Credit Crunch in the Classroom: School District Financing Under Liquidity Constraints*

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Abstract

In this paper, I examine how municipal bond market credit ratings affect future funding and staffing decisions in the US public education system. Using a novel and comprehensive dataset of all municipal bonds issued by US public school districts since 1987, I apply machine learning techniques to identify districts near key credit rating thresholds. Leveraging a regression discontinuity design, I then estimate the causal impact of diminished credit access across these thresholds. Focusing on the AAA-AA margin, I find that a reduced credit rating results in approximately 6% lower spending in the fiscal year following a ratings update. I show that this is primarily driven by decreases in capital expenditure, property tax revenue, and maintenance spending with the largest effects observed for mid-sized school districts.

Keywords: School district finance; municipal bond market; credit ratings; liquidity constraints; regression discontinuity design; education funding; capital expenditure.

JEL: I22, H41, H75, G12

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Public education in the United States is primarily funded through a combination of federal grants, state revenue, and local property taxes. While operating budgets are largely determined by revenues tied to local tax bases, intergovernmental transfers, and statutory funding rules, these sources typically arrive in predictable streams and are earmarked for ongoing instructional and administrative expenses. By contrast, capital projects and other extraordinary expenditures often require a large and immediate infusion of resources that exceeds the scope of annual revenue. To meet such needs, districts rely heavily on the municipal bond market, which provides an influx of liquid funds that can be deployed to finance new construction, facility upgrades, or unexpected temporary shortfalls.

At the start of 2025, approximately $4.4 trillion of municipal bond debt was outstanding across all sectors. In 2024, U.S. state and local governments issued an additional $450 billion in tax-exempt municipal bonds, of which more than $70 billion were designated for K–12 education projects, making primary and secondary education the largest issuing sector of tax-exempt securities (Municipal Securities Rulemaking Board, 2025; O'Hara, 2012). This reliance means that the terms under which districts borrow, including the ratings they receive and the interest costs they face, play a pivotal role in shaping their budgetary flexibility and, ultimately, the educational opportunities they can provide.

Despite the importance of the municipal bond market for school districts, relatively little is known about how the conditions of access to credit influence district financial decisions. Much of the existing research on school finance has examined how resource levels respond to shifts in local revenue capacity or voter approval of bond measures. A large body of work studies school bond elections, exploiting close outcomes to estimate the causal effect of additional capital funding on district expenditures, facilities, and student achievement (Cellini, Ferreira, & Rothstein, 2010; Martorell, Stange, & McFarlin, 2016; DeVries, Kodra, & Hay, 2023; Yang, 2024; Biasi, Lafortune, & Schönholzer, 2025). A related literature leverages variation in local property wealth to study the consequences of fiscal capacity for school finance. For instance, shocks to land values or the housing market have been used to trace out the relationship between changes in the local tax base, district revenues, and student outcomes (Neilson & Zimmerman, 2014; Hong & Zimmer, 2016; Conlin & Thompson, 2017; Brunner, Hoen, & Hyman, 2022).

In contrast, the role of credit ratings in determining borrowing costs and financial flexibility remains poorly understood. Ratings agencies such as Moody's, Standard & Poor's, and Fitch issue categorical scores with the intent to summarize a district's financial health and ability to repay debt. While higher-rated bonds reliably trade at lower yields (Livingston & Zhou, 2020), far less is known about whether, and to what extent, small differences in credit ratings translate into meaningful differences in the revenues and expenditures of school districts themselves. Unlike voter-approved bonds or property wealth shocks, which directly alter the flow of resources available to schools, variation in credit ratings and associated borrowing costs modifies the terms on which districts can convert future tax revenues into present liquidity, conditional on their existing balance sheets. This channel is forward-looking as small increases in borrowing costs today may compound into significant differences in the resources districts are able to mobilize for staffing, maintenance, or capital investment over time, even if their underlying tax bases or transfers remain stable. This paper focuses on answering these questions. Specifically, does a downgrade in creditworthiness affect the fiscal capacity of a school district in ways that influence hiring, staffing, and investment? Or are districts largely insulated from such shifts by the stability of tax bases and intergovernmental transfers?

This paper addresses these questions by examining how access to bond market liquidity, as proxied by credit ratings, affects future funding and staffing decisions in public school districts. To do this, I develop and analyze a novel dataset linking the universe of municipal bonds issued by U.S. school districts since 1987 which includes more than one million individual securities digitized from the Municipal Securities Rulemaking Board's (MSRB)

Electronic Municipal Market Access (EMMA) database. I match these issuances with fiscal and non-fiscal panel data on districts from the Annual Survey of School System Finances and the National Center for Education Statistics' (NCES) Common Core of Data (CCD). This represents, to my knowledge, the first comprehensive dataset of school district bond issuances matched to detailed district-level fiscal outcomes.

A central challenge for identification is that credit ratings are neither randomly assigned nor fully observed. Agencies' decisions reflect both observable characteristics like a districts balance sheet or student demographics and potentially unobserved factors that correlate with district outcomes. Moreover, ratings are missing for the majority of school district bonds, as proprietary assessments are not systematically disclosed in public filings. These gaps cannot be easily addressed with conventional approaches such as logit or ordered-probit models, which impose strong functional form assumptions and often fail to capture the nonlinear thresholds that drive rating assignments. To overcome these limitations, I follow Boehnke & Bonaldi's (2019) synthetic regression discontinuity (RD) design to generate a synthetic score that mimics the ratings evaluation process of the major credit ratings agencies via a supervised machine learning model trained on the subset of bonds with observed ratings. This approach flexibly replicates the rating process, achieving out-of-sample predictive accuracy exceeding 90 percent. The resulting imputed scores allow me both to recover the distribution of credit quality across districts and to construct a continuous running variable that measures proximity to the key AAA–AA ratings boundary. Leveraging this running variable, I implement a regression discontinuity design to estimate the causal impact of reduced credit access on district finances.

The results reveal that access to top-tier credit ratings has real and measurable consequences for district finances. Districts that narrowly receive a AAA rating raise and spend roughly 6% more per pupil in the subsequent fiscal year compared to otherwise similar AA rated districts. These gains are primarily driven by increases in local property tax revenues and are spent disproportionately on capital projects and maintenance staff compensation. Importantly, the effects are heterogeneous across district size and dependence on capital projects. While mid-sized districts experience the largest fiscal shocks from a ratings change, very large districts, typically urban systems with more diversified revenue streams, appear largely insulated.

The implications of these findings are twofold. First, they highlight the importance of credit ratings in shaping the fiscal capacity of school districts, underscoring that access to favorable bond market terms is not merely a technical matter of interest rates but one with real consequences for educational finance. Second, they suggest that the municipal bond market may reinforce existing disparities between districts where larger districts with diverse tax bases are better positioned to absorb the costs of lower ratings, while mid-sized districts are more directly constrained. This has potential consequences for the equity of public education, particularly given that many mid-sized districts serve growing or disadvantaged populations and rely heavily on new capital investment to meet student needs.

This paper contributes to the literature in three principal ways. First, it poses and answers a novel question at the intersection of school finance and municipal bond markets: how do credit ratings influence the financial decisions of public school districts? While prior work has emphasized the roles of property taxes, state aid, and intergovernmental transfers in shaping school resources (Cellini et al., 2010; Martorell et al., 2016; DeVries et al., 2023; Yang, 2024; Biasi et al., 2025), the capital financing channel through bond markets remains comparatively understudied. Second, the paper adds to our understanding of the real effects of credit ratings and capital market access by showing how ratings shifts translate into meaningful differences in school district revenues and expenditures, thereby connecting insights from financial economics (Benmelech & Dlugosz, 2010; Barberis, 2013; Livingston & Zhou, 2020; Peppe & Unal, 2022), to the economics of education. Third, it improves and extends existing machine learning approaches for municipal bond rating classification and adapts synthetic regression discontinuity methods to this context, advancing tools originally developed in the finance and computer science literatures (Ang & Patel, 1975; Kaplan & Urwitz, 1979; Papay, Willett, & Murnane, 2011; Wong, Steiner, & Cook, 2013; Boehnke & Bonaldi, 2019; Jabeur, Sadaaoui, Sghaier, & Aloui, 2019; Takawira, 2024).

The rest of this paper proceeds as follows. First, I provide a bit of background about the municipal bond market and specifically the school bond market. Next, I describe the data I assembled for the project. I then provide a detailed description of my application of the synthetic RD design to my setting. I follow that up with a discussion of my results, and I conclude by contextualizing those results in terms of financial implications, student achievement, and policy relevance.

Background

Overview of the Municipal Bond Market

The United States municipal bond market is a vital source of financial liquidity for state and local governance structures. Its primary use is to raise funds for the construction of new infrastructure and capital projects. At the start of 2025 there were $4.4 trillion in outstanding municipal bonds available for public trading and in the most recent years over $400 billion in additional bonds are issued at all levels of state and local governance (O'Hara, 2012). Table 1 provides a breakdown of the nearly $450 billion in tax-exempt municipal bonds issued in 2024. Other than the general purpose bonds sector which mostly reflects the issuance of new bonds to refinance older ones at a different interest rate or issuance term, the primary and secondary public education sector is the largest issuing sector of municipal securities in the country comprising $73 billion in new bonds (Municipal Securities Rulemaking Board, 2025). The K-12 education sector has led the nation as the largest source of annual bond issuances since at least 1989 (O'Hara, 2012).

Today, the vast majority of bonds are issued as General Obligation (GO) Bonds meaning the full face value and interest accrued from the security is backed by the full faith, credit, and taxing power of the issuing entity. For the primary and secondary education sectors, that issuing entity are school districts themselves which primarily use local property taxes to cover the issuance of a bond. The revenue raised from GO bonds is state and federal tax free. Taxable bonds, especially those issued under authority from the American Recovery and Reinvestment Act of 2009, make up a far smaller slice of the bond market and are not used frequently in funding capital projects in the education sector.

For this paper, data on municipal bonds from the education sector is drawn from the Municipal Securities Rulemaking Board (MSRB) which is the chief regulatory body for municipal securities in the US. The MSRB has been in existence since 1975 and has recorded all issuances and transactions regarding municipal bonds since their founding. A more in depth description of the data I use in my analysis from the MSRB is provided in the data section below but, for the purposes of this overview, I use the MSRB's database to help disaggregate issuance data for the primary and secondary public education sector.

Figures 1 and 2 serve to illustrate two important facts about the municipal bond market for the primary and secondary education sector. Figure 1 plots the nominal value of issuances by school districts since 1975. Notice that recorded municipal bond issuances began to increase dramatically around 1987 which coincides with the passage of the Tax Reform Act of 1986. This legislation clarified the regulatory space of tax-free municipal bonds and ensured all GO bonds be issued publicly (O'Hara, 2012). Since then, the amount of annual issuances has followed the business cycle with sizable dips around the 2008 financial crisis and the COVID-19 pandemic. The municipal bond market has largely recovered from the pandemic lull to set a new record high for issuances of $73 billion dollars. In Figure 2, I plot the sum total real value (in 2024 dollars) of issuances by individual districts since 1987 aggregated into percentile groups. I observe here that the pattern bond issuances by districts follows a distribution where a few districts in about the 80th percentile and above make up the vast majority of bond issuances. This is consistent with the governance structure of US public education where a few large urban school districts educate the majority of students and thus incur the majority of capital expenditures. Among the largest issuers are the school districts representing the District of Columbia, Los Angeles, the major urban centers in Texas, and the Chicago area school districts.

Municipal Bond Issuing Process for School Districts

The process for issuing new bonds for most school districts begins with an analysis for the infrastructure needs of the district prior to the start of the fiscal year. In interviewing several central office district officials in large school districts, I found that the typical procedure starts with a survey of the state of infrastructure maintenance for the district along with a projection of how the student population will change geographically over the next decade, so that new schools can be built or existing ones "right-sized" to account for changing demographics. This survey forms the basis for a district's master infrastructure plan which is essentially an order list of priorities about new construction and maintenance goals district officials need to address.

