# Municipal Bond Insurance and Public Infrastructure: Evidence from Drinking Water*

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**Abstract**

Although bond insurance intermediaries are frequently relied upon by local governments for external financing, there is significant debate about the value that bond insurers provide. In this paper, we study U.S. drinking water to estimate the real effects of bond insurance on public infrastructure. We show that exogenous reductions in municipalities' access to bond insurance cause local governments to face higher borrowing costs, reduce external bond issuance, decrease investment in water infrastructure, and experience greater drinking water pollution. The evidence supports the view that well-functioning insurance markets for municipal debt have significant real effects on public infrastructure.

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# 1 Introduction

The role of insurance intermediaries in financial markets is a major issue facing academics and policy makers (Hufeld et al., 2016). One context in which insurance has been especially important is the municipal sector. For many years, local governments in the U.S. relied heavily on bond insurance to finance investments in public infrastructure. At its peak, almost half of the $2.6 trillion in municipal debt raised for public projects was insured. During the financial crisis, however, the bond insurance industry largely collapsed due to several insurers' exposures to securitized financial products unrelated to municipal debt. These events have since triggered debate about bond insurance intermediaries and their impact on the public sector (U.S. House of Rep. Comm. on Fin. Services, 2009; Kriz and Joffe, 2017; Cornaggia et al., 2021b).

In this paper, we provide some of the first empirical estimates of the real effects of bond insurance on infrastructure investment and quality. We do so by studying U.S. drinking water infrastructure, which is of particular interest for several reasons. Drinking water infrastructure is almost exclusively financed and maintained by local governments, and provides a setting that is conducive towards precisely estimating the causal impact of bond insurance on infrastructure (Curley, 2017; Smull et al., 2022). Furthermore, unlike other forms of infrastructure, there are well-accepted measures of drinking water quality that are granular, available at high frequency, and comparable across regions. Recent drinking water emergencies have also spurred broader interest in the causes of water pollution across the U.S.

Our identification strategy exploits institutional features of the bond insurance industry. For decades, bond insurers were nearly all AAA-rated in credit quality, and were responsible for any debt repayment shortfalls due to municipal default. Starting in the 1990's, some—but not all—AAA-rated insurers began to insure structured financial products such as residential mortgage backed securities (RMBS) (Moldogaziev, 2013; Richard, 2010). When these products unexpectedly crashed in value in 2007, these insurers were faced with massive insurance claims, causing their credit quality to plummet (Cornaggia et al., 2021a). As a result, several bond insurers stopped insuring new municipal bonds entirely, while other insurers continued to operate (Kriz and Joffe, 2017).

We hypothesize that municipalities that had historically relied upon bond insurers that unexpectedly crash in 2007, subsequently face relatively higher borrowing costs and raise less external financing. These municipalities then cut back on investment in water infrastructure, which leads to increased drinking water pollution in these regions. Our hypothesis is based on a model in which municipal bond insurance eases external financing frictions faced by local governments.

An important friction that is commonly used to describe municipal bond markets is asymmetric information between issuers and investors. U.S. municipalities are often branded as opaque because they do not face the same disclosure requirements as public corporations, and many of the tools thought to mitigate information frictions, such as municipal credit ratings, appear helpful, but unable to fully resolve information asymmetries (see Aguilar (2015); Adelino et al. (2017); Cornaggia et al. (2018)). To help overcome this opacity, bond insurance can serve as a signalling device that enables local governments to credibly convey their credit-worthiness to otherwise uninformed investors (Thakor, 1982).

In practice, once an insurer performs due diligence and ascertains the credit quality of a municipal issuer, it is less costly for that same insurer to provide insurance on subsequent debt issues relative to other insurers, *ceteris paribus*. Information frictions thus give rise to the industry-wide phenomena of persistent relationships between municipal issuers and bond insurers. If an insurer suddenly becomes unable to provide bond insurance, a municipality that was previously reliant on that insurer now has to form a new relationship with a different insurer in order to obtain insurance, or issue uninsured bonds at higher yields. Either way, the municipality now faces higher effective borrowing costs when its pre-existing insurer no longer provides bond insurance.

Our theory stands in contrast to the oft-cited view—i.e. the null hypothesis—that insurance intermediaries for municipal bonds do not impact infrastructure. This view is theoretically compelling for several reasons, and may explain why the link between bond insurance and drinking water quality has not been established previously. For example, municipal issuers may be able to use alternative tools such as credit ratings and voluntary disclosures to sufficiently overcome adverse selection. Additionally, local officials may be able to respond to insurance shocks by raising capital from other sources, such as tax revenues, service fees, and intergovernmental transfers, in order to overcome any shortfall in debt financing due to insurance unavailability. Municipal default is also historically rare, so the effects of insurer shocks may not be empirically meaningful. Recent empirical studies support the null hypothesis by arguing that bond insurance provides little to no value to local governments after the crisis (Kriz and Joffe, 2017; Cornaggia et al., 2021b).

To empirically test our hypothesis, we exploit exogenous variation in shocks to municipal issuer-bond insurer relationships triggered by the mortgage crisis. Prior to 2007, 99% of all insured bonds raised for drinking water infrastructure were backed by 10 AAA-rated bond insurers. Different municipalities had varying amounts of outstanding debt that was insured by these companies. In 2007, 8 bond insurers experienced a sudden decline in credit quality due to their exposures to securitized loan defaults, and ceased to insure new municipal bond issues (Cornaggia et al., 2021a; Kriz and Joffe, 2017). We refer to these insurers as "troubled", following Bergstresser et al. (2015). The 2 other insurers, which were less exposed to structured debt products, continued to insure new municipal bond issues even after 2007 (Moldogaziev, 2013).

We measure the fraction of a municipality's outstanding debt that is insured by troubled insurers as of 2006 (i.e. when these insurers still had AAA ratings and were insuring new municipal debt issues). We hypothesize that municipalities with high fractions of municipal debt backed by these insurers, subsequently face a larger shock to financial constraints than municipalities with low fractions of debt backed by these insurers. All else equal, we interpret any differences in infrastructure outcomes between the two groups as evidence of the causal impact of bond insurance.

Our central identification assumption is that the 2007 crash in structured financial products was unanticipated and exogenous to pre-crisis variation in relationships between municipalities and bond insurers. In other words, we assume that municipalities had previously formed relationships with AAA-rated bond insurers without the foresight that some AAA insurers would cease insuring new debt after 2007, while other AAA insurers would remain relatively unscathed. This assumption is consistent with detailed accounts of industry practices prior to the crisis (Richard, 2010; Muni. Bond Adv., 2020).

We also document numerous empirical evidence that supports our identification assumption. Prior to 2007, municipalities in our "high exposure" and "low exposure" groups appear statistically indistinguishable across a number of observable characteristics, such as credit ratings, borrowing costs, and investment behavior. They also have similar population sizes, tax revenues, and reliance on external debt financing. The data suggest that the shocks to bond insurers that we exploit are not correlated with municipal characteristics that would otherwise explain the outcomes that we study.

Our identification strategy does *not* require that pre-crisis heterogeneity in municipality-insurer relationships is random. Instead, we assume that municipality-insurer relationships reflect a competitive equilibrium that is endogenously determined by municipality and insurer optimization decisions. Our empirical strategy takes the pre-existing relationships between municipalities and insurers as given, and assumes that the 2007 shock to monoline insurance is exogenous to variation in these relationships.

In our main specifications, we define high exposure (low exposure) based on whether the fraction of a municipality's outstanding debt that is backed by troubled insurers is above (below) 53%—the sample median in 2006. To illustrate our identification strategy, it is helpful to consider an example of two municipalities in our sample. In 2006, Saline and Geary counties in Kansas are similar across many dimensions: both municipalities have approximately 68% of their outstanding water infrastructure bonds insured by AAA-rated insurers, and both municipalities face a 6% cost of debt. However, while all of Geary county's insured debt is backed by MBIA (a troubled insurer), Saline County's debt is backed by two companies: 48% by MBIA and 20% by FSA (a relatively healthy insurer). We thus classify Geary (Saline) county as "high exposure" ("low exposure").

We present a number of new empirical findings that provide support for our hypothesis and reject the null. First, we document the significant rise and fall of bond insurance intermediaries around the crisis. In 2007, the total debt raised by local municipalities for water infrastructure was $26.2 billion, and 47.5% of this debt was insured. In 2008, although $24.6 billion in municipal debt was raised for water infrastructure, the fraction of this debt that was insured was only 21.5%. The sudden drop in insured debt due to the exit of eight insurers illustrates the empirical significance of the shocks that we exploit.

Second, we find that high-exposure municipalities raise less debt than low-exposure municipalities after 2007. Our regression estimates imply that if a municipality's bond insurers stop insuring new debts, the municipality reduces new debt issuance by approximately 5.2% of its current outstanding debt. In aggregate, this figure amounts to an $8.15 billion reduction in municipal bonds raised for water infrastructure. The data support our hypothesis and indicate that negative shocks to bond insurers reduce municipalities' ability to raise external bond financing.

Third, we provide estimates of the increased borrowing costs faced by municipalities as a result of the 2007 shocks to bond insurance intermediaries. We do so by examining total borrowing costs for new debt issues and debt refinancings (which incorporate both municipal bond yields and financing fees such as bond insurance premia), and by examining total debt servicing fees paid by municipalities annually (which incorporates interest expenses paid on existing debt). Both of these measures are inherently truncated, since municipalities choose not to issue bonds or refinance existing debt when borrowing costs are sufficiently high. Our regression estimates thus represent a lower bound of the impact of bond insurance shocks on borrowing costs. Nonetheless, the data imply that municipalities experience a 26-28 basis point increase in total borrowing costs. In aggregate, the total debt servicing fees paid by local governments increase by $732 million following negative insurance shocks.

Fourth, we show that treated municipalities reduce investment into public drinking water infrastructure (relative to control municipalities) after 2007. Our regression estimates imply that if a municipality's bond insurers ceased to insure new water bonds, the municipality would spend approximately 6-7% less annually on capital outlays aimed at maintaining and improving drinking water infrastructure. In aggregate, these figures amount to a $1.05 billion reduction in water infrastructure investment across local governments.

Collectively, the regression estimates suggest that local governments respond to shortfalls in external bond financing and increases in debt servicing fees, by seeking alternative sources of capital for water infrastructure investment. These alternative sources likely include internal funds, bank loans (Ivanov and Zimmermann, 2021), and intergovernmental transfers such as Drinking Water State Revolving Funds (Curley, 2017; Travis et al., 2004). Despite these efforts, however, our investment results indicate that alternative capital sources are unable to fully compensate for the shortfalls triggered by bond insurance shocks.

The empirical findings thus far are consistent with anecdotes by local government officials. Bob Inzer, executive director of the Sunshine State Governmental Financing Commission, claims that as a result of the bond insurance industry collapse, cities are "paying a huge interest rate penalty or being denied access to the [bond] market" (Barkin, 2009). He argues for instance, that Quincy, a town of 20,000 people, cannot raise $10 million to expand its water systems, and that even municipalities as large as Orlando and Miami-Dade county cannot find insurance for their public projects.

Our estimated reductions in water infrastructure investment are economically significant partly because local governments are already financially constrained, particularly during the post-crisis sample period. Water utilities report that nearly half of all capital spending on water infrastructure is a reaction to system failures (EPA, 2002). Additionally, 60-70% of total expenditures are directed towards the replacement and refurbishment of aging and deteriorating pipe networks (EPA, 2018)—assets that are most associated with water pollution, through leakages, main breaks, and biofilm deposits (EPA, 2002; Amer. Soc. of Civil Eng., 2017; Renwick et al., 2019).

In our data, we observe that high exposure municipalities experience increased drinking water pollution following the collapse of bond insurance. Using U.S. Environmental Protection Agency (EPA) data on contaminants such as coliform bacteria, treatment byproducts, and inorganic compounds, we estimate that high-exposure municipalities exhibit a 6% relative increase in the number of violations of federal drinking water standards observed for public water systems. We observe these effects even after controlling for federal changes in EPA standards over time. If we account for the population sizes served by these systems, this figure amounts to an increase of 19.7 million people who become exposed to drinking water pollution. Our estimates suggest that bond insurance shocks can explain nearly 32% of the total variation in drinking water pollution observed across sample municipalities.

We present additional cross-sectional and time-series results that are consistent with our hypothesis. For example, we find that our results are particularly strong for municipalities that have low ratios of water revenues to debt servicing fees—i.e. municipalities whose infrastructure investments are likely to be more sensitive to external financing constraints.

We also document persistent water pollution for high-exposure municipalities after 2007, consistent with the fact that the bond insurance industry has taken time to recover and meet investors' pent up demand for insurance (Gillers, 2020).

We critically assess a number of alternative explanations for our findings. For example, we consider whether our results reflect a spurious correlation between municipal outcomes and insurer types; municipalities of lower credit quality may have been more likely to receive insurance from insurers that had greater exposure to securitized products. These municipalities may have simply experienced greater economic decline during the crisis than municipalities that were able to obtain insurance from insurers that remained healthy.

We document numerous evidence that is inconsistent with this explanation. For example, we find that our results on borrowing costs pertain to revenue bonds, but not general obligation (G.O.) bonds. Revenue bonds are securities that are raised for a specific infrastructure project (in our case, drinking water infrastructure); repayments for these bonds are restricted to the cash flows generated by the project. In contrast, G.O. bonds can be paid using any income stream available to a municipality, including service fees for projects unrelated to water infrastructure. If our results are driven by treatment municipalities simply experiencing greater economic decline than control municipalities in the crisis, we should have observed differences in borrowing costs for G.O. bonds.

Second, we show that our results do not reflect changes in the demand for clean drinking water; it is theoretically possible that cuts to water infrastructure stem from shrinking local populations or dwindling municipal tax revenues. We find, however, that municipalities in the high and low exposure samples do not show significant differences in population growth or property tax revenues after 2007. Moreover, we find no significant differences in drinking water service revenues between the two groups in the immediate years following the crisis. Thus, our shocks do not appear to be correlated with changes in demand for water infrastructure investment.

We also present evidence that rules out additional alternative explanations for our findings. For example, we show that our results are not mechanically driven by our definition of high and low exposures to troubled insurers. We also argue that tax-related motives for purchasing municipal bonds and bond insurance do not play a meaningful role in explaining our findings. Finally, we show that our results are not driven by the recalibration of municipal credit ratings that took place in 2010.

Our paper contributes to a growing literature on the role of insurance intermediaries in financial markets (Hufeld et al., 2016). We explore this topic in the context of municipal finance, which is important given the size of the sector ($4.2 trillion as of 2020) and the presence of unique frictions that differ from those that characterize private capital markets. Our paper complements recent research that examines the asset pricing implications of insurance intermediaries for municipal bonds (Kriz and Joffe, 2017; Chun et al., 2018; Cornaggia et al., 2021b), as well as work that studies the effects of credit ratings on municipal outcomes (Adelino et al., 2017; Cornaggia et al., 2018). We add to the literature by providing novel estimates of the real effects of insurance on infrastructure. Our findings demonstrate that well-functioning insurance markets are critical for the adequate provision of public goods and services.

The remainder of this paper is as follows. Section 2 describes the theoretical framework. Section 3 details the data. Section 4 describes our empirical framework. Section 5 presents the empirical findings. Section 6 concludes.

# 2 Theoretical Framework

## 2.1 Background

### 2.1.1 Drinking water pollution

Public drinking water infrastructure in the U.S. is largely financed and maintained by municipal governments, who work in partnership with public and/or private water authorities. The health standards that all public water systems must satisfy are governed by the EPA at the federal level under the 1974 Safe Drinking Water Act (SDWA). The SDWA specifies the maximum permitted levels of contaminants that are allowed in community drinking water systems. Local governments must regularly test their public water systems and report the results to the EPA, who in turn monitor whether the water quality is compliant with regulations. Despite federal regulations being in place since 1974, however, many studies find that violations of drinking water health standards are on the rise. According to Allaire et al. (2018), nearly 21 million people who relied on community water systems for their drinking water were exposed to contaminants such as lead and E. Coli in 2015. These pollutants have been known to cause significant long-term damage to both infants and adults. Well-publicized cases of drinking water contamination have highlighted significant variation in water quality across regions in the U.S. (Snider, 2017; Rihl, 2020).

Drinking water pollution is frequently attributed to aging and deteriorating water infrastructure (Amer. Soc. of Civil Eng., 2017; Renwick et al., 2019). Drinking water capital stock is comprised of four main components: pipe networks used for water transmission and distribution, treatment facilities, water storage sites, and source processing plants (EPA, 2002). Of these assets, pipes are considered the most critical: EPA surveys of public water systems consistently report that the largest infrastructure investment needs —ranging between 60-70% of total spending budgets—correspond to projects related to the replacement and refurbishment of deteriorating pipes (EPA, 2018). These projects include the improvement of aging water mains, installation of new pipes to eliminate stagnant water, and the creation of cleaner distribution networks for existing homes.

Much of the existing network of pipes used for drinking water dates back to the early 20th century, and has now exceeded its life expectancy (Renwick et al., 2019). According to a National Academies of Science report, the deterioration of pipes used for water distribution compromises barriers to microbial, chemical, and radiological contamination (Nat. Res. Council, 2006). For example, the EPA reports that older water pipes tend to contain higher levels of biofilm, which are typically associated with microbiological contaminants such as E. coli (Renwick et al., 2019). Other studies have shown that fissures in aging pipes can also lead to water contamination from groundwater sources (Fox et al., 2016).[1] Many observers argue that government spending devoted to drinking water infrastructure is inadequate, thereby exacerbating public health risks from water contamination. For example, industry experts claim that investment in water infrastructure falls short by $82 billion annually (Val. of Water Camp., 2020). Public water systems further report that 47% of all maintenance work

[1] See Renwick et al. (2019) and Nat. Res. Council (2006) for further details describing additional mechanisms by which infrastructure deterioration leads to increased pollution.

undertaken by utilities is reactive and only initiated in response to system failures (EPA, 2002). Finally, surveys of public water systems reveal that the two most pressing needs that they face are the renewal and replacement of aging water infrastructure, and the procurement of financing for capital improvements (Amer. Water Works Assoc., 2016). The current state of affairs thus motivates the need to better understand the fundamental drivers of drinking water investment and pollution across the U.S.

