ending months. The following analyses adjust differences in fiscal year-ending months by computing weighted averages between the appropriate preceding or following year.[9]

The third main data set is the Census Bureau's Survey of Public Employment and Payroll

[7] Deal characteristics differ from bond-level characteristics. For example, I observe the maturity date of the longest-maturity bond in the deal instead of the maturity date of each bond.

[8] The filtering process is done using the Census Bureau's Data Flags. Specifically, I consider data points with K, R, U, V, B, D, and Z flags to be reported data and the rest to be imputed data. Refer to the Census Bureau's website for more detail: `https://www.census.gov/programs-surveys/apes/technical-documentation/code-lists/data-flags.html`.

[9] Refer to the Online Appendix for additional detail.

(ASPEP). This data set contains each government entity's annual employment and payroll data, collected at the end of the first quarter of each year. Employment and payroll data are disaggregated by type (e.g., full-time, part-time, and full-time equivalent) and function (e.g., financial administration, judicial, fire protection, and many more). For the following analyses, I use total full-time equivalent employment numbers. Total employment numbers are computed as the sum across all functions reported. Similar to the ASSLGF, the data set's coverage is more comprehensive in years ending in 2 and 7.

The three main data sets are hand matched together based on the government entity's name and county. Other supplementary data sets include county employment data from the Bureau of Labor Statistics, county house price index data from the Federal Housing Finance Agency (FHFA), and insurers' RMBS insurance portfolio risk from S&P's credit risk reports. The credit reports provide detailed information on each insurer's ABS insurance portfolio. Most importantly, the reports show the credit rating composition of each insurer's RMBS insurance portfolios, which I use to construct the instrumental variable.

4 Descriptive Analyses

This section presents descriptive analyses, which explores the use of bond insurance prior to the GFC. The analyses shed light on the types of local governments that prefer to buy bond insurance and provide empirical evidence of the identifying assumption that I make in the second part of the paper.

4.1 Who Buys Bond Insurance?

Conditional on bond deal characteristics, which types of municipalities tend to buy bond insurance? I use data from SDC Platinum to construct a sample of municipal bond deals from 1980 to 2006. Thet top panel of Table 1 presents summary statistics on this sample of bond deals. Approximately one-quarter of the deals are issued with insurance. For the majority of insured bond deals (95%), all bonds in the deal are insured, 21% of the deals were issued by governments with junk credit ratings, and 67% were issued by governments with no rating at all. For completeness, the bottom panel of Table 1 presents summary statistics of the same variables for bond deals that were made between 2007 and 2017.

I supplement the bond deal data set with total expenditure data from the ASSLGF. I begin by computing average total expenditure by state-type-year. Government entities in the ASSLGF data set are classified as one of five types: state, county, city, school district, other special district. I merge these average total expenditure numbers into the bond deal data set.[10] The merged data set contains data on issuer and bond deal characteristics. I use it to run variants of the following panel OLS regression:

$$\mathbb{1}(Insured)_{ijt} = \alpha + \beta'\mathbf{G_{it}} + \gamma'\mathbf{B_j} + State\,FE + Year\,FE + \epsilon_{ijt}. \tag{1}$$

i indexes governments, j indexes bond deals, and t indexes years. $\mathbb{1}(Insured)_{ijt}$ is an indicator variable, which equals 1 if the bond deal was issued with at least one insured bond. $\mathbf{G_{it}}$ is a vector of time-varying government characteristics. $\mathbf{B_j}$ is a vector of bond deal characteristics. The variables of interest are Log Expenditure, Special District, Not Rated, and High Yield. Log Expenditure, Special District, and Not Rated are proxies for issuers' opacity. Smaller (lower total expenditures) and special district governments often do not regularly disclose their financial positions, which implies that they are more opaque when compared to general governments such as states, counties, and cities.[11] Special district governments are defined as government entities that are not state, county, city, or state agencies.[12] All else equal, issuers with no credit rating are more opaque because there is no third party that produces information about their creditworthiness for the investment community.

[10] I use average expenditures instead of entity-level expenditures because the merging procedure is overly cumbersome. An entity-level merge requires merging on strings, which is too cumbersome when there are more than 45,000 unique issuers that issued municipal bonds between 1980 and 2006. Refer to the Online Appendix for more detail on government type mapping between SDC Platinum and ASSLGF.

[11] Financial disclosures by state and local governments are mostly voluntary (Baber and Gore, 2008). Anecdotally, general governments such as states, counties, and cities are more likely to regularly report their financial data.

[12] State agencies are specialized entities that are managed and funded by the state government (e.g., the Connecticut Development Authority).

Table 2 reports regression results for variants of Equation 1.[13] Regressions shown in columns 1 through 3 include each of the four government characteristics individually and bond deal characteristics.[14] Results from columns 1 through 3 suggest that opaque governments are more likely to issue bond deals with insurance. Results from column 3 also show that high-yield issuers are more likely to issue bond deals with insurance, which agrees with the findings from Cornaggia et al. (2020). Column 4 includes all four government characteristics at the same time and finds the same qualitative results.[15] The magnitudes of these coefficients are large. The sample's unconditional probability of buying bond insurance is 28%, which means that special district, unrated, and high-yield issuers are 3%, 139%, and 40%, respectively, more likely to buy bond insurance. By revealed preference, these results suggest that more-opaque and riskier issuers are more likely to buy bond insurance and provide support for the aforementioned information view of bond insurance.

4.2 Bond Insurance Usage Intensity

This subsection explores the correlation between issuers' characteristics and bond insurance usage intensity. I construct a measure for bond insurance usage intensity, insurance ratio. For a given government entity, its insurance ratio is the inflation-adjusted amount of debt that it issued via insured municipal bonds divided by the total inflation-adjusted amount of debt that it issued via all municipal bonds. I use the sample of all municipal bond issuance between 1980 and 2006 to construct this measure.

For each issuer that issued at least one insured bond during this time period, I construct seven variables that capture each issuer's average characteristics from 1980 to 2006.[16] The first set of variables can be classified as government-type variables. These are categorical variables that

[13]The sample size is smaller than that of Table 1 because singletons and observations with missing coupon rates are dropped.

[14]Not Rated and High Yield need to be included together because a government entity is investment grade, high yield, or unrated and the comparison that is being made in column 3 is against investment-grade issuers.

[15]Results shown in column 4 seem to suggest that size, measured by total expenditures, is not strongly associated with bond insurance usage. However, since size is imputed by using group averages, the coefficient is likely to be attenuated by the variable's relative lack of variation.

[16]Issuers that issued at least one insured bond between 1980 and 2006 make up a nontrivial subset of the universe of municipal bond issuers. As a group, these issuers issued approximately 90% of the total inflation-adjusted municipal debt that were sold between 1980 and 2006. Therefore, if bond insurance has any economic importance, the loss of bond insurance should have had a widespread impact on the universe of local governments.

indicate whether an issuer is a state agency, state, county, city, or special district government. The next variable is size, measured by average total expenditures. This variable is the average total expenditures of government entities that match the issuer's state and type, averaged across all observations of the ASSLGF from 1980 to 2006. The last set of variables relates to credit ratings. If an issuer issued a bond between 1980 and 2006 without a long-term issuer credit rating from S&P or Moody's, then Not Rated equals one. If an issuer issued a bond between 1980 and 2006 while it had a speculative grade long-term issuer credit rating from S&P or Moody's, then High Yield equals one.[17]

In the last step, I sort issuers into four groups according to their insurance ratio and tabulate each group's average characteristics. Table 3 presents the results. Starting with issuer type, I find that the percentages of issuers that are general governments and state agencies decrease monotonically as the insurance ratio increases. On the other hand, the percentage of issuers that are special district governments increases monotonically with insurance ratio. Next, average government size, measured by average total expenditures, decreases with insurance ratio and the percentage of issuers with no credit rating increases with insurance ratio. The economic magnitudes are large. For example, compared to the group of issuers with insurance ratios less than 0.25, the percentage of special district governments is almost twice as large in the group of issuers with the highest insurance ratios. These results show that, leading up to the GFC, issuers that were more opaque used bond insurance more intensively. In line with the qualitative results from Cornaggia et al. (2020), high-yield issuers also tend to use bond insurance more intensively. It is important to note that, conditional on bond characteristics, the average yield to maturity of bonds issued by unrated governments is lower than the average yield to maturity of bonds issued by governments with speculative credit ratings. This empirical fact suggests that the correlation between being unrated and bond insurance usage is capturing something other than higher default risks.

[17] All results are qualitatively similar when the most recent pre-crisis credit ratings are used to construct Not Rated and High Yield.

4.3 Bond Insurance Relationships

Are bond insurance relationships persistent? Insights from the banking literature suggests that insurance relationships should be persistent because insurers produce private information about insurees and the lemons problem induced by information asymmetry between insurees and potential insurers makes switching costly (Sharpe, 1990). To answer this question, I construct a data set of insured bond deals, their insurers, and potential insurers. For each insured bond deal completed between 1980 and 2006, I merge in insurance companies that had insured at least one bond during the deal year. For example, if there are ten active insurers in year t, then every insured bond deal that appeared in year t would show up ten times. In other words, the unit of observation of this data set is a deal-insurer pair. The regression can be interpreted as a choice model where the issuer chooses to buy bond insurance from a set of potential insurers. I use this data set to run variants of the following panel regression:

$$\mathbb{1}(Current\,Insurer)_{ijkt} = \alpha + \beta \times \mathbb{1}(Previous\,Insurer)_{ijkt} + Issuer\,FE + Year\,FE + \epsilon_{ijkt}. \quad (2)$$

i indexes bond deals, j indexes issuers, k indexes insurers, and t indexes years. Among active insurers that were paired with each deal, one of them is the insurer that actually insured the bond deal. Current Insurer equals one for realized pairs and zero otherwise. The main explanatory variable of interest is Previous Insurer, which equals one if the insurer insured the issuer's most recent insured bond deal.[18] A positive correlation between Current Insurer and Previous Insurer suggests that insurance relationships are persistent because issuers are more likely to repeatedly use the same insurer.

Table 4 presents the results. Column 1 shows that the coefficient on Previous Insurer is positive and statistically different from zero. The sample mean of Current Insurer is 0.14, which suggests that issuers are almost twice as likely to use the previous insurer for its next insured bond

[18]The sample excludes issuers that issued only one insured bond deal between 1980 and 2006 because previous insurers are not observable for these issuers.

deal than to pick an insurer at random. This result shows that, on average, insurance relationships are persistent.

In columns 2 through 4, I explore whether insurance relationships are more persistent for more-opaque and riskier issuers. Results from columns 2 and 3 show that this is the case. The interaction terms between Previous Insurer and proxies of opacity (e.g., Special District and Not Rated) are positive and statistically different from zero. The economic magnitudes are also large. For example, special district governments are 20% ($\frac{0.048}{0.24}$) more likely to use the same insurer, when compared to general governments. Results from column 3 show that insurance relationships are also more persistent for high-yield issuers. Column 4 shows regression results for when I include all three interaction terms and additional fixed effects. The fixed effects account for each insurer's specialization in certain submarkets. For example, insurer fixed effects interacted with the special district indicator variable accounts for each insurer's market share among special district issuers. The results show that insurance relationships are more persistent for opaque issuers, but not high-yield issuers.

5 Identification Strategy

This section outlines the identification strategy that I use to conduct causal analyses of the effects that loss of bond insurance has on associated governments. This identification strategy exploits cross-sectional variation in government entities' exposure to bond insurance company failures. The strategy is built on three ingredients. The first ingredient is persistent insurance relationships and high switching costs. These features imply that, once a government lost its insurance company during the GFC, it could not easily switch to a surviving insurer due to information asymmetry between insurers and insurees (Sharpe, 1990). This friction implies that the government would not be able to issue new insured debt. Without insurance, the government faces credit rationing (Stiglitz and Weiss, 1981) and is forced to cut spending.

Second, the strategy relies cross-sectional variation in insurance companies' health. This variation in insurance company health allows me to compare outcomes of government entities that were associated with healthy insurance companies to those that were associated with ones that failed.