With the master plan in hand, district leaders work with financial experts to determine the correct size of the bond issuance in order to put the details before their approving authority. In most US states, the approval needed to issue a bond comes from the voters of a school district directly in the form of a bond referendum. In others[1] school districts need to go before the state legislative body for approval. In either case, this exposes a potential bond issuance to political risk especially since school bond issuances typically need to be offset with corresponding increases in local property tax. As such, district officials need to carefully consider the timing of the US election cycle and the local political atmosphere in

[1] One such example is the state of Indiana, at least prior to 2008 state education reforms (Hiller & Spradlin, 2010).

order to secure the necessary funding.

If a school bond referendum or other approval process is successful, the school district begins the process of negotiation with an underwriting institution or bond issuing bank to determine a yield and coupon (interest) rate acceptable to both parties. The underwriting institution considers the financial status of the issuing district, its most recent credit rating update usually determined at the last time a bond was issued, and the size of the tax base available to support the bond in order to offer the district underwriting terms. Once the legal framework and underwriting negotiations are completed, the underwriter provides funds to the district in exchange for the rights to issue the bond for sale to the general public.

It is at this point that the public becomes aware of the details of the bond issuance through mandatory reporting to the MSRB in accordance with Securities and Exchange Commission (SEC) regulations. The underwriter, with permission from the issuing school district, may also submit the bond for credit rating analysis which can impact the sell-ability of the bond on the secondary transaction market. It is to the benefit of school district officials to get a bond rated, especially if they are confident in their ability to back the bond financially given the difference in interest rate can by as high as 40 to 60 basis points (Peppe & Unal, 2022). As such, the majority of municipal bonds are submitted for a rating to at least one of the major credit ratings agencies (Standard & Poor's, Moody's Investors Service, or Fitch Ratings) for evaluation usually in exchange for a percentage fee of the value of the bond. The ultimate rating the bond receives is a function of the value, yield, coupon rate, time to maturity, and financial health of the school district. However, the exact formula that the major credit ratings agencies use is a trade secret.

Table 2 presents a list of ratings categories and their meanings developed by Standard & Poor's. The other ratings agencies have similar scales and one rating can easily be converted to another by a potential investor. Figure 3 depicts the distribution of ratings data from the K-12 public school municipal bonds sector. Once again this data is generated from my own efforts to collect and digitize MSRB records the details of which are described in the data section below. I observe that nearly all of the bonds issued fall into the A, AA, and AAA categories. Only about 0.002% of all issuances between 1987 and 2023 resulted in default.

After the bond is rated, the MSRB updates their records with the bond rating and the underwriting agency offers the bond up to the primary debt market for purchase by investors. The bond can continue to be bought and sold in the primary and secondary investment markets or packaged into derivatives in accordance with MSRB and SEC regulations until it reaches its maturity date.

Data

US School District Fiscal and Non-Fiscal Data

The data for this paper is organized as a district-year panel and I rely on three primary sources for its construction. First, I rely on the F-33 survey, commonly known as the Annual Survey of School System Finances to serve as the main source of financial data for each school district (US Census Bureau, 2025).

The results of the F-33 survey are of interest to both the US census bureau as part of their Annual Survey of State and Local Government Finances (ALFIN), and the National Center for Education Statistics (NCES) which includes them in the Common Core of Data Fiscal Surveys. The reason this matters for this project is that the two governmental entities tabulate the data in different ways for their different purposes and, importantly, use two different definitions of what counts as a school district. The NCES uses much more granular divisions for school districts (known as Local Education Agencies or LEAs) which can include special governance entities like independent charter schools or special schools like those for the deaf and blind. The NCES also disaggregates districts that are subsidiaries of other districts despite sharing the same managing governance structure. The Census Bureau, on the other hand, uses a definition for school district that attempts to reconcile different categories of LEAs into what it considers the primary government entity for each survey respondent. This is the more relevant definition for the purposes of my work here as smaller independent LEAs generally do not issue bonds or, if they do, they do so through their managing governance structure. Using census definitions also ensures that school finance parameters are properly mapped between federal, state and local sources in the survey reports helping to ensure I do not double count any funding or expenditure sources. For this reason I use the Census Bureau aggregation in this project.

For the non-fiscal school district variables, I use the Common Core of Data Non-Fiscal Survey from the NCES (National Center For Educational Statistics, 2025). Using the two surveys in tandem requires linking district fiscal years to the non-fiscal survey usually conducted in October. This means that the non-fiscal survey is a snapshot in time for the district fall enrollment window while the fiscal F-33 survey covers the entirety of a fiscal year. In order to produce an accurate panel of district-year links from these two data sources, I follow the best practices laid out in the excellent guide to school finance data from the EdFund Data Dictionary project (Sibilia, 2025). In addition to the data processing recommendations of EdFund, I also take care to align the start dates of fiscal years to school years and the municipal bond issuance data which I describe in greater detail below. Since state law differs as to the start date and frequency a budget is issued, I elect to calculate all fiscal years from July 1st which is the most commonly chosen start date[2].

Table 3 contains the summary statistics for the combined fiscal and non-fiscal data on all district year observations between 1987 and 2023 under the full sample heading. Since the F-33 survey questions changed over time, particularly on the fiscal side, the sample effectively reflects the data since 1993 when the key financial variables at the district level

[2] According to The National Association of State Budget Officers, "Forty-six states and Puerto Rico begin their fiscal years in July and end them in June. New York starts its fiscal year on April 1; Texas starts on September 1; and Alabama, Michigan, DC, Guam and the Virgin Islands start their fiscal years on October 1" (White, 2024).

took the form used today. This results in approximately 312,000 district-year observations. Though not required for my identification strategy, it is interesting to note that districts in the "ever-issued" sample look very similar to the full sample especially in terms of student demographics.

Municipal Bond Data for US Public School Districts

Building from the foundation of the fiscal and non-fiscal surveys, I make a novel contribution to this body of school finance data by linking the district-year observations that form the full sample described above to a new data set containing the complete universe of municipal bonds issued by all public school districts between 1987 and 2023. This data is drawn from the publicly recorded statements collected by the Municipal Securities Rulemaking Board's Electronic Municipal Market Access (EMMA) database after a district issues a bond for sale to the general public (Municipal Securities Rulemaking Board, 2023). I digitized over 27,000 documents from the MSRB public listings and then extracted the issuing entity name, date of issuance, term length, coupon rate, value, and credit rating where available for each of the bonds listed in the public education sector. After filtering out issuances by state entities or higher education institutions, I was left with approximately 1.07 million bonds issued by public school districts. Using a combination of fuzzy matching techniques and hand matches, I linked the name of the issuing entity to its relevant school district-year observation. By the end of this process, I was able to match just shy of 1 million of these individual bonds to their districts. Table 4 provides an overview of these bonds.

It is worth noting here that I rely on two other important sub-samples for the analysis in this paper. Not all public school districts issue municipal bonds. As mentioned earlier, most school districts only seek bonds when they have to raise funds for a large capital project. And some school districts, particularly smaller more rural ones, do not rely on the bond market at all for capital. As such, I define a subsample of the combined fiscal and non-fiscal survey data that contains only those districts for which I observe at least one instance of a bond issuance as the “ever issued bond” subsample in table 3. This set of districts forms the subsample of interest for the remainder of the project. Importantly, it is worth noting that focusing on this subsample is not sample selection on my part but rather amounts to restricting attention to the relevant population of districts for which access to credit markets is a feasible option.

The last subsample noted in table 3 is the set of all district-year observations which have a recorded credit rating from the EMMA database. Only about 20% of the bonds recorded in the public education sector of the EMMA database have a credit rating by one of the big 3 credit ratings agencies. The vast majority of bonds are professionally rated in this sector, only about 13% of all municipal bonds go unrated across all sectors since 1998 (O’Hara, 2012). Instead, the ratings I do observe are district level ratings rather than bond ratings directly. Credit ratings agencies do publicly announce the overall institutional rating for significant players in the bond market. Whenever possible, the MSRB links these institutional ratings to the bonds that entity issues and I incorporate that information into my constructed dataset.

This data forms the basis and necessity for using machine learning techniques to approximate the ratings decision by the credit rating companies. These techniques are described in the methodology section in greater detail. However, to better understand the demographics of the pool of districts that have know ratings, I also break out my main summary statistics by this sample as well in the “rated districts” column of table 3. I find that the districts with listed ratings tend to be larger school districts in terms of enrollment and expenditures and have student populations that are poorer and more racially diverse. In my subsequent analysis, I attempt to adjust for this by focusing on the predictive factors that underlie a ratings decision rather than the decision itself when building my synthetic running variable which improves my ability to make out of sample predictions. I also take care to control and account for these differences in demographics and financial health in the final regression discontinuity analysis.

Methodology

In order to identify the effects of a ratings difference on the future financial decisions of a school district, I intend to exploit variation in credit ratings. Using credit ratings directly is not sufficient to make causal claims about the effects of differences in these ratings on any set of outcomes. This is because credit ratings alone are not randomly assigned. Indeed, if they are worth anything to investors in terms of a signal of creditworthiness, we would expect that credit ratings agencies carefully calculate out what the appropriate ratings ought to be for each bond issued. But it is precisely this calculation that makes it possible for me to use bond ratings as a source of identification. If I am able to reconstruct the underlying calculations that go into a bond ratings decision, then I can identify similar districts that have close ratings decisions but fall on opposite sides of a rating cutoff, and compare these directly to determine the impact. One way to do this is to use machine learning techniques to intuit what combination of characteristics determine a bond rating, and then to reverse engineer a score which effectively measures how close a particular district-year observation is from a ratings cutoff. The constructed score then sets up naturally as a running variable for a regression discontinuity (RD) design where the cutoff is the tipping point between ratings classes.

This was the idea behind Boehnke & Bonaldi's (2019) synthetic regression discontinuity which is a new econometric method proposed to address situations like this where a continuous score outcome is unobservable but a categorical secondary outcome which is directly based on the continuous score is observable. The analogy for my setting is that I do not observe the underlying calculations that go into bond ratings but I do observe a subset of the district level ratings (which I call my rated districts sample). From this known data, I can build out a synthetic running variable using machine learning tools and then estimate a traditional RD to identify my causal effects. In essence, I am trying to recreate the model by which a ratings agency makes its decisions and used that generated score to compare districts with different ratings in my sample.

Boehnke & Bonaldi show that the following assumptions must be satisfied in order to use their synthetic regression discontinuity design:

1. The unobserved score determining observed treatment status is plausibly continuous.
2. The unobserved score is determined by a large set of observable predictors.
3. The predictors, when used in a machine learning model, are able to achieve a high level of accuracy in predicting the observed secondary outcome.
4. The synthetic score satisfies standard RD assumptions of continuity and no manipulation around the cutoff.

In the remainder of the methodology section, I present a more detailed description of how I construct my synthetic running variable and verify each of the assumptions that Boehnke & Bonaldi lay out.

Overview of the Identification Strategy

Identification of the effects of access to liquidity through the municipal bond market begins with a measure of creditworthiness. To get at this, I rely on the credit ratings recorded by the MSRB alongside the basic statistics of a bond issuance. Recalling the distribution of credit ratings from Figure 3, I determined that the best case for detecting an effect from differences in creditworthiness is to compare bond issuing school districts close to the boundary of AAA and AA ratings. I do this for several reasons. First, since nearly 90% of all bonds in my data set are rated either AA or AAA, this margin has the maximum amount of power to detect any effect. This is especially important in order to satisfy assumption (3) of the synthetic RD method. The fewer categories I am interested in predicting out, the more accurate my machine learning model will be. As it turns out, this is really the only margin for which I have a sufficiently high accuracy to carry forward with the rest of the strategy. Second, AAA municipal bonds, and indeed any highly rated security, have an important psychological effect for investors. AAA bonds receive consistently lower interest rates and are preferred by investors to all other assets, including those rated just below AAA for their perceived safety (Barberis, 2013; Benmelech & Dlugosz, 2010; Livingston & Zhou, 2020). And lastly, school district officials themselves pay attention to credit ratings closely and recognize that reduced borrowing costs from high ratings can help to ensure financial stability and flexibility to provide quality programs for their students and employees. For these reasons, if an effect from differences in creditworthiness were to be observable anywhere, it would be on the AAA-AA margin.