### 2.1.2 Municipal financing and bond insurance

Bond insurance intermediaries have been frequently used by municipalities for new debt issues, purportedly because it allows local governments to overcome information frictions in financial markets (Thakor, 1982; Barkin, 2009; Gillers, 2020). Bond insurance is a form of credit enhancement where the insurer commits to paying any shortfall in interest and principal owed on a municipal bond in case of municipal default. Bond insurance thus enables municipalities to raise debt at lower yields when investors view insurance as a valuable safety net against municipal default (Barkin, 2009; Chun et al., 2018; Cornaggia et al., 2021b).

Thakor (1982) provides a theoretical model of bond insurance as a signalling device used by municipalities to credibly convey their *unobservable* credit quality to otherwise uninformed investors. The model assumes that municipalities of high credit quality face a lower cost of purchasing bond insurance than municipalities of low credit quality. This assumption is consistent with the industry practice of bond insurers performing due diligence and charging municipalities with insurance premiums that reflect municipal default risk. In equilibrium, high-quality municipalities have a greater demand for bond insurance than low-quality municipalities, because they realize relatively greater net benefits from insurance.

The signalling value of bond insurance to investors and municipalities is supported by numerous anecdotal and empirical evidence (Bergstresser et al., 2015). Practitioners frequently cite investor demand for bond insurance as a pre-requisite for municipalities to issue bonds at low yields, as it allows investors to avoid performing costly due diligence (Barkin, 2009). Dan Hartman, Managing Director at PFM Financial Advisors LLC (an advisor to government borrowers), states that "putting insurance on top of it [a municipal bond offering] is attractive to some investors who then don't have to do all the research" (Gillers, 2020).

The value of bond insurance is also implicitly illustrated by its frequent usage by municipalities. In 2006, the total debt raised by local municipalities for water infrastructure was \$27.5 billion; 58.7% of this debt was insured. Several academic studies have further estimated that bond insurers can add value when they are of sufficiently high credit quality, by allowing municipalities to offer bonds at lower yields than they would otherwise be able to offer (see Chun et al. (2018) and Cornaggia et al. (2021b)).

#### 2.1.3 The municipal bond insurance industry and its collapse

The municipal bond insurance industry is comprised of a small number of monoline insurers. As of 2006, we estimate that ten bond insurance companies insured approximately 99% of all U.S. municipal water infrastructure debt. More than 90% of this debt was insured by just four insurers: Financial Security Assurance (FSA), Municipal Bond Insurance Association (MBIA), Financial Guaranty Insurance Company (FGIC), and American Municipal Bond Assurance Corporation (AMBAC).

Prior to 2007, municipal bond insurers were nearly all AAA-rated. Even the lone exceptions, such as Dexia, ACA Financial Guaranty, and Radian Asset Assurance, had investment-grade credit ratings of at least A, and only insured less than 1.3% of all municipal water infrastructure debt. Thus, almost all insured municipal debt prior to 2006 was essentially backed by AAA-rated insurers, and bond insurance was a valuable backup against municipal default during this period (Cornaggia et al., 2021b).

During the period of high insurer credit ratings, several municipal insurers began to offer insurance for products unrelated to municipal bonds. Specifically, starting in the 1990's, several insurers—but not all—became actively involved in structured financial products tied to real estate, such as mortgage backed securities and collateralized debt obligations tied to subprime mortgages (Drake and Neale, 2011; Moldogaziev, 2013). Insurer growth in these business lines accelerated through the 2000's (Jayasuriya, 2019). As of 2006, monoline insurers backed approximately \$3.3 trillion in total outstanding paper across all financial products (The Economist, 2007).

The 2007 crash in the residential loan market, however, triggered billions of dollars in claims for the municipal bond insurers that were heavily invested in structured financial products (Moldogaziev, 2013). Eight out of the ten municipal bond insurers in our sample experienced significant decreases in credit quality, and then ceased insuring new municipal debt issues altogether. Cornaggia et al. (2021a), for example, shows that CDS spreads increased dramatically, while market capitalizations fell significantly, for MBIA and AMBAC around July, 2007. FSA and Assured Guaranty Corporation had relatively less exposure to the same structured financial products that had overwhelmed their competitors. These two firms (which later merged) were able to maintain their credit-worthiness through the financial crisis and continue insuring new municipal debt issues (Moldogaziev, 2013; Bergstresser et al., 2015).

The consequences of these events for municipal borrowing have been dramatic. Figure 2 shows that in 2007, \$26.2 billion in municipal debt was raised for water infrastructure, and the fraction of this debt that was insured was only 47.5%—a large drop from the previous year. This percentage further decreased to 21.5% in 2008, and has remained well below its level in 2006.

Figure 3 shows that this time-series change was accompanied by a significant shift in the composition of firms that supplied bond insurance. Monoline insurers such as MBIA, FGIC, and AMBAC had previously insured large amounts of capital prior to 2007 when they were rated AAA. After 2007, however, these firms ceased to insure new municipal debt for water infrastructure once they became saddled by structured product obligations. Assured Guaranty (which now owns FSA), on the other hand, has continued to insure new water bond issues after 2007.

Figures 2 and 3 illustrate that the 2007 crisis has had a lasting, negative impact on the supply of municipal bond insurance. Although investors and municipalities have continued to demand bond insurance—as evidenced by Assured Guaranty's continued growth, as well as analyst reports of investor preferences for insured municipal debt —there are several factors that have limited growth in the supply of bond insurance (Stone, 2015; Gillers, 2020). First, it takes time for insurers to generate the capital bases required to cover potential losses on newly insured debts (Weitzman, 2021). Second, new entrants typically lack the same expertise and reputational capital that incumbent insurance firms previously built over decades (Jayasuriya, 2019). Third, post-financial crisis regulations tied to the municipal bond market remain in flux, creating added uncertainty for embattled insurers.

## 2.2 Hypothesis

In this paper, we argue that the collapse of the municipal bond insurance industry has a significant real impact on drinking water infrastructure. We posit that information frictions in the municipal bond market give rise to persistent relationships between municipalities and bond insurers. When a municipal issuer first decides to use bond insurance to raise external debt, the municipality faces a competitive marketplace of bond insurers competing and bidding amongst themselves to insure the municipality's proposed offering. Once a bond insurer has performed its due diligence and wins its bid to insure a municipality's debt, the bond insurer will continue to monitor the municipality as part of its normal risk management practices (Muni. Bond Adv., 2020).

One consequence of this process is that when a municipality wishes to insure any subsequent debts—either by restructuring existing debts or raising new debt—it will be able to purchase insurance from its pre-existing bond insurer(s) at a lower expected price than what it would otherwise receive from other bond insurers. This difference in prices stems from the fact that existing bond insurers will have already gathered information on the municipality's credit quality over time, and will not have to incur the same fixed costs of initial due diligence that an outside insurer would need to incur in order to assess the municipality's credit worthiness (ceteris paribus).

Our conjecture is consistent with industry practice, as we confirm with several practitioners.[2] They all note that when a municipality seeks insurance for a debt issue, it typically first approaches a pre-existing insurer for backing. Consistent with this observation, we find supporting empirical evidence of repeat insurance contracts between municipal governments and bond insurers in our data. Figure 4, for example, illustrates that 80% of all insurance engagements for new municipal debt issues are with insurers that municipalities have previously relied on for insurance.

[2]Most notably: Suzanne Finnegan, Chief Credit Officer at Build America Mutual, who discussed this paper at the Brookings Municipal Finance Conference on July 14, 2021; Richard Ryffel, Managing Director at First Bank, July 16, 2021; and Marc Joffe, Senior Policy Analyst at the Reason Foundation, July 16, 2021.

The insurance relationships that we propose between municipal issuers and bond insurance intermediaries are similar to the lending relationships between firms and banks that have been studied previously (Rajan, 1992; Petersen and Rajan, 1994). The difference between the municipal insurance context and the bank lending context, however, is in the nature of the information received by various parties. Bank lending relationships stem from banks gaining access to *private* information about firms that is unavailable to other banks. In contrast, insurance relationships stem from existing insurers facing lower costs than outside insurers to process *public* information about municipalities.

We hypothesize that the 2007 shock to municipal bond insurers unexpectedly raised borrowing costs for municipalities that were in pre-existing relationships with adversely affected insurers. Because troubled insurers no longer insured new debt issues, municipalities that had been reliant on these insurers now had to form new insurance relationships with different bond insurers in order to insure new debt (or else issue uninsured bonds at higher yields). New insurers, however, would charge higher premiums than an existing insurer, due to the relatively greater amount of due diligence that the new insurer would need to perform, *ceteris paribus.*

In contrast, municipalities that were already in relationships with healthy bond insurers could continue to purchase insurance at more favorable terms. This reasoning applies to both new debt issues as well as debt restructurings. Thus, the first testable implication of our hypothesis is the following:

**Prediction 1.** *Municipalities with greater dependence on relationships with troubled bond insurers, face relatively higher borrowing costs following the crisis.*

We then argue that higher borrowing costs lead municipalities to raise less debt. In other words, we claim that municipalities cannot maintain high debt levels and fully pass on higher borrowing costs to local residents in the form of higher water service fees, tax rates, or the redirection of capital from other public sector projects. State laws, for example, typically constrain municipal governments from increasing prices for water, electricity, and other utilities. It is also difficult for elected officials to raise utility fees and tax rates, as doing so is procedurally cumbersome and often raises the ire of local residents (Edwards, 2020). Moreover, even when municipalities do raise water service fees, local residents may refuse to pay, leaving local governments with lower-than-expected service revenues (Layne, 2019)

Redirecting capital from other public projects to pay for water infrastructure bonds is also often infeasible, because the debt raised for water infrastructure typically takes the form of revenue bonds. Legally, revenue bonds can only be repaid using cash flows generated by drinking water projects—not by cash flows tied to other public projects (O'Hara, 2012). These legal and institutional constraints on the sources of capital available to local governments motivate our second empirical prediction:

**Prediction 2.** *Municipalities in relationships with troubled insurers respond to higher borrowing costs by raising less debt.*

As described in Section 2.1.1, investment in water infrastructure encompasses four main areas. The majority of investment corresponds to the replacement and renewal of pipes used for water transmission and distribution. Water infrastructure investment also includes capital directed towards treatment plants, water storage facilities, and source processing.

We argue that reductions in total borrowing lead to reduced investment into drinking water infrastructure. As described above, we posit that there are numerous institutional constraints that limit municipalities' ability to raise investment capital from alternative sources (such as service fees or other public projects). We also assume that local municipalities are able to only partially—but not fully—make up for shortfalls in debt financing by obtaining state and federal subsidies of equal measure; loan programs for drinking water (such as Drinking Water State Revolving funds (DWSRF)) tend to be orders of magnitude smaller than the capital raised through municipal bonds. The third prediction of our hypothesis is therefore the following:

**Prediction 3.** *Municipalities in relationships with troubled insurers respond to higher borrowing costs by cutting investment into public drinking water infrastructure.*

We then postulate that reductions in water infrastructure investment have real effects on drinking water quality. As described in Section 2.1.1, numerous studies find links between aging infrastructure and drinking water pollution (see for example, Renwick et al. (2019)), especially with respect to deteriorating pipe networks. Moreover, public water authorities claim that infrastructure improvements are their most critical need, while numerous industry experts argue that existing infrastructure spending is inadequate. We thus hypothesize that reductions in infrastructure investment have a binding, detrimental effect on water pollution.

These effects could materialize in both the short-run and long-run. In the short-run, increased borrowing costs likely hamper municipalities' ability to address immediate problems such as emergency contamination (as described in Section 2.1.1, nearly half of all municipal spending on drinking water is a reaction to system failures). Constraints on investment may also lead to long-run deterioration of water quality (for example, by failing to replace deteriorating pipes and other aging water infrastructure that contributes to bacterial and inorganic water contamination). Our fourth prediction is therefore:

**Prediction 4.** *Municipalities in relationships with troubled insurers experience relatively greater drinking water pollution following the crisis.*

## 2.3 Alternative Views

The null hypothesis that we test against is the view that the collapse of municipal bond insurance has no causal impact on drinking water infrastructure or quality. This view is theoretically compelling for several reasons, and may explain why the connection between bond insurance and water pollution has not been studied previously. This perspective is also supported by recent empirical research that concludes that bond insurance adds little to no value for local governments after the crisis (Kriz and Joffe, 2017; Cornaggia et al., 2021a). We describe several models below that give rise to the null hypothesis.

First, if information frictions are insignificant in practice, then shocks to bond insurance relationships should have no impact on municipal borrowing costs or investment activities. Bond insurance claims would simply represent state-contingent payments that can be replicated by investors and issuers on their own. Thus, there should be no empirical link between insurer relationships and municipal borrowing costs.

Second, even if information frictions are significant in practice, municipalities may have other means of overcoming these frictions. For example, perhaps credit ratings on municipal debt issues are sufficient for municipalities to signal their credit quality. In this scenario, existing relationships with insurers should be irrelevant for municipal borrowing costs because they will have alternative signalling tools for raising capital.

Third, bond insurance may exist solely as a means of preserving the tax-exempt status of municipal bonds (Nanda and Singh, 2004). Municipal bond insurance is unique among the various means that are available to investors for hedging security risk, in that payments made to investors by bond insurers in case of municipal default remain tax exempt (unlike other potential insurance tools, such as credit default swaps). If this model were the sole reason why municipalities use bond insurance, we should not observe persistent insurance relationships, since the tax benefits of bond insurance could be provided equally by all insurers irrespective of past insurance relationships. Moreover, we should not observe any differences in borrowing costs across municipalities with different bond insurer relationships, since the 2007 shock to bond insurers should affect all municipalities equally.

Finally, shocks to bond insurer relationships may not impact drinking water pollution if governments have alternative sources of capital—outside of external debt financing—that they are able to access in order to continue investing in drinking water infrastructure. For example, perhaps local governments respond to increased borrowing costs by redirecting capital from other public projects to drinking water infrastructure. Additionally, municipalities may be able to raise capital through federal or state subsidies such as DWSRF. If these alternative funding sources are sufficient to overcome capital shortfalls due to bond insurance shocks, then we should not observe an empirical link between bond insurer relationships and municipal investments in water infrastructure.

# 3 Data

## 3.1 Sources

We construct a unique panel dataset from several different data sources. In this section, we summarize the dataset assembly and describe our sample. We provide further details in the Appendix.

First, we obtain data from the U.S. Census Annual Survey of State and Local Government Finances from 1980 to 2019. These data contain detailed information on the finances and investment activities of local U.S. municipalities. In particular, the data contain detailed records of capital expenditures for supplies and repairs to water infrastructure, financing sources and debt servicing expenses, and water service revenues.

Second, we collect detailed information on municipal debt issues from SDC Platinum's Global Public Finance database over the years 1966 to 2019. These data enable us to construct a detailed time-series of debt used to finance public drinking water infrastructure for each municipality in our sample. SDC also contains information about whether an individual bond issue is insured, and if so, the identity of the insurance company that is backing the debt. We supplement these data with information on credit ratings for individual debt issues, municipal issuers, and bond insurers using information from Capital IQ and Eikon.

Third, we collect data on public drinking water quality from the U.S. EPA. The EPA maintains a database called the Safe Drinking Water Information System (SWDIS), which contains information on local community water systems throughout the U.S. The database contains records of federal violations of drinking water standards from 1980 to 2019, such as instances of community water systems containing hazardous contaminant levels that exceed the limits set forth by the SDWA.[3] These data are frequently used in studies of drinking water pollution. We collect information on contaminants such as coliform bacteria, treatment by-products, and inorganic compounds; as discussed in Section 2.1.1, these are the most commonly observed contaminants found in drinking water, and they are also closely attributed to aging and deteriorating water infrastructure (Allaire et al., 2018; Renwick et al., 2019; Nat. Res. Council, 2006).

## 3.2 Descriptive Statistics

Table 1 presents summary statistics that describe all the municipalities for which we are able to collect data (columns denoted by "All Municipalities"). There are 3,134 unique

[3] The database also maintains records of non-health related violations, such as water system reporting failures

municipalities that we are able to observe in the Census extracts. The data consists of large cities as well as small townships: the average number of people in a given municipality-year is 189.2 thousand, with a standard deviation of 648.6 thousand.

Table 1 shows that across all municipalities over the sample period, there are on average 1.765 federal drinking water violations observed per year. There is significant variation in drinking water pollution over time and across municipalities. As Figure 1 shows, the number of drinking water violations observed over time has increased significantly, particularly over the past 15 years. Furthermore, the increasing standard errors around the annual averages illustrate greater cross-sectional dispersion in water pollution over time.

To quantify the importance of these pollution figures, we weight the number of observed drinking water violations by the number of people exposed to these violations (i.e. the population sizes served by individual water systems). The data suggest that up to 22.8 million people per year suffer from poor water quality in the U.S. Our figures are consistent with Allaire et al. (2018), who estimate that between 9-45 million people have been possibly affected by drinking water pollution each year in the U.S. from 1982 and 2015.

Table 1 also characterizes municipal drinking water infrastructure. The annual drinking water service revenues earned by the average U.S. municipality is \$11.89 million between 1980 and 2019. The average amount of annual municipal investment into drinking water infrastructure is \$8.131 million across all sample years. The high standard deviation of \$47.36 million in investment across all municipality-year observations reflects significant variation in infrastructure investment both across municipalities and over time within a given municipality.

When municipalities raise debt to finance drinking water infrastructure, the average amount of debt raised is \$11.3 million. Aggregating these debt issuances over time and accounting for debt repayment, the average amount of municipal debt outstanding for water infrastructure is approximately \$107.8 million in a given year. This debt is primarily in the form of revenue bonds, which constitute approximately \$92.31 million in outstanding debt.