Third, the strategy needs to address the selection problem – riskier government entities matching with riskier insurance companies, which would likely yield the same empirical result, but invalidates the causal interpretation. I use an instrumental variable approach that exploits cross-sectional variation in insurers' RMBS insurance portfolio risk to address this problem. With the instrument, the identifying assumption becomes that government entities do not choose insurance companies based on their RMBS insurance portfolio risk. This assumption is plausible because most sophisticated people did not anticipate the housing market crash that started the GFC (Cheng et al., 2014) and local governments' financial managers are, on average, not very sophisticated (Chen et al., 2021). The following subsections describe these components in more detail.

5.1 High Switching Cost During and After the GFC

Section 4.3 provides empirical evidence that, prior to the GFC, insurance relationships are persistent, which suggests that switching costs during the GFC may be high. This subsection provides empirical evidence that switching costs are indeed high. I begin by constructing a data set of issuer-insurer pairs where each issuer that issued at least one insured bond between 1980 and 2007 is paired with each insurer that is active during the crisis period, defined as 2008Q1 to 2009Q2. Next, I construct two indicator variables: (1) Prior Relationship, which equals 1 if the issuer-insurer pair completed at least one bond deal between 1980 and 2007, and (2) Issued, which equals 1 if the issuer-insurer pair completed at least one bond deal during the crisis period.

Using this data set, I compute simple averages of the Issued variable by prior relationship status. I find that the probability that an issuer-insurer completed an insured bond deal during the crisis period is 0.94%, if the pair has no prior business relationship. On the other hand, the probability that an issuer-insurer completed an insured bond deal during the crisis period is 2.69%, if the pair has a prior business relationship. This simple analysis suggests that switching costs are high because the probability completing an insured bond deal decreases by approximately 65% if the pair has no prior business relationship.

To be sure, the simple means comparison does not account for many important issuer characteristics such as credit ratings, reliance on bond insurance, financing needs, and many more. I provide evidence of high switching costs in a more rigorous way by estimating variants of the following regression equation:

$$\mathbb{1}(Issued)_{ij} = \alpha + \beta \times \mathbb{1}(Prior\,Relationship)_{ij} + \boldsymbol{\gamma' x_i} + FE + \epsilon_{ij}. \tag{3}$$

i indexes issuers and j indexes insurers. $\boldsymbol{x_i}$ is a vector of issuer characteristics that may influence the issuer's ability to issue insured bonds during the crisis period and its general preference to issue insured bonds. The vector includes Special District, High Yield, and Not Rated indicators, which earlier analyses suggest to be important. Total Debt Issued, the total inflation-adjusted amount of municipal bond debt that the issuer raised prior to 2008, is a proxy for issuer size and reliance on debt. Insurance Ratio, the ratio of insured to total municipal bond debt that the issuer raised prior to 2008, is a proxy for the issuer's reliance on insured bonds. I include state, insurer, and year of last issue fixed effects. Insurer fixed effect controls for cross-sectional variation in insurer's health during this time period. Year of last issue fixed effect aims to account for issuers' need to issue new bonds. If switching costs are high, then β should be positive and large, which suggests that prior business relationships are valuable during the crisis period.

Table 5 presents the regression results. Column 1 shows the result for a variant of Equation 3 where I exclude the vector of issuer characteristics. The coefficient on Prior Relationship is 1.57%, which is more than 100% larger than the sample's unconditional probability of issuing an insured bond, which is 1.27%. Column 2 adds issuer controls and column 3 interacts the three sets of fixed effects, which gives the most conservative estimate of the value of prior business relationships. The coefficients on Prior Relationship are slightly smaller in columns 2 and 3, but the economic magnitudes are similar, which suggests that switching costs are high during the crisis period.

I repeat the previous exercise using 1980Q1 to 2009Q2 as the relationship formation period and 2009Q3 to 2017Q4 as the issuance period. Columns 4 to 6 of the same table present the regression results. The number of observations is smaller because there were fewer active insurance companies in this time period. I find that having a prior relationship with a surviving insurer increases the probability that an issuer completes an insured bond deal between 2009Q3 and 2017Q4 by 40% to 70%. The results suggests that switching costs remain high many years after the GFC has ended.

5.2 Variation in Insurers' Health

This subsection documents cross-sectional variation in insurers' healt during the GFC. Leading up to the GFC, bond insurers began to insure asset-backed securities. In this period, there were nine active bond insurers – ACA Financial Guaranty Corp. (ACA), Assured Guaranty Corp. (AGC), American Municipal Bond Assurance Corp. (AMBAC), CIFG Assurance North America Inc. (CIFG), Financial Guaranty Insurance Co. (FGIC), Financial Security Assurance Inc. (FSA), MBIA Insurance Corp. (MBIA), Radian Asset Assurance Inc. (RADIAN), and XL Capital Assurance Inc. (XLCA). When the housing market bubble popped in 2006 and 2007, these insurance companies began to experience losses from policies written on ABS. The amount of loss varied with how much risk each company took in underwriting insurance policies on ABS from the 2006 and 2007 vintages. Table 6 summarizes each insurance company's municipal bond insurance underwriting and financial enhancement ratings dynamics throughout the crisis.[19] Out of the nine active insurance companies, only AGC and FSA maintained their AAA financial enhancement ratings from S&P and continued to underwrite new bond insurance policies throughout the crisis.[20]

Insurance companies are regulated such that they must have enough capital to back each new policy that they underwrite. As insurance companies take losses from their ABS insurance business, their capital position deteriorates and their ability to write new business suffers. Hence, a proxy of insurance companies' health during the financial crisis is the growth in their municipal bond insurance business between the pre-crisis and crisis period.

[19] The financial enhancement rating is the rating that gets assigned to bonds that the insurance company insures. This rating is separate from, but is highly correlated with, the insurance company's long-term issuer credit rating.

[20] There are several potential reasons why FSA did not underwrite as many new insurance policies during the GFC. First, FSA was able to maintain its AAA rating during the GFC only because it received several large capital injections from its parent company, Dexia. Second, the activist hedge fund manager, Bill Ackman, was very vocal about FSA's negative future prospects, which potentially reduced trust in the company's insurance product.

For each issuer, I construct a measure of the change in related insurers' health from the pre-crisis period to the crisis period. The first component of the measure is V_{ij}^P. For each issuer-insurer pair, I calculate the amount of municipal debt that insurer j insured in the pre-crisis period (2006Q1 to 2007Q2) minus the amount of municipal debt issued by issuer i that insurer j insured. The second component is V_{ij}^C. For each issuer-insurer pair, I calculate the amount of municipal debt that insurer j insured in the crisis period (2008Q1 to 2009Q2) minus the amount of municipal debt issued by issuer i that insurer j insured. The construction of these two variables leaves out insurance activity related to issuer i so that there is no mechanical relationship between the measure and issuer i's insured bond issuance.

The final component is α_{ij}. This quantity is the share of insured municipal bonds that insurer j insured for issuer i between 1980Q1 to 2005Q4, adjusted for inflation. This quantity captures the complete set of insurance relationships that each issuer had prior to the crisis and the relative importance of each insurer. I choose to start the calculation in 1980 because I want to capture the complete set of insurance relationships. I choose to end the calculation in 2005Q4 to make sure that the results are not driven by issuers switching to healthier insurers in anticipation of the crisis.[21] With all three components, I define, for each local government, related insurers' health as follows:

$$\Delta I_i = \sum_{j=1}^{n} \alpha_{ij} \times [log(1 + V_{ij}^C) - log(V_{ij}^P)]. \tag{4}$$

This measure is the weighted average change in insurers' health, measured by the log difference in municipal bond insurance that each insurer was able to underwrite from the pre-crisis period to the crisis period. A higher value of ΔI_i means that the group of insurance companies associated with issuer i was healthier because it was able to underwrite relatively more insurance policies during the crisis period.[22] With this ΔI_i measure, I estimate variants of the following

[21]Debt raised by bond issues that have multiple insurers is divided evenly among all participating insurers. All results are qualitatively and quantitatively similar if these issues were divided according to insurers' pre-crisis market shares.

[22]Table 7 shows that the average value of ΔI_i is -3.55. Using the information provided in Table A1, the average value of ΔI_i can be interpreted as the average government in the sample being paired with MBIA, which experienced a decline in its municipal bond insurance business of approximately 97.5% during the GFC. A one standard deviation increase in ΔI_i is roughly equivalent to the government being paired with RADIAN, which lost approximately 93% of its municipal bond insurance business during the same time period. In other words, a one standard deviation increase in ΔI_i is equivalent to almost a three-fold increase in the insurer's remaining insurance capacity, in percentage terms.

cross-sectional regression:

$$Y_i = \alpha + \beta \times \Delta I_i + \boldsymbol{\gamma' x_i} + State\,FE + \epsilon_i. \tag{5}$$

Y_i is a placeholder for government-level outcomes related to financing, expenditures, and employment. $\boldsymbol{x_i}$ is a vector of issuer characteristics. This cross-sectional regression relies on a strong identification assumption, which is that there is random matching between issuers and insurers. This assumption may not hold, but the direction of the omitted variable bias is unclear because insurance demand can reflect either a healthy municipality wanting to expand or an unhealthy municipality wanting to cushion revenue shortfalls.

5.3 Instrumental Variable

To relax the identification assumption described in Section 5.2, I instrument for ΔI_i with each issuer's exposure to safe RMBS via its associated insurers, observed at the end of 2007Q3. The instrument is constructed as the weighted average of related insurers' exposure to AAA RMBS bonds via its insurance portfolio where the weights are the same as those used to construct ΔI_i:

$$IV_i = \sum_{j=1}^{n} \alpha_{ij} \times AAA_j. \tag{6}$$

With the instrument, the identifying assumption becomes that matching between issuers and insurers is random with respect to insurers' RMBS insurance portfolio risk. To be included in the sample, the issuer must have issued at least one insured bond between 1980 and 2005 and one insured bond in the pre-crisis period (2006Q1 to 2007Q2). This requirement ensures that these issuers have similar financial needs, i.e., having recently raised funds by issuing new debt. This requirement is important when I analyze the relationship between insurers' health and these governments' ability to issue new bonds during the financial crisis. The summary statistics on this sample of municipal bond issuers are presented in Table 7.

Table 8 sort issuers into four groups according to their exposure to AAA RMBS through related insurers and reports each group's average government-level characteristics. First, note that there is a strong relationship between AAA RMBS exposure and ΔI_i. Moving from the first quartile of AAA RMBS exposure to the fourth increases ΔI_i by more than two standard deviations, which suggests that RMBS insurance portfolio risk is a key determinant of insurers' survival during the GFC. More relevant to the identifying assumption, government characteristics are well-balanced across groups. In other words, there is no systematic pattern to suggest that riskier governments are paired with riskier insurers, with respect to AAA RMBS exposure. For example, long-term issuer credit ratings are very similar across groups. It is important to note that this credit rating is the issuer's *underlying* credit rating, which is *not* the credit rating on its insured bonds. Furthermore, there is no clear relationship between local economic conditions, as measured by county employment and house price growth, and AAA RMBS exposure. Proxies of opacity, Not Rated and Special District, also do vary with AAA RMBS exposure in a systematic way, which suggests that, to the extent that these variables are proxies of some unobservable credit risks, those risks do not seem to be systematically correlated with the proposed instrument. Panel B of Table 8 shows that issuers' geographic distribution is also similar across groups.

The last thing to check is whether the instrument is sufficiently strong. AAA RMBS exposure should have a strong positive correlation with ΔI_i if excessive ABS risk caused insurance companies to fail. Table 9 presents first-stage regression results where I regress ΔI_i on AAA RMBS exposure:

$$\Delta I_i = \alpha + \beta \times IV_i + \boldsymbol{\gamma' x_i} + State\,FE + \epsilon_i. \tag{7}$$

Column 1 shows the result where I regress ΔI_i on AAA RMBS exposure without other covariates. I find that there is a strong positive correlation between AAA RMBS exposure and ΔI_i. The economic magnitude of the estimated slope coefficient is also large. A ten percentage point increase in AAA RMBS exposure is associated with a 1.1 point increase in ΔI_i, which is almost equivalent to a one standard deviation increase. Furthermore, the R^2 is 85%, which suggests that an insurer's ABS insurance portfolio risk is a major determinant of its survival during the crisis. Columns 2 and 3 show results from regressions where I include government-level characteristics and state fixed effects. The coefficient on AAA RMBS exposure and the regression's R^2 remain effectively unchanged. These results suggest that the correlation between the instrument and ΔI_i is sufficiently high.[23]

6 Loss of Bond Insurance and Government Outcomes

This section uses the identification strategy outlined above to study the causal impact that loss of bond insurance has on government entities that relied on it.