In the context of school municipal bonds, assumptions (1) and (2) of the synthetic RD are naturally satisfied. First, the unobserved score determining ratings decisions is a continuous index by construction. Ratings agencies rely on a weighted combination of financial indicators, demographic indicators, and governance measures, none of which admit discrete jumps that would render the latent score discontinuous. In fact, Boehnke & Bonaldi (2019) use corporate bond market ratings as their demonstrating case in their paper describing the synthetic RD design. Certainly then, their methods would extend naturally to the municipal bond market as well. Second, this latent score is, in practice, determined by a broad and well-documented set of observable predictors. Ratings agencies publish methodological overviews[3] outlining the financial and economic variables they evaluate. These include fund balances, debt ratios, revenue stability, and local economic capacity all of which are observable in the publicly available district finance data.

[3]See for example `https://www.spglobal.com/ratings/en/regulatory/article/-/view/sourceId/6176952`

Taking all of this together suggests a three step plan to identify the causal effects of differences in creditworthiness on future financial decisions by school districts. First, I use the "rated districts" sample to train a machine learning classification model to predict out the ratings of districts that issued bonds. Next, I take the individual factors that predict bond ratings in the machine learning model and search for points in their domain that produce major changes to the probability of a district moving from one ratings category to another signaling a cutoff point for use in an RD. From these breakpoints, I follow econometric techniques for combining several different running variables which contain discontinuities into a single index and estimate the difference in creditworthiness. I now describe each of these steps in greater detail.

Machine Learning Credit Rating Predictions

The problem of predicting credit ratings for bonds and other assets is an old one within the finance literature[4]. The traditional approach was to use an ordinal logistic regression or other similar categorical statistical predictor to categorize securities into ratings buckets. I experimented with these models and was able to get rates of accuracy no higher than about 74% in my use case. Although Boehnke & Bonaldi do not offer a target accuracy score for assumption (3) to be satisfied, this is almost certainly not high enough to meet their conception of high accuracy.

In recent years, however, supervised machine learning (SML) techniques have been found to frequently outperform previous statistical methods in prediction accuracy (Takawira, 2024). The bond ratings prediction problem is one that suits itself well to the development of a classifier model. In a supervised classifier model, I present the computer with a set of district-year observations that have been professionally rated alongside all of the school district characteristics of the issuing entity. From these, the computer applies a chosen SML

[4]See (Ang & Patel, 1975; Kaplan & Urwitz, 1979)

technique and attempts to optimize the related utility function[5] that measures accuracy of its predictions in comparison to the true ratings. The critical tradeoff to consider for my purposes is efficiency in terms of computing power versus quality of prediction for which I always prioritize quality despite longer computing times.

To test the ultimate quality of a classifier model, SML researchers use a train-test evaluation where they split the professionally classified items into two datasets. A training dataset which is used to teach the classifier model to properly predict the class of an input and a test dataset which is given to the trained classifier model to check for how closely it is able to match the classifications in the test set with its own predictions. Importantly, by using a train-test framework, I can actually test for satisfaction of assumption (3) by comparing the baseline accuracy of assigning the largest class to all observations to the prediction accuracy of the model. Different academic literatures vary in their guidance on what the ideal split of data is into training and testing sets, but the typical rule of thumb used in computer science is to train on a randomly selected 80% of already classified data and test on the remaining 20% (Vrigazova, 2021). This is the rule I follow for my work in this project. The last step to using a supervised machine learning model is to retrain the model on the full set of available classified data and then apply it to the unclassified data.

Following best practices in this literature, I experiment with several SML methodologies including tree based methods, Markov models, naive Bayes techniques, nearest neighbors, neural network methods, and support vector machine while also curating the list of SML model inputs (i.e. school district-year characteristics) included in the training process. I ultimately settle on a Gradient Boosted Trees model for the overall classifier which has precedent for its quality within the finance literature for my use case (Jabeur et al., 2019).

[5]Here I refer to utility functions not in the economic sense but as a term of art within the computer science and machine learning literatures to describe the conditions that need to be satisfied to constitute a high quality class classification for a vector of descriptive features. In my case, what bond rating class is appropriate given the financial decriptives of a school district. Describing these utility functions for different techniques is well beyond the scope of this paper but their forms are fairly standardized to the chosen technique within the computer science literature.

The list of variables I select to go into the SML model are given in table 5. In the selection of variables for the SML process, I took care to ensure the model only had access to the data that existed at the time of issuance and would have been available to the ratings agencies. This meant, in practice, that only present or lagging variables relative to the date of issuance were included. Further, since the interest rate, date to maturity, and value of an issued bond are all codetermined with credit rating, I exclude these to preserve the chain of causality between district characteristics and credit rating. To avoid overfitting, I only include lagged school district-year characteristics for the most predictive numeric components of the classifier model as measured by SHAP value[6].

For the general SML model, I restrict the possible ratings pool which the model is allowed to search over to just AAA, AA, and an Other category which effectively filters out all other possible ratings. Results of the train-test experiment conducted on the roughly 7500 district year observations that make up the "rated district" sample described in the data section are provided in figure 4. On a baseline accuracy of 79.6% which is the accuracy the model would have produced by simply applying the class of most well represented rating to all observations, I am able to accurately classify over 90% of bonds correctly from the testing dataset. This is in line with the best performing SML models in the finance literature and lends strong evidence that I am able to accurately fill in the missing ratings for the districts in accordance with assumption (3) of the synthetic RD design.

Construction of The Running Variable

The next step in implementing the regression discontinuity design is to construct a continuous running variable that captures the proximity of a district-year observation to the AAA–AA credit rating threshold. Since ratings categories are discrete, they cannot them-

[6] SHAP values (SHapley Additive exPlanations) adapt the Shapley value from cooperative game theory (Shapley, 1953) to machine learning, treating each feature as a "player" in a game that produces a model's prediction. They assign to each feature its average marginal contribution across all possible feature coalitions, ensuring a decomposition of the prediction that is fair, consistent, and additive. As such, they are commonly used to measure the predictive power each feature of a machine learning model provides.

selves serve as a valid running variable. To overcome this, I leverage the supervised machine learning (SML) model described in the previous subsection, which emulates the classification process of ratings agencies using observable district financial characteristics. By doing so, I am able to identify specific values of district covariates that correspond to sharp changes in the probability of receiving a AAA rating, and then synthesize these into a single, continuous score.

Formally, I begin by examining the component inputs to the SML model presented in table 5 and plotting the predicted probability of a AAA rating across the domain of each predictor. To reduce noise in the prediction surface, I stratify the sample into bins by total district revenue before conducting this exercise. This stratification reveals much clearer probability shifts and allows for the identification of discontinuities in the probability of a AAA rating along the domain of individual predictors. For each variable, I record the point at which the predicted probability of a AAA rating crosses the 0.5 probability threshold if one exists. These values serve as candidate cutoff points, representing empirical estimates of the thresholds ratings agencies implicitly use to distinguish between AAA and AA classifications.

The challenge then is to aggregate these multiple cutoff points across predictors into a single running variable. While a standard RD relies on a single, continuous assignment variable, in this setting the underlying assignment process is more complex. Credit ratings agencies evaluate districts using a multidimensional set of financial indicators, and thus the implicit "running variable" is a combination of several assignment scores rather than one. This motivates the use of a multiple-assignment or multi-score RD as first pioneered by Papay, Willett, and Murnane (2011). In such designs, treatment assignment is determined by a vector of assignment variables, each of which may contain discontinuities at points corresponding to thresholds in the rating process. Direct estimation with multiple scores is challenging because it is not straightforward to determine a district's relative position to the treatment threshold when assignment occurs in multiple dimensions. To address this issue, I apply the centering approach outlined in Wong, Steiner, and Cook (2013), which reduces the multidimensional assignment structure into a single continuous index by calculating the standardized distance of each observation to the nearest cutoff point. This transformation preserves the key quasi-experimental variation generated by the thresholds while ensuring comparability across predictors. In practice, this approach allows me to treat proximity to the AAA–AA boundary as a one-dimensional running variable, while still leveraging the full predictive information embedded in the multidimensional financial data.

To implement the centering estimation procedure, I first calculate each district-year observation's standardized distance to the nearest identified cutoff across all predictors. This minimized distance forms the basis of the joint running variable, with the sign determined by whether the observation lies above (toward AAA) or below (toward AA) the cutoff. Then, I re-center the variable so that zero corresponds to the threshold itself by orienting each calculated distance in accordance with the direction of probability change. Effectively, this ensures that observations with a joint running variable value below zero are AA issuers and those above zero are AAA issuers. Taken together, the resulting measure provides a continuous index of proximity to the AAA–AA boundary for each district-year observation, and it can be used as the running variable in the RD estimation.

To summarize, this approach transforms discrete, categorical ratings into a continuous score that captures how "close" a district is to the AAA–AA margin, while preserving the economic interpretation that underpins the RD. By combining information across multiple predictors, the running variable maximizes predictive power and more faithfully replicates the holistic process by which ratings agencies evaluate creditworthiness.

Results

Before presenting the RD estimates following the construction of the running variable according to the procedure outlined in the previous section, I first describe the empirical framework common to all specifications in this section. All my RD models are estimated using the bias-correction and robust inference procedures developed in Calonico, Cattaneo, & Farrell (2018, 2020) and Calonico et al. (2020). Specifically, I employ data-driven optimal bandwidth selection and report robust bias-corrected standard errors, ensuring that statistical inference is not unduly sensitive to arbitrary bandwidth choices or local polynomial specifications. Each model incorporates a common set of district-level covariates that capture socioeconomic and demographic characteristics, including the share of students eligible for free or reduced-price lunch, the fraction of Title I schools, and the racial and gender composition of the student body. Taking advantage of the panel nature of the data, I also elect to include year and state fixed effects wherever possible to account for legal and economic differences across geography and time. All outcomes are scaled in per-pupil terms, allowing for meaningful comparisons across districts of varying size.

A further feature of the empirical design is the temporal structure used to measure fiscal outcomes. If a district receives a close ratings decision signaled by nearness to the running variable cutoff in year t, then fiscal responses are measured from the subsequent fiscal year $t + 1$. This lead outcome structure is intended to capture the effect of a ratings decision on district finances after local budgets have had sufficient time to adjust. This design ensures that estimates reflect changes in revenues and expenditures attributable to the rating outcome itself, rather than contemporaneous fiscal conditions in the year of issuance. All results reported below should therefore be interpreted as the real (in 2024 dollars) per-pupil changes in district finances observed one fiscal year following a close ratings decision. Further, because the running variable is positive for districts with higher probabilities of being AAA as determined by the SML classifications, positive coefficients should be interpreted as increases in the outcome variable for AAA rated districts relative to similar AA rated districts.

Validating the Research Design

Before turning to estimates of the causal effects of credit ratings on district finances, I first assess the validity of the regression discontinuity (RD) design. I have already demonstrated in the methodology section that I am able to satisfy Boehnke & Bonaldi's (2019) first three assumptions for a valid synthetic RD. To tackle the last assumption, I test whether districts appear to strategically manipulate their position relative to the AAA–AA threshold. Following the test laid out in McCrary (2008), figure 5 displays the McCrary density test, which formally evaluates whether the distribution of the running variable is continuous at the cutoff. The test compares estimated local densities on either side of the threshold, with a significant discontinuity interpreted as evidence of bunching or sorting behavior. In this case, the results show smooth continuity in the distribution of the running variable around the cutoff, with no evidence of excess mass just above or below the boundary given the insignificant 0.78 test statistic. This provides support for assumption (4); that districts cannot precisely manipulate their credit ratings in a way that determines treatment status.