Table 1 and Figure 2 illustrate the cross-sectional and time-series distribution of insurance usage for municipal water bonds. For example, Table 1 shows that the four largest monoline insurers in the U.S.—FSA, MBIA, FGIC, and AMBAC—back the vast majority of insured debt in our sample. Figure 2 shows historically that when municipalities issue bonds for water infrastructure, they become increasingly reliant on bond insurance up until 2006.

Table 1 and Figure 4 depict the nature of relationships observed between bond insurers and municipal issuers. Table 1 shows that the average number of bond insurers used by municipalities in our sample is 2.06. Figure 4 illustrates significant persistence in these relationships over time. Among municipalities that use bond insurance more than once, approximately 80% obtain bond insurance from an insurer that they have worked with previously.

Finally, Table 1 describes other sources of financing used by municipalities for drinking water infrastructure. For example, intergovernmental transfers from federal, state, and local governments are approximately \$0.664 million per year from 2013 to 2018 (the years when such data is available). For comparison, municipalities raise approximately \$18.69 million in water infrastructure debt over the same time period. These figures illustrate that external debt financing is significantly more important for water infrastructure than other sources of capital such as intergovernmental transfers.

# 4 Empirical Framework

## 4.1 Identification Strategy

To estimate the causal effects of municipal bond insurance on drinking water pollution, we devise an identification strategy that exploits heterogeneity in municipality-insurer relationships. In particular, we exploit variation in the amounts of outstanding municipal debts that are insured by different insurance companies prior to the 2007 crash. As discussed in Section 2.3, the ten bond insurers in our sample nearly all had AAA credit ratings prior to 2006, yet there is significant heterogeneity in the amounts of debt that are insured by different insurers across municipalities (see Table 1).

Our central identification assumption is that the 2007 crash in structured financial products—which caused eight out of the ten bond insurers in our sample to experience severe financial troubles—was unanticipated and exogenous to pre-crisis heterogeneity in relationships between municipalities and bond insurers. In other words, we assume that municipalities formed relationships with AAA-rated bond insurers without the foresight that some AAA insurers would cease insuring new debts after 2007, while other AAA insurers would continue to do so.

Our identification assumption does *not* require that pre-crisis heterogeneity in relationships between municipalities and issuers is random. Instead, we assume that municipality-insurer relationships reflect a competitive equilibrium endogenously formed by individual optimization decisions by municipalities and insurers; this assumption is based on common descriptions of industry practice, as initial insurance relationships are essentially formed through a competitive bidding process among insurers for municipal debt issues (Muni. Bond Adv., 2020). Our empirical strategy takes the pre-existing relationships between municipalities and insurers as given, and assumes that the events of 2007 are exogenous to variation in these relationships. We later provide evidence to support the validity of this assumption, and we also present evidence to rule out potential violations of it.

We use the market exit of bond insurers as proxies for negative shocks to the relationships between bond insurers and municipalities. We assume that municipalities that had larger fractions of outstanding debts insured by these troubled insurers suffered larger negative shocks to their financing capabilities. More specifically, for each municipality in our sample, we measure the fraction of total outstanding debt (as of 2006) that is insured by any of the eight troubled insurers. We then compute the sample median of this measure across municipalities, and categorize each municipality as having a "high" (above sample-median) or "low" (below sample-median) fraction of debt that is insured by troubled insurers. We characterize municipalities that have high (low) exposures to troubled insurers as having relatively larger (smaller) negative shocks to their financing constraints starting in 2007.[4] Figure 5 plots the sample distribution of outstanding debt that is insured by troubled insurers. There is significant dispersion in this measure across municipalities, and the median fraction of debt backed by troubled insurers is 53%.

[4]We use 2007 as our treatment year, following Cornaggia et al. (2021a) and Chun et al. (2018), who establish that the stock prices and credit quality of insurers such as MBIA and AMBAC experience significant declines in 2007. All of the empirical results that we present are also robust to using 2008 as the start of our treatment.

It is important to note that municipalities in both the high- and low- exposure groups are affected by the shock. If the relative difference in the impact of the shock between the two groups are statistically significant, then we interpret the data as supportive of the view that bond insurance has a causal effect on municipal outcomes. To quantify the full impact of bond insurance on municipalities, we multiply our regression estimates by a factor of 2, to estimate how much a municipality's outcomes would change if all of its pre-existing bond insurers were to cease insuring new debt. This scaling stems from the fact that our regression estimates are based on above vs. below median sample comparisons.

The full set of municipalities that we analyze using this identification strategy are described in Table 1 ("Analysis Sample"). As illustrated in Table 1, the analysis sample is comprised of relatively large U.S. municipalities. For example, the average municipal population in a given sample year is 362.3 thousand, while the average annual property tax revenue is $194.2 million; both of these figures are higher than their respective averages for the full sample. The sample that we analyze also corresponds to municipalities that experience relatively higher levels of water pollution (2.34 average SDWA violations per year versus 1.77 average SDWA violations per year in the full sample).

## 4.2 Plausibility of Identification Assumption

We present theoretical arguments and empirical evidence to support the credibility of our identification strategy. The plausibility of our identification assumption enables us to infer a causal link between bond insurance and drinking water pollution. Prior to 2007, we estimate that 99% of all insured municipal debt raised for water infrastructure was essentially backed by AAA-rated insurers. It is reasonable to assume that neither investors nor municipalities could distinguish bond insurers given their homogeneous credit ratings. Moreover, it is unlikely that market participants could predict the sudden downgrades of individual bond insurers. It is therefore plausible to assume that the bond insurer shock that we exploit is unlikely to be correlated with municipal characteristics that otherwise explain differences in borrowing costs, investment behavior, etc.

Consistent with this assumption, Table 2 shows that municipalities across the high-exposure and low-exposure samples have statistically indistinguishable characteristics across a number of observable, pre-crisis metrics that relate to the outcomes we study. For example, municipalities in the two groups have similar credit ratings, they face similar borrowing costs, and they share the same reliance on external debt financing prior to 2007. If municipalities in the high-exposure group were riskier or more likely to perform worse in the crisis relative to low-exposure municipalities, we should expect such differences to be reflected in these metrics.

We also find that municipalities in the high- and low-exposure samples share similar population sizes, water service revenues, and property tax revenues prior to the crisis. Figure 6 further shows that the distribution of municipalities across the treatment and control samples is relatively well dispersed throughout the U.S., and not concentrated in geographic areas that might otherwise be subject to idiosyncratic economic trends. These data reinforce the identification assumption that municipalities in the treatment group do not appear to systematically differ from municipalities in the control group in a manner that would otherwise explain divergences in borrowing, investment, and pollution after 2007.

Additionally, Figure 5 suggests that municipalities do not appear to deliberately target insured debt levels near our defined threshold for high versus low exposures. There is little sign of an increased concentration of municipalities around the sample-median threshold of 53%. The evidence thus suggests that prior to 2007, different types of municipalities do not appear to be sorting across different insurers in a manner that would invalidate our identification assumption.

The main differences that we observe between high and low exposure municipalities in 2006 are in the average fraction of outstanding debt that is insured and the average number of insurer relationships. These differences are to be expected for two reasons. First, by construction, high exposure municipalities have a greater fraction of outstanding debt that is insured by firms that become troubled after 2007. Second, the majority of bond insurers in the sample (i.e. eight out of ten) become troubled. As a consequence, the municipalities that are most likely to enter the treatment sample are those municipalities that have a greater total fraction of debt that is insured by multiple insurers prior to the crisis.

If differences in insured debt fractions and/or numbers of insurer relationships correlate with omitted factors that impact the outcomes we study, then our identification assumption would be invalid. For example, it is theoretically possible that bond insurers that were more involved with structured financial products provided more insurance for riskier municipalities that later experienced greater decline during the crisis. Such sorting between insurers and municipalities would constitute an omitted factor in our regression analysis. We critically assess this (and other) possibilities in our empirical analysis (Section 5.5).

### 4.3 Sample Selection

It is important to note that our regression estimates are identified off of variation in municipalities' relationships with bond insurers. As such, our treatment effect estimates are only applicable to municipalities that use bond insurance; we do not assess the potential impact of bond insurance on municipalities that do not use insurance. We exclude uninsured municipalities from our analysis for two reasons.

First, focusing on insured municipalities improves the plausibility of the identification assumption, as uninsured municipalities likely differ from insured municipalities along unobservable dimensions such as inherent credit quality (hence the signaling value of bond insurance in Thakor (1982)). Cornaggia et al. (2021b) present empirical evidence of these differences by estimating various selection models of municipal insurance choice. Second, municipalities that use bond insurance contain a large majority (73%) of the U.S. population. Our findings thus remain relevant, because they describe the effects of bond insurance for a significant number of people who rely on public drinking water.

## 5 Findings

### 5.1 Borrowing Costs

We test our first empirical prediction by analyzing two complementary measures of municipal borrowing costs: the true interest cost (TIC) of debt issues, and the total financing expenses paid for all outstanding debts. The first measure, TIC, is a term commonly used in municipal debt offerings. It is the effective yield on a bond that equates the price of the bond with the time value of all interest payments, par values, and other expenses such as bond insurance premia. We collect this measure from SDC for all new and restructured debt issues.

The second measure, total financing expenses, captures the total costs paid by municipalities for its outstanding debt. This measure implicitly incorporates the volume of outstanding debt for which the municipality is paying TIC, which not only includes new and restructured debt, but also includes existing debt that has not been restructured. This measure, taken from the Census, is useful to examine because it illustrates the absolute scale of financing burdens on municipalities.

We estimate "difference-in-difference"-like measures of the relative changes in borrowing costs for high- versus low- exposure municipalities around 2007. More specifically, we estimate the following regression specification:

$$BorrowingCost_{i,t} = \alpha_1 + \beta_1 \cdot Treatment_{i,t} + \beta_{c,1} \cdot Controls_{i,t} + y_i + v_t + \epsilon_{i,t} \tag{1}$$

where for municipality $i$ in year $t$, $BorrowingCost_{i,t}$ takes on one of two values. The first value is the weighted average of the true interest cost of revenue bonds issued by municipality $i$ in year $t$ (where the weights are the dollar amounts of each issuance). The second value is the logarithm of the total financing expenses paid by municipality $i$ in year $t$.[5]

$Treatment_{i,t}$ is a binary indicator that equals one if municipality $i$ is in the high-exposure group and year $t$ is 2007 or later (and equals zero otherwise). $Controls_{i,t}$ include: the logarithm (log) of the weighted average maturity of the new revenue bonds issued by municipality $i$ in year $t$, the (log) amount of total new revenue bonds issued by municipality $i$ in year $t$, the (log) number of drinking water health violations observed in municipality $i$ in year $t-1$, the (log) amount of drinking water service revenues earned by municipality $i$ in year $t-1$, the (log) amount of pre-existing debt outstanding (which includes both revenue bonds and general obligation bonds) of municipality $i$ in year $t-1$, the (log) of property taxes in year $t-1$, the (log) population of municipality $i$ in year $t-1$, the fraction of total outstanding debt that is insured for municipality $i$ in year $t-1$, an indicator for whether municipality $i$ in year $t$ has a credit rating, a numerical score corresponding to the credit rating of municipality $i$ in year $t$ where applicable, and the total number of unique insurer relationships

[5] See Table A1 for a more detailed description of these measures.

entered into by municipality $i$ in year $t$. We also include municipality and year fixed effects, and we cluster standard errors by municipality and year.

The main regressor of interest is $Treatment_{i,t}$. Under our key identification assumption, the estimated coefficient for $Treatment_{i,t}$ provides a measure of the causal effect of bond insurer downgrades on municipal borrowing costs for the high- vs. low- exposure groups. Scaling the treatment effect by a factor of 2 provides an estimate of how much the borrowing costs change for a sample municipality whose pre-existing insurers all cease to insure new debt.

The various controls added to the regression proxy for factors that likely influence borrowing costs, such as issuer credit ratings, municipal income (service revenues), investment needs (drinking water health violations), the total amount of debt that is insured, and proxies for general economic conditions (population and property taxes). Municipality fixed effects are included to control for time-invariant components of borrowing costs for a given municipality. Year fixed effects control for aggregate changes in borrowing costs across all municipalities in a given year.

Table 3 depicts the regression estimates for Specification (1) using TIC as the dependent variable. The columns in Table 3 illustrate coefficient estimates for the regressions with increasing numbers of controls, to illustrate the robustness of the results across model choice. The coefficient estimate for $Treatment$ is approximately 14 basis points across all specifications. The regression estimates imply that the TIC for new debt increase from 5.87% to 6.15% if a municipality' bond insurers all cease to insure new debt (as per Table 1). The stability of the coefficient estimates for $Treatment$ across columns shows that our treatment effect estimates are robust to different empirical specifications.[6]

The results in Table 3 indicate that the 2007 crash increased the borrowing costs of municipalities that were more reliant on relationships with troubled insurers. Even though municipalities in the high- and low- exposure samples have similar borrowing costs prior to 2007, high-exposure municipalities paid higher TIC than low-exposure municipalities. These higher costs are mostly reflected in higher yields, rather than other borrowing costs such as

[6] We also note that our results are robust to alternative measures of municipal credit ratings, such as categorical indicators rather than numerical scores.

insurance fees, as the vast majority of municipal debt raised after 2007 is uninsured.

Table 4 depicts the regression results for Specification (1) using total financing expenses as the dependent variable (while removing new debt issuance and maturity from the controls). The treatment effect estimates in Table 4 are at least 0.101 across all columns. The estimates remain stable across specifications. The results imply that municipalities pay approximately 20.6% higher financing expenses if their insurers cease to insure new debt. Because the average municipality in the low-exposure group pays financing expenses of \$3.156 million per year, this coefficient implies that the municipalities in our sample spend \$732 million more in financing expenses annually following the shock ($\approx 1,014 \cdot (\exp(20.6\%) - 1) \cdot 3.156$).

We estimate (approximately) how the treatment effect on total financing expenses varies over time, by allowing the treatment effect to vary each year in Specification 1. We plot the estimated treatment coefficients in Figure 7. Panel A shows that the collapse of bond insurance has had a persistent impact on municipal borrowing costs. Prior to 2007, the treatment effect is positive and statistically significant only once (in 2004); high and low exposure municipalities share similar borrowing costs every year. Starting in 2007, however, the treatment effect is positive and statistically significant in eight out of eleven years. These effects are consistent with the prolonged collapse of bond insurance, as discussed in Section 2.

Taken together, the results in Table 3, Table 4, and Figure 7 show that the collapse of municipal bond insurance has had a significant impact on municipal borrowing costs. Municipalities that were more dependent on insurers that became troubled in 2007 have faced relatively high costs of debt financing over time. The data thus support our first empirical prediction.

## 5.2 Debt Outstanding

To test our second empirical prediction, we examine changes in the amounts of debt outstanding held by municipalities following the 2007 shock to monoline insurers. Specifically, we estimate the following regression model:

$$Log(Debt\ Outstanding_{i,t}) = \alpha_3 + \beta_3 \cdot Treatment_{i,t} + \beta_{c,3} \cdot Controls_{i,t} + y_i + v_t + \epsilon_{i,t} \quad (2)$$

where $Log(Debt\ Outstanding_{i,t})$ is the logarithm of the total amount of debt outstanding held by municipality $i$ in year $t$. All other variables, other than new debt issuance and maturity, remain the same as in Specification (1).

The results are presented in Table 5. The coefficient for $Treatment_{i,t}$ is at least $-0.0259$ across all columns. The results indicate that sample municipalities reduce their outstanding debt by at least 5.18% per year when their pre-existing bond insurers cease to insure new debt. To illustrate the economic magnitude of this effect, it is worth noting that the average municipality in the low-exposure group has \$159.2 million in revenue bonds outstanding. The regression estimates thus imply that municipalities raise \$8.1 billion less revenue debt annually after the shock ($\approx 1014 \cdot (\exp(5.18\%) - 1) \cdot 159.2$). The data support the second prediction of our hypothesis: high-exposure municipalities reduce their relative reliance on external debt financing after 2007.

## 5.3 Investment in Public Drinking Water Infrastructure

To test our third prediction we estimate the following model:

$$Log(Investment_{i,t}) = \alpha_4 + \beta_4 \cdot Treatment_{i,t} + \beta_{c,4} \cdot Controls_{i,t} + y_i + v_t + \epsilon_{i,t} \quad (3)$$

where $Log(Investment_{i,t})$ is the logarithm of the total expenditures devoted to water infrastructure by municipality $i$ in year $t$. As explained in Table A1, investment in drinking water infrastructure encompasses the servicing of pipes, upkeeping of supply stations and water treatment facilities, etc. All other variables in Specification (3) remain the same as in Specification (2).

The results are presented in Table 6. The regression coefficient for $Treatment$ ranges from approximately $-2.7\%$ to $-3.7\%$ across all columns. The magnitudes of the treatment effect are broadly similar across regression specification, illustrating the robustness of the estimates. The data imply that municipalities reduce investment into public drinking water infrastructure by approximately 6.54% annually when their insurers stop insuring new bonds. Because the average municipality in the low-exposure group invests \$16.31 million in drinking water infrastructure per year, this coefficient implies that the municipalities in our sample invest \$1.046 billion less capital per year in drinking water infrastructure after the shock ($\approx 1,014 \cdot (\exp(6.54\%) - 1) \cdot 16.31$).

We also estimate (approximately) how the treatment effect varies over time in Specification 3. Panel B of Figure 7 shows that while there are no significant differences in investment levels between high- and low- exposure municipalities in the years leading up to the crisis, there are significant differences in investment levels observed after the crisis. These results follow naturally from the persistent effect of the shock on municipal borrowing costs.

The findings in Table 6 and Figure 7 are consistent with our hypothesis. Negative shocks to bond insurers cause municipalities to experience higher borrowing costs, which leads to reductions in external debt financing and reductions in drinking water infrastructure investment. The effect of insurer downgrades on investment is slightly larger in magnitude than the effect of insurer downgrades on debt servicing expenses. The results imply that increases in financing expenses lead to offsetting reductions in infrastructure investment.