6.1 Impact on Bond Issuance

I begin by examining the effects that loss of bond insurance has on government entities' ability to issue new bonds. To do so, I run variants of regression Equation 5 where the dependent variable is the growth in issuer i's inflation-adjusted bond issuance amount between the pre-crisis (2006Q1 and 2007Q2) and crisis period (2008Q1 and 2009Q2).[24] This variable is defined as follows:

$$g_i = \frac{q_{c,i} - q_{p,i}}{0.5 \times (q_{c,i} + q_{p,i})} \times 100. \tag{8}$$

The formulation is a second-order approximation of the log difference in growth rates around zero and it is bounded between -2 and 2. $q_{p,i}$ is some quantity related to issuer i in the pre-crisis period. $q_{c,i}$ is some quantity related to issuer i in the crisis period.

Table 10 presents regression results where bond issuance growth is regressed onto related insurers' health ΔI_i. For control variables, I include issuer characteristics that may affect a government entity's ability to issue new debt during the GFC. High Yield and Not Rated indicator

[23] First-stage F-statistics for all subsequent regressions are sufficiently large with respect to the standard imposed by Stock and Yogo (2005). All F-statistics are sufficiently large such that no standard error adjustment is required (Lee et al., 2021).

[24] I cluster standard errors on unique groups of insurance companies or insurance company syndicates. For example, if the issuer is related to insurance company A, this is one group. The union of insurance companies A and B is another group. I cannot cluster by the insurance company that has the largest relationship share because the resulting number of clusters would be too small (Cameron and Miller, 2015). Clustering standard errors by insurance company syndicate makes sense because this is the data granularity level that determines the variation of ΔI_i. All results are qualitatively similar when I cluster standard errors by state.

variables capture the issuer's credit quality. Multiple Insurers indicator variable controls for how diversified the issuer's insurance relationships are. Insurance Ratio captures the issuer's reliance on bond insurance. Debt Due in Crisis indicator variable controls for the issuer's immediate need to roll over its debt. Total Debt Issued is a proxy for the issuer's size and its reliance on municipal bonds. Lastly, Special District indicator variable is a proxy for the issuer's opacity.

Column 1 presents OLS regression results for growth in insured bond issuance. A one standard deviation increase in ΔI_i increases growth in insured bond issuance amount by 5%. Column 2 presents two-staged least squares (2SLS) regression results where ΔI_i is instrumented with AAA RMBS exposure. The results are similar to that of column 1 and suggest that municipalities that were related to ailing insurers that suffered losses from their RMBS insurance portfolios were able to issue less insured debt during the GFC. Note that if it were costless to switch insurers, then this result would not show up because municipalities would be able to switch to one of the surviving insurers and issue new insured bonds.

Columns 3 and 4 present the OLS and 2SLS regression results for total bond issuance (insured and uninsured). The coefficient estimates are essentially identical to those shown in columns 1 and 2, which suggests that municipalities that lost the ability to issue insured bonds were unable to substitute the shortfall by issuing uninsured bonds.[25] The economic magnitude is also large. Moving from a municipality at the 90th percentile value of ΔI_i to one at the 10th percentile translates to a decrease in bond issuance growth of approximately 13%. Recall from Section 2 that the amount of long-term debt that the average government entity issues each year is approximately equivalent to 13% of its annual total expenditure. Therefore, a 13% drop in debt issuance implies a 1.7% drop in total expenditure.

Columns 5 and 6 present 2SLS regression results for special district and general governments. The results suggest that the effects are concentrated among special district governments, which is in line with the notion that these governments are more opaque and face higher switching costs. The results are more suggestive than conclusive because the coefficient on ΔI_i in column 6 is not a precisely estimated zero. Taken together, the results presented in Table 10 are in line with the

[25] In untabulated results where the dependent variable is the growth rate of uninsured bond issuance, the coefficient on ΔI_i is not statistically different from zero.

story that governments associated with ailing insurers were not able to issue new insured bonds because their insurers did not have the capacity to underwrite new policies and the governments were unable to switch to employ healthier insurers because of high switching costs, induced by asymmetric information.

A natural question that arises is: How long did these financing effects last? Table 11 presents regression results where I replace the dependent variable with total bond issuance growth between the pre-crisis period and the long run, which is defined as the time between 2008Q1 and 2017Q4. Columns 1 and 2 present the OLS and 2SLS regression results for all government entities in the sample. Notice that both point estimates for a one standard deviation increase in ΔI_i are statistically indistinguishable from 5%, which suggests that affected government entities were unable to catch up by issuing more bonds in the long run. Columns 3 and 4 present results for special district and general governments, separately. The difference between the two types of governments is stark. I find that the effect that ΔI_i has on long-run bond issuance is concentrated among special district governments, while the coefficient on ΔI_i for general governments is negative and indistinguishable from zero.

It is important to note that the mechanisms that drive these long-run results may differ from those that drive the crisis-period results. After the GFC, the municipal bond insurance industry effectively disappeared. This time-series dynamic suggests that the value of bond insurance has decreased substantially. If bond insurance had maintained its value, then we should have seen a resurgence of usage as existing insurers get recapitalized and new insurers enter to fill any remaining gap in demand. The loss of value could be due to lack of investor demand or the fact that no insurer was able to obtain a AAA rating in this time period.[26] If bond insurance serves to provide access to the municipal bond market, then governments that were unable to issue new insured debt during the GFC would remain cut off from the municipal bond market in the long run because bond insurance had lost its access-granting function.

The regressions above use a relatively small sample of government entities and so the results could be interpreted as having little external validity. Figure 2 gives suggestive evidence that the

[26] AGC lost its AAA financial enhancement rating in October 2009.

documented effects may be more widespread. The figure plots bond issuance probability by issuers' insurance ratio. The sample consists of all municipal bond issuers that issued at least one insured bond between 1980 and 2006. Like before, an issuer's insurance ratio is the amount of debt it raised from insured bonds divided by the total amount of debt it raised from all municipal bonds, both adjusted for inflation. The blue bars plot the percentage of issuers that issued at least one bond during the financial crisis, defined as anytime between 2008 and 2009. The red bars plot the percentage of issuers that issued at least one bond between 2008 and 2017. Green bands are 95% confidence intervals. The key takeaway from this plot is that there is a clear monotonically decreasing relationship between an issuer's dependence on bond insurance before the crisis and its ability to issue new municipal bonds during and after the GFC. Hence, it is plausible that the demise of bond insurers significantly decreased many government entities' ability to issue new debt for many years.

6.2 Impact on Yield Spreads

This subsection explores whether government entities associated with less healthy bond insurers experienced larger increases in bond yield spreads during the GFC. The reason why poor bond insurer health would lead to higher yield spreads on insured bonds is straightforward. As shown in Table 6, insurers' inability to underwrite new bond insurance policies is associated with decreasing financial enhancement ratings. Therefore, new bonds that are wrapped with insurance policies from these ailing insurers would naturally have lower insured credit ratings and, hence, larger yield spreads than those that received insurance from healthier insurers. The implication for uninsured bonds is less obvious. Yield spreads on uninsured bonds could increase by more for issuers that are associated with less healthy insurers because the issuer's inability to issue cheap insured bonds implies that it has to roll over its existing cheap insured debt into more expensive uninsured debt, which makes all equivalent senior and subordinated debt riskier.

To explore the impact that related insurers' health has on issuers' bond yield spreads, I run variants of the following cross-sectional regression where each observation is a bond pair:

$$\Delta S_{ij} = \alpha + \beta \times \Delta I_i + \boldsymbol{\gamma_1'} \boldsymbol{x_i} + \boldsymbol{\gamma_2'} \boldsymbol{z_j} + State\,FE + \epsilon_{ij}. \tag{9}$$

i indexes issuers and j indexes bond pairs. Each observation is a bond pair issued by the same government entity. One bond is issued in the pre-crisis period and the other is issued in the crisis period. To be included in the sample, the bond pair must have the same characteristics and similar issue amounts.[27] Specifically, I match bonds on maturity, source of funds (general obligation or revenue), tax status, insurance status, and coupon type (fixed rate or zero coupon). For issuers that issued more than one bond in the pre-crisis period, I keep the bond that was issued nearest to the end of the pre-crisis period. Each issuer appears in the sample only once. I use coupon equivalent treasury yield data from Gürkaynak et al. (2007) to calculate yield spreads and ΔS_{ij} is the difference in yield spreads between the two bonds. $\boldsymbol{x_i}$ is the vector of issuer characteristics and $\boldsymbol{z_j}$ is the vector of bond characteristics.

Table 12 presents OLS and 2SLS regression results. The number of observations is small because of the restrictive matching procedure. Column 1 shows OLS regression results for all bonds. A one standard deviation increase in ΔI_i decreases the change in yield spreads by 16 bps. Columns 2 and 3 estimate the regression for insured and uninsured bond pairs, separately. I find that the effect is concentrated among insured bond pairs. Columns 4 to 6 present the respective 2SLS regression results, which are similar to the OLS regression results. Moving from a municipality at the 90th percentile value of ΔI_i to one at the 10th percentile translates to an increase in yield spreads change of approximately 60 bps, which is nontrivial compared to the sample's average change in yield spread of 240 bps.[28] These results show that changes in bond insurers' health had direct effects on municipalities' funding costs.

[27] For issue amount, the crisis bond's issue amount must be within 25% of the pre-crisis bond's issue amount, i.e., $0.75 \times a_p \leq a_c \leq 1.25 \times a_p$, where a_p is the pre-crisis bond's issue amount and a_c is the crisis bond's issue amount. Results are quantitatively and qualitatively similar when I use tighter amount bands.

[28] This result is not in conflict with those of Cornaggia et al. (2020) because this exercise compares changes in yield spreads within insured bond pairs, which is different from comparing yield spreads between insured and uninsured bonds.

6.3 Impact on Wage Expenditure

What happens to government entities' operations when they are unable to issue debt? I answer this question by estimating variants of regression Equation 5 where dependent variables are various measures of inflation-adjusted expenditure growth, calculated using Equation 8.[29]

The ASSLGF data set breaks each government entity's annual expenditure down into detailed categories.[30] For the analyses in this subsection, I group expenditures into two major categories – wage and non-wage expenditures excluding debt servicing. Wage expenditure captures the government's ability to hire people and provide public goods that require labor as an input. Non-wage expenditures include current operations expenditures, subsidies, insurance trust benefits, intergovernmental transfers, and capital outlays. This second set of expenditures captures the government's ability to perform non-labor related functions such as execute long-term infrastructure projects. This breakdown is helpful in shedding light on which type of expenditures gets cut first or gets cut by more when governments face financing frictions.

Table 13 presents regression results for insurers' health and wage expenditure growth. The number of observations decreases to 1,195 because not every issuer appears in the ASSLGF data set. Special district governments make up 94% of the sample and so the following results should be interpreted as being mostly relevant to this type of government. Columns 1 and 2 present OLS and 2SLS regression results for real wage expenditure growth between the pre-crisis and crisis periods. The 2SLS regression estimate shows that a one standard deviation increase in ΔI_i causes a 44 basis points (bps) increase in wage expenditure growth. Moving from a government entity at the 90th percentile value of ΔI_i to one at the 10th percentile translates to approximately a 1.3% decrease in wage expenditure growth. These results show that special district governments related to ailing insurers were forced to reduce workers' hours or hire fewer workers, as a result of insurance-related financing frictions.

Columns 3 and 4 present OLS and 2SLS regression results for long-term wage expenditure growth. Expenditure growth is calculated for between the pre-crisis period and the end of each

[29] Refer to the Online Appendix for more detail on this calculation.

[30] Refer to the Classification Manual for the complete list of expenditure categories: `https://www2.census.gov/govs/pubs/classification/2006_classification_manual.pdf`.

government entity's 2017 fiscal year. The 2SLS regression estimate shows that a one standard deviation increase in ΔI_i causes a 1.2% increase in long-run wage expenditure growth. This point estimate is noticeably larger than the one shown in column 2, which suggests that the gap in wage expenditure growth between governments associated with healthy insurers and those associated with less healthy insurers did not shrink in the long run. Moving from a government entity at the 90th percentile value of ΔI_i to one at the 10th percentile translates to approximately a 3.6% decrease in long-run wage expenditure growth. This result is consistent with the long-run bond issuance results and suggests that insurance-related financing frictions have long-term effects on local governments' ability to purchase labor.