To further validate the constructed running variable as a valid discriminator and index for proximity to the AAA-AA rating line for districts, I need to demonstrate that there is a significant change in the frequency of districts rated AAA on either side of this cutoff. This constitutes the first stage evidence for the RD. The nature of the data and my lack of a complete set of professionally issued credit ratings means I'm restricted to testing only the subsample of bonds for which I do have those ratings. Figure 6 presents a plot of the fraction of AAA rated district-year observations by binned values of the constructed running variable. To calculate the value for each bin, I take the number of district-year observations in a bin which have a professional rating of AAA and divide by the number of district-year observations with any sort of professional rating. For strong first stage evidence, I would expect to see a significant change in the proportion of districts rated AAA across the cutoff at 0. In Figure 6, there is a strong suggestion that such a break exists. Comparing bins on either side of the AAA-AA cutoff location suggested by the machine learning process reveals an increase in the fractions of AAA rated districts by 20 percentage points moving from the AA side to AAA side. Further, within any reasonable bandwidth of the cutoff, I also observe an overall distribution of ratings that demonstrates an increase in the fraction of observed AAA ratings generally as the value of the constructed running variable increases. This observation is consistent with the interpretation that the constructed running variable represents a measure of how likely a district-year observation is to be a AAA district.

In addition to the first stage evidence, I also examine whether the constructed running variable aligns with meaningful differences in district finances across the AAA-AA boundary. Figures 7, 8, and 9 present binned averages of per-pupil local revenue, per-pupil expenditures (including capital outlay), and per-pupil debt issuance plotted against the running variable. In each case, districts on the AAA side of the cutoff exhibit higher values relative to those on the AA side, with the shift occurring at or very near the cutoff. This descriptive evidence is consistent with a mechanism in which stronger credit ratings allow districts to issue more debt, finance repayment with higher property tax collections, and channel the additional resources into both current and capital expenditures. Importantly, these patterns also lend support to the validity of the research design because the discontinuity in outcomes across the AAA-AA threshold suggests that the running variable successfully captures the margin of credit access on which districts operate.

At the same time, these plots should be interpreted as suggestive rather than definitive. Because the binned means do not account for optimal bandwidth selection, sampling error, or covariate adjustment, they cannot provide precise causal estimates. The regression discontinuity design that follows offers a more reliable assessment by formally modeling the functional relationship between outcomes and the running variable, estimating discontinuities with robust standard errors, and yielding headline effects that properly weight observations near the cutoff. Nonetheless, the second-stage descriptive patterns reinforce the plausibility of the causal story and provide intuitive evidence that districts with marginally better ratings are able to mobilize additional fiscal resources.

Main RD Estimates

Table 7 reports the principal RD estimates for two subsamples of districts. The first, the ever issued sample, includes all districts that have issued at least one bond since 1987. The second, the rated districts sample, is limited to the smaller group with professional credit ratings recorded in the MSRB data.

Results from the rated districts subsample show no statistically meaningful discontinuities at the AAA–AA threshold. Point estimates indicate that AAA-rated districts may raise and spend somewhat more than their AA counterparts in the year following a close ratings decision, but the limited number of observations in this sample yields imprecise inference. By contrast, the broader ever issued sample provides substantially greater statistical power. In this setting, I find robust evidence of expenditure increases of approximately 6% per-pupil[7] for districts narrowly assigned the higher rating. These gains are largely attributable to increased spending on capital projects and newly issued debt and are offset by increases in local property tax revenue of a similar magnitude. Taken together, these findings indicate that districts narrowly securing a AAA rating experience tangible fiscal benefits, although such effects are empirically detectable only in the larger bond-issuing sample.

I should also point out that the effect sizes on increases for capital outlay spending and newly issued debt are quite large. Doing the math relative to the means from table 3 would suggest increases of up to 19%. However, in order to properly contextualize this value, it is important to note that districts with the higher AAA rating issue about 16%

[7] I calculated this number by taking the coefficient from the per-pupil total expenditure main RD results and divided it by the mean total expenditure value from table 3 under the ever-issued sample.

more debt per-pupil than AA districts on average as demonstrated by table 8. This means that the effects of a close ratings change are far smaller relative to this baseline than the coefficient might suggest. A better way to interpret my results might be to recognize that the baseline differences I observe in the means of long-term debt issuance are largely explained by differences in credit ratings directly rather than any other underlying characteristic.

The full sample main results provide strong evidence that small changes in credit ratings translate into real fiscal capacity for school districts, allowing them to increase both capital investment and staffing expenditures. However, there is substantial diversity between districts in terms of how impactful a change in rating might be. It is reasonable to expect that a district highly dependent on access to the additional credit a higher bond rating would seem to bestow would observe a more dramatic shock to its budget following a credit rating downgrade for example. This is difficult to test directly with the data available to me, but I can try to break down the results from table 7 to gain some greater clarity into how different sized school districts are affected by this shock.

To this end, table 9 presents heterogeneity in treatment effects by quartiles of per-pupil capital outlay expenditures which can be though of as a proxy for seeking credit and thus exposure to credit rating changes as well as size of the district. Results reveal stark differences in the role of credit access across district size. Table 9 shows that most of the effects that I pick up in the main results are driven by mid-sized districts in quartile three of the capital expenditure distribution. This is especially true for effects on local revenue and total expenditures where nearly all the effect size can be attributed to these districts. The concentration of effects among mid-sized districts suggest to me that credit ratings are most salient when districts are sufficiently active in bond markets to be exposed to borrowing constraints, but not so large that they can offset rating changes through alternative financial strategies.

Robustness

The results described above suggest that credit ratings are an important factor in determining the structure of a school district's future finances. However, the credibility of these results ultimately rests on the strength of the underlying research design. To ensure that the observed effects are not artifacts of pre-existing differences across districts or spurious correlations in the data, I next turn to a series of robustness exercises.

First, to rule out the possibility of my results being driven by anticipatory effects or other structural changes to school finances that are timed to a credit ratings update, table 6 presents a set of placebo estimates using lagged district financials as outcomes. As mentioned in the introductory paragraph for this section, my main results focus on the $t + 1$ fiscal year after a close AAA-AA ratings decision. One way I can verify I am not picking up spurious effects is to demonstrate that in fiscal years prior to the close ratings decision, there is no significant change in headline budget numbers. In table 6, I present the RD estimates from the $t - 1$ fiscal year to test for "pre-period balance". For good measure, I also demonstrate balance in key demographic parameters. Consistent with the identifying assumptions of the design, almost none of the covariates show significant effects in the year prior to treatment, implying that observed post-rating effects are unlikely to be driven by pre-existing differences between AAA and AA districts.

Next, I compare the regression discontinuity estimates to a set of ordinary least squares (OLS) regressions that use the machine learning model's predicted ratings to classify districts, treating AAA districts as the treatment group. These specifications include the same set of controls as the RD models, including year and state fixed effects, and estimate each outcome separately. Once again, I use the fiscal year following a realized rating (i.e. the $t + 1$ year) to draw my outcomes from. Table 10 presents the results of these regressions. The OLS results present a somewhat mixed picture. While capital outlay expenditures increase in line with expectations, local revenue moves in the opposite direction, and in several cases the magnitudes differ substantially from those obtained in the RD framework.

I interpret these findings with caution. Although they suggest that there is some sensitivity of the conclusions to specification choice, OLS does not exploit the quasi-experimental variation at the AAA–AA threshold, instead imposing a linear relationship across the entire distribution of predicted ratings. This leaves the estimates vulnerable to confounding from unobserved heterogeneity across districts that is not adequately absorbed by covariates or fixed effects. Moreover, the OLS framework does not incorporate the careful weighting that the RD design applies through bandwidth selection, which focuses estimation on observations close to the threshold where identification is most credible.

Lastly, I explore how the estimated effects vary between recession and non-recession years. Using the NBER Business Cycle Dating Committee definitions, I classify 1990, 2001, 2008–2009, and 2020 as recession years and re-estimate the main RD specifications for recession and non-recession years. Table 11 presents those results. Consistent with expectations, recession years exert a strongly negative influence on district finances. As described in the background section, bond issuances in the education sector are pro-cyclical; downturns are associated with sharp declines in new debt issuance. These contractions in borrowing translate directly into lower capital investment and reduced local revenue collections during recession periods. Comparing these estimates with non-recession years suggests that recessions dampen the effects of close rating decisions, even after accounting for year fixed effects along side other controls, implying that the business cycle interacts with and partially moderates the impact of credit ratings.

Perhaps more interesting, however, is the comparison of non-recession year estimates with the full sample main results. When recession periods are excluded, the fiscal advantages of higher ratings appear not only in capital expenditures and local revenue, that is to say, the headline effects observed in the full sample, but also extend to other budget categories. In particular, districts on the AAA side of the cutoff display higher spending on support services and wage and benefit outlays for both faculty and non-faculty staff. While it is difficult to disentangle the exact share of these effects attributable to credit ratings as opposed to broader cyclical dynamics, the evidence is consistent with a mechanism in which better-rated districts use access to lower-cost credit to create fiscal flexibility. This could occur either by refinancing existing debt obligations to free up non-discretionary spending away from interest payments, or by reallocating funds from deferred maintenance and toward instructional and support expenditures. These findings suggest that the fiscal impact of credit ratings may be broader than capital projects alone, particularly in non-recession years when credit markets are more liquid and districts have greater scope to adjust their spending priorities.

Conclusion

With this paper, I set out to investigate how differences in creditworthiness for US school districts impact future finance decisions. Using variation in credit ratings as identified by my synthetic regression discontinuity score, I find that AAA rated school districts tend to outspend their AA counterparts by approximately 6% and is offset by a roughly equivalent increase in local revenue. This is consistent with the story that districts with better bond ratings have greater flexibility to seek more credit but mechanically must raise property taxes to do so. I go on to show that this additional credit translates to large increases in capital outlay expenditures and debt issued, but on a baseline of higher debt issuance on average for AAA rated districts. Taken together, I argue that this evidence suggests the baseline differences I observe in bond debt issued between AAA and AA districts is largely explained by the ratings differences themselves rather than any other demographic or financial factor. Lastly, I show that these effects are driven largely by the mid-sized districts in terms of capital expenditure and that when filtering out recession years from the analysis, a higher credit rating may also translate to spending increases in wages, benefits, and support services for all district employees. Though I want to be cautious in claiming that the magnitudes attached to these non-recession year effects are accurate given that I cannot fully disentangle the effects of the business cycle and the credit ratings variation with my identification strategy alone.

There is not much in the way of comparative research that can help to contextualize this effect size, but the nearest paper in the literature to mine is perhaps Yang (2024) which looks at the effects of state level credit enhancement programs on district expenditures and student outcomes. Yang finds that per-pupil spending increases by 2-7% for districts which take advantage of the credit enhancement program. My estimates fall comfortably within this range suggesting that at least my main results are accurate in magnitude. Another way to think about this is to work out how much money a district close to the AAA cutoff but marginally rated AA is missing out on. A quick back of the envelope calculation suggest that in the fiscal year after a close ratings decision, AA districts are forced to spend nearly $5 million[8] less in total expenditures as a result of the lower credit rating.

What is less clear is the impact these credit rating differences have on student achievement and broader general equilibrium effects. The question of whether school finance interventions actually matter when it comes to student outcomes, especially in the US education system, is largely unsettled (Handel & Hanushek, 2023). In this paper, I wanted to stick to the financial outcomes precisely for this reason and because I think they are already policy relevant in their own right. However, I would be remiss if I did not at least mention how these results might impact student outcomes given the broader literature on school finance issues and achievement. Just using simple means of test scores from the National Assessment of Educational Progress (NAEP) commonly known as the nation's report card reported by Handel and Hanushek (2023) suggests that a 10% increase in spending is correlated with an increase in reading scores of 0.01-0.03 SD and in math of 0.02-0.09 SD pre-pandemic. Scaling

[8]I took the main RD estimate for total expenditures which is in per-pupil terms and scaled it by the mean number of students in the ever-issued sample in table 3 which is what the RD results are based on. The exact value I calculated was $4,927,943.15

these proportionately to my 6% number suggests that credit rating increases are associated with score increases in math and reading of at most 0.018 SD and 0.054 SD respectively. It is important to note, however, that these estimates are correlational not casual and should be interpreted with skepticism. More research is certainly required to confirm these estimated effects on student achievement.