As discussed in Section 2.1.1, public water systems report that capital expenditures for repairing aging and deteriorating water infrastructure is their most pressing concern. Moreover, nearly half of all such expenditures are incurred as a reaction to system failures. The evidence that we document thus suggests that the shock to bond insurance exacerbates already tight investment constraints faced by water systems.

## 5.4 Drinking Water Pollution

To test our fourth empirical prediction, we measure the number of federal health violations observed for contaminants that are specifically associated with worsening infrastructure (such as coliform and treatment by-products), and the total number of people who are exposed to these violations. We then estimate the following regression model:

$$Log(Water\ Pollution_{i,t}) = \alpha_5 + \beta_5 \cdot Treatment_{i,t} + \beta_{c,5} \cdot Controls_{i,t} + y_i + v_t + \epsilon_{i,t} \quad (4)$$

where $Log(Water\ Pollution_{i,t})$ takes on one of two values. The first measure is the logarithm of health-related SDWA violations observed across all public water systems in municipality $i$ in year $t$. The second measure is the logarithm of the product of the number of health-related violations times the number of people served by all public water systems in municipality $i$ in year $t$. All other variables remain the same as in Specification (2).

The results are presented in Table 7. In Panel A, the regression coefficient for $Treatment$ ranges between 0.0588 and 0.0728 across all columns. The estimates imply that the number of health violations of federal drinking water standards increase by approximately 5.88% in high-exposure municipalities relative to low-exposure municipalities. To understand the economic magnitude of this effect, we note that municipalities in the low-exposure group averaged 2.34 drinking water violations annually. The estimated treatment effect thus implies that municipalities in our sample have at least 296 more water violations per year when their insurers no longer insure new debt ($\approx 1014 \cdot (\exp(11.76\%) - 1) \cdot 2.34$).

To illustrate the (approximate) time-series variation in the treatment effect on pollution, we estimate the treatment effect each year using Specification 4. Panel C of Figure 7 shows increased drinking water pollution in both the short-run and long-run following the collapse of bond insurance. These effects are consistent with our predictions in Section 2.

In Panel B of Table 7, the treatment effect coefficient ranges between 0.377 and 0.447 across different specifications. These estimates indicate that bond insurer downgrades lead to a 45.6% increase in the number of people who are exposed to drinking water pollution in high- vs. low- exposure municipalities. To interpret this figure in terms of the absolute number of people who are affected by these shocks, we note that the average population exposed to drinking water pollution prior to 2007 in low-exposure municipalities is approximately 3,318 per municipality. Our estimates thus imply that negative shocks to bond insurance have caused a relative increase of 1.54 million people to be exposed to health violations of federal drinking water standards in high-exposure vs. low-exposure municipalities ($\approx$

$1014 \cdot (\exp(37.7\%) - 1) \cdot 3318$).

These findings are consistent with our hypothesis, and reject the null. In fact, our estimates indicate that the collapse of municipal bond insurance explains 32% of the relative rise in drinking water pollution observed across between high-exposure and low-exposure municipalities. Prior to 2007, while low-exposure municipalities averaged 1.04 SDWA violations per year, high-exposure municipalities averaged 0.93 SWDA violations annually. After 2007, however, while low-exposure municipalities averaged 2.00 SWDA violations per year, high-exposure municipalities now averaged 2.08 SWDA violations annually. These figures imply a relative increase of 0.19 SWDA violations per year ($\approx [1.04 - 0.93] - [2.00 - 2.08]$), of which, 0.06 SWDA violations can be attributed to the collapse of municipal bond insurance.[7]

## 5.5 Alternative Hypotheses

### 5.5.1 Sorting Between Insurers and Municipalities

One alternative hypothesis for our findings is that the results represent a spurious correlation that reflects sorting between specific types of bond insurers and municipalities. Bond insurers that were more involved in structured financial products may have been more likely to form relationships with municipalities that were riskier or of worse credit quality. For example, perhaps troubled insurers had a greater risk appetite for municipalities that were potentially more likely to experience general economic decline and/or changes in the demand for clean water. Our results could therefore reflect general economic decline in high-exposure municipalities following the crisis, rather than the direct effects of bond insurer shocks.

There are numerous pieces of evidence that are inconsistent with this explanation. First, Table 2 shows that municipalities in the high-exposure and low-exposure samples share remarkably similar conditions prior to the crisis, such as similar credit ratings, borrowing costs, property tax revenues, etc. If high-exposure municipalities were poorly run or if they issued riskier bonds, one would expect that investors would charge them higher bond yields or that these municipalities would have worse credit ratings. The evidence to the contrary supports the identification assumption that municipalities of worse credit quality were not

[7] Our estimates in Table 7 show that the collapse of bond insurance leads low-exposure municipalities to experience an increase of 0.06 SWDA violations annually ($\approx 1.04 \cdot (\exp(5.88\%) - 1)$)

more likely to work with insurers that experienced financial troubles in the crisis.

Second, Figure 7 shows that time-series trends in borrowing costs, investment behavior, and water quality are statistically indistinguishable between the two groups of municipalities prior to the 2007 shock (i.e. the treatment estimates across almost all pre-crisis years are statistically indistinguishable from 0). The evidence suggests that municipalities in the high-exposure and low-exposure samples were not trending in different directions prior to the crisis.

Third, Table 8 shows that our results are not driven by demand-side changes in water consumption. To see this fact, we estimate Specification (3), but use the logarithm of water service revenues for municipality $i$ in year $t$ as the dependent variable (all other variables remain the same as in Specification (3), with the exclusion of water service revenues as a control). If the observed increases in high-exposure municipalities' borrowing costs are driven by contemporaneous declines in water service revenues, then we should observe a negative correlation between water service revenues and credit rating downgrades of insurers in the immediate years after the 2007 shock. Our findings to the contrary, however, suggest that there are no demand-side reductions in municipalities' water service revenues that might otherwise explain increased borrowing costs after 2007.

Fourth, Table 9 shows that even after 2007, high-exposure and low-exposure municipalities do not show significant differences in outcomes such as population growth or property taxes—proxies for general economic conditions that might otherwise explain municipal borrowing costs or infrastructure investment needs. We estimate these effects using Specification (3), but use the logarithms of municipal population (Panel A) and property taxes (Panel B) as the dependent variables; all other variables remain the same as in the original specification (we exclude the lagged outcome variables from the controls). The coefficient for the treatment effect is statistically insignificant across all columns. These findings reinforce the interpretation of the main results, i.e. that the observed differences between high-exposure and low-exposure municipalities in borrowing costs and investment behavior after 2007 are driven by insurance unavailability rather than general economic conditions.

Fifth, we show that our results hold primarily for revenue bonds, but not for general obligation bonds. If high-exposure and low-exposure municipalities experience divergent economic fortunes after 2007, we should also observe our main results for G.O. bonds, since the payments for these bonds stem from all revenue streams earned by a municipality, and therefore reflect municipalities' general economic conditions. Table 10 shows results for Specifications 1 and 2, estimated using G.O. bond yields and G.O. bond amounts as dependent variables. The insignificant treatment coefficients across all columns of Panels A and B of Table 10 illustrate that the 2007 shock does not predict changes in G.O. bond yields or G.O. borrowing amounts. These results further suggest that changes in general economic conditions are unlikely to explain our results.

### 5.5.2 Mechanical Relationship between Treatment and Outcomes?

Another important consideration is whether the treatment that we study is mechanically related to municipal outcomes such as borrowing costs and water pollution. As discussed in Section 4, our treatment is based on the total fraction of municipal debt that is insured by companies that later become severely troubled. Because the majority of bond insurers in our sample become troubled in the crisis (i.e. 8 out of 10), municipalities that use a relatively larger number of insurers prior to 2007 are more likely to enter the high-exposure group than municipalities that use fewer insurers, *ceteris paribus*.

Such assignment is a problem if municipalities that use greater numbers of insurers differ from other municipalities along unobservable dimensions that otherwise explain the outcomes that we study. For example, municipalities that are inherently riskier may use more bond insurers than municipalities that are safer, as individual bond insurers may be only willing to insure small fractions of a risky municipality's total debt. If riskier municipalities suffer greater economic decline in the crisis, then we would observe a spurious correlation between the treatment and municipal outcomes such as borrowing costs and pollution levels.[8]

There are several pieces of evidence that are inconsistent with this hypothesis. First, all of our results are robust to controlling for the number of insurers that a municipality has a relationship with, as well as the total fraction of municipal debt that is insured. Second, Table 2 shows that municipalities in the high-exposure and low-exposure samples do not

[8]Similar arguments can be made for municipalities that differ in size or the total amounts of municipal debt that are insured.

differ along dimensions that would otherwise suggest differences in underlying credit quality or general economic conditions prior to the crisis, such as borrowing costs. Third, our results in Table 10 show that even after the crisis, the yields of G.O. bonds across the high-exposure and low-exposure samples are similar, suggesting that differences in borrowing costs for revenue bonds, infrastructure investment, and water pollution levels are not simply driven by mechanical correlations between high-exposure assignment and municipal outcomes.

Finally, we repeat our analysis in Tables 3 through 6 using different sample definitions for the high-exposure and low-exposure groups. We measure the 25th and 75th percentiles of the fraction of sample municipal debt that is insured by troubled insurance companies as of 2006. The low-exposure (high-exposure) sample consists of municipalities that are below the 25th percentile (above the 75th percentile) of this measure. All other variables remain the same as in the original specifications.

This analysis allows us to see whether the effects of bond insurance for high-exposure vs. low-exposure municipalities are in line with our hypothesis, as they should be larger in magnitude than our main sample results given that we are now comparing municipalities that experience relatively larger vs. smaller bond insurer shocks. The results are presented in Table 12. Consistent with our hypothesis, the treatment effect estimates are almost double our main effects (the statistical significance decreases due to the smaller size).

#### 5.5.3 Demand versus Supply of Bond Insurance?

Another alternative explanation for our findings is that the changes in borrowing and investment behavior that we document are driven by changes in the demand for bond insurance, rather than supply-side shocks to bond insurers. Perhaps after the crisis, high-exposure municipalities that had been reliant on troubled insurers determined that bond insurance was actually not helpful for them.

We assess this explanation in several ways. First, if bond insurance was deemed to be unhelpful for municipalities, it is unclear why we would observe changes in investment behavior or differences in drinking water quality between high-exposure and low-exposure municipalities after the crisis. Second, we show that our results are stronger when we examine municipalities that have lower interest coverage ratios. These are the municipalities that are likely to be more sensitive to changes in external financing constraints. The results are presented in Table 11 for all our main specifications in Tables 3 through 6. These findings further reinforce that our main results are driven by supply-side shocks to bond insurers, rather than relative changes in the demand for bond insurance by high-exposure vs. low-exposure municipalities.

#### 5.5.4 2010 Moody's Credit Rating Recalibration

Another alternative explanation for our findings is that they are spuriously correlated with municipal credit rating changes implemented by Moody's in 2010. Cornaggia et al. (2018) and Adelino et al. (2017) find that Moody's recalibration of municipal credit ratings (which was implemented to bring municipal credit rating methodologies more in line with the ratings practices used for corporate credit) had a significant impact on municipal yields and public sector employment. We assess whether these changes can also explain the patterns that we observe for water infrastructure.

There are two analyses that suggest that the Moody's recalibration is not driving our results. First, we note that all of our main results control for the credit ratings of municipal issuers, as well as year fixed effects. If our results are explained by changes in issuer ratings due to the Moody's recalibration, then we should not have observed the significant treatment effects that we document. Second, we re-estimate all of our main specifications using a truncated sample that ends in 2009 (i.e., we exclude sample observations after the recalibration event). Table 13 shows that all of our main results hold even for this subsample. These results therefore reinforce our hypothesis and support the view that bond insurance intermediaries have a significant impact on public infrastructure.

# 6 Conclusion

This paper presents new empirical evidence that municipal bond insurance intermediaries have significant real effects on public infrastructure investment and quality. Our findings suggest that the exit of major municipal bond insurers from the market for new insured debt offerings—due to their involvement in securitized financial products—has led to tighter financial constraints for many local governments. We study public drinking water, and document that local municipalities respond to higher borrowing costs by reducing external borrowing, cutting back on investment in drinking water infrastructure, and subsequently experiencing higher levels of drinking water pollution.

The findings illustrate that the inability to provide safe drinking water—arguably the most critical public good provided by local governments—can be partially traced back to market failures in the bond insurance industry. Our paper adds to a growing literature that studies the importance of insurance intermediaries in financial markets, illustrates the empirical importance of well functioning insurance markets for public good provision.

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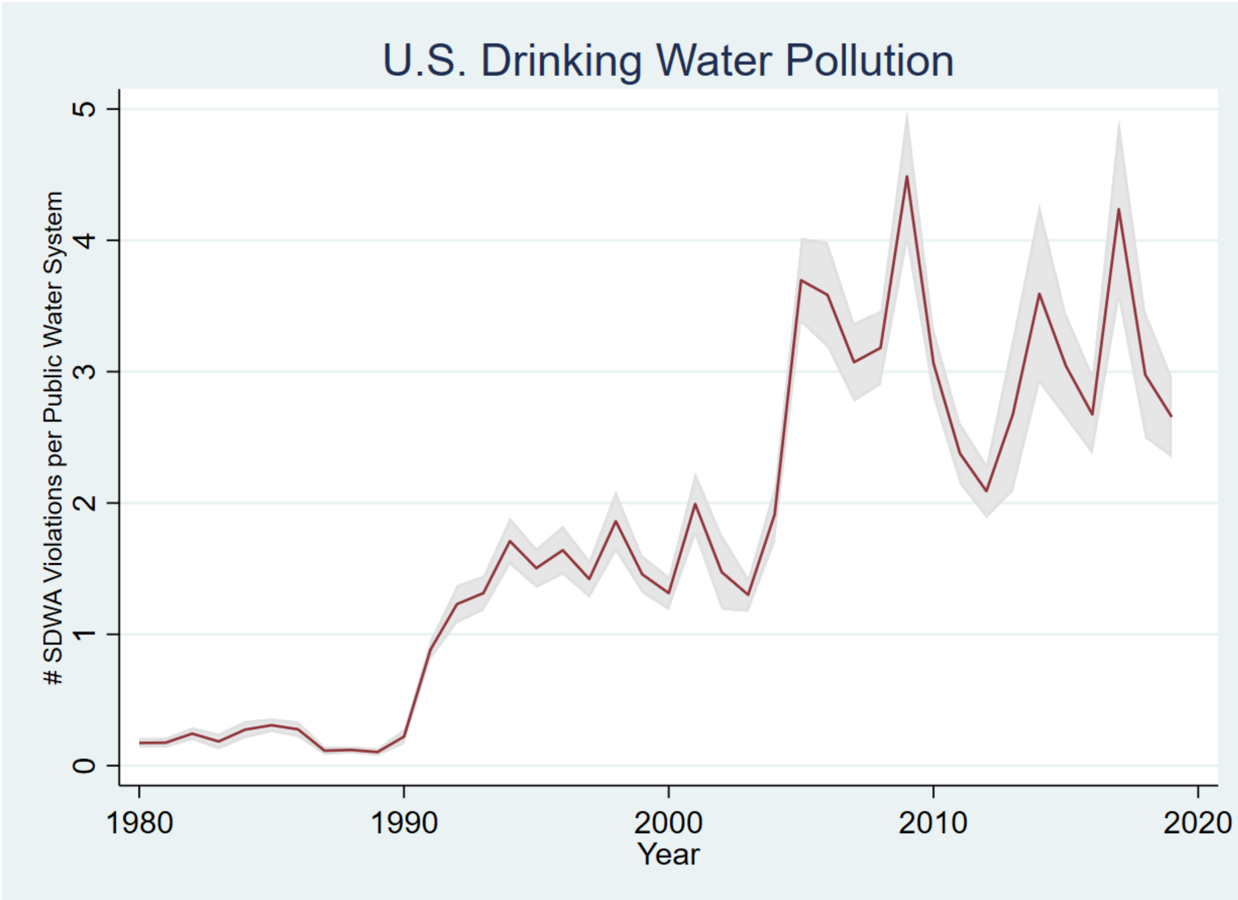


Figure 1: Time-Series of Federal Drinking Water Health Violations

This graph depicts annual violations of the U.S. Safe Drinking Water Act across U.S. municipalities. The x-axis depicts the year, the y-axis depicts the average number of SDWA health-related violations observed across all public drinking water systems contained within U.S. municipalities. Confidence intervals (95%) are presented in grey around the annual averages depicted in red.