Following Chodorow-Reich (2013), I use the estimates from column 4 to compute the aggregate impact that insurance-related financing frictions have on issuers' wage expenditure growth between the pre-crisis period and 2017. I begin by computing the counterfactual wage expenditure growth rate for the case where related insurers did not experience any contraction in their municipal bond insurance business:

$$g_i^* = \hat{g}_i + \beta \times -\Delta I_i. \tag{10}$$

i indexes issuers. $\hat{g}_i$ is the predicted wage expenditure growth rate and β is the elasticity between ΔI_i and wage expenditure growth computed from the same regression. Next, I define $Q(x)$ as the mapping from symmetric wage expenditure growth rates to the end-period levels, holding the initial wage expenditure level fixed:

$$Q(x) = \frac{1 + 0.5x}{1 - 0.5x} e_{t,i}. \tag{11}$$

t indicates the initial period and $t + 1$ indicates the end period. The counterfactual end period wage expenditure level is given by the following expression:

$$y_{t+1,i}^* = Q(g_i^*). \tag{12}$$

In a similar fashion, the fitted end-period wage expenditure level is given by the following expression:

$$\hat{y}_{t+1,i} = Q(\hat{g}_i). \tag{13}$$

Lastly, the total wage expenditure lost from financing frictions, across all governments in the sample, is the following expression, which is the difference between the counterfactual and predicted wage expenditure levels:

$$\sum_{i=1}^{n} y^*_{t+1,i} - \hat{y}_{t+1,i}. \tag{14}$$

Using the method outlined above, I find that the aggregate loss of 2017 wage expenditures that could be attributed to financing frictions related to loss of bond insurance is approximately \$20 billion. The aggregate 2017 wage expenditures for this sample of government entities is \$185 billion, which implies that aggregate wage expenditures for these governments would have been almost 10% higher if bond insurance companies did not fail during the GFC.[31]

6.4 Impact on Non-Wage Expenditure

I use the same sample of government entities to explore the impact that insurance-related financing frictions have on non-wage expenditures. Table 14 presents OLS and 2SLS regression results. Columns 1 and 2 present results for real non-wage expenditure growth between the pre-crisis and crisis periods. The coefficient on ΔI_i is not statistically different from zero. This result suggests that, in response to insurance-related financing frictions, government entities associated with ailing insurance companies did not cut non-wage expenditures.

Columns 3 and 4 present results for non-wage expenditure growth between the pre-crisis period and 2017. Here, I find that a one standard deviation increase in ΔI_i caused long-run non-wage expenditure growth to increase by approximately 2%. Similarly to the effect on wage

[31] All expenditure amounts are adjusted for inflation using 2007 as the base year.

expenditure, the gap between governments associated with healthy insurers and those associated with less healthy insurers did not close in the long-run. Moving from a government entity at the 90th percentile value of ΔI_i to one at the 10th percentile translates to approximately a 6.5% decrease in long-run wage expenditure growth. Taken together with the wage expenditures results, I find that, during the financial crisis, affected governments cut wage expenditure first and left non-wage expenditures intact. However, when these governments remained cut off from the municipal bond market in the long run, they were forced to also cut non-wage expenditures.

Lastly, I use the estimates from column 4 to compute the aggregate impact that insurance-related financing frictions have on issuers' non-wage expenditure growth between the pre-crisis period and 2017. The aggregate loss of 2017 non-wage expenditures that could be attributed to financing frictions related to loss of bond insurance is approximately \$65 billion. The aggregate 2017 non-wage expenditures for this sample of government entities is \$874 billion. Comparing these two numbers implies that aggregate non-wage expenditures for these governments would have been almost 7% higher if bond insurance companies did not fail.

These expenditure results have two main implications. First, they show that insurance-related financing frictions impaired local governments' ability to provide public goods, both during the GFC and in the long run. Second, they imply that the same frictions also caused local economic growth to slow down. The second implication follows from the fact that estimates of local government expenditure multipliers are positive and large (Chodorow-Reich, 2019).

6.5 Impact on Employment

This last subsection analyzes the effect that insurance-related financing frictions have on public sector employment growth. Section 6.3 shows that government entities related to less healthy insurers experienced lower wage expenditure growth both during the crisis and in the long run. Hence, it follows that employment growth at these government entities should also be slower in both periods. I verify this intuition by estimating variants of the regression Equation 5 where the dependent variables are various measures of employment growth, calculated using Equation 8.[32]

[32] Refer to the Online Appendix for more detail on this calculation.

Table 15 presents regression results for full-time equivalent employment growth during the GFC.[33] The sample size is smaller than that of previous tables because not every issuer reports employment numbers in the ASPEP data set. Columns 1 and 2 present OLS and 2SLS regression results for all governments in the sample. The instrumental variable result shows that a one standard deviation increase in ΔI_i causes employment growth to increase by 37 bps. Columns 3 and 4 present 2SLS regression results for special district and general governments, separately. Once again, the employment effects are concentrated among special district governments. A one standard deviation increase in ΔI_i causes employment growth to increase by 1.2% for special district governments, while the effect is essentially nil for general governments. These results are in line with the bond issuance and wage expenditure results.

Table 16 presents regression results for long-term employment growth, which is the employment growth rate between 2007Q2 and 2017Q1. First, the employment growth gap between governments associated with healthy insurers and those associated with less healthy insurers did not close in the long run. Second, the effects are concentrated among special district governments. Third, the economic magnitude is large. A one standard deviation increase in ΔI_i causes long-run employment growth to increase by almost 3%. Moving from a government entity at the 90th percentile value of ΔI_i to one at the 10th percentile translates to approximately a 9% decrease in long-run employment growth.

I use the estimates from column 3 to compute the aggregate impact that insurance-related financing frictions have on this sample of special district governments' employment growth between the pre-crisis period and 2017. Using the same procedure as before, I find that financing frictions related to bond insurance caused this group of government entities to lose 90,610 full-time equivalent employees. In 2017, the total number of full-time equivalent workers employed by this sample of governments is 1,411,946, which means that the loss of bond insurance caused long-term aggregate employment level to decrease by approximately 6%. The economic magnitude is large when compared to the number of employees that state and local governments lost after the GFC.

[33]The ASPEP data set reports employment numbers as of the end of the year's first quarter. Given that I define the pre-crisis period to cover 2006Q1 and 2007Q2, all pre-crisis employment numbers are converted to be as of the end of 2007Q2, which is calculated as the weighted average between 2007Q1 and 2008Q1 values, e.g., 2007Q2 employment = $0.75 \times$ 2007Q1 employment + $0.25 \times$ 2008Q1 employment. The same procedure is applied to crisis-period employment numbers, which is defined as employment level at the end of 2009Q2.

Aggregate employment by state and local governments peaked at approximately 19.8 million in 2008 and bottomed out at approximately 19.05 million in 2013, which is equivalent to a 4% drop (Harrison, 2020).

7 Conclusion

This paper documents the impact that the loss of bond insurance had on local governments during and after the GFC. I find that, compared to government entities that were associated with healthy bond insurers, those that were related to ailing bond insurers issued fewer bonds, cut expenditures, and hired fewer works. These effects lasted at least until 2017. The economic magnitudes of the spending and employment effects are large. For the sample of governments that I study, financing frictions related to loss of bond insurance caused long-term wage and non-wage expenditures to decrease by 10% and 7%, respectively. These results suggest that insurance-related financing frictions have significantly impaired local governments' ability to provide public goods long after the GFC. Furthermore, these results could potentially explain why, relative to private companies, local governments experienced an especially slow recovery in aggregate employment level after the GFC (Harrison, 2020).

It remains an open question as to why municipal bond insurance never recovered after the GFC. Potential explanations include low insurer credit ratings, lack of trust in bond insurance, a low-rates environment, and inflated municipality credit ratings. There is room for rigorous empirical analyses to quantify the relative importance of each explanation. Lastly, the results from this paper pose an important policy question, which is how to improve local governments' access to the municipal bond market in the absence of bond insurance. In light of the recent COVID-19 crisis, which decreased local governments' aggregate employment level to below their post-GFC trough, this policy question is a particularly pressing one.

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Figure 1: Annual Municipal Bond Issuance

This chart shows annual U.S. municipal bond issuance in billions of U.S. dollars. Issuance amounts are adjusted for inflation, using 2007 as the base year. The blue bars capture total issuance volume. The red bars capture insured issue volume. The green line captures the percentage of insured bonds issued in each year. The sample includes all municipal bond issuance between 1980 and 2017.

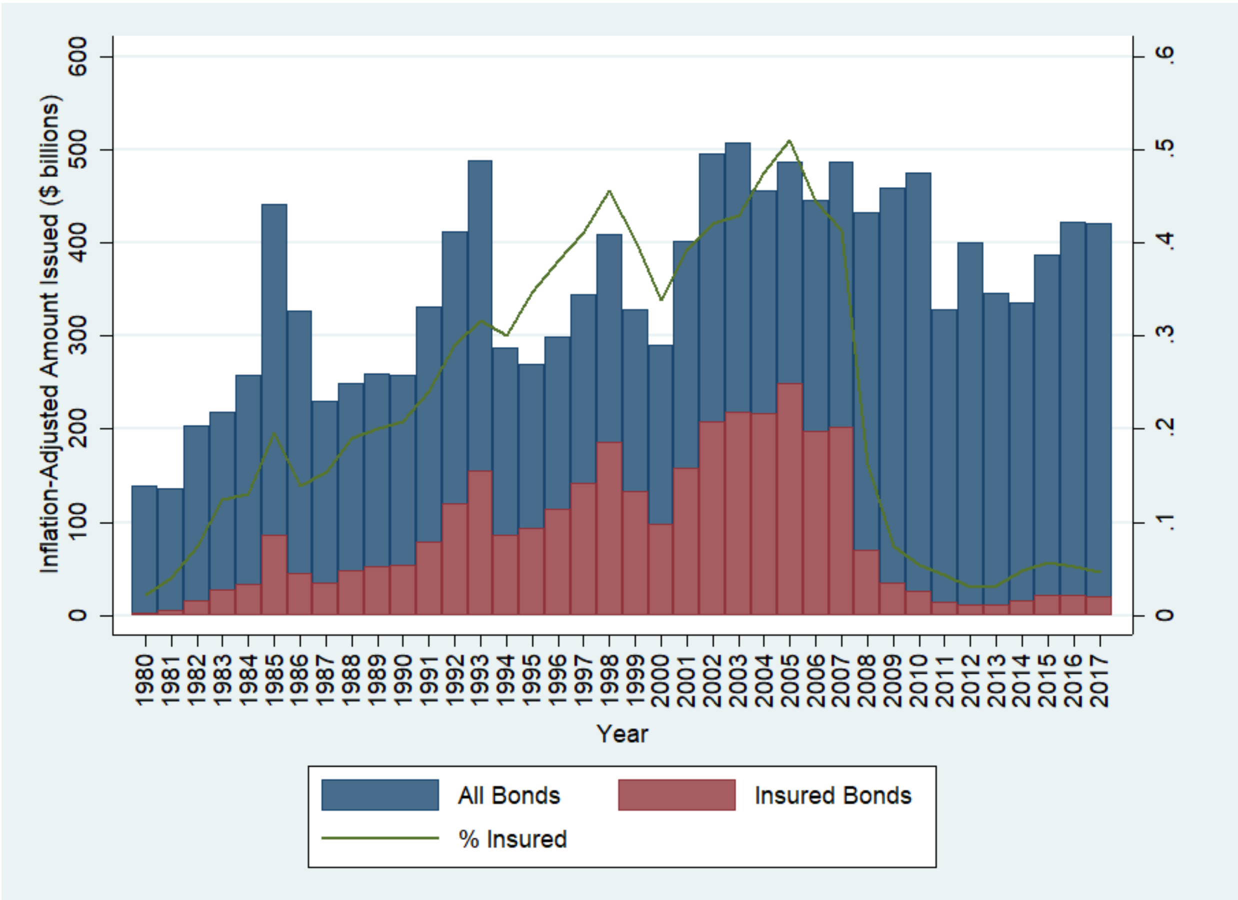

Figure 2: Insurance Ratio and Bond Issuance

This bar chart shows the relationship between reliance on bond insurance in the pre-crisis period and probability of bond issuance during and after the Global Financial Crisis. Municipal bond issuers that issued at least one bond between 1980 and 2007 are sorted into four groups according to their insurance ratios. Insurance ratio is calculated as the inflation-adjusted amount of debt raised from insured bonds divided by the total inflation-adjusted amount of debt raised from all bonds between 1980 and 2007. Bond issuance probability is the proportion of issuers that issued at least one bond during the specified time period. The blue bars plot bond issuance probability between 2008 and 2009 by insurance ratio group. The red bars plot bond issuance probability between 2008 and 2017 by insurance ratio group. 95% confidence intervals are shown in green.