I want to conclude by considering the policy implications for my findings. Certainly, one of the most important takeaways for policymakers is that there are real gains to be found in terms of additional funding and access to credit for districts on the margin of a ratings cutoff. School district leaders should weigh carefully the costs and benefits of financial reforms in light of my findings. In particular, questions of whether or not a district ought to engage with a credit enhancement program or issue insurance backed bonds are easier to answer now that we have a clearer picture of the benefits a ratings increase might entail. The results of this paper also hint at the possibility that school bond ratings are yet another margin over which students and households will sort due to competition between school districts in accordance with the famous Tiebout model (Tiebout, 1956). Lastly, this paper also helps to inform important policy discussions around the fairness and accuracy of ratings agency decisions. This was of great concern to regulators coming out of the great recession where ratings agencies were criticized for inaccurately estimating the risks involved with mortgage backed securities. Similar concerns were raised about municipal bonds, and policy makers were rightly worried that municipalities like school districts were being forced to pay more in borrowing cost than was strictly necessary (Appleson, Haughwout, & Parsons, 2012). My research quantifies these differences in ratings outcomes and may help to guide debate over future regulatory decisions on this topic.

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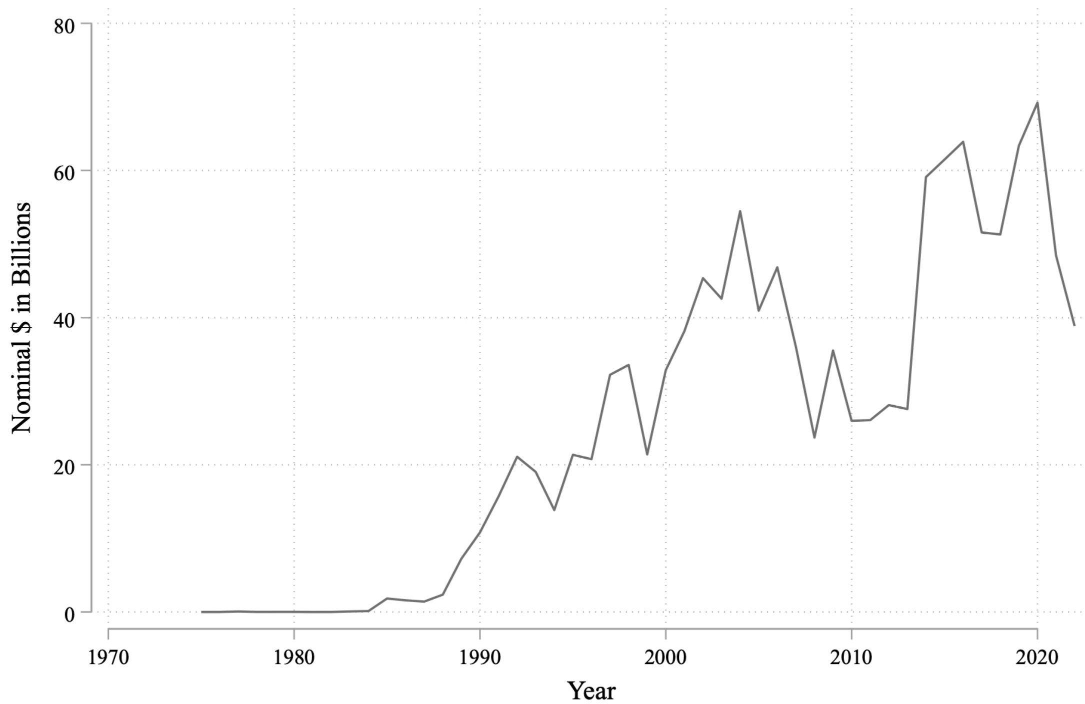
Tables and Figures

Table 1: US Municipal Bond Market Issuances by Sector in 2024

Use of Bond Proceeds	Tax Exempt		Taxable	
	Amount ($ Billion)	Percentage	Amount ($ Billion)	Percentage
General Purpose	110.4	25%	9.8	26%
Primary & Secondary Education	73.0	16%	1.8	5%
Water & Sewer Facilities	44.9	10%	2.5	7%
Single and Multi Family Housing	36.9	8%	11.9	31%
Higher Education	34.1	8%	2.6	7%
General Acute Care Hospital	28.3	6%	1.4	4%
Public Power	26.1	6%	0.7	2%
Mass Transportation	22.9	5%	0.8	2%
Toll Roads, Highways & Streets	17.2	4%	< 0.1	$< 1\%$
Other Proceeds	55.8	12%	6.3	17%
Industry Total	**449.8**		**37.9**	

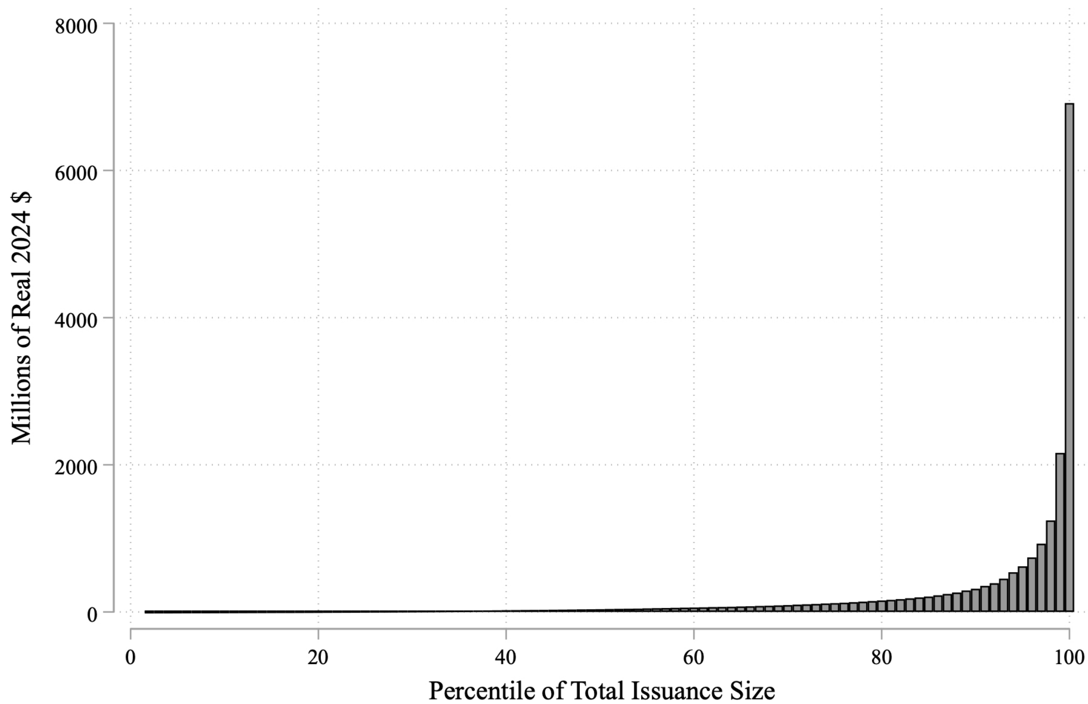
Source: Municipal Securities Rulemaking Board

Figure 1: Value of K-12 Education Sector Municipal Bonds Issued Annually 1975-2023



Source: Municipal Securities Rulemaking Board. Values expressed in billions of dollars not adjusted for inflation.

Figure 2: Distribution of Aggregate School District Bond Issuances by Percentile, 1987–2023



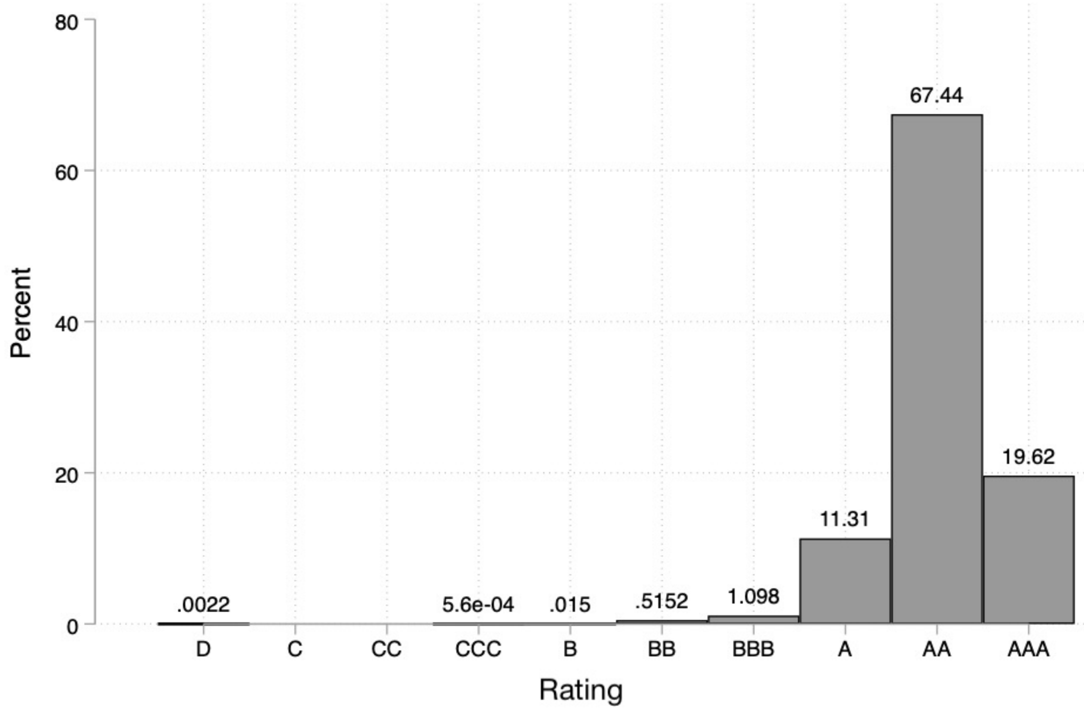
Source: Municipal Securities Rulemaking Board (MSRB). Values expressed in millions of 2024 dollars, adjusted for inflation. Aggregate issuance amounts are calculated by percentile of district issuers; percentile 100 represents the largest issuers, percentile 1 the smallest. Data cover all public school districts in the United States with bond issuance activity between 1987 and 2023. All values are inflation-adjusted to constant 2024 dollars using the CPI-U (Consumer Price Index for All Urban Consumers). Issuance amounts represent the total face value of bonds issued, not outstanding debt balances.

Table 2: Standard & Poor's Credit Rating Scale

Rating	Description	
AAA	Highest Credit Quality	
AA	Very High Credit Quality	Investment Grade
A	High Credit Quality	
BBB	Good Credit Quality	
BB	Speculative	
B	Highly Speculative	Non-Investment Grade
CCC	Substantial Credit Risk	
CC	Very High Levels of Credit Risk	
C	Near Default	
RD	Restricted Default	
D	Default	

This table reproduces the Standard & Poor's long-term issuer credit rating scale. Ratings from *AAA* to *BBB* are classified as investment grade, while ratings from *BB* to *D* are considered non-investment grade. Ratings indicate relative creditworthiness, with *AAA* denoting the highest level of credit quality and *D* indicating default.

Figure 3: Histogram of K-12 Public Education Sector Bond Ratings Observed in MSRB Records, 1987-2023



Source: Municipal Securities Rulemaking Board (MSRB). All ratings converted to Standard and Poor's Rating Scale equivalent. Bonds receiving different ratings from multiple agencies are averaged together.