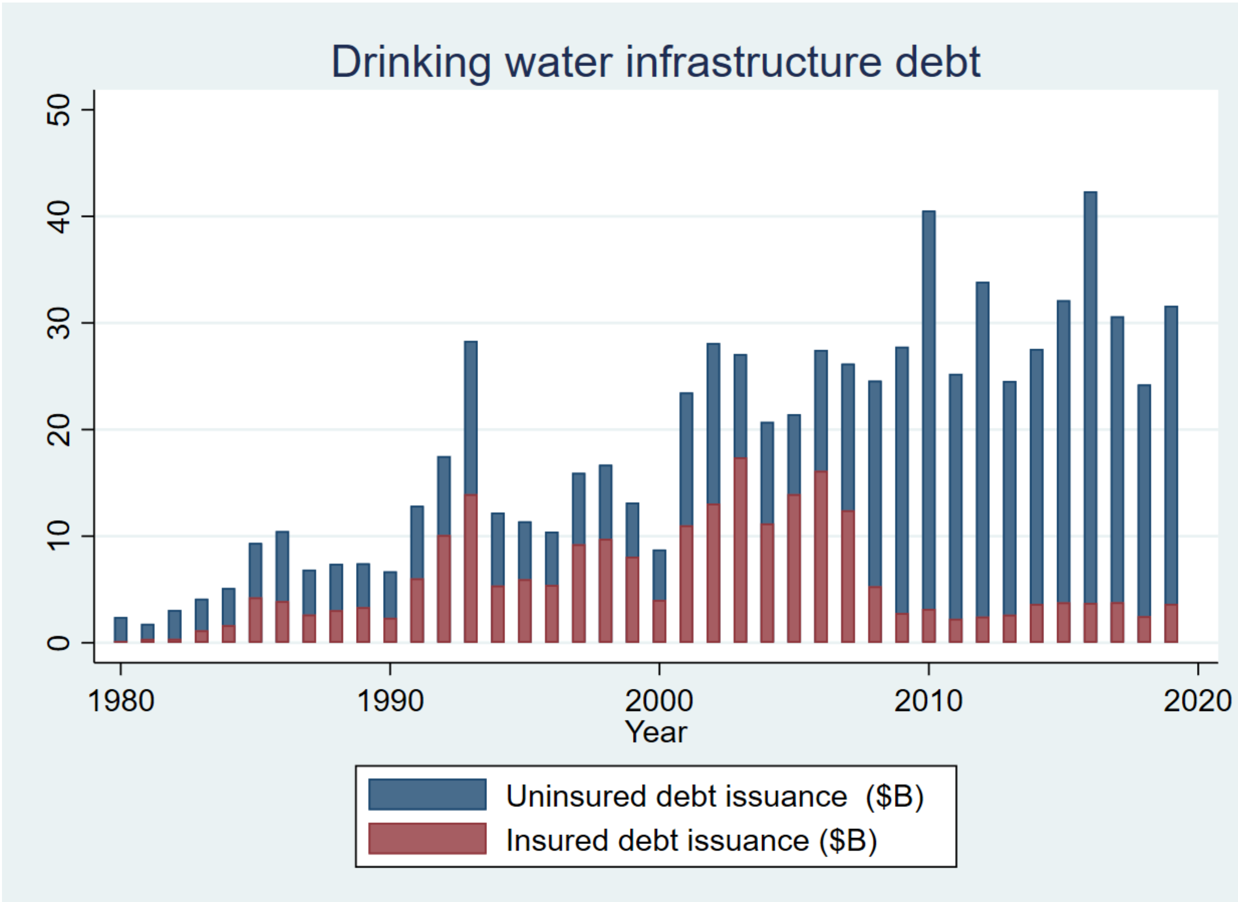


Figure 2: Time-Series of Municipal Debt Issuances

This figure illustrates the time-series of new municipal debt issued each year for drinking water infrastructure (total and insured) across all sample municipalities.

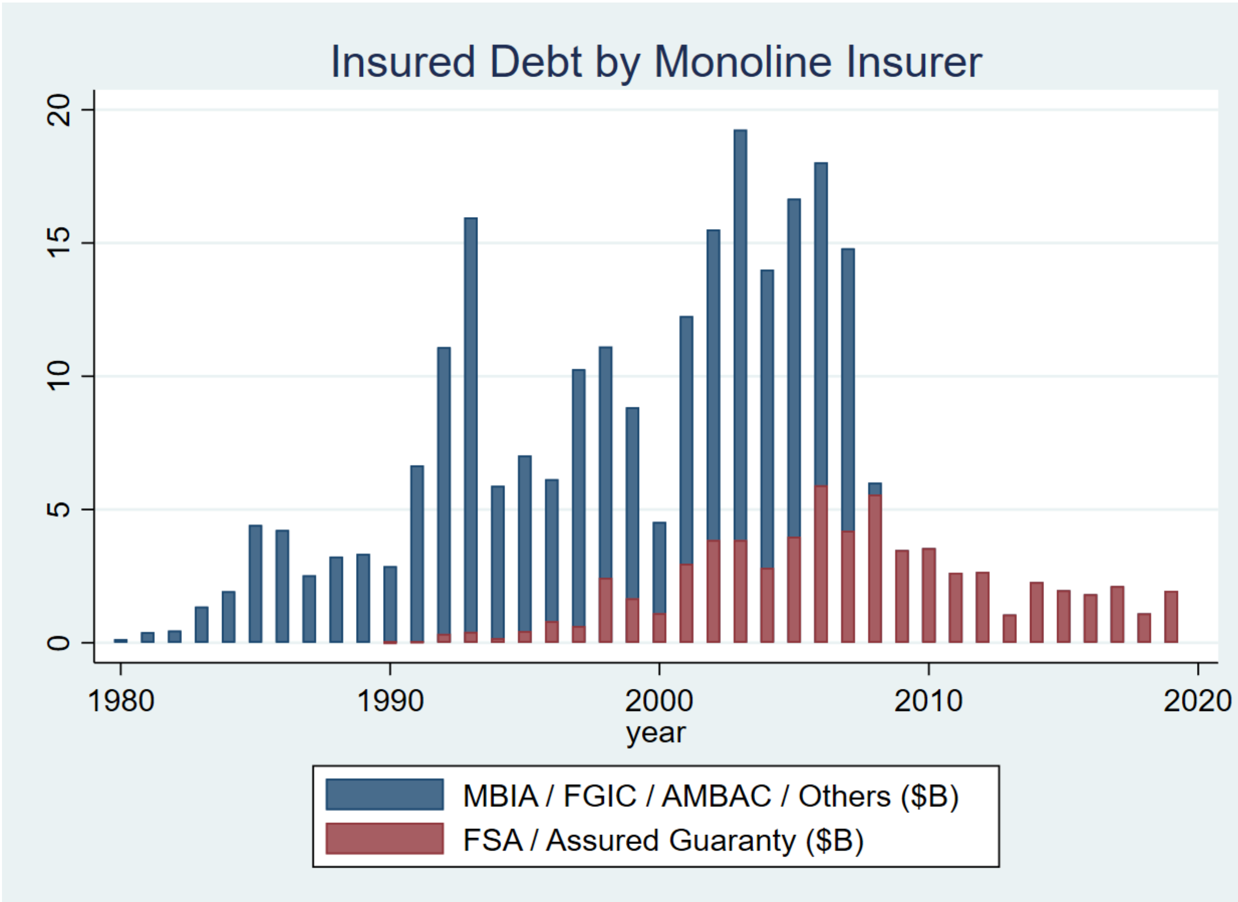


Figure 3: Insured Debt by Monoline Insurer

This figure illustrates the annual amount of total new municipal debt issued for drinking water infrastructure, insured by the ten monoline insurers in our sample. Eight out of the ten insurers (which include MBIA, FGIC, and AMBAC) experience severe credit rating downgrades in the crisis; the remaining two firms, FSA and Assured Guaranty, merge and maintain relatively high credit quality through the crisis.

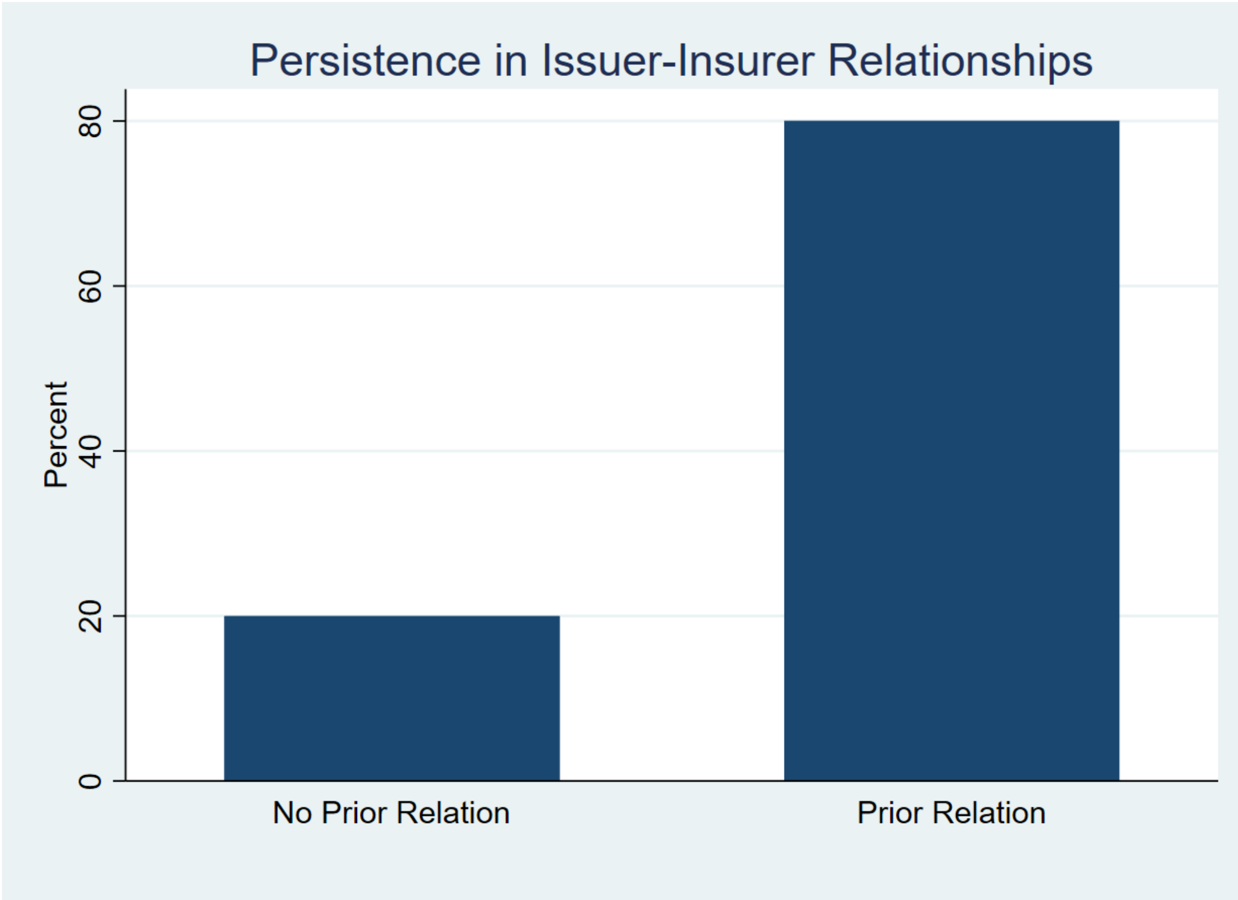


Figure 4: Persistence of Municipal Issuer-Bond Insurer Relationships

This bar chart depicts the percentage (y-axis) of new municipal debt issues that are insured by two types of monoline bond insurers (x-axis): those insurers that have not previously insured debts raised by the same municipality ("No Prior Relation") and those insurers that have previously insured debts raised by the same municipality ("Prior Relation").

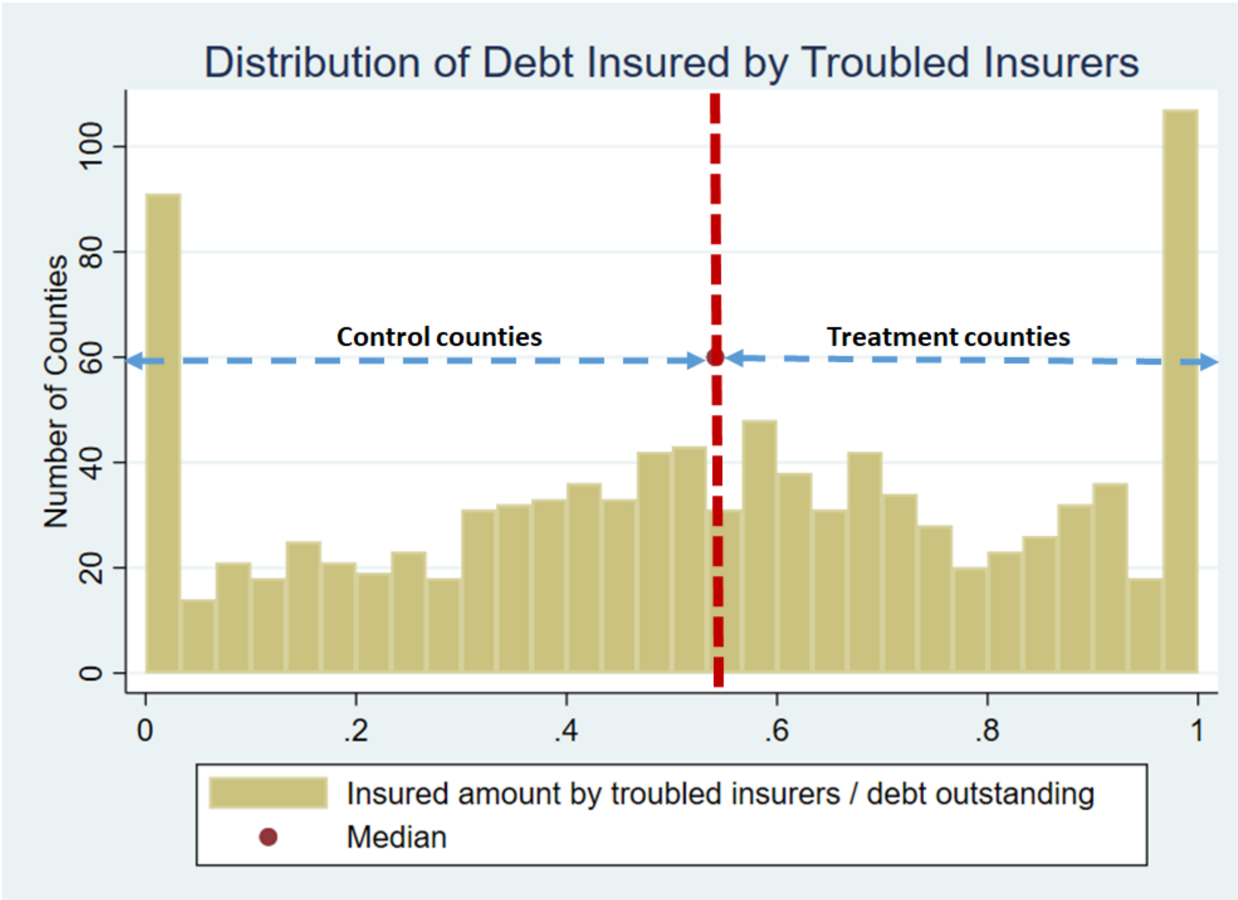


Figure 5: Distribution of Municipal Debt Insured by Downgraded Insurers

This histogram depicts the distribution of municipal debt that is insured by troubled insurers. The x-axis depicts the fraction of total outstanding debt (by municipality) in 2006 that is backed by troubled insurers (the median is 53%).

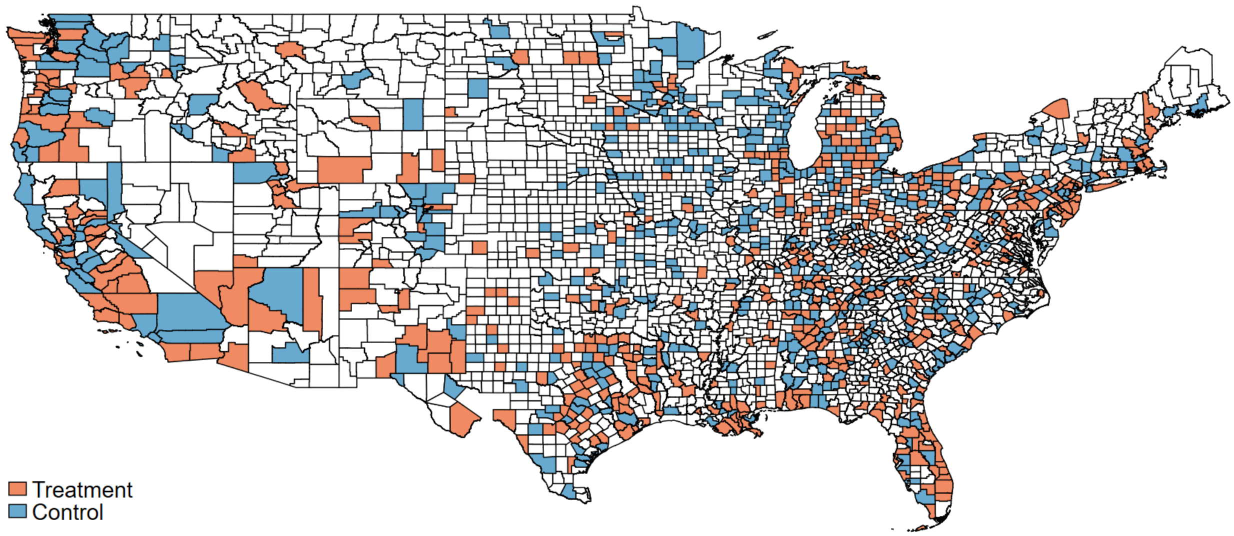


Figure 6: Geographic Distribution of Sample Municipalities

This heat map depicts municipalities that comprise the control and treatment samples in our analysis. Treatment (control) municipalities in orange (blue) refer to municipalities that have above (below) sample median issuance of debt in 2006 that is insured by monoline companies that become significantly downgraded following the 2007 shock to insurers.