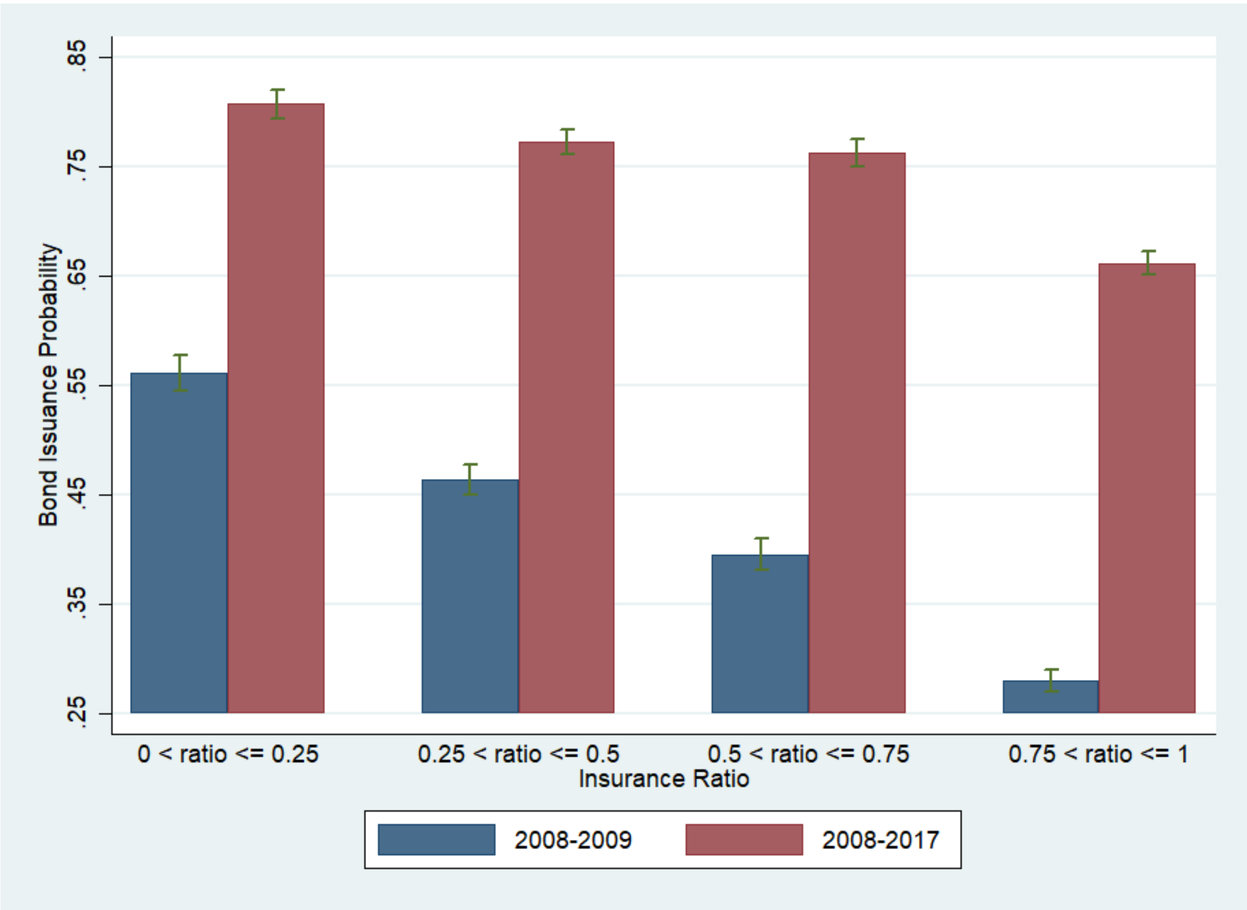

Table 1: Bond Deal Summary Statistics

This table presents summary statistics on municipal bond deals. Each observation is a bond deal, which may contain one or more individual bonds. The top panel presents summary statistics on deals that were made between 1980 and 2006. The bottom panel presents summary statistics on deals that were made between 2007 and 2017. Percent Insured is the percentage of the deal amount that was issued with bond insurance. The line includes only bond deals that contain at least one insured bond. Issue Amount is, using 2007 as the base year, the inflation-adjusted total amount of debt raised from each deal. Maturity is the years to maturity of the longest maturity bond in the deal. Coupon Rate is the coupon rate on the longest maturity bond in the deal. The remaining variables are indicator variables.

1980 – 2006						
Variable	N	Mean	S.D.	25th	50th	75th
Insured	355,878	0.24	0.43	0.00	0.00	0.00
Percent Insured	86,309	0.98	0.10	1.00	1.00	1.00
Issue Amount ($ millions)	355,878	21.85	49.66	1.90	5.63	16.44
Maturity	355,788	16.80	18.05	4.58	15.00	21.00
Coupon Rate	288,058	5.40	1.77	4.30	5.15	6.38
High Yield	355,878	0.21	0.41	0.00	0.00	0.00
Not Rated	355,878	0.67	0.47	0.00	1.00	1.00
General Obligation	355,878	0.58	0.49	0.00	1.00	1.00
Variable Rate	355,878	0.03	0.16	0.00	0.00	0.00
Callable	355,878	0.55	0.50	0.00	1.00	1.00
Taxable	355,878	0.09	0.29	0.00	0.00	0.00
Sinking Fund Provision	355,878	0.20	0.40	0.00	0.00	0.00
Bank Qualified	355,878	0.34	0.47	0.00	0.00	1.00

2007 – 2017						
Variable	N	Mean	S.D.	25th	50th	75th
Insured	165,808	0.13	0.34	0.00	0.00	0.00
Percent Insured	22,000	0.97	0.12	1.00	1.00	1.00
Issue Amount ($ millions)	165,808	23.50	53.71	1.99	5.78	17.53
Maturity	165,804	13.77	9.93	4.76	13.46	20.15
Coupon Rate	152,938	3.48	1.49	2.38	3.63	4.50
High Yield	165,808	0.41	0.49	0.00	0.00	1.00
Not Rated	165,808	0.44	0.50	0.00	0.00	1.00
General Obligation	165,808	0.67	0.47	0.00	1.00	1.00
Variable Rate	165,808	0.02	0.13	0.00	0.00	0.00
Callable	165,808	0.59	0.49	0.00	1.00	1.00
Taxable	165,808	0.11	0.32	0.00	0.00	0.00
Sinking Fund Provision	165,808	0.28	0.45	0.00	0.00	1.00
Bank Qualified	165,808	0.47	0.50	0.00	0.00	1.00

Table 2: Who Buys Bond Insurance?

This table presents panel OLS regression results for variants of Equation 1. The sample includes all bond deals issued by state and local government entities between 1980 and 2006. Issuers with missing issuer type are excluded. Each observation is a bond deal. The dependent variable is Insured, which equals 1 if the bond deal is issued with bond insurance and zero otherwise. Issuer characteristics are the Log Expenditure, Special District indicator, Not Rated indicator, and High Yield indicator. All specifications include year and state fixed effects. Standard errors are clustered at the issuer-level and reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level.

	(1)	(2)	(3)	(4)
Log Expenditure	-0.007**			-0.001
	[0.003]			[0.003]
Special District		0.026***		0.011**
		[0.005]		[0.005]
Not Rated			0.388***	0.386***
			[0.006]	[0.007]
High Yield			0.110***	0.108***
			[0.006]	[0.007]
Log Amount	0.053***	0.052***	0.073***	0.073***
	[0.002]	[0.002]	[0.002]	[0.002]
Maturity	0.006***	0.006***	0.010***	0.010***
	[0.000]	[0.000]	[0.000]	[0.000]
Coupon Rate	-0.001	-0.001	-0.003	-0.003
	[0.002]	[0.002]	[0.002]	[0.002]
General Obligation	0.073***	0.067***	0.088***	0.087***
	[0.005]	[0.005]	[0.005]	[0.004]
Variable Rate	0.023*	0.019	0.030***	0.027**
	[0.012]	[0.012]	[0.011]	[0.011]
Callable	0.151***	0.152***	0.169***	0.170***
	[0.004]	[0.004]	[0.004]	[0.004]
Taxable	-0.099***	-0.096***	-0.054***	-0.054***
	[0.009]	[0.009]	[0.008]	[0.008]
Sinking Fund Provision	0.028***	0.028***	0.012***	0.012***
	[0.004]	[0.004]	[0.004]	[0.004]
Bank Qualified	0.026***	0.025***	0.015***	0.015***
	[0.003]	[0.003]	[0.003]	[0.003]
State FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	286,818	286,818	286,818	286,818
R-squared	0.247	0.247	0.339	0.339

Table 3: Issuer Characteristics and Bond Insurance Usage Intensity

This table presents summary statistics on issuer characteristics and reliance on bond insurance. Each observation is a government entity. The sample contains municipal bond issuers that issued at least one insured bond between 1980 and 2006. Issuers with unidentifiable type are excluded. Issuers are sorted into four groups according to their insurance ratio. Insurance ratio is calculated as the inflation-adjusted amount of debt raised from insured bonds divided by the total inflation-adjusted amount of debt raised from all bonds between 1980 and 2006. State Government, State Agency, County Government, City Government, and Special District Government are indicator variables. State agencies are specialized entities that are managed and funded by the state government (e.g., the Connecticut Development Authority). Special district government is defined as government entities that are not state governments, county governments, city governments, or state agencies. Total Expenditure is imputed using data from the Census Bureau's Annual Survey of State and Local Government Finances. Each government entity's total expenditure is the average total expenditure for its state type across all years between 1980 and 2006. High Yield equals 1 if, at any point in time, the issuer was rated as a high-yield issuer by S&P or Moody's. Not Rated equals 1 if, at any point in time, the entity issued a bond without a long-term issuer credit rating from S&P or Moody's.

Insurance Ratio (r)	$0 < r \leq 0.25$	$0.25 < r \leq 0.5$	$0.5 < r \leq 0.75$	$0.75 < r \leq 1$
Sample Size	3,493	4,844	4,331	7,823
Type				
State Government	0.8%	0.1%	0.1%	0.0%
State Agency	4.7%	2.8%	2.4%	2.2%
County Government	10.6%	7.8%	7.6%	4.8%
City Government	37.2%	29.6%	22.9%	15.3%
Special District Government	46.6%	59.7%	66.9%	77.7%
Size				
Total Expenditure ($ millions)	291.13	79.54	65.87	55.55
Credit Rating				
Not Rated	11.5%	21.4%	26.0%	53.5%
High Yield	46.1%	60.2%	64.8%	82.3%

Table 4: Pre-Crisis Insurance Relationships

This table presents panel OLS regression results for variants of Equation 2. The unit of observation is an insured bond deal and potential insurer pair. For each insured bond deal that was issued, the data set contains one observation for each potential insurer. A potential insurer is an insurer that insured at least one municipal bond in the deal year. The dependent variable is Current Insurer, which equals 1 if insurance company j serves as the insurer for the current bond deal k and zero otherwise. Previous Insurer equals 1 if insurance company j insured issuer i's previous bond deal and zero otherwise. The sample contains insured bond deals issued between 1980 and 2006. The number of observations decreases in column 4 because singletons are dropped. Standard errors are clustered at the issuer level and reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level.