Table 3: Summary Statistics by Sample

	Full Sample	Ever Issued Bond	Rated Districts
Enrollment			
Total Enrollment	3,290.69 (11,681.77)	4,086.90 (13,155.71)	7,825.25 (21,582.30)
Per-Pupil Revenues			
Total Revenue: Federal Sources	1,540.76 (2,946.73)	1,375.46 (3,034.16)	1,564.50 (13,441.92)
Total Revenue: State Sources	8,811.37 (19,633.95)	8,761.45 (24,410.80)	10,872.93 (118,027.10)
Total Revenue: Local Sources	8,520.83 (13,311.21)	8,784.71 (15,721.91)	9,865.25 (63,351.46)
Local Revenue: Property Taxes	6,846.61 (10,046.28)	7,163.29 (11,338.87)	7,829.42 (36,750.57)
Per-Pupil Expenditures			
Total General Expenditure	18,737.04 (20,840.06)	18,926.42 (24,698.25)	21,397.76 (109,277.60)
Total Current Spending	15,801.53 (18,663.10)	15,766.51 (22,509.27)	17,980.80 (103,906.50)
Employee Benefits	3,229.07 (4,607.66)	3,338.67 (5,779.65)	4,095.07 (26,315.08)
Capital Outlay Expenditure	1,803.62 (4,235.65)	1,963.42 (4,330.71)	2,285.75 (9,166.06)
Per-Pupil Debt			
Interest on Debt	374.76 (560.22)	479.66 (617.30)	588.27 (1,558.50)
Outstanding Debt	8,947.30 (13,195.03)	11,408.72 (12,956.93)	14,337.77 (23,081.85)
Long-Term Debt Issued	1,433.67 (4,948.82)	1,835.45 (5,529.89)	2,345.21 (6,060.01)
Long-Term Debt Retired	1,014.08 (2,463.91)	1,295.14 (2,862.42)	1,608.71 (3,578.16)
Demographics			
Frac. Schools with Title I Status	0.54 (0.46)	0.54 (0.46)	0.64 (0.42)
Frac. Students with FRL Status	0.42 (0.25)	0.40 (0.25)	0.44 (0.23)
Frac. Students who are Non-White	0.25 (0.27)	0.26 (0.27)	0.35 (0.29)
Fraction Students who are Female	0.49 (0.04)	0.49 (0.02)	0.49 (0.02)
District-Year Observations	311,602	179,544	7,963

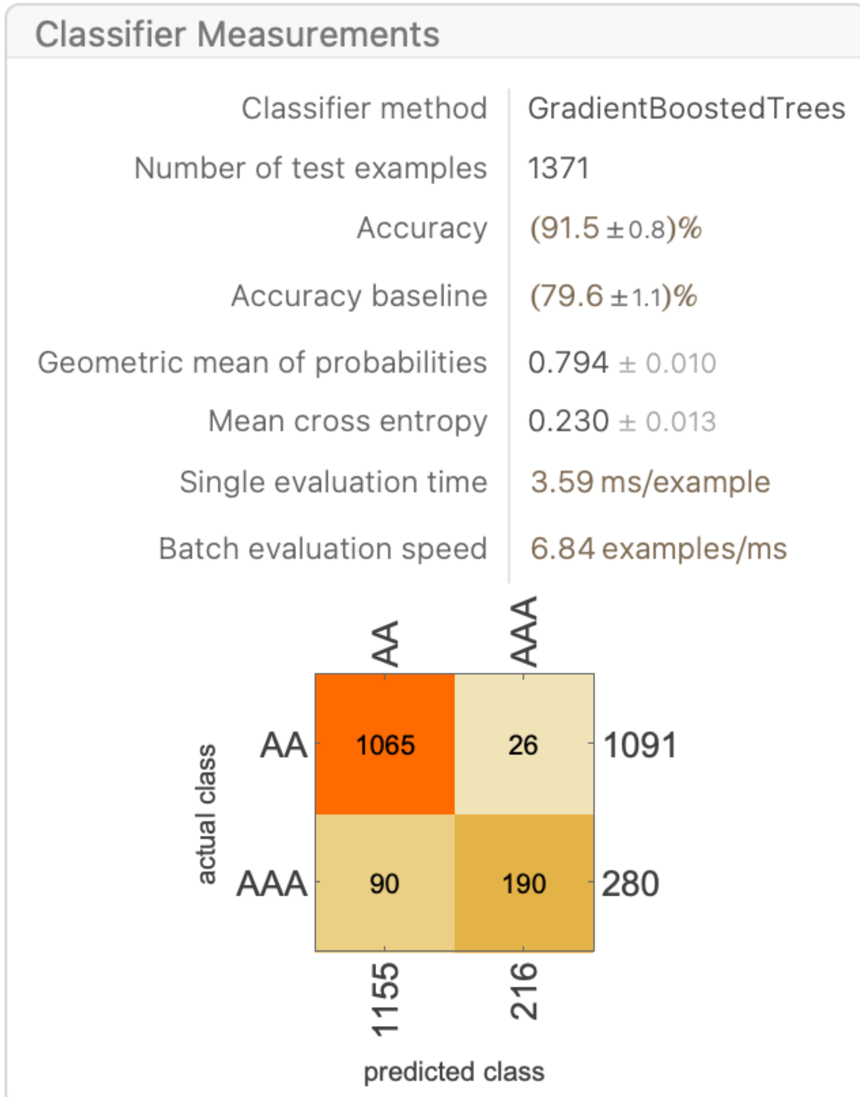
Note: This table contains the means with standard deviations in parenthesis for key fiscal and demographic data for three different samples of district-year observations organized according to their participation in the bond market. All fiscal related variables are in real 2024 dollars per pupil. “Full Sample” refers to all districts as defined by the census bureau for the unbalanced panel across the years 1987 and 2023. “Ever Issued Bond” restricts the full sample by considering only districts who issued at least one municipal bond since 1987. Lastly, “Rated Districts”, refers to the subsample of all districts which received an observed rated as recoded by the Municipal Securities Rulemaking Board. School District debt refers to all private sources of “short-term” credit (time to maturity of less than 1 year) and bond related “long term” (time to maturity greater than 1 year) debt.

Table 4: Summary Statistics for Municipal Bond Sample (1987–2023)

Variable	**N**	**Mean**	**Std. Dev.**	**Median**
Length (days)	997,843	3,383.07	2,138.90	3,073
Value (2024 $)	956,548	1,842,583	7,665,747	694,830.5
Coupon (%)	997,843	4.153	1.424	4.125

This table contains summary statistics from all municipal bonds issued by public school districts between 1987 and 2023. All dollar values are in real 2024 dollar terms. Coupon refers to the issuing interest rate of the bond.

Figure 4: Results from the Machine Learning 80-20 Train-Test Evaluation

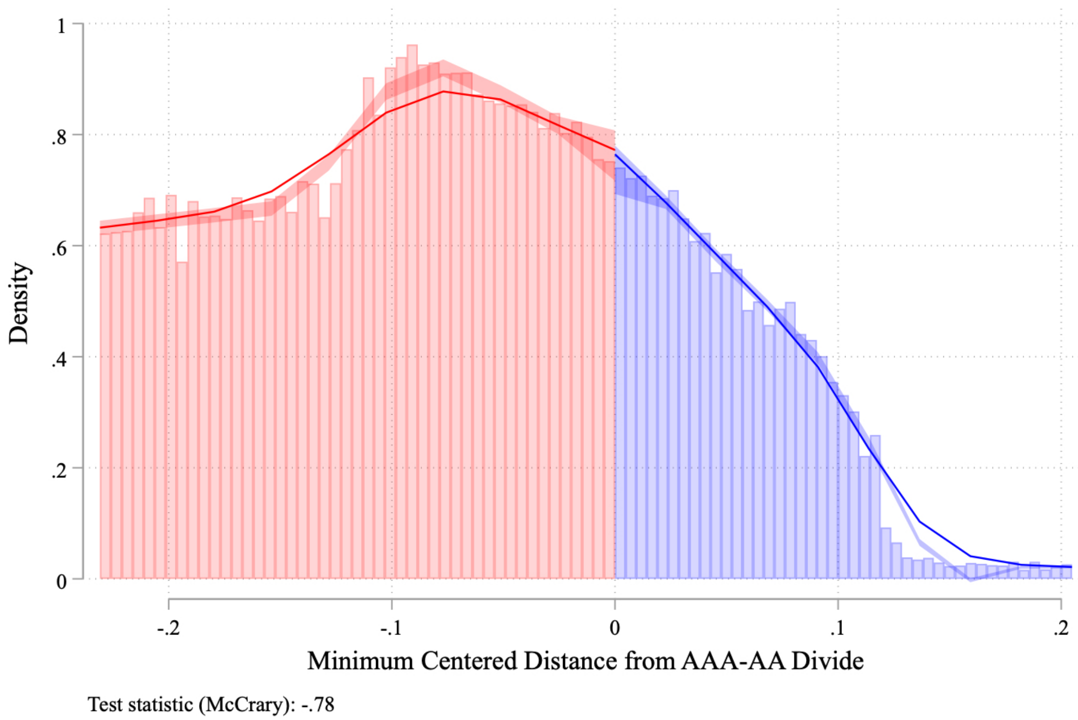


Notes: This figure reports the machine learning diagnostics from the 80-20 train test evaluation. The Other category is omitted here for simplicity. Accuracy refers to number of classifications the supervised machine learning (SML) model gets correct from the test data set. Accuracy baseline provides a comparison for the accuracy value by reporting the expected accuracy if I naively assigned the class with the largest representation in the sample to all observations.

Table 5: Variables Used in Machine Learning Model to Classify Bonds

Included Variable	Lags Included	Lag Years
Revenues		
Total General Revenue	No	–
Total Revenue: Federal Sources	No	–
Federal Chapter 1 Revenue	No	–
Federal Revenue: Special Education	No	–
Federal Revenue: Nutrition	No	–
Federal Revenue: Other Aid	No	–
Total Revenue: State Sources	No	–
State Rev: General Formula	No	–
State Rev: Special Education	No	–
State Rev: Transportation	No	–
State Rev: Other	No	–
Total Revenue: Local Sources	Yes	1, 3, 5
Local Revenue: All Taxes	No	–
Local Revenue: Property Taxes	No	–
Local Rev: Parent Contributions	No	–
Local Rev: Cities/Counties	No	–
Local Rev: Other School Systems	No	–
Local Rev: Charges	No	–
Local Rev: Other Revenues	No	–
Expenditures		
Total General Expenditure	No	–
Total Current Spending	Yes	1, 3, 5
Salaries and Wages (All)	No	–
Employee Benefits (All)	No	–
Instruction	No	–
Faculty Salaries	No	–
Faculty Benefits	No	–
Support Svcs (All)	No	–
Student Support Svcs	No	–
Support Staff	No	–
General Administration	No	–
School Administration	No	–
Maintenance Staff	No	–
Other Current Spending	No	–
Capital Outlay Expenditure	No	–
Payments to Other Govts	No	–
Interest on Debt	No	–
Debt		
Outstanding Debt	Yes	1, 3, 5
Long-Term Debt Issued	No	–
Long-Term Debt Retired	No	–
Demographics		
District Name	No	–
State in which the District is Located	No	–
Total Enrollment	Yes	1, 3, 5
Frac. of Students who are Non-White	No	–
Frac. of Schools with Title I Status	No	–
Frac. of Students with FRL Status	No	–
Fraction of Students who are Female	No	–

Figure 5: McCrary Test for the Joint Running Variable



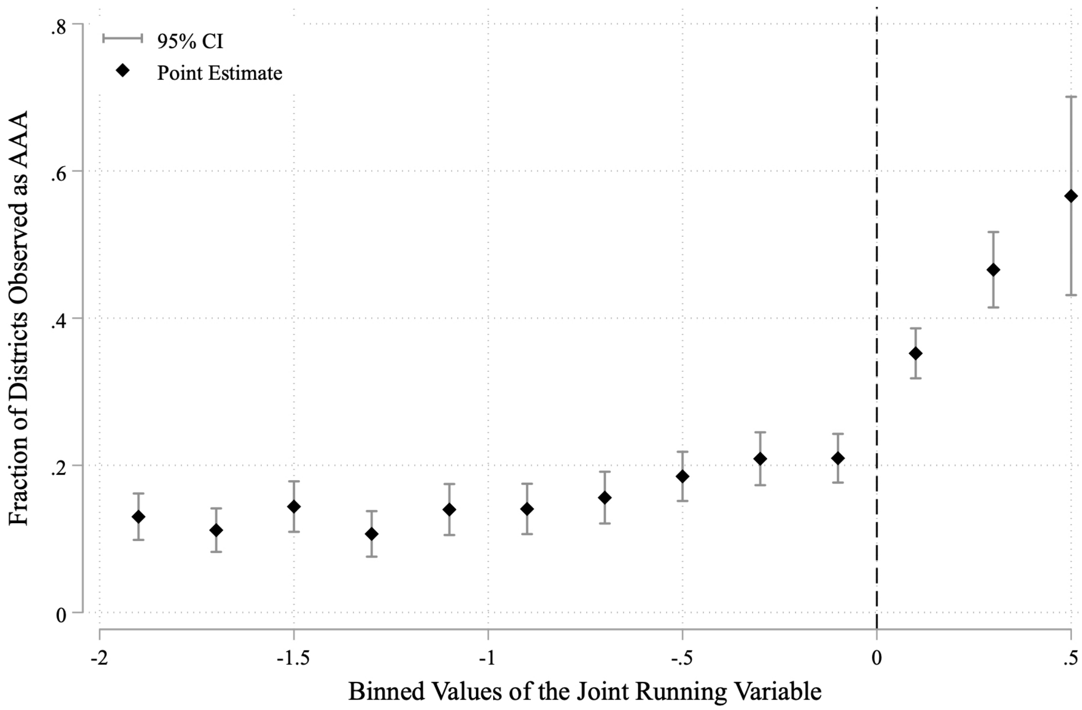
Notes: McCrary test results for the joint running variable. The horizontal axis of this plot reflects the values of the constructed running variable where 0 is the AA-AAA cutoff as determined by applying the centering method from (Wong et al., 2013). The vertical axis indicates binned density of observations at a given value of the running variable as is typical of histograms. Overlayed are the predicted distribution shape left and right of the cutoff. Shaded areas indicate margins of error for the distribution estimates.