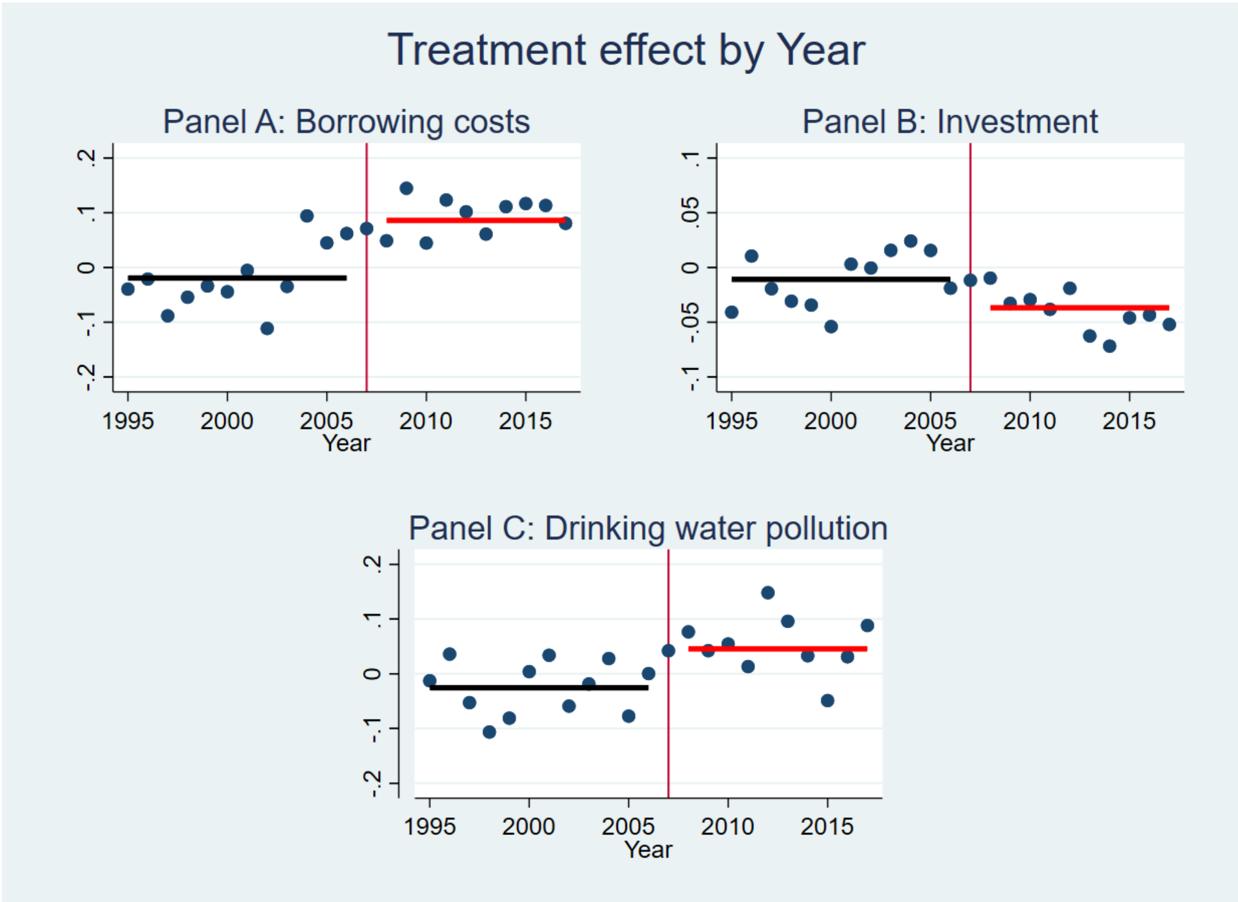


Figure 7: Graphical Illustration of Treatment Effect over Time

This figure illustrates the treatment effect estimates of Specifications 1, 3, and 4 (with all controls) using all municipalities in our sample, for each of 12 years before and after 2007. The solid lines depict the average treatment effect before versus after the 2007 shock. The dependent variable for each regression is presented at the top of each sub-figure: Borrowing costs (municipal debt servicing fees), Investment (investments into drinking water infrastructure), and Drinking water pollution (U.S. SDWA Violations).

Table 1: Sample Descriptive Statistics

This table presents sample descriptive statistics for the municipalities in our data. Variable definitions are provided in Table A1. "All Municipalities" refers to all municipalities for which we are able to collect data using the sources described in the paper; "Analysis Sample" refers to the municipalities that we analyze using our empirical identification strategy. For each characteristic listed below, the sample size, mean, and standard deviation (SD) of the characteristic across all municipality-year observations is presented. For each bond insurer below, the total amount of insured debt across all sample years is listed in millions (M).

| | All Municipalities | | | Analysis Sample | | |
|---|---|---|---|---|---|---|
| | N | Mean | SD | N | Mean | SD |
| Municipality Characteristics | | | | | | |
| Population (K) | 86,792 | 189.2 | 648.6 | 33,198 | 362.3 | 935.7 |
| Property tax revenues (M) | 86,792 | 103.6 | 470.2 | 33,198 | 194.2 | 581.4 |
| Drinking water service revenues (M) | 86,792 | 11.89 | 68.17 | 33,198 | 23.54 | 101.8 |
| Water infrastructure investment (M) | 86,792 | 8.131 | 47.36 | 33,198 | 16.31 | 73.15 |
| Pollution: SDWA Violations | 106,920 | 1.765 | 7.571 | 40,400 | 2.340 | 10.22 |
| Pollution: SDWA Violations pop wgt (K) | 106,920 | 8.550 | 81.21 | 40,400 | 17.28 | 124.2 |
| Municipal Borrowing for Water Infrastructure | | | | | | |
| Total debt outstanding (M) | 66,519 | 107.8 | 884.5 | 37,935 | 184.7 | 1,165 |
| Revenue bonds outstanding (M) | 66,519 | 92.31 | 842.9 | 37,935 | 159.2 | 1,111 |
| Annual new debt issuance (M) | 66,519 | 11.30 | 104.2 | 37,935 | 19.24 | 137.1 |
| True interest costs | 66,188 | 0.0594 | 0.0165 | 37,885 | 0.0587 | 0.0155 |
| Debt servicing expenses (M) | 86,792 | 1.771 | 17.04 | 33,198 | 3.156 | 13.29 |
| Has received a credit rating | 119,922 | 0.0371 | 0.189 | 40,552 | 0.0936 | 0.291 |
| Has investment grade rating | 4,446 | 0.829 | 0.377 | 3,795 | 0.823 | 0.382 |
| Credit rating (weighted) | 4,446 | 15.63 | 5.500 | 3,795 | 15.53 | 5.485 |
| Bond Insurance | | | | | | |
| Total insured debt outstanding (M) | 66,519 | 44.10 | 277.8 | 37,935 | 77.12 | 364.4 |
| Number of insurer relationships | 28,123 | 2.064 | 1.374 | 26,915 | 2.113 | 1.381 |
| FSA | 66,519 | 7.940 | 69.06 | 37,935 | 13.84 | 90.99 |
| Assured Guaranty | 66,519 | 0.630 | 9.493 | 37,935 | 1.067 | 12.53 |
| MBIA | 66,519 | 11.31 | 73.78 | 37,935 | 19.82 | 96.83 |
| FGIC | 66,519 | 12.72 | 109.7 | 37,935 | 22.30 | 144.5 |
| AMBAC | 66,519 | 8.621 | 51.74 | 37,935 | 15.09 | 67.80 |
| XL Capital Assurance Inc. | 66,519 | 0.771 | 17.69 | 37,935 | 1.348 | 23.41 |
| Radian Asset Assurance Inc. | 66,519 | 0.346 | 10.89 | 37,935 | 0.606 | 14.42 |
| Dexia Group | 66,519 | 0.0789 | 4.429 | 37,935 | 0.138 | 5.864 |
| CIFG NA | 66,519 | 0.0912 | 1.778 | 37,935 | 0.158 | 2.352 |
| ACA Financial Guaranty | 66,519 | 0.0226 | 0.559 | 37,935 | 0.0397 | 0.740 |
| Intergovernmental Funds: 2013-2018 | | | | | | |
| Debt issuance (M) | 9,712 | 18.69 | 141.5 | 5,769 | 30.28 | 181.5 |
| Intergovernmental revenue: Federal (M) | 9,712 | 0.108 | 0.976 | 5,769 | 0.143 | 1.176 |
| Intergovernmental revenue: State (M) | 9,712 | 0.289 | 2.105 | 5,769 | 0.408 | 2.556 |
| Intergovernmental revenue: Local (M) | 9,712 | 0.267 | 4.052 | 5,769 | 0.429 | 5.244 |

Table 2: Comparison of Municipalities in the Treatment and Control Samples

This table presents descriptive statistics for municipalities that comprise the treatment and control samples in our analysis. Variable definitions are provided in Table A1. For each characteristic listed in the panel, the sample size, mean, and standard deviation of the characteristic across municipalities is presented. T-test statistics for the differences in mean characteristics between treatment and control samples are also shown. The sample year is 2006.

| | Control | | | Treatment | | | Comparison |
|---|---|---|---|---|---|---|---|
| | N | mean | sd | N | mean | sd | T-test |
| Population (K) | 389 | 259.8 | 256.0 | 376 | 264.8 | 263.7 | −0.27 |
| Property tax revenues (M) | 389 | 135.2 | 128.0 | 376 | 135.7 | 130.6 | −0.05 |
| Has a credit rating | 507 | 0.195 | 0.397 | 507 | 0.168 | 0.374 | 1.11 |
| Rated Investment grade | 99 | 0.838 | 0.370 | 85 | 0.859 | 0.350 | −0.40 |
| Credit Rating (weighted) | 99 | 16.48 | 3.985 | 85 | 16.16 | 5.201 | 0.46 |
| Water service revenues (M) | 389 | 12.53 | 12.78 | 376 | 13.65 | 12.68 | −1.22 |
| Water infrastructure investment (M) | 389 | 8.362 | 8.412 | 376 | 9.165 | 8.562 | −1.31 |
| Total debt outstanding (M) | 507 | 63.11 | 81.33 | 507 | 66.66 | 82.89 | −0.69 |
| Revenue debt outstanding (M) | 507 | 59.88 | 91.46 | 507 | 63.94 | 91.38 | -0.71 |
| New debt issuance (M) | 507 | 2.837 | 4.577 | 507 | 3.087 | 4.871 | −0.84 |
| True interest costs | 507 | 0.0516 | 0.0080 | 507 | 0.0520 | 0.0072 | −0.84 |
| Debt servicing expenses (M) | 389 | 1.257 | 1.685 | 376 | 1.380 | 1.642 | −1.02 |
| Pollution: SDWA Violations | 506 | 2.688 | 3.210 | 504 | 2.274 | 2.934 | 2.14 |
| Pollution: SDWA Violations pop wgt (K) | 506 | 7.465 | 10.91 | 504 | 6.623 | 10.55 | 1.25 |
| Insurance fraction | 507 | 0.509 | 0.269 | 507 | 0.846 | 0.134 | -25.25 |
| Number of insurance relationships | 507 | 2.158 | 1.387 | 507 | 2.430 | 1.393 | -3.12 |

Table 3: Effects of Bond Insurer Downgrades on the True Interest Costs of Municipal Debt

This table presents OLS regression estimates of the effects of bond insurer credit rating downgrades on the true interest costs of new municipal debt financing for public drinking water infrastructure. The dependent variable is the weighted average true interest cost (percentage) on revenue bonds offered by a municipality in a given year (where the weights are the bond amounts). The key independent variable of interest is *Treatment*: an interaction term between whether a given observation is taken in 2007 or afterwards, and whether a given municipality has a high or low (i.e. above- or below- the 2006 sample median) fraction of outstanding debt that is insured by downgraded monoline companies. Controls are described in Table A1. The sample period is from 1980-2019. Standard errors are clustered at the municipality and year level.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Treatment | 0.137** | 0.137** | 0.136** | 0.136** | 0.136** | 0.140** | 0.144** |
| | (0.0641) | (0.0640) | (0.0639) | (0.0637) | (0.0638) | (0.0626) | (0.0628) |
| Maturity | 0.0313 | 0.0315 | 0.0309 | 0.0331 | 0.0333 | 0.0245 | 0.0243 |
| | (0.0241) | (0.0241) | (0.0241) | (0.0243) | (0.0242) | (0.0238) | (0.0239) |
| Debt issuance | −0.146*** | −0.145*** | −0.147*** | −0.148*** | −0.148*** | −0.160*** | −0.165*** |
| | (0.0310) | (0.0310) | (0.0311) | (0.0316) | (0.0317) | (0.0306) | (0.0291) |
| Lag log violation | | 0.0102 | 0.0105 | 0.0104 | 0.0105 | 0.0103 | 0.0101 |
| | | (0.0137) | (0.0136) | (0.0136) | (0.0136) | (0.0136) | (0.0136) |
| Lag log water revenue | | | 0.0504 | 0.0381 | 0.0418 | 0.0483 | 0.0474 |
| | | | (0.0402) | (0.0388) | (0.0358) | (0.0352) | (0.0349) |
| Lag log debt out' | | | | 0.0326 | 0.0341 | 0.0218 | 0.0109 |
| | | | | (0.0331) | (0.0319) | (0.0312) | (0.0340) |
| Lag log property tax | | | | | −0.0117 | 0.0249 | 0.0238 |
| | | | | | (0.0496) | (0.0558) | (0.0556) |
| Lag log population | | | | | | −0.0665 | −0.0696 |
| | | | | | | (0.0450) | (0.0446) |
| Total insurance frac | | | | | | 0.276*** | 0.219*** |
| | | | | | | (0.0850) | (0.0896) |
| Has credit rating | | | | | | | 0.00524 |
| | | | | | | | (0.0578) |
| Credit rating wgt | | | | | | | 0.000197 |
| | | | | | | | (0.00313) |
| No. of Relationships | | | | | | | 0.0507 |
| | | | | | | | (0.0308) |
| Observations | 9,513 | 9,513 | 9,513 | 9,513 | 9,513 | 9,513 | 9,513 |
| County FE | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Effects of Bond Insurer Downgrades on Municipal Financing Expenses

This table presents OLS regression estimates of the effects of bond insurer credit rating downgrades on the total financing expenses paid by municipalities for all outstanding debt raised for public drinking water infrastructure. The dependent variable is the logarithm of the total interest, principal, and other financing expenses paid by a municipality in a given year. The key independent variable of interest is *Treatment*: an interaction term between whether a given observation is taken in 2007 or afterwards, and whether a given municipality has a high or low (i.e. above- or below- the 2006 sample median) fraction of outstanding debt that is insured by downgraded monoline companies. Controls are described in Table A1. The sample period is from 1980-2019. Standard errors are clustered at the municipality and year level.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Treatment | 0.102*** | 0.102*** | 0.101*** | 0.102*** | 0.101*** | 0.101*** | 0.103*** |
| | (0.0335) | (0.0334) | (0.0317) | (0.0310) | (0.0307) | (0.0308) | (0.0307) |
| Lag log violation | | 0.00809 | 0.00836 | 0.00888 | 0.00879 | 0.00838 | 0.00813 |
| | | (0.00896) | (0.00854) | (0.00822) | (0.00823) | (0.00831) | (0.00830) |
| Lag log water revenue | | | 0.210*** | 0.172*** | 0.166*** | 0.163*** | 0.163*** |
| | | | (0.0270) | (0.0258) | (0.0273) | (0.0270) | (0.0271) |
| Lag log debt out' | | | | 0.104*** | 0.102*** | 0.102*** | 0.0960*** |
| | | | | (0.0113) | (0.0113) | (0.0117) | (0.0122) |
| Lag log property tax | | | | | 0.0185 | 0.00849 | 0.00932 |
| | | | | | (0.0210) | (0.0265) | (0.0265) |
| Lag log population | | | | | | 0.0200 | 0.0171 |
| | | | | | | (0.0208) | (0.0208) |
| Total insurance frac | | | | | | 0.0526* | 0.0260 |
| | | | | | | (0.0309) | (0.0357) |
| Has credit rating | | | | | | | 0.00959 |
| | | | | | | | (0.0447) |
| Credit rating wgt | | | | | | | 5.50e-05 |
| | | | | | | | (0.00244) |
| No. of Relationships | | | | | | | 0.0227* |
| | | | | | | | (0.0126) |
| Observations | 11,609 | 11,609 | 11,609 | 11,609 | 11,609 | 11,589 | 11,589 |
| County FE | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Effects of Bond Insurer Downgrades on Municipal Debt Outstanding

This table presents OLS regression estimates of the effects of bond insurer credit rating downgrades on the amounts of municipal debt raised for public drinking water infrastructure. The dependent variable is the logarithm of the total amount of outstanding revenue bonds offered by a municipality in a given year. The key independent variable of interest is *Treatment*: an interaction term between whether a given observation is taken in 2007 or afterwards, and whether a given municipality has a high or low (i.e. above- or below-the 2006 sample median) fraction of outstanding debt that is insured by downgraded monoline companies. Controls are described in Table A1. The sample period is from 1980-2019. Standard errors are clustered at the municipality and year level.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Treatment | −0.0208* | −0.0211* | −0.0209* | −0.0216* | −0.0219** | −0.0250** | −0.0259** |
| | (0.0106) | (0.0107) | (0.0107) | (0.0107) | (0.0107) | (0.0113) | (0.0115) |
| Lag log revenue debt out' | 0.921*** | 0.921*** | 0.920*** | 0.890*** | 0.890*** | 0.889*** | 0.883*** |
| | (0.00969) | (0.00970) | (0.00989) | (0.0112) | (0.0112) | (0.0120) | (0.0128) |
| Lag log violation | | 0.00368 | 0.00369 | 0.00459 | 0.00453 | 0.00412 | 0.00229 |
| | | (0.00365) | (0.00365) | (0.00358) | (0.00357) | (0.00344) | (0.00344) |
| Lag log water revenue | | | 0.0103** | 0.00644 | 0.00341 | 0.00447 | 0.00483 |
| | | | (0.00497) | (0.00526) | (0.00522) | (0.00550) | (0.00539) |
| Lag log debt out' | | | | 0.0407*** | 0.0400*** | 0.0314*** | 0.0256** |
| | | | | (0.00910) | (0.00912) | (0.00922) | (0.00978) |
| Lag log property tax | | | | | 0.0106 | 0.0120 | 0.0246*** |
| | | | | | (0.00669) | (0.00758) | (0.00834) |
| Lag log population | | | | | | −0.00128 | −0.0131** |
| | | | | | | (0.00539) | (0.00591) |
| Total insurance frac | | | | | | 0.137*** | 0.113*** |
| | | | | | | (0.0367) | (0.0337) |
| Has credit rating | | | | | | | 0.173*** |
| | | | | | | | (0.0231) |
| Credit rating wgt | | | | | | | −0.00182 |
| | | | | | | | (0.00130) |
| No. of Relationships | | | | | | | 0.0337*** |
| | | | | | | | (0.00685) |
| Observations | 27,583 | 27,583 | 27,583 | 27,583 | 27,583 | 27,566 | 27,566 |
| County FE | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Effects of Bond Insurer Downgrades on Municipal Investment in Drinking Water Infrastructure