	(1)	(2)	(3)	(4)
Previous Insurer	0.272***	0.240***	0.199***	0.139***
	[0.005]	[0.010]	[0.011]	[0.014]
Previous Insurer × Special District		0.048***		0.051***
		[0.011]		[0.011]
Special District		0.001		
		[0.001]		
Previous Insurer × Not Rated			0.092***	0.083***
			[0.011]	[0.012]
Not Rated			-0.010***	
			[0.001]	
Previous Insurer × High Yield			0.025**	0.023
			[0.013]	[0.014]
High Yield			-0.004**	
			[0.002]	
Insurer FE	Y	Y	Y	-
Year FE	Y	Y	Y	-
Insurer × Year FE	-	-	-	Y
Insurer × State FE	-	-	-	Y
Insurer × Special District FE	-	-	-	Y
Insurer × Not Rated FE	-	-	-	Y
Insurer × High Yield FE	-	-	-	Y
Observations	440,689	440,689	440,689	440,668
R-squared	0.162	0.162	0.163	0.200

Table 5: Switcher Regressions

This table presents cross-sectional OLS regression results for variants of Equation 3. The unit of observation is a government-insurer pair. The dependent variable in columns 1 to 3 is an indicator variable, which equals one if the government issued at least one insured bond with the paired insurer between 2008Q1 and 2009Q2, multiplied by 100. The dependent variable in columns 1 to 3 is an indicator variable, which equals one if the government issued at least one insured bond with the paired insurer between 2009Q3 and 2017Q4, multiplied by 100. Only insurers that insured at least one bond deal during the specified time period are included. Prior Relationship equals one if the government has issued at least one insured bond with the paired insurer. All right-hand side variables are calculated using data up to the prior quarter of the issuance period (e.g., 1980 to 2007 for issuance period 2008Q1 to 2009Q2). Year of Last Issue is the year that the government issued a municipal bond before the specified time period. Standard errors are clustered by issuer. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level.

Issued Insured Bond in:	2008Q1 to 2009Q2			2009Q3 to 2017Q4		
	(1)	(2)	(3)	(4)	(5)	(6)
Prior Relationship	1.57***	1.30***	1.12***	4.18***	3.11***	1.85***
	[0.08]	[0.08]	[0.08]	[0.25]	[0.24]	[0.25]
Special District		-0.30***	-0.35***		-1.99***	-2.13***
		[0.06]	[0.06]		[0.15]	[0.16]
High Yield		0.01	0.06		2.74***	2.93***
		[0.11]	[0.11]		[0.25]	[0.27]
Not Rated		0.05	0.07		3.45***	3.52***
		[0.11]	[0.11]		[0.26]	[0.28]
Insurance Ratio		1.35***	1.43***		15.05***	15.26***
		[0.09]	[0.09]		[0.21]	[0.22]
Log Total Debt Issued		0.36***	0.39***		1.43***	1.50***
		[0.02]	[0.02]		[0.05]	[0.05]
Average Outcome Value	1.27%	1.27%	1.27%	5.63%	5.63%	5.63%
(1) Insurer FE	Y	Y	-	Y	Y	-
(2) State FE	Y	Y	-	Y	Y	-
(3) Year of Last Issue FE	Y	Y	-	Y	Y	-
(1) x (2) x (3) FE	-	-	Y	-	-	Y
Observations	211,960	211,960	209,910	107,995	107,995	106,950
R-squared	0.05	0.06	0.10	0.12	0.17	0.24

Table 6: Municipal Bond Insurance During the Global Financial Crisis

Panel A summarizes nominal municipal bond insurance volume by insurer-half-year. For deals where there are more than one insurer, the insured amount is split equally among insurers. Panel B summarizes S&P financial enhancement (FE) rating by insurer-half-year. This table excludes insurers that entered the market during the crisis. A rating of "R" means that the insurance company is being reviewed by regulators.

Panel A: Volume ($ billions)	06H2	07H1	07H2	08H1	08H2	09H1
ACA	0.27	0.49	0.16	0.00	0.00	0.00
AGC	1.55	1.45	3.62	21.34	9.94	20.40
AMBAC	24.13	30.00	21.50	0.74	0.00	0.00
CIFG	5.30	6.19	1.11	0.04	0.00	0.00
FGIC	18.46	22.96	10.00	0.24	0.00	0.00
FSA	28.46	28.69	26.07	38.59	5.49	3.00
MBIA	27.28	27.41	24.06	2.65	0.00	0.00
RADIAN	1.63	1.44	0.98	0.32	0.00	0.00
XLCA	6.68	7.14	7.78	0.03	0.00	0.00

Panel B: S&P FE Rating	06H2	07H1	07H2	08H1	08H2	09H1
ACA	A	A	CCC	CCC	NR	NR
AGC	AAA	AAA	AAA	AAA	AAA	AAA
AMBAC	AAA	AAA	AAA	AA	A	BBB
CIFG	AAA	AAA	AAA	A-	B	CC
FGIC	AAA	AAA	AAA	BB	CCC	NR
FSA	AAA	AAA	AAA	AAA	AAA	AAA
MBIA	AAA	AAA	AAA	AA	AA	BBB
RADIAN	AA	AA	AA	A	BBB+	BBB-
XLCA	AAA	AAA	AAA	BBB-	B	R

Table 7: Government Summary Statistics

This table presents summary statistics on government entities. The sample includes government entities that issued at least one insured bond prior to the end of 2005 and at least one insured bond in the pre-crisis period (2006Q1 and 2007Q2). Government entities not located in the main 50 states are excluded. All dollar amounts are inflation-adjusted to 2007 dollars. All spending growth rates are inflation-adjusted. Numbers of observations for credit ratings variables are fewer than 4,771 because not every issuer has a rating. Numbers of observations for expenditure and employment variables are fewer than 4,771 because not every issuer could be matched to the Census Bureau's survey data.

Variable	N	Mean	S.D.	25th	50th	75th
Change in Insurers' Health ΔI_i	4,771	-3.55	1.33	-4.52	-3.74	-2.84
Insurer Count	4,771	2.37	1.18	1.00	2.00	3.00
Insurance Ratio	4,771	0.62	0.27	0.40	0.64	0.87
Moody's Credit Rating	2,025	16.86	1.45	16.00	17.00	18.00
S&P Credit Rating	2,026	17.75	1.83	17.00	18.00	19.00
Not Rated	4,771	0.35	0.48	0.00	0.00	1.00
Total Debt Issued ($ billions)	4,771	0.80	2.54	0.05	0.13	0.38
Deals Per Year	4,771	1.11	1.44	0.41	0.67	1.19
Special District	4,771	0.64	0.48	0.00	1.00	1.00
Total Employment in 2007 ('000s)	3,954	1.14	2.92	0.13	0.36	0.90
Total Expenditure in 2007 ($ billions)	1,974	0.29	1.28	0.02	0.05	0.11
Wage Spending Growth (07:09)	1,202	0.04	0.06	0.01	0.04	0.07
Wage Spending Growth (07:17)	1,152	-0.18	0.25	-0.27	-0.16	-0.05
Non-Wage Spending Growth (07:09)	1,202	0.03	0.27	-0.10	0.04	0.15
Non-Wage Spending Growth (07:17)	1,152	-0.13	0.33	-0.32	-0.12	0.06
Employment Growth (07:09)	1,299	0.01	0.09	-0.03	0.01	0.06
Employment Growth (07:17)	1,297	-0.02	0.21	-0.12	0.00	0.10

Table 8: AAA RMBS Exposure and Government Characteristics

This table presents summary statistics on the relationship between the instrument, AAA RMBS Exposure, and governments' characteristics. The table sorts government entities into quartiles according to their AAA RMBS Exposure. The last column presents the sample standard deviation for each variable. Panel A presents summary statistics on governments' observable characteristics and panel B presents their geographic distribution.

Panel A	AAA RMBS Exposure Quartile				Sample
Characteristics	1st	2nd	3rd	4th	S.D.
AAA RMBS Exposure	0.17	0.23	0.28	0.43	0.11
Change in Insurers' Health ΔI_i	-4.84	-3.98	-3.53	-1.85	1.33
Insurer Count	1.95	2.89	2.55	2.09	1.18
Insurance Ratio	0.65	0.62	0.61	0.61	0.27
Moody's Credit Rating	16.79	16.81	16.93	16.91	1.45
S&P Credit Rating	17.69	17.75	17.79	17.78	1.83
Not Rated	0.39	0.33	0.33	0.34	0.48
Total Debt Issued ($ billions)	0.49	1.28	0.99	0.45	2.54
Deals Per Year	0.86	1.44	1.22	0.93	1.44
Special District	0.60	0.51	0.56	0.72	0.49
Total Employment in 2007 ('000s)	0.88	1.47	1.32	0.92	2.92
Total Expenditure in 2007 ($ billions)	0.18	0.57	0.39	0.15	1.28
County Employment Growth (05:07)	0.03	0.03	0.03	0.03	0.03
County Employment Growth (07:09)	-0.04	-0.03	-0.04	-0.04	0.04
County HPI Growth (07:09)	-0.11	-0.09	-0.10	-0.11	0.12

Panel B	AAA RMBS Exposure Quartile				Sample
Census Bureau Regions	1st	2nd	3rd	4th	S.D.
(1) New England	4%	6%	6%	4%	22%
(2) Middle Atlantic	20%	19%	19%	18%	39%
(3) East North Central	25%	17%	20%	27%	41%
(4) West North Central	7%	6%	10%	12%	28%
(5) South Atlantic	7%	9%	8%	5%	26%
(6) East South Central	5%	5%	5%	4%	22%
(7) West South Central	11%	17%	10%	7%	31%
(8) Mountain	6%	6%	6%	5%	23%
(9) Pacific	16%	15%	16%	18%	37%

Table 9: First-Stage Regressions

This table presents cross-sectional OLS regression results for variants of Equation 6. Change in insurers' health, ΔI_i, is regressed onto AAA RMBS Exposure, which is the issuer's weighted average exposure to AAA RMBS through its insurance relationships. AAA RMBS Exposure is computed as of 2007Q3. The unit of AAA RMBS Exposure is percentage point. Each observation is a government entity. Standard errors are clustered at the insurance-syndicate level and reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level.

	(1)	(2)	(3)
AAA RMBS Exposure	0.116***	0.116***	0.117***
	[0.004]	[0.003]	[0.003]
High Yield		-0.032*	-0.010
		[0.017]	[0.018]
Not Rated		0.009	0.034
		[0.016]	[0.032]
Multiple Insurers		-0.061	-0.067
		[0.129]	[0.122]
Insurance Ratio		0.068	0.020
		[0.058]	[0.071]
Debt Due in Crisis		-0.018	-0.022
		[0.019]	[0.017]
Log Total Debt Issued		0.003	0.008
		[0.016]	[0.015]
Special District		0.050	0.056*
		[0.031]	[0.030]
State FE	-	-	Y
Observations	4,771	4,771	4,770
R-squared	0.851	0.852	0.858

Table 10: Insurers' Health and Bond Issuance During the Global Financial Crisis

This table presents cross-sectional OLS and 2SLS regression results for variants of Equation 5. The unit of observation is a government entity. The dependent variable for columns 1 and 2 is the growth rate in the amount of insured bonds issued between the pre-crisis period (2006Q1 to 2007Q2) and the crisis period (2008Q1 to 2009Q2), multiplied by 100. The dependent variable for columns 3 to 6 is the growth rate in the amount of all bonds issued between the pre-crisis period and the crisis period, multiplied by 100. All growth rates are adjusted for inflation. ΔI_i is the measure for related insurers' health described in Section 5. It is normalized to have its standard deviation equal to 1. ΔI_i is instrumented with AAA RMBS Exposure, which is the issuer's weighted average exposure to AAA RMBS through its insurance relationships. AAA RMBS Exposure is computed as of 2007Q3. All specifications include state fixed effects. Standard errors are clustered by insurance syndicates and reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level.