Table 6: Placebo RD Balance Test: Using Ever Issued Sample

	RD Estimate
Revenues	
Total General Revenue	42.050 (115.45)
Total Revenue: Federal Sources	33.779 (28.80)
State Rev: General Formula	-43.414 (27.57)
Total Revenue: Local Sources	-13.021 (85.90)
Local Revenue: All Taxes	-36.027 (62.06)
Local Revenue: Property Taxes	-34.930 (61.79)
Expenditures	
Total General Expenditure	201.319 (144.03)
Total Current Spending	-11.874 (38.20)
Current Spending: Salaries & Wages	-3.826 (14.15)
Current Spending: Employee Benefits	22.115** (10.73)
Current Spending: Instruction	-1.019 (18.46)
Current Spending: Faculty Salaries	-0.620 (10.88)
Current Spending: Faculty Benefits	9.774 (6.36)
Current Spending: Support Svcs (All)	-20.006 (17.76)
for Students	-4.175 (3.85)
Support Staff	-0.261 (4.16)
General Admin	3.793 (3.55)
School Admin	-4.844 (3.17)
Maintenance Staff	-14.342 (14.78)
Other Current Spending	10.847 (10.90)
Capital & Debt	
Capital Outlay Expenditure	205.200* (121.97)
Interest on Debt	2.253 (7.14)
Outstanding Debt	-157.884 (171.18)
Long-Term Debt Issued	-157.626 (195.43)
Long-Term Debt Retired	-27.220 (67.90)

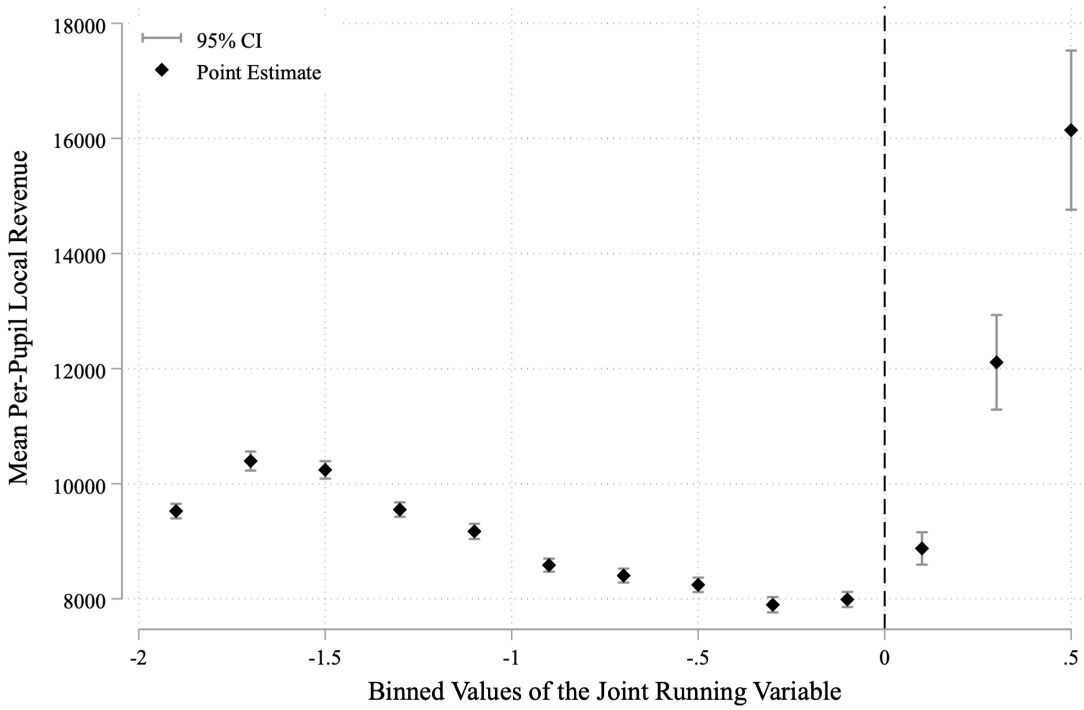
Notes: This table presents the per-pupil placebo test results of a AAA rating compared to similar AA rated districts on a school districts finances measured 1 fiscal year before a close ratings decision. Robust standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Standard errors unavailable for some outcomes are shown as “.”.

Figure 6: First Stage Evidence - Fraction of AAA Rated Bonds by Binned Running Variable Values



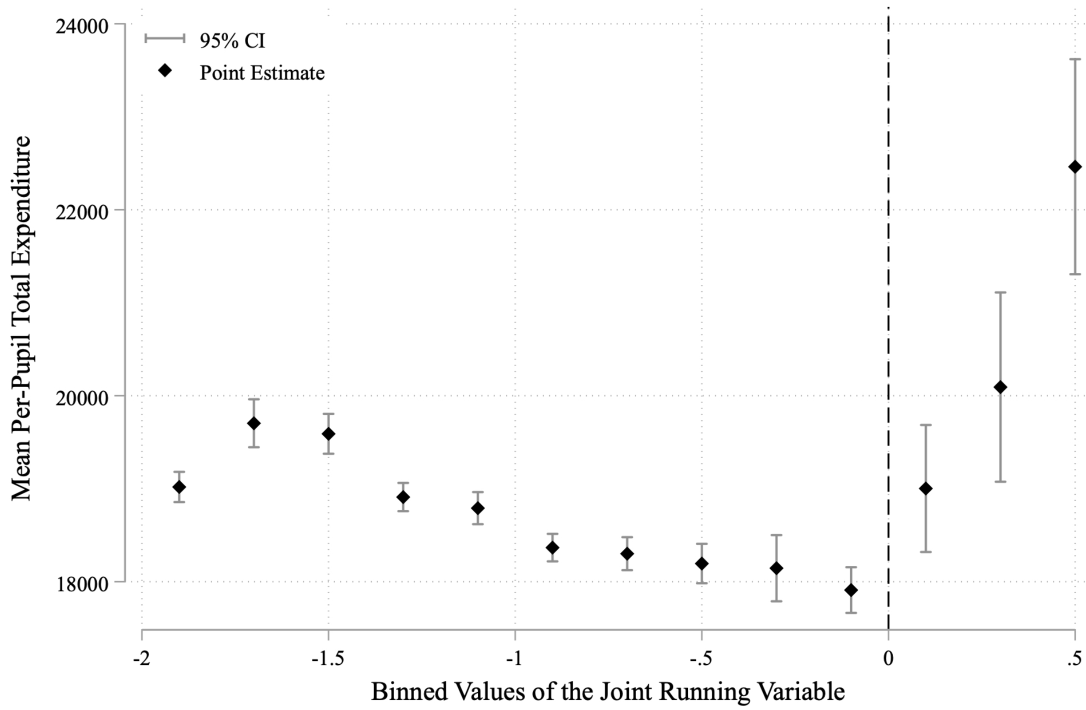
Notes: This figure presents the fraction of observed ratings which are recorded AAA relative to other rated district-year observations across binned values of the synthetic (joint) running variable. Values of the running variable that are negative are expected to be rated AA or worse. Those above 0 are expected to be rated AAA. The running variable is centered at 0 such that this point represents the cutoff between AAA and AA rated bonds.

Figure 7: Second Stage - Mean Per-Pupil Local Revenue by Binned Running Variable Values



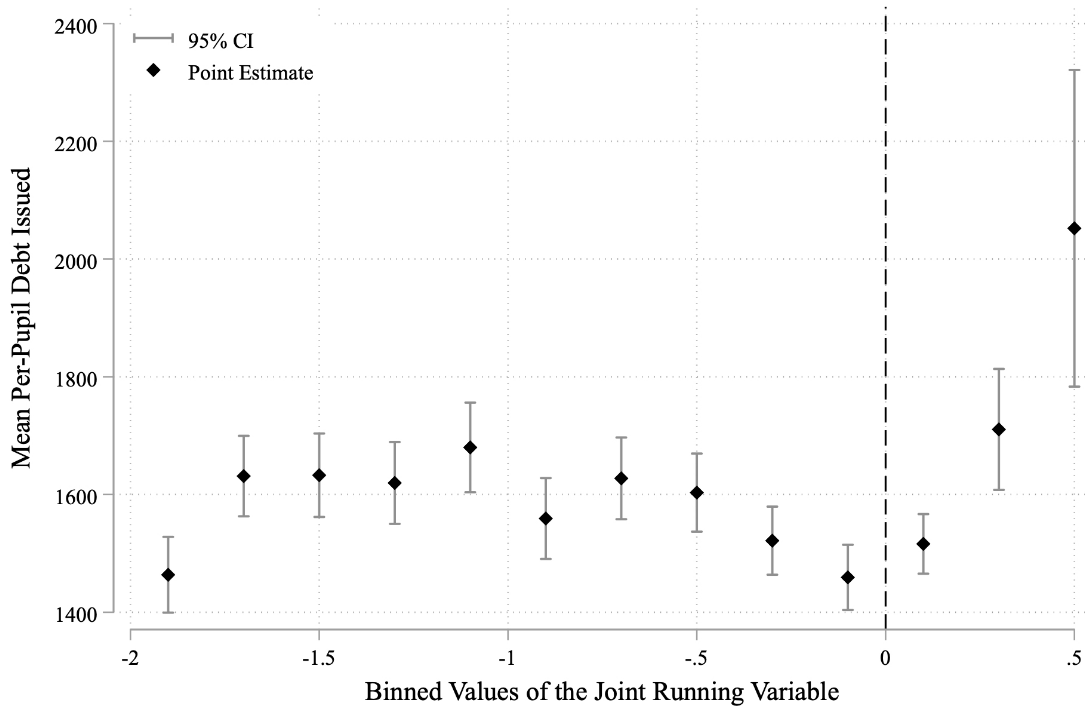
Notes: This figure presents the mean per-pupil local revenue calculated across binned values of the synthetic (joint) running variable. The vertical access reflects real 2024 $'s. Values of the running variable that are negative are expected to be rated AA or worse. Those above 0 are expected to be rated AAA. The running variable is centered at 0 such that this point represents the cutoff between AAA and AA rated bonds.

Figure 8: Second Stage - Mean Per-Pupil Total Expenditure by Binned Running Variable Values



Notes: This figure presents the mean per-pupil total expenditure calculated across binned values of the synthetic (joint) running variable. The vertical access reflects real 2024 $'s. Values of the running variable that are negative are expected to be rated AA or worse. Those above 0 are expected to be rated AAA. The running variable is centered at 0 such that this point represents the cutoff between AAA and AA rated bonds.