This table presents OLS regression estimates of the effects of bond insurer credit rating downgrades on municipal investment into public drinking water infrastructure. The dependent variable is the logarithm of the total investment into drinking water infrastructure by a municipality in a given year. The key independent variable of interest is $Treatment$: an interaction term between whether a given observation is taken in 2007 or afterwards, and whether a given municipality has a high or low (i.e. above- or below- the 2006 sample median) fraction of outstanding debt that is insured by downgraded monoline companies. Controls are described in Table A1. The sample period is from 1980-2019. Standard errors are clustered at the municipality and year level.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Treatment | −0.0365 | −0.0373 | −0.0271* | −0.0270* | −0.0322** | −0.0329** | −0.0327** |
| | (0.0277) | (0.0277) | (0.0156) | (0.0157) | (0.0155) | (0.0155) | (0.0155) |
| Lag log violation | | 0.0148** | 0.0124** | 0.0127** | 0.0123** | 0.0129** | 0.0129** |
| | | (0.00684) | (0.00539) | (0.00542) | (0.00536) | (0.00544) | (0.00547) |
| Lag log water revenue | | | 0.453*** | 0.441*** | 0.405*** | 0.410*** | 0.410*** |
| | | | (0.0515) | (0.0525) | (0.0538) | (0.0524) | (0.0525) |
| Lag log debt out' | | | | 0.0378*** | 0.0288*** | 0.0282*** | 0.0276*** |
| | | | | (0.00772) | (0.00690) | (0.00681) | (0.00664) |
| Lag log property tax | | | | | 0.115*** | 0.138*** | 0.138*** |
| | | | | | (0.0250) | (0.0309) | (0.0307) |
| Lag log population | | | | | | −0.0388** | −0.0389** |
| | | | | | | (0.0169) | (0.0169) |
| Total insurance frac | | | | | | 0.00363 | -0.000420 |
| | | | | | | (0.0184) | (0.0188) |
| Has credit rating | | | | | | | -0.0181 |
| | | | | | | | (0.0204) |
| Credit rating wgt | | | | | | | 0.000919 |
| | | | | | | | (0.00109) |
| No. of Relationships | | | | | | | 0.00315 |
| | | | | | | | (0.00667) |
| Observations | 27,505 | 27,505 | 27,505 | 27,505 | 27,505 | 27,469 | 27,469 |
| County FE | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Effects of Bond Insurer Downgrades on Drinking Water Pollution

This table presents OLS regression estimates of the effects of bond insurer credit rating downgrades on drinking water pollution. In Panel A, the dependent variable is the logarithm of the number of violations of federal health standards for drinking water observed in a municipality in a given year. In Panel B, the dependent variable is the logarithm of the product of the number of violations of federal drinking water health standards times the number of people served by community water systems in a municipality in a given year. The key independent variable of interest is $Treatment$: an interaction term between whether a given observation is taken in 2007 or afterwards, and whether a given municipality has a high or low (i.e. above- or below- the 2006 sample median) fraction of outstanding debt that is insured by downgraded monoline companies. Controls are described in Table A1. The sample period is from 1980-2019. Standard errors are clustered at the municipality and year level.

| Panel A: Water Pollution (Number of U.S. SDWA Violations) | | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Treatment | 0.0728** | 0.0610** | 0.0610** | 0.0610** | 0.0600** | 0.0588** | 0.0588** |
| | (0.0333) | (0.0270) | (0.0270) | (0.0270) | (0.0270) | (0.0270) | (0.0271) |
| Lag log violation | | 0.244*** | 0.244*** | 0.244*** | 0.244*** | 0.243*** | 0.243*** |
| | | (0.0258) | (0.0257) | (0.0257) | (0.0256) | (0.0255) | (0.0255) |
| Lag log water revenue | | | 0.00271 | 0.00440 | −0.00268 | −0.00384 | −0.00423 |
| | | | (0.0165) | (0.0164) | (0.0168) | (0.0172) | (0.0172) |
| Lag log debt out' | | | | −0.00509 | −0.00693 | −0.00818 | −0.0120 |
| | | | | (0.00868) | (0.00869) | (0.00867) | (0.00932) |
| Lag log property tax | | | | | 0.0242 | 0.0159 | 0.0182 |
| | | | | | (0.0162) | (0.0224) | (0.0230) |
| Lag log population | | | | | | 0.0137 | 0.0111 |
| | | | | | | (0.0212) | (0.0216) |
| Total insurance frac | | | | | | 0.0273 | 0.0151 |
| | | | | | | (0.0238) | (0.0285) |
| Has credit rating | | | | | | | 0.0482 |
| | | | | | | | (0.0518) |
| Credit rating wgt | | | | | | | −0.00211 |
| | | | | | | | (0.00269) |
| No. of Relationships | | | | | | | 0.0130 |
| | | | | | | | (0.0112) |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Observations | 30,543 | 30,543 | 30,543 | 30,543 | 30,543 | 30,506 | 30,506 |
| County FE | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES |

Panel B: Water Pollution (Number of U.S. SDWA Violations weighted by population)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Treatment | 0.447** | 0.390** | 0.390** | 0.390** | 0.385** | 0.378** | 0.377** |
| | (0.173) | (0.159) | (0.159) | (0.159) | (0.159) | (0.158) | (0.159) |
| Lag log violation wgt | | 0.154*** | 0.154*** | 0.154*** | 0.154*** | 0.153*** | 0.153*** |
| | | (0.0196) | (0.0195) | (0.0195) | (0.0195) | (0.0194) | (0.0193) |
| Lag log water revenue | | | 0.0548 | 0.0686 | 0.0283 | 0.0171 | 0.0148 |
| | | | (0.0886) | (0.0876) | (0.0884) | (0.0929) | (0.0925) |
| Lag log debt out’ | | | | -0.0411 | -0.0516 | -0.0588 | -0.0800 |
| | | | | (0.0467) | (0.0474) | (0.0472) | (0.0510) |
| Lag log property tax | | | | | 0.138 | 0.0659 | 0.0806 |
| | | | | | (0.101) | (0.127) | (0.130) |
| Lag log population | | | | | | 0.116 | 0.101 |
| | | | | | | (0.112) | (0.114) |
| Total insurance frac | | | | | | 0.200 | 0.138 |
| | | | | | | (0.132) | (0.147) |
| Has credit rating | | | | | | | 0.376 |
| | | | | | | | (0.262) |
| Credit rating wgt | | | | | | | -0.0182 |
| | | | | | | | (0.0132) |
| No. of Relationships | | | | | | | 0.0695 |
| | | | | | | | (0.0631) |
| Observations | 30,543 | 30,543 | 30,543 | 30,543 | 30,543 | 30,506 | 30,506 |
| County FE | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Effects of Bond Insurer Downgrades on Drinking Water Revenue

This table presents OLS regression estimates of the effects of bond insurer credit rating downgrades on the drinking revenues earned by municipalities. The dependent variable is the logarithm of the total drinking water service fees earned by a municipality in a given year. The key independent variable of interest is *Treatment*: an interaction term between whether a given observation is taken in 2007 or afterwards, and whether a given municipality has a high or low (i.e. above- or below- the 2006 sample median) fraction of outstanding debt that is insured by downgraded monoline companies. Controls are described in Table A1. The sample period is from 1980-2014. Standard errors are clustered at the municipality and year level.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Treatment | −0.0104 | −0.0112 | −0.00979 | −0.0180 | −0.0183 | −0.0173 |
| | (0.0282) | (0.0283) | (0.0271) | (0.0248) | (0.0250) | (0.0251) |
| Lag log violation | | 0.0173** | 0.0178** | 0.0156** | 0.0151** | 0.0149** |
| | | (0.00808) | (0.00762) | (0.00713) | (0.00709) | (0.00714) |
| Lag log debt out' | | | 0.112*** | 0.0840*** | 0.0852*** | 0.0815*** |
| | | | (0.0113) | (0.00913) | (0.00948) | (0.00954) |
| Lag log property tax | | | | 0.250*** | 0.234*** | 0.236*** |
| | | | | (0.0349) | (0.0387) | (0.0387) |
| Lag log population | | | | | 0.0243 | 0.0217 |
| | | | | | (0.0311) | (0.0311) |
| Total insurance frac | | | | | −0.000181 | −0.0158 |
| | | | | | (0.0233) | (0.0265) |
| Has credit rating | | | | | | 0.0440 |
| | | | | | | (0.0438) |
| Credit rating wgt | | | | | | −0.00253 |
| | | | | | | (0.00227) |
| No. of Relationships | | | | | | 0.0148 |
| | | | | | | (0.0102) |
| Observations | 25,279 | 25,279 | 25,279 | 25,279 | 25,244 | 25,244 |
| County FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9: Effects of Bond Insurer Downgrades on Population Growth and Property Tax

This table presents OLS regression estimates of the effects of bond insurer credit rating downgrades on municipal population growth (Panel A) and on the total property tax revenue earned by municipalities (Panel B). The dependent variable is the logarithm of the total population of a municipality in a given year. The key independent variable of interest is *Treatment*: an interaction term between whether a given observation is taken in 2007 or afterwards, and whether a given municipality has a high or low (i.e. above- or below- the 2006 sample median) fraction of outstanding debt that is insured by downgraded monoline companies. Controls are described in Table A1. The sample period is from 1980-2019. Standard errors are clustered at the municipality and year level.

Panel A: Population Growth

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Treatment | 0.0245 | 0.0239 | 0.0282 | 0.0284 | 0.0164 | 0.0170 |
| | (0.0243) | (0.0242) | (0.0229) | (0.0226) | (0.0204) | (0.0204) |
| Lag log violation | | 0.0123 | 0.0110 | 0.0114 | 0.0106 | 0.00897 |
| | | (0.00802) | (0.00726) | (0.00727) | (0.00667) | (0.00658) |
| Lag log water revenue | | | 0.192*** | 0.178*** | 0.0658*** | 0.0638*** |
| | | | (0.0343) | (0.0336) | (0.0227) | (0.0224) |
| Lag log debt out' | | | | 0.0411*** | 0.0176 | 0.00200 |
| | | | | (0.00989) | (0.0109) | (0.0114) |
| Lag log property tax | | | | | 0.355*** | 0.356*** |
| | | | | | (0.0639) | (0.0640) |
| Total insurance frac | | | | | −0.0766*** | −0.135** |
| | | | | | (0.0278) | (0.0325) |
| Has credit rating | | | | | | 0.0772** |
| | | | | | | (0.0319) |
| Credit rating wgt | | | | | | −0.00190 |
| | | | | | | (0.00159) |
| No. of Relationships | | | | | | 0.0588*** |
| | | | | | | (0.0131) |
| Observations | 28,272 | 28,272 | 28,272 | 28,272 | 28,237 | 28,237 |
| County E | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |

Panel B: Property Tax Revenues

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Treatment | 0.0360 | 0.0359 | 0.0422 | 0.0425 | 0.0350 | 0.0352 |
| | (0.0308) | (0.0307) | (0.0276) | (0.0270) | (0.0252) | (0.0249) |
| Lag log violation | | 0.00333 | 0.00155 | 0.00220 | −0.00188 | −0.000842 |
| | | (0.00716) | (0.00647) | (0.00620) | (0.00587) | (0.00583) |
| Lag log water revenue | | | 0.278*** | 0.250*** | 0.170*** | 0.169*** |
| | | | (0.0369) | (0.0331) | (0.0263) | (0.0257) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Lag log debt out' | | | | 0.0823*** | 0.0760*** | 0.0795*** |
| | | | | (0.0110) | (0.0104) | (0.0112) |
| Lag log population | | | | | 0.252*** | 0.254*** |
| | | | | | (0.0536) | (0.0536) |
| Total insurance frac | | | | | 0.0260 | 0.0290 |
| | | | | | (0.0247) | (0.0301) |
| Has credit rating | | | | | | −0.143*** |
| | | | | | | (0.0404) |
| Credit rating wgt | | | | | | 0.00499** |
| | | | | | | (0.00215) |
| No. of Relationships | | | | | | −0.00945 |
| | | | | | | (0.0121) |
| Observations | 28,272 | 28,272 | 28,272 | 28,272 | 28,237 | 28,237 |
| County FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 10: Effects of Bond Insurer Downgrades on Municipal General Obligation Bonds

This table presents OLS regression estimates of the effects of bond insurer credit rating downgrades on the yields and amounts of general obligation bonds offered by municipalities. The dependent variable in Panel A is the weighted average yield of general obligation bonds offered by a municipality in a given year (where the weights are the bond amounts). The dependent variable in Panel B is the logarithm of the total amount of general obligation bonds offered by a municipality in a given year. The key independent variable of interest is *Treatment*: an interaction term between whether a given observation is taken in 2007 or afterwards, and whether a given municipality has a high or low (i.e. above- or below- the 2006 sample median) fraction of outstanding debt that is insured by downgraded monoline companies. Controls are described in Table A1. The sample period is from 1980-2019. Standard errors are clustered at the municipality and year level.

Panel A: Yield (in %) for general obligation bonds

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Treatment | 0.119 | 0.117 | 0.118 | 0.117 | 0.117 | 0.121 | 0.123 |
| | (0.0843) | (0.0843) | (0.0842) | (0.0843) | (0.0848) | (0.0836) | (0.0832) |
| Maturity | 0.102*** | 0.103*** | 0.103*** | 0.103*** | 0.104*** | 0.0943*** | 0.0945*** |
| | (0.0194) | (0.0194) | (0.0194) | (0.0194) | (0.0192) | (0.0192) | (0.0192) |
| Debt issuance | −0.329*** | −0.329*** | −0.327*** | −0.326*** | −0.325*** | −0.325*** | −0.325*** |
| | (0.0497) | (0.0496) | (0.0499) | (0.0497) | (0.0501) | (0.0494) | (0.0495) |
| Lag log violation | | 0.0177 | 0.0187 | 0.0152 | 0.0150 | 0.0150 | 0.0136 |
| | | (0.0199) | (0.0200) | (0.0193) | (0.0192) | (0.0187) | (0.0183) |
| Lag log water revenue | | | −0.101* | −0.0835* | −0.0592 | −0.0634 | −0.0644 |
| | | | (0.0505) | (0.0477) | (0.0448) | (0.0451) | (0.0442) |
| Lag log debt out' | | | | −0.0761* | −0.0689 | −0.0880* | −0.0973** |
| | | | | (0.0448) | (0.0428) | (0.0429) | (0.0453) |
| Lag log property tax | | | | | −0.0699 | −0.0663 | −0.0679 |
| | | | | | (0.0613) | (0.0758) | (0.0754) |
| Lag log population | | | | | | 0.00410 | 0.00176 |
| | | | | | | (0.0622) | (0.0611) |
| Total insurance frac | | | | | | 0.366*** | 0.304** |
| | | | | | | (0.113) | (0.130) |
| Has credit rating | | | | | | | −0.0469 |
| | | | | | | | (0.100) |
| Credit rating wgt | | | | | | | −0.000698 |
| | | | | | | | (0.00543) |
| No. of Relationships | | | | | | | 0.0410 |
| | | | | | | | (0.0406) |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Observations | 5,679 | 5,679 | 5,679 | 5,679 | 5,679 | 5,679 | 5,679 |
| County FE | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES |

Panel B: General obligation debt flow

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Treatment | 0.00961 | 0.00975 | 0.00976 | 0.0112 | 0.0115 | 0.0108 | 0.00902 |
| | (0.0122) | (0.0122) | (0.0121) | (0.0121) | (0.0121) | (0.0122) | (0.0124) |
| Lag log go debt out' | 0.936*** | 0.936*** | 0.936*** | 0.928*** | 0.928*** | 0.928*** | 0.926*** |
| | (0.00774) | (0.00773) | (0.00776) | (0.00866) | (0.00866) | (0.00857) | (0.00863) |
| Lag log violation | | −0.00336 | −0.00336 | −0.00363 | −0.00360 | −0.00339 | −0.00454 |
| | | (0.00358) | (0.00356) | (0.00355) | (0.00356) | (0.00358) | (0.00365) |
| Lag log water revenue | | | 0.000378 | −0.00390 | 0.000837 | 0.00333 | 0.00391 |
| | | | (0.00755) | (0.00765) | (0.00772) | (0.00782) | (0.00792) |
| Lag log debt out' | | | | 0.0187** | 0.0198*** | 0.0185** | 0.0173** |
| | | | | (0.00719) | (0.00713) | (0.00758) | (0.00750) |
| Lag log property tax | | | | | −0.0152* | −0.00666 | 0.000186 |
| | | | | | (0.00783) | (0.00914) | (0.00910) |
| Lag log population | | | | | | −0.0144** | −0.0197** |
| | | | | | | (0.00712) | (0.00738) |
| Total insurance frac | | | | | | −0.00367 | 0.00556 |
| | | | | | | (0.0202) | (0.0193) |
| Has credit rating | | | | | | | 0.122*** |
| | | | | | | | (0.0298) |
| Credit rating wgt | | | | | | | −0.00158 |
| | | | | | | | (0.00172) |
| No. of Relationships | | | | | | | 0.0507 |
| | | | | | | | (0.0308) |
| Observations | 20,678 | 20,678 | 20,678 | 20,678 | 20,678 | 20,659 | 20,659 |
| County FE | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 11: Municipalities with Low Interest Coverage Ratios

This table presents our main regression specifications for a subsample of municipalities that have relatively lower interest coverage ratios. We define this sample as those municipalities that have below sample-median ratios of drinking water service revenues to interest expenses. All variables are the same as presented in Tables 3 through 6. Controls are described in Table A1. The sample period is from 1980-2019. Standard errors are clustered at the municipality and year level.