Dependent Variable	Insured Bonds		All Bonds			
	(1)	(2)	(3)	(4)	(5)	(6)
ΔI_i	5.04***	4.69***	4.36***	5.32***	5.17***	4.68
	[1.06]	[1.18]	[1.23]	[1.34]	[1.71]	[2.89]
High Yield	4.17	4.15	-1.64	-1.60	-6.46	4.51
	[3.99]	[3.99]	[3.77]	[3.78]	[5.23]	[5.96]
Not Rated	6.14	6.12	-2.71	-2.64	-1.53	-5.64
	[4.27]	[4.27]	[5.23]	[5.24]	[6.67]	[7.74]
Multiple Insurers	16.79***	16.76***	13.64***	13.73***	15.33***	6.85
	[3.86]	[3.89]	[3.49]	[3.55]	[4.54]	[6.12]
Insurance Ratio	26.37***	26.26***	-17.17**	-16.89**	-3.19	-29.29*
	[5.31]	[5.27]	[7.44]	[7.44]	[8.25]	[16.90]
Debt Due in Crisis	10.63***	10.64***	18.11***	18.09***	13.14***	19.50***
	[2.49]	[2.48]	[2.76]	[2.75]	[3.96]	[5.34]
Log Total Debt Issued	3.67***	3.64***	17.85***	17.93***	17.62***	19.72***
	[0.99]	[0.98]	[1.33]	[1.35]	[1.72]	[1.88]
Special District	-9.64***	-9.52***	-14.92***	-15.24***		
	[3.22]	[3.25]	[4.12]	[4.13]		
State FE	Y	Y	Y	Y	Y	Y
Method	OLS	2SLS	OLS	2SLS	2SLS	2SLS
First-Stage F-stat	-	1540.89	-	1540.89	2301.81	586.81
Sample	All	All	All	All	Special	General
Observations	4,770	4,770	4,770	4,770	3,040	1,726
R-squared	0.07	0.07	0.17	0.17	0.16	0.20

Table 11: Insurers' Health and Long-Run Bond Issuance

This table presents cross-sectional OLS and 2SLS regression results for variants of Equation 5. The unit of observation is a government entity. The dependent variable is the growth rate in amount of all bonds issued between the pre-crisis period (2006Q1 to 2007Q2) and the long run (2008Q1 to 2017Q4), multiplied by 100. All growth rates are adjusted for inflation. ΔI_i is the measure for related insurers' health described in Section 5. It is normalized to have its standard deviation equal to 1. In columns 2 to 4, ΔI_i is instrumented with AAA RMBS Exposure, which is the issuer's weighted average exposure to AAA RMBS through its insurance relationships. AAA RMBS Exposure is computed as of 2007Q3. All specifications include state fixed effects. Standard errors are clustered by insurance syndicates and reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level.

	(1)	(2)	(3)	(4)
ΔI_i	4.15**	5.13**	6.92**	-1.44
	[1.87]	[2.25]	[3.46]	[2.29]
High Yield	-5.99*	-5.95*	-7.57	-3.12
	[3.29]	[3.30]	[5.98]	[4.45]
Note Rated	-5.19	-5.11	-3.43	-9.85*
	[4.26]	[4.30]	[7.49]	[5.66]
Multiple Insurers	36.43***	36.52***	34.73***	34.50***
	[5.21]	[5.24]	[8.19]	[4.54]
Insurance Ratio	-15.54*	-15.24*	-6.29	-25.93*
	[8.74]	[8.78]	[10.12]	[14.73]
Bond Due in Crisis	8.41***	8.39***	3.32	12.98**
	[2.06]	[2.05]	[2.25]	[5.44]
Log Total Debt Issued	11.99***	12.07***	13.11***	11.98***
	[0.74]	[0.76]	[1.20]	[1.47]
Special District	-17.44***	-17.78***		
	[3.18]	[3.21]		
State FE	Y	Y	Y	Y
Method	OLS	2SLS	2SLS	2SLS
First-Stage F-stat	-	1540.88	2301.81	586.81
Sample	All	All	Special	General
Observations	4,770	4,770	3,040	1,726
R-squared	0.18	0.18	0.16	0.25

Table 12: Insurers' Health and Changes in Yield Spreads

This table presents cross-sectional OLS and 2SLS regression results for variants of Equation 9. The unit of observation is a bond pair issued by the same government entity. Each government entity appears in the sample once. A bond pair consists of one bond from the pre-crisis period (2006Q1 to 2007Q2) and one bond from the crisis period (2008Q1 to 2009Q2). Two bonds form a pair if they have similar issuance amounts and the same characteristics. The dependent variable is the difference in coupon-equivalent yield spreads between the two bonds. ΔI_i is normalized to have its standard deviation equal to 1. In columns 3 to 6, ΔI_i is instrumented with AAA RMBS Exposure, which is the issuer's weighted average exposure to AAA RMBS through its insurance relationships. AAA RMBS Exposure is computed as of 2007Q3. Pre-Crisis Spread is the pre-crisis bond's yield spread. Insured equals 1 if the bond pair is insured. All specifications include state fixed effects. Standard errors are clustered by insurance syndicates and reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level.

	(1)	(2)	(3)	(4)	(5)	(6)
ΔI_i	-0.16**	-0.22**	-0.03	-0.18**	-0.19*	-0.11
	[0.07]	[0.10]	[0.10]	[0.08]	[0.11]	[0.10]
High Yield	0.21	0.06	0.12	0.22	0.06	0.13
	[0.16]	[0.24]	[0.31]	[0.15]	[0.24]	[0.29]
Not Rated	-0.05	-0.17	0.24	-0.05	-0.17	0.21
	[0.13]	[0.15]	[0.32]	[0.13]	[0.16]	[0.31]
Multiple Insurers	-0.19	-0.82***	0.37	-0.21	-0.79**	0.33
	[0.24]	[0.27]	[0.30]	[0.26]	[0.30]	[0.30]
Insurance Ratio	-0.13	0.04	-0.55	-0.13	0.04	-0.53
	[0.33]	[0.41]	[0.58]	[0.32]	[0.42]	[0.59]
Debt Due in Crisis	-0.01	0.02	0.02	-0.01	0.02	-0.04
	[0.13]	[0.15]	[0.32]	[0.13]	[0.15]	[0.31]
Log Total Bond Issued	-0.07	-0.10	-0.10	-0.07	-0.10	-0.11
	[0.05]	[0.06]	[0.08]	[0.05]	[0.06]	[0.08]
Special District	0.12	0.11	0.32	0.12	0.11	0.34
	[0.13]	[0.18]	[0.21]	[0.13]	[0.18]	[0.21]
Pre-Crisis Spread	-0.24***	-0.13	-0.24***	-0.24***	-0.13	-0.24***
	[0.05]	[0.14]	[0.07]	[0.05]	[0.14]	[0.07]
Insured	0.13			0.13		
	[0.18]			[0.19]		
State FE	Y	Y	Y	Y	Y	Y
Method	OLS	OLS	OLS	2SLS	2SLS	2SLS
First-Stage F-stat	-	-	-	1199.36	590.53	524.28
Sample	All	Insured	Uninsured	All	Insured	Uninsured
Observations	205	118	74	205	118	74
R-squared	0.38	0.26	0.60	0.38	0.26	0.59

Table 13: Insurers' Health and Governments' Wage Expenditures

This table presents cross-sectional OLS and 2SLS regression results for variants of Equation 5. The unit of observation is a government entity. The dependent variable for columns 1 and 2 is the growth rate of wage expenditures between the pre-crisis period (2006Q1 to 2007Q2) and the crisis period (2008Q1 to 2009Q2), multiplied by 100. The dependent variable for columns 3 and 4 is the growth rate of wage expenditures between the pre-crisis period (2006Q1 to 2007Q2) and the long run (2017 fiscal year), multiplied by 100. Spending growth rates are adjusted for inflation, using 2007 as the base year. ΔI_i is the measure for related insurers' health described in Section 5. It is normalized to have its standard deviation equal to 1. In columns 2 and 4, ΔI_i is instrumented with AAA RMBS Exposure, which is the issuer's weighted average exposure to AAA RMBS through its insurance relationships. AAA RMBS Exposure is computed as of 2007Q3. All specifications include state fixed effects. Standard errors are clustered by insurance syndicates and reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level.

	Wage Exp Growth		LT Wage Exp Growth	
	(1)	(2)	(3)	(4)
ΔI_i	0.41***	0.44***	1.21***	1.16**
	[0.13]	[0.14]	[0.42]	[0.43]
High Yield	0.71	0.71	2.05	2.04
	[0.52]	[0.52]	[2.77]	[2.77]
Not Rated	0.38	0.39	1.02	1.01
	[0.63]	[0.63]	[2.94]	[2.95]
Multiple Insurers	0.40	0.41	2.57**	2.56**
	[0.35]	[0.36]	[1.16]	[1.14]
Insurance Ratio	1.15	1.16	-7.34	-7.37
	[0.85]	[0.85]	[5.72]	[5.73]
Debt Due in Crisis	0.00	0.01	-2.38	-2.39
	[0.43]	[0.43]	[1.56]	[1.56]
Log Total Bond Issued	0.33	0.33	-0.79	-0.80
	[0.40]	[0.40]	[2.18]	[2.19]
Log Total Expenditure 2007	-0.15	-0.15	2.16	2.17
	[0.47]	[0.47]	[2.29]	[2.29]
Special District	-0.74	-0.74	42.38***	42.38***
	[1.18]	[1.18]	[12.32]	[12.33]
State FE	Y	Y	Y	Y
Method	OLS	2SLS	OLS	2SLS
First-Stage F-stat	-	1.6e+04	-	1.4e+04
Sample	All	All	All	All
Observations	1,195	1,195	1,145	1,145
R-squared	0.27	0.27	0.35	0.35

Table 14: Insurers' Health and Governments' Non-Wage Expenditures

This table presents cross-sectional OLS and 2SLS regression results for variants of Equation 5. The unit of observation is a government entity. The dependent variable for columns 1 and 2 is the growth rate of non-wage expenditures between the pre-crisis period (2006Q1 to 2007Q2) and the crisis period (2008Q1 to 2009Q2), multiplied by 100. Non-wage expenditures include all expenditures except for wages and debt service. The dependent variable for columns 3 and 4 is the growth rate of non-wage expenditures between the pre-crisis period (2006Q1 to 2007Q2) and the long run (2017 fiscal year), multiplied by 100. Spending growth rates are adjusted for inflation, using 2007 as the base year. ΔI_i is the measure for related insurers' health described in Section 5. It is normalized to have its standard deviation equal to 1. In columns 2 and 4, ΔI_i is instrumented with AAA RMBS Exposure, which is the issuer's weighted average exposure to AAA RMBS through its insurance relationships. AAA RMBS Exposure is computed as of 2007Q3. All specifications include state fixed effects. Standard errors are clustered by insurance syndicates and reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level.

Dependent Variable	Non-Wage Exp Growth		LT Non-Wage Exp Growth	
	(1)	(2)	(3)	(4)
ΔI_i	-0.12	-0.36	2.42***	2.13***
	[1.02]	[1.07]	[0.44]	[0.47]
High Yield	-2.08	-2.10	3.57	3.55
	[1.69]	[1.69]	[2.73]	[2.73]
Not Rated	-2.94	-2.99	2.20	2.13
	[2.49]	[2.49]	[3.00]	[3.00]
Multiple Insurers	-1.37	-1.43	4.21***	4.13***
	[2.58]	[2.67]	[1.23]	[1.23]
Insurance Ratio	0.13	0.01	-4.47	-4.62
	[3.86]	[3.83]	[4.93]	[4.89]
Debt Due in Crisis	-1.22	-1.25	0.82	0.79
	[1.24]	[1.24]	[1.94]	[1.94]
Log Total Bond Issued	5.81***	5.79***	4.70***	4.67***
	[1.32]	[1.32]	[1.57]	[1.56]
Log Total Expenditure 2007	-7.89***	-7.88***	-5.59***	-5.57***
	[1.31]	[1.31]	[1.51]	[1.50]
Special District	-10.63**	-10.57**	-4.55	-4.50
	[4.13]	[4.11]	[5.48]	[5.47]
State FE	Y	Y	Y	Y
Method	OLS	2SLS	OLS	2SLS
First-Stage F-stat	-	1.6e+04	-	1.5e+04
Sample	All	All	All	All
Observations	1,195	1,195	1,145	1,145
R-squared	0.15	0.15	0.17	0.17

Table 15: Insurers' Health and Employment Growth

This table presents cross-sectional OLS and 2SLS regression results for variants of Equation 5. The unit of observation is a government entity. The dependent variable is the government entity's employment growth rate between 2007Q2 and 2009Q2, multiplied by 100. ΔI_i is normalized to have its standard deviation equal to 1. In columns 2 to 4, ΔI_i is instrumented with AAA RMBS Exposure, which is the issuer's weighted average exposure to AAA RMBS through its insurance relationships. AAA RMBS Exposure is computed as of 2007Q3. Column 3 presents results for special district governments. Special district governments are entities that are not state-run agencies, state, county, or city governments. Column 4 presents results for general governments. All specifications include state fixed effects. Standard errors are clustered by insurance syndicates and reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level.

	(1)	(2)	(3)	(4)
ΔI_i	0.49***	0.37**	1.21***	-0.25
	[0.17]	[0.16]	[0.36]	[0.32]
High Yield	0.31	0.30	0.72	0.40
	[0.51]	[0.51]	[1.03]	[0.54]
Not Rated	-0.17	-0.17	-1.57	0.30
	[0.73]	[0.73]	[1.17]	[0.76]
Multiple Insurers	-0.35	-0.36	-0.01	-1.10
	[0.40]	[0.43]	[1.14]	[0.85]
Insurance Ratio	0.05	0.04	0.12	0.46
	[1.07]	[1.07]	[2.91]	[1.13]
Debt Due in Crisis	0.20	0.20	1.02	-0.25
	[0.49]	[0.49]	[0.83]	[0.45]
Log Total Bond Issued	0.45*	0.44*	0.14	0.73**
	[0.25]	[0.25]	[0.43]	[0.34]
Log Employment 2007	-0.62***	-0.60***	-0.84**	-0.71**
	[0.21]	[0.21]	[0.34]	[0.34]
County Employment Growth (07:09)	0.33***	0.33***	0.38*	0.32***
	[0.10]	[0.10]	[0.21]	[0.09]
Special District	1.20**	1.24**		
	[0.53]	[0.53]		
State FE	Y	Y	Y	Y
Method	OLS	2SLS	2SLS	2SLS
First-Stage F-stat	-	4315.59	6346.07	2335.38
Sample	All	All	Specialized	General
Observations	1,296	1,296	475	816
R-squared	0.13	0.13	0.20	0.15

Table 16: Insurers' Health and Long-Run Employment Growth

This table presents cross-sectional OLS and 2SLS regression results for variants of Equation 5. The unit of observation is a government entity. The dependent variable is the government entity's employment growth rate between 2007Q2 and 2017Q1, multiplied by 100. ΔI_i is normalized to have its standard deviation equal to 1. In columns 2 to 4, ΔI_i is instrumented with AAA RMBS Exposure, which is the issuer's weighted average exposure to AAA RMBS through its insurance relationships. AAA RMBS Exposure is computed as of 2007Q3. Column 3 presents results for special district governments. Special district governments are entities that are not state-run agencies, state, county, or city governments. Column 4 presents results for general governments. All specifications include state fixed effects. Standard errors are clustered by insurance syndicates and reported in brackets. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) level.

	(1)	(2)	(3)	(4)
ΔI_i	1.76***	1.74***	2.94***	-0.07
	[0.65]	[0.57]	[0.66]	[0.98]
High Yield	-0.36	-0.36	-0.02	-0.47
	[1.26]	[1.26]	[2.68]	[1.72]
Not Rated	0.21	0.21	-4.11*	2.04
	[1.71]	[1.72]	[2.28]	[2.08]
Multiple Insurers	-1.12	-1.12	-2.19	0.69
	[1.25]	[1.26]	[1.61]	[2.95]
Insurance Ratio	0.46	0.46	7.22	-4.84
	[3.16]	[3.15]	[5.59]	[3.17]
Debt Due in Crisis	-0.48	-0.48	-0.84	0.37
	[1.00]	[1.00]	[2.45]	[1.31]
Log Total Bond Issued	1.27	1.27	1.04	0.49
	[0.78]	[0.77]	[1.34]	[0.87]
Log Employment 2007	-2.69***	-2.69***	-3.85***	-1.60*
	[0.76]	[0.75]	[0.97]	[0.93]
County Employment Growth (07:17)	0.43***	0.43***	0.65***	0.33***
	[0.08]	[0.08]	[0.13]	[0.10]
Special District	2.80*	2.80**		
	[1.42]	[1.39]		
State FE	Y	Y	Y	Y
Method	OLS	2SLS	2SLS	2SLS
First-Stage F-stat	-	4413.19	6274.49	2393.95
Sample	All	All	Special	General
Observations	1,294	1,294	474	815
R-squared	0.17	0.17	0.26	0.19

A Main Appendix

A.1 Economic Magnitude of ΔI

A.2 Deal-Level Variable Definitions

Insured – Equals 1 if at least one bond in the bond deal was issued with bond insurance.

Percent Insured – For each bond deal, the amount of insured debt divided by the total amount of debt.

Issue Amount – Amount of debt issued in the bond deal in millions of 2007 USD.

Maturity – Years to maturity of the longest-maturity bond in the deal.

Coupon Rate – Coupon rate on the longest-maturity bond in the deal.

High Yield – Equals 1 if the issuer's long-term issuer credit rating is speculative, either according to S&P or Moody's.

Not Rated – Equals 1 if the issuer has no long-term issuer credit rating from S&P or Moody's.

General Obligation – Equals 1 if bonds in the deal are general obligation bonds.

Variable Rate – Equals 1 if at least one bond in the deal has a non-fixed coupon rate.

Callable – Equals 1 if bonds in the deal are callable.

Taxable – Equals 1 if bonds in the deal are not tax-exempt.

Sinking Fund Provision – Equals 1 if the bond deal was issued with a sinking fund provision.

Bank Qualified – Equals 1 if bonds in the deal are bank qualified. Bank-qualified bonds are those that enjoy tax-advantaged status when purchased by commercial banks.

Total Expenditure (Tables 2 and 3) – For each government entity in the Census Bureau's Survey of State and Local Government Finances, I observe its state and type (state, county, city, education-related, and other special district governments). For each year, I calculate the average total expenditure by state-type. These averages are merged into the SDC Platinum data set by state-type-year. The natural log of these expenditures are used in regressions.

Special District – Equals 1 if the issuer is not a state government, state agency, county government, or city government. Special district governments are government entities with specialized purposes. Examples of special district governments are school districts, fire departments, utility districts, etc.

A.3 Government-Level Variable Definitions

Change in Insurers' Health ΔI_i – Weighted average of related insurers' growth in municipal bond insurance business between the pre-crisis (2006Q1 to 2007Q2) and crisis periods (2008Q1 to 2009Q2). Refer to Section 5 for more detail.

Insurer Count – Number of active insurers that the issuer had done business with before 2006. Active insurers are those that were underwriting new business during the pre-crisis period (2006Q1 to 2007Q2).

High Yield – Equals 1 if the issuers long-term issuer credit rating is speculative, either according to S&P or Moody's. The variable is constructed based on the most recent bond deal prior to the period of analysis.

Not Rated – Equals 1 if the issuer has no long-term issuer credit rating from S&P nor Moody's. The variable is constructed based on the most recent bond deal prior to the period of analysis.

Insurance Ratio – Inflation-adjusted amount of debt raised from insured bonds divided by the total inflation-adjusted amount of debt raised from all bonds. The variable is constructed based on the most recent bond deal prior to the period of analysis.

Moody's Credit Rating – Moody's alphabetical credit ratings are converted to numerical values, ranging from 1 to 21.

S&P Credit Rating – S&P's alphabetical credit ratings are converted to numerical values, ranging from 1 to 22.

Total Debt Issued – Inflation-adjusted amount of debt raised from issuing municipal bonds. The variable is constructed based on the most recent bond deal prior to the period of analysis.

Total Employment in 2007 – The government entity's number of full-time equivalent employees in 2007Q2, which is the weighted average between 2007Q1 and 2008Q1 employment numbers.

Total Expenditure in 2007 – The government's total expenditure at the end of its 2007 fiscal year.

Wage Expenditure Growth – Growth rate in the government's expenditures related to wages and salaries between two time periods. The growth rate is calculated as the second-order approximation of the log difference growth rate around zero. Refer to the main text for more details. The growth rate is calculated using inflation-adjusted numbers.

Non-Wage Expenditure Growth – Growth rate in the government's non-wage expenditures between two time periods. This expenditure includes current operations expenses, capital expenditures, subsidies, insurance benefit payments, and intergovernmental transfers. This expenditure excludes wage expenditures and debt service payments. The growth rate is calculated as the second-order approximation of the log difference growth rate around zero. Refer to the main text for more details. The growth rate is calculated using inflation-adjusted numbers.

Employment Growth – The growth rate of the government's full-time equivalent employees between two time periods. The growth rate is calculated as the second-order approximation of the log difference growth rate around zero. Refer to the main text for more details.

County Employment Growth – Log difference of county employment levels between two time periods. This number is calculated for the county where the government entity is located. State governments are assumed to be located in the county where the state's capital is located. Employment data are collected from the Bureau of Labor Statistics.

County HPI Growth – Log difference of county all-transaction house price index levels between two time periods. This number is calculated for the county where the government entity is located. State governments are assumed to be located in the county where the state's capital is located. HPI data are collected from the FHFA.

AAA RMBS Exposure – The government's weighted average exposure to AAA RMBS through its insurance relationships. AAA RMBS Exposure is computed as of 2007Q3.

Multiple Insurers – Equals 1 if the issuer has more than one related active insurer.

Debt Due in Crisis – Equals 1 if the issuer has at least one bond due during the crisis period (2008Q1 to 2009Q2). Due dates are calculated from bond deals' longest-maturity bonds' maturity dates.

Table A1: Growth in Insurers' Municipal Bond Insurance Volume During the GFC

This table presents the change in each insurer's municipal bond insurance business volume during the Global Financial Crisis. Column 1 presents the total amount of new municipal bond debt that each insurer insured during the pre-crisis period in millions of 2007 USD. The pre-crisis period begins in 2006Q1 and ends in 2007Q2. For bond deals with multiple insurers, the total insured amount is divided equally among all insurers that are involved in the deal. Column 2 presents the total amount of new municipal bond debt that each insurer insured during the crisis period in millions of 2007 USD. The crisis period begins in 2008Q1 and ends in 2009Q2. Column 3 presents the percentage change in municipal bond insurance volume between the pre-crisis and the crisis periods. Column 4 presents the log difference between one plus the quantity in column 2 and the quantity in column 1. The quantities in column 4 are used to compute ΔI.

	(1)	(2)	(3)	(4)
Insurer	Pre-Crisis Volume ($ millions)	Crisis Volume ($ millions)	Percentage Change	Log Difference
ACA	1,062.57	0.00	-100.00%	-6.97
AGC	3,012.97	42,518.78	1311.19%	2.65
AMBAC	73,595.28	738.27	-99.00%	-4.60
CIFG	12,637.45	36.65	-99.71%	-5.82
FGIC	50,752.60	238.06	-99.53%	-5.36
FSA	72,007.80	41,253.34	-42.71%	-0.56
MBIA	70,230.89	1,777.09	-97.47%	-3.68
RADIAN	4,533.15	318.10	-92.98%	-2.65
XLCA	23,105.33	34.22	-99.85%	-6.49

B Online Appendix

B.1 Issuer Type Mapping

The ASSLGF data set classifies government entities into six types. The types are as follows – state governments (0), county governments (1), cities (2), towns (3), special district governments that are not school districts (4), and school districts and universities (5).

The SDC Platinum data set uses the variable Issuer Type to put issuers into the following categories – state governments (10), county governments (11), cities and towns (12), universities (13), school districts (14), state-run agencies (15), special district governments that are not school districts or state-run agencies (16), Native American entities (17), cooperatives (18), and other non-profit organizations and utilities (21).

A natural government type mapping between the two data sets is the following: 0 = 10, 1 = 11, 2 = 12, 3 = 12, 4 = 15, 16, 17, 18, 21, and 5 = 13, 14.

B.2 Fiscal Year-End Adjustments

Government entities in the ASSLGF data set have fiscal year-ends that range from January to December. I account for differences in fiscal year-ends by computing a weighted average of the quantity of interest (e.g., wage expenditure) between the current and subsequent years such that the resulting number is equivalent to the quantity of interest observed at the end of the current calendar year. For example, suppose that a certain government i ends its fiscal year in January. Then, its 2006 wage expenditure with December fiscal year-end is (1/12) $\times$ January 2006 quantity + (11/12) $\times$ January 2007 quantity. Once I have adjusted all expenditures to having December fiscal year-end, I calculate pre-crisis (2006Q1 to 2007Q2) expenditure amounts as the following sum:

$$e_{i,p} = e_{i,2006} + 0.5 \times e_{i,2007}.$$

The same method is used to calculate crisis period expenditures. Note that the analyses above do not apply the same adjustments to 2017 expenditures because differences in fiscal year-ends matter less for growth rates calculated over long horizons.