| | Debt flow | Yield | Investment | Viol | Wgt Viol |
|---|---|---|---|---|---|
| Treatment | -0.0326** | 0.00196** | -0.0415** | 0.0712* | 0.410* |
| | (0.0138) | (0.000796) | (0.0190) | (0.0355) | (0.211) |
| Maturity | | 0.000115 | | | |
| | | (0.000317) | | | |
| Debt issuance | | -0.00163*** | | | |
| | | (0.000335) | | | |
| Lag log violation | 0.00156 | 6.01e-05 | 0.0144** | 0.205*** | |
| | (0.00405) | (0.000174) | (0.00601) | (0.0278) | |
| Lag log water revenue | 0.00370 | 0.000560 | 0.408*** | 0.0129 | 0.0917 |
| | (0.00791) | (0.000507) | (0.0499) | (0.0190) | (0.0999) |
| Lag log debt out' | 0.0349** | 0.000216 | 0.0368*** | -0.0154 | -0.124* |
| | (0.0162) | (0.000460) | (0.00868) | (0.0130) | (0.0733) |
| Lag log property tax | 0.0258** | -0.000519 | 0.141*** | 0.0101 | 0.0650 |
| | (0.0116) | (0.000693) | (0.0296) | (0.0274) | (0.153) |
| Lag log population | -0.00845 | -0.000232 | -0.0380** | 0.00853 | 0.0674 |
| | (0.00788) | (0.000526) | (0.0183) | (0.0241) | (0.133) |
| Total insurance frac | 0.148*** | 0.00280** | -0.0193 | 0.00932 | 0.181 |
| | (0.0382) | (0.00109) | (0.0246) | (0.0353) | (0.178) |
| Has credit rating | 0.150*** | 0.000244 | -0.0295 | 0.0214 | 0.360 |
| | (0.0289) | (0.000767) | (0.0271) | (0.0594) | (0.336) |
| Credit rating wgt | -0.000833 | 1.12e-05 | 0.00137 | 0.000639 | -0.0147 |
| | (0.00169) | (4.20e-05) | (0.00148) | (0.00291) | (0.0167) |
| No. of Relationships | 0.0296*** | 0.000522 | 0.0165* | 0.0252 | 0.108 |
| | (0.00854) | (0.000399) | (0.00841) | (0.0156) | (0.0860) |
| Lag log revenue debt out' | 0.869*** | | | | |
| | (0.0164) | | | | |
| Lag log violation wgt | | | | | 0.128*** |
| | | | | | (0.0212) |
| Observations | 16,162 | 5,682 | 15,500 | 17,719 | 17,719 |
| County FE | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES |

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 12: Municipalities in the 25th vs 75th percentiles

This table presents our main regression specifications using a different cutoff for treatment and control sample designation. We measure the 25th and 75th percentiles of the fraction of debt that is insured by troubled companies as of 2006. The control (treatment) sample consists of municipalities that are below the 25th percentile (above the 75th percentile) of this measure. All variables are the same as presented in Tables 3 through 6. Controls are described in Table A1. The sample period is from 1980-2019. Standard errors are clustered at the municipality and year level.

| | Debt flow | Yield | Investment | Viol | Wgt Viol |
|---|---|---|---|---|---|
| Treatment | -0.0352** | 0.00190* | -0.0413* | 0.0718* | 0.497** |
| | (0.0160) | (0.00104) | (0.0241) | (0.0405) | (0.240) |
| Maturity | | 0.000338 | | | |
| | | (0.000403) | | | |
| Debt issuance | | -0.00191*** | | | |
| | | (0.000426) | | | |
| Lag log violation | 0.00273 | 0.000296 | 0.00234 | 0.256*** | |
| | (0.00593) | (0.000222) | (0.00699) | (0.0281) | |
| Lag log water revenue | 0.0104 | 0.00100 | 0.318*** | 0.0239 | 0.167 |
| | (0.00843) | (0.000633) | (0.0495) | (0.0261) | (0.138) |
| Lag log debt out' | 0.0412*** | -0.000208 | 0.0220** | -0.0105 | -0.0603 |
| | (0.00998) | (0.000432) | (0.00943) | (0.0125) | (0.0694) |
| Lag log property tax | 0.0228* | 0.000995 | 0.133*** | 0.0460 | 0.314* |
| | (0.0119) | (0.000916) | (0.0294) | (0.0318) | (0.181) |
| Lag log population | -0.0149* | -0.000301 | -0.0443** | 0.00382 | 0.00706 |
| | (0.00770) | (0.000681) | (0.0170) | (0.0250) | (0.148) |
| Total insurance frac | 0.128*** | 0.00304** | 0.0446* | 0.0245 | 0.114 |
| | (0.0345) | (0.00131) | (0.0247) | (0.0368) | (0.205) |
| Has credit rating | 0.208*** | 0.000223 | -0.0680* | 0.0832 | 0.531 |
| | (0.0389) | (0.000996) | (0.0343) | (0.0687) | (0.361) |
| Credit rating wgt | -0.00160 | -2.03e-06 | 0.00405** | -0.00388 | -0.0242 |
| | (0.00207) | (5.13e-05) | (0.00194) | (0.00374) | (0.0203) |
| No. of Relationships | 0.0318*** | 0.000430 | -0.0369*** | 0.0169 | 0.0937 |
| | (0.00990) | (0.000398) | (0.0114) | (0.0153) | (0.0914) |
| Lag log revenue debt out' | 0.868*** | | | | |
| | (0.0144) | | | | |
| Lag log violation wgt | | | | | 0.161*** |
| | | | | | (0.0230) |
| Observations | 12,649 | 3,686 | 12,786 | 14,417 | 14,417 |
| County FE | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES |

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 13: Main Results using pre-2010 data

This table presents our main regression specifications using data for the sample years 1980 to 2009. All variables are the same as presented in Tables 3 through 6. Controls are described in Table A1. Standard errors are clustered at the municipality and year level.

| | Debt flow | Yield | Investment | Viol | Wgt Viol |
|---|---|---|---|---|---|
| Treatment | -0.0377** | 0.00148** | -0.0223* | 0.0832*** | 0.638*** |
| | (0.0150) | (0.000657) | (0.0122) | (0.0281) | (0.135) |
| Maturity | | 0.000159 | | | |
| | | (0.000286) | | | |
| Debt issuance | | -0.00165*** | | | |
| | | (0.000317) | | | |
| Lag log violation | 0.00566 | 8.62e-05 | 0.00285 | 0.237*** | |
| | (0.00414) | (0.000161) | (0.00527) | (0.0311) | |
| Lag log water revenue | 0.0210*** | 0.000549 | 0.230*** | 0.00496 | 0.0632 |
| | (0.00704) | (0.000398) | (0.0522) | (0.0189) | (0.106) |
| Lag log debt out’ | 0.00215 | -0.000360 | 0.0394*** | -0.0120 | -0.0676 |
| | (0.0151) | (0.000394) | (0.00849) | (0.0110) | (0.0587) |
| Lag log property tax | 0.0406*** | 0.000112 | 0.0687** | 0.0284 | 0.181 |
| | (0.00963) | (0.000580) | (0.0256) | (0.0265) | (0.148) |
| Lag log population | -0.0211*** | -0.000591 | -0.0340* | 0.00486 | 0.0529 |
| | (0.00704) | (0.000513) | (0.0196) | (0.0239) | (0.125) |
| Total insurance frac | 0.269*** | 0.00146 | 0.0567*** | -0.0197 | 0.0298 |
| | (0.0427) | (0.00109) | (0.0204) | (0.0333) | (0.181) |
| Has credit rating | 0.207*** | 0.000543 | -0.0953*** | 0.0971 | 0.837** |
| | (0.0293) | (0.000657) | (0.0321) | (0.0650) | (0.360) |
| Credit rating wgt | -0.00432** | -3.39e-05 | 0.00383** | -0.00445 | -0.0402** |
| | (0.00159) | (3.59e-05) | (0.00159) | (0.00347) | (0.0170) |
| No. of Relationships | 0.0417*** | 0.000628* | -0.0416*** | 0.0230 | 0.135 |
| | (0.00864) | (0.000366) | (0.0106) | (0.0151) | (0.0860) |
| Lag log revenue debt out’ | 0.836*** | | | | |
| | (0.0168) | | | | |
| Lag log violation wgt | | | | | 0.141*** |
| | | | | | (0.0216) |
| Observations | 20,355 | 7,233 | 20,723 | 22,440 | 22,440 |
| County FE | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES |

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

# Appendix

In this section, we provide a detailed description of the dataset construction.

We first obtain data from the U.S. Census Annual Survey of State and Local Government Finances from 1980 to 2019. These data are publicly available online at: https://www.census.gov/programs-surveys/gov-finances.html. As described on the Census website, this survey provides comprehensive information on the finances and investment activities of local governments across the U.S. For example, the data contain information on the assets, revenues, and expenditures of local governments across specific functions such as water supply, utilities, transit, etc. The Census survey is conducted annually, and corresponds to a large, randomized sample of local municipalities. Additionally, every five years (i.e. years ending in '2' and '7'), the Census gathers data for the entire population of local municipalities in the U.S.

The key variables that we use to extract information from the Census Surveys are described in Table A1. For example, "Water Utility" is the Census governmental unit that corresponds to drinking water infrastructure: the Census defines this entity as being "responsible for the operation and maintenance of water supply systems...to the general public". Table A1 describes other variables that we collect from the Census, such as measures of drinking water revenues, investment expenditures into drinking water infrastructure, property tax revenues, etc.

We supplement these data with information on the credit ratings of municipalities. Specifically, we obtain detailed time-series data on the credit ratings (by Moody's) of municipal entities from Eikon. We codify the credit ratings (such as Aaa, Aa1, etc.) numerically by assigning each credit rating a value, such that Aaa=21, Aa1=20...C=1, following Cornaggia et al. (2018). If a municipality does not have a credit rating, we leave this value as 'missing'.

Second, we collect detailed information on municipal debt issues from SDC Platinum's Global Public Finance database. These data contain records for every individual debt offering made by U.S. municipal entities from 1962 to 2019. For each debt issue, we observe the total amount of capital raised, the debt's maturity, debt type (revenue bond or general obligation bond), and the stated purpose of the debt issue (for example: water infrastructure). SDC also provides information on true interest costs (see "True Interest Costs" in Table A1 for an explanation).

In addition to these data, SDC contains information about whether an individual bond issue is insured, and if so, the identity of the insurance company that is backing the debt. For each bond insurance company in our sample, we obtain its credit ratings history from S&P Capital IQ, and cross-check these data with other studies such as Bergstresser et al. (2010) and Cornaggia et al. (2021a). These data enable us to precisely identify changes in bond insurers' financial health.

We use these data to construct a detailed time-series of debt used to finance public drinking water infrastructure for each municipality in our sample. The vast majority ($> 95\%$) of debt issues are fixed rate, fully amortized securities; we use full amortization schedules to construct estimates of the total municipal debt outstanding each year, based on observed prior history of debt issuances for each municipality. We construct these measures for all insured and uninsured debt, and compute the total amount of a municipality's debt outstanding that insured by each bond insurance company in our sample.

Finally, we collect data on public drinking water quality from the U.S. EPA. The EPA maintains a database called the Safe Drinking Water Information System (SDWIS), which contains information on public water systems throughout the U.S., as required by the 1974 Safe Drinking Water Act (SDWA). The database is publicly available at https://www.epa.gov/ground-water-and-drinking-water/safe-drinking-water-information-system-sdwis-federal-reporting.

The database contains records of federal violations of drinking water standards by public water systems. These standards are set by the SDWA, and apply equally across all local jurisdictions in the U.S. The SDWIS contains detailed information about the types of violations observed by local water systems, such as instances of contaminant levels that exceed the limits set forth by the SDWA. The database also maintains records of violations of federally approved water treatment techniques and reporting requirements.

We use the SDWIS data to measure changes in drinking water quality across municipalities in our sample. The individual records in the SDWIS are uniquely identified by individual violations of specific SDWA rules committed by public drinking water systems each year. The database identifies whether individual violations have health-based implications (for example, whether there are high levels of lead or bacteria in a water system), or whether the violations are unrelated to health (such as whether the water system failed to submit water testing results on time to monitoring agencies).

There are typically multiple public drinking water systems that serve all the constituents of a given county. The database lists the county served by a given drinking water system, along with the number of people that are served by the system. To construct county-level measures of drinking water violations, we aggregate the observed health-related violations of all public drinking water systems in a given municipality, by year. We also weight these figures by the sizes of the populations served by these systems, to approximate the number of people affected by these violations.

We combine information from these different data sources into a single dataset, by aggregating the Census and SDC data to the county-year level (a county is the most disaggregated geographical unit for which we are able to observe changes in drinking water quality from the SDWIS, and both the Census and SDC list the county associated with a municipal entity in each data source). For example, the Census lists the county in which each individual municipal government belongs. We thus aggregate data on quantities such as municipal revenues and capital expenditures each year across all municipal governments within a given county. Similarly, SDC provides information on the county to which each municipal debt issuer belongs; we thus aggregate data on total debt raised and total outstanding debt (insured and uninsured) across municipalities to the county-level each year.

Aggregating and merging these data yield a panel dataset that consists of observations at the county-year level from 1980 to 2019. Each record contains information on annual drinking water revenues and investments into drinking water infrastructure. In each record, we also observe the total amount of municipal debt outstanding (insured and uninsured) raised for water infrastructure up to a given year. Each observation also contains information on federal violations of drinking water standards recorded for community water systems in a given county-year.

Table A1: Variable Definitions

| Source: U.S. Census of Government Finances | |
|---|---|
| Water utility | Entity responsible for the operation and maintenance of water supply systems including the acquisition and distribution of water to the general public or to other local governments for domestic or industrial use. The acquisition and distribution of water for irrigation of agricultural lands is excluded. |
| Water revenue | Revenue from sale of utility commodities and services to the public and to other governments. Does not include amounts from sales to the parent government. Also excludes income from utility fund investments and from other nonoperating properties. Excludes any monies from taxes, special assessments, and intergovernmental aid. Raw data are available at sub-county-year levels, and are aggregated to the municipality-year level. |
| Water interest expense | Amounts paid to service outstanding municipal debt that is issued specifically to finance city-owned and operated water utility facilities. Raw data are available at sub-county-year levels, and are aggregated to the municipality-year level. |
| Water investment | Includes maintenance expenditure for works and structures related to drinking water infrastructure. Includes direct expenditure for compensation of officers and employees and for supplies, materials, and contractual services. Raw data are available at sub-county-year levels, and are aggregated to the municipality-year level. |
| Population | Number of residents. Raw data are available at sub-county-year levels, and are aggregated to the municipality-year level. |
| Property tax | Taxes conditioned on ownership of property and measured by its value. Includes general property taxes related to property as a whole, real and personal, tangible or intangible, whether taxed as a single rate or at classified rates, and taxes on selected types of property, such as motor vehicles or certain or all intangibles. Raw data are available at sub-county-year levels, and are aggregated to the municipality-year level. |
| Intergovernmental revenue: Federal | Intergovernmental revenue received by the government directly from the Federal Government. Excludes Federal aid channeled through state governments. Raw data are available at sub-county-year levels, and are aggregated to the municipality-year level. |
| Intergovernmental revenue: State | All intergovernmental revenue received from the state government, including amounts originally from the Federal Government but channeled through the state. Raw data are available at sub-county-year levels, and are aggregated to the municipality-year level. |
| Intergovernmental revenue: Local | Fiscal aid revenue that allows the receiving government unrestricted use as to function or purpose. Raw data are available at sub-county-year levels, and are aggregated to the municipality-year level. |

| Source: SDC Platinum | |
|---|---|
| New Debt issuance | Sum of par amounts of related issues considered a single issue by the issuer. Purposes are given by SDC Platinum or inferred by the name of the issuing entity. Raw data are available at sub-county-year levels, and are aggregated to the municipality-year level. |
| Insured amount of new debt issuance | Total par amount insured. For one or more bond insurers, the insured amount of debt is the total par amount of the insured tranches. Raw data are available at sub-county-year levels, and are aggregated to the municipality-year level. |
| Total debt outstanding | We use full amortization schedules to construct estimates of total debt outstanding based on historical debt issues, maturities, and coupon rates. |
| Total debt insured | We use full amortization schedules to construct estimates of total insured debt outstanding based on historical debt issues, maturities, and coupon rates. |
| True interest cost | SDC-provided measure defined as the rate, compounded semi-annually, necessary to discount the amounts payable on the respective principal and interest payment dates to equal the purchase price received for the new debt issuance. If true interest cost is not provided by SDC, we use the bond yield, as defined below. Raw data are available at sub-county-year levels, and are aggregated to the municipality-year level. |
| Yield of final maturity | SDC-defined measure: The yield or the price of ending serial maturities in ranges of serial maturities. Raw data are available at sub-county-year levels, and are aggregated to the municipality-year level. |
| Coupon of final maturity | SDC-provided measure: The coupon of the final term maturity or final serial maturity in the final range of serial maturities. Raw data are available at sub-county-year levels, and are aggregated to the municipality-year level. |
| Yield | This measure is provided by SDC. If this value is missing in SDC, Yield is constructed using the following procedure: Yield = "Yield of final maturity" if available. If this value is not available, Yield is then calculated using the bond price if available, along with maturities and coupon rates. Finally, if these inputs are not available, Yield = "coupon of final maturity." Raw data are available sub-county levels. We aggregate them up to county-year level. |
| Source: U.S. EPA Safe Drinking Water Information System (SDWIS) | |

| | |
|---|---|
| SDWA violations | The number of federal health-related violations of the U.S. Safe Drinking Water Act by public community water systems. We observe three types of violations: maximum contaminant level violations, maximum residual disinfectant level violations, and water treatment technique violations. These violation types are designated as health-related by the EPA. For example, violations of maximum contaminant levels include instances of coliform bacteria, lead, and nitrates that exceed federal limits set forth by the U.S. SDWA. Raw data are available at sub-county-year levels; data are aggregated to the municipality-year level. |
| SDWA violations (pop wgt) | The number of federal health-related violations of the U.S. Safe Drinking Water Act by public community water systems (weighted by the population served by the community water system, where indicated). We observe three types of violations: maximum contaminant level violations, maximum residual disinfectant level violations, and water treatment technique violations. Raw data are available at sub-county-year levels; data are aggregated to the municipality-year level. |
| **Source: Refinitive Eikon** | |
| Credit rating | Municipal issuer's credit rating assigned by Moody's. Ratings are available at sub-county-year levels; ratings data are aggregated to the municipality-year level using debt amounts as weights. Moody's letter ratings are assigned numerical values: Aaa is 21, Aa1 is 20, and so on. Investment grade is defined as a credit rating of 12 (Baa3) or higher; non-investment grade is a credit rating below 12. |