Figure 9: Second Stage - Mean Per-Pupil Long Term Debt Issued by Binned Running Variable Values



Notes: This figure presents the mean per-pupil long term debt issued calculated across binned values of the synthetic (joint) running variable. The vertical access reflects real 2024 $'s. Values of the running variable that are negative are expected to be rated AA or worse. Those above 0 are expected to be rated AAA. The running variable is centered at 0 such that this point represents the cutoff between AAA and AA rated bonds.

Table 7: Main RD Estimates: Ever Issued vs. Rated Only Samples

	Ever Issued RD Estimate (SE)	Rated Districts RD Estimate (SE)
Per-Pupil Revenues		
Total General Revenue	980.42*** (264.01)	3,953.78 (4,777.48)
Total Revenue: Federal Sources	133.06* (72.01)	207.41 (204.59)
Total Revenue: State Sources	-0.45 (71.00)	1,570.38 (2,610.15)
Total Revenue: Local Sources	802.67*** (258.79)	919.05 (2,336.09)
Local Revenue: All Taxes	709.08*** (246.26)	780.55 (1,635.91)
Local Revenue: Property Taxes	732.27*** (246.71)	752.33 (1,620.28)
Per-Pupil Expenditures		
Total General Expenditure	1,205.79*** (288.17)	7,553.37 (8,211.06)
Total Current Spending	247.00* (150.13)	3,463.25 (3,446.30)
Current Spending: Salaries and Wages (All)	130.07 (96.50)	579.57 (721.51)
Current Spending: Employee Benefits (All)	38.54 (30.71)	276.50 (356.04)
Current Spending: Instruction	123.58 (95.28)	2,397.21 (2,173.61)
Current Spending: Faculty Salaries	73.86 (53.77)	88.49 (237.78)
Current Spending: Faculty Benefits	29.12 (18.79)	105.89 (169.16)
Current Spending: Support Svcs (All)	97.35* (58.59)	928.23 (1,173.69)
Current Spending: Support Svcs for Students	6.92 (17.47)	228.02 (221.26)
Current Spending: Support Staff	5.14 (14.24)	229.95 (277.23)
Current Spending: Gen Admin	-1.27 (14.73)	323.86* (193.22)
Current Spending: School Admin	2.53 (8.29)	28.38 (91.41)
Current Spending: Maintenance Staff	64.85** (30.11)	183.45 (444.59)
Other Current Spending	15.59 (16.16)	96.57 (79.95)
Per-Pupil Capital & Debt		
Capital Outlay Expenditure	392.44** (157.30)	4,380.02 (4,669.38)
Interest on Debt	5.80 (13.82)	29.70 (183.68)
Outstanding Debt	808.80** (330.98)	3,451.62 (6,523.35)
Long-Term Debt Issued	416.96*** (160.54)	-853.18 (1,776.55)
Long-Term Debt Retired	99.65 (69.81)	-98.61 (354.80)
Observations	155,126	3,907
Effective Observations	41,470	1,145

Notes: This table presents the per-pupil estimates of a AAA rating compared to similar AA rated districts on a school districts finances measured 1 fiscal year after a close ratings decision. The two samples are defined identically to those referenced in the data section. Ever issued includes all district-year observations which are from districts that have issued at least 1 municipal bond since 1987. Rated districts refers to only the districts which had a professional rating recoded in the MSRB database in a given year. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 8: Mean Per-Pupil Long Term Debt Issuance by Rating

Rating	Observations	Enrollment	Per-Pupil Long-Term Debt Issued
D	1	3458 (.)	0 (.)
CCC	1	34526 (.)	12287.63 (.)
B	7	1039 (1154.452)	716.291 (1895.128)
BB	111	40824.811 (92035.585)	2336.641 (6216.567)
BBB	174	9227.144 (21107.860)	1486.006 (3489.379)
A	812	9164.350 (35258.475)	2025.617 (6049.828)
AA	5405	6077.591 (12554.172)	2209.213 (6082.845)
AAA	1452	11133.548 (21311.989)	2569.615 (5604.356)

Notes: A comparison of mean long-term debt issuance by credit rating level. All financial values are in per-pupil terms and represent real 2024 $'s. Standard deviations are in parenthesis.

Table 9: RD Estimates of Ever Issued Districts by Quartile of Capital Outlay Expenditures

Outcome	Q2 Estimate (SE)	Q3 Estimate (SE)	Q4 Estimate (SE)
Revenues			
Total General Revenue	295.058 (571.755)	1022.841* (530.660)	-16.209 (577.315)
Total Revenue: Federal Sources	-29.592 (87.817)	135.854 (101.946)	195.539 (196.898)
Total Revenue: State Sources	-10.592 (142.242)	-23.602 (113.478)	225.810* (118.931)
Total Revenue: Local Sources	466.488 (546.424)	947.860* (500.389)	-348.461 (500.980)
Local Revenue: All Taxes	409.534 (508.528)	893.672* (475.259)	-336.565 (476.778)
Local Revenue: Property Taxes	450.591 (507.967)	903.944* (477.305)	-297.562 (476.424)
Expenditures			
Total General Expenditure	303.707 (541.639)	1258.263** (615.898)	486.230 (666.080)
Total Current Spending	44.597 (230.587)	59.183 (163.994)	-13.251 (225.686)
Current Spending: Salaries & Wages	34.381 (122.239)	90.745 (95.693)	91.499 (113.574)
Current Spending: Employee Benefits	11.346 (43.024)	38.856 (40.056)	48.898 (51.341)
Current Spending: Instruction	86.344 (110.804)	-10.330 (92.921)	-11.704 (121.153)
Current Spending: Faculty Salaries	26.583 (70.829)	57.305 (65.286)	61.722 (69.612)
Current Spending: Faculty Benefits	6.305 (24.904)	14.823 (27.051)	28.207 (32.647)
Current Spending: Support Svcs (All)	12.855 (115.557)	72.028 (79.164)	-16.698 (106.488)
Support Svcs for Students	0.318 (23.421)	20.996 (17.066)	-34.435 (22.303)
Support Staff	5.366 (30.539)	9.772 (18.131)	-30.540 (27.023)
General Admin	13.291 (26.445)	-0.327 (21.475)	39.578** (19.110)
School Admin	-4.418 (13.092)	1.907 (15.156)	-10.760 (13.921)
Maintenance Staff	-17.782 (60.228)	36.363 (42.116)	22.802 (54.181)
Other Current Spending	-53.469 (34.193)	15.717 (26.711)	25.149 (18.618)
Capital & Debt			
Capital Outlay Expenditure	-40.203 (115.881)	560.028* (317.288)	914.741** (432.726)
Interest on Debt	3.241 (22.164)	25.094 (28.629)	17.643 (30.715)
Outstanding Debt	489.280 (544.257)	1025.257 (725.948)	744.161 (668.763)
Long-Term Debt Issued	-14.259 (290.770)	278.248 (453.227)	542.914* (319.148)
Long-Term Debt Retired	90.733 (107.909)	79.043 (135.920)	225.447 (167.597)
Range of Per-Pupil Capital Outlay	397.56 - 792.68	792.68 - 1818.25	> 1818.25

Notes: 1-year lead RD estimates with year fixed effects, using the joint running variable. Quartiles defined by total capital outlay. Robust standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 10: Main Result Estimates Using OLS: Ever Issued v. Rated Only Samples

Outcome	Ever-Issued	Rated Only
Per-Pupil Revenues		
Total General Revenue	-136.547*** (52.477)	1144.419*** (193.400)
Total Revenue: Federal Sources	-65.895*** (5.640)	66.547*** (20.894)
Total Revenue: State Sources	87.188*** (20.861)	-665.208*** (75.425)
Total Revenue: Local Sources	-95.319** (43.309)	1887.809*** (159.816)
Local Revenue: All Taxes	-207.383*** (40.659)	1503.226*** (148.404)
Local Revenue: Property Taxes	-226.486*** (40.442)	1513.779*** (147.633)
Per-Pupil Expenditures		
Total General Expenditure	43.319 (52.351)	2199.880*** (192.569)
Total Current Spending	-7.206 (46.103)	-11.393 (167.351)
Current Spending: Salaries & Wages	105.457*** (25.585)	193.367** (92.776)
Current Spending: Employee Benefits	7.353 (10.991)	-74.882* (39.836)
Current Spending: Instruction	72.433*** (27.542)	-45.803 (99.852)
Current Spending: Faculty Salaries	76.247*** (17.111)	71.391 (61.970)
Current Spending: Faculty Benefits	2.647 (7.236)	-53.163** (26.221)
Current Spending: Support Svcs (All)	-53.292*** (18.897)	22.738 (68.747)
Support Svcs for Students	22.830*** (4.380)	41.328*** (15.840)
Support Staff	16.165*** (3.422)	95.059*** (12.630)
General Admin	-41.470*** (3.576)	-109.689*** (12.941)
School Admin	11.421*** (2.520)	7.545 (9.133)
Maintenance Staff	-62.237*** (10.087)	-11.506 (36.662)
Other Current Spending	-26.348*** (2.858)	11.672 (10.336)
Per-Pupil Capital & Debt		
Capital Outlay Expenditure	242.267*** (14.511)	1270.327*** (53.275)
Interest on Debt	28.509*** (3.394)	311.864*** (12.279)
Outstanding Debt	645.507*** (79.267)	11386.940*** (287.370)
Long-Term Debt Issued	293.555*** (35.338)	8191.710*** (129.822)
Long-Term Debt Retired	149.294*** (16.986)	2575.799*** (61.351)

Notes: 1-year lead OLS estimates with year and state fixed effects for full sample and rated only sample, using the joint running variable. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 11: RD Estimates Comparing Recession to Non-Recession Years

	Recession Years RD Estimate (SE)	Non-Recession Years RD Estimate (SE)
Per-Pupil Revenues		
Total General Revenue	-1202.937 (858.484)	1162.524*** (289.480)
Total Revenue: Federal Sources	336.045 (299.656)	72.504 (61.889)
Total Revenue: State Sources	129.930 (153.707)	-29.968 (79.498)
Total Revenue: Local Sources	-1594.108** (776.760)	1112.219*** (283.492)
Local Revenue: All Taxes	-1342.324* (727.688)	976.204*** (273.438)
Local Revenue: Property Taxes	-1357.199* (731.788)	1005.019*** (274.026)
Per-Pupil Expenditures		
Total General Expenditure	-1654.250 (1020.495)	1445.905*** (310.243)
Total Current Spending	-549.597* (280.668)	412.091** (179.134)
Current Spending: Salaries & Wages	-190.273 (134.698)	202.149* (108.897)
Current Spending: Employee Benefits	-39.304 (55.307)	67.554** (33.710)
Current Spending: Instruction	-212.279 (154.751)	203.892* (105.305)
Current Spending: Faculty Salaries	-104.050 (95.114)	109.965** (54.809)
Current Spending: Faculty Benefits	-18.822 (34.302)	49.453** (20.647)
Current Spending: Support Svcs (All)	-211.923* (125.621)	170.400** (69.507)
for Students	-25.182 (31.250)	18.048 (19.796)
Support Staff	-39.478 (26.070)	12.395 (16.533)
General Admin	-10.120 (31.012)	-1.838 (16.767)
School Admin	-37.294** (17.851)	12.829 (9.406)
Maintenance Staff	-147.327* (79.604)	112.754*** (35.771)
Other Current Spending	-69.032* (39.784)	32.932* (17.515)
Per-Pupil Capital & Debt		
Capital Outlay Expenditure	-9.744 (613.643)	438.075*** (142.005)
Interest on Debt	-50.377 (38.251)	15.855 (15.794)
Outstanding Debt	-1018.503 (836.285)	1091.147*** (376.487)
Long-Term Debt Issued	-282.646 (386.723)	489.285*** (178.428)
Long-Term Debt Retired	2.769 (164.328)	111.825 (78.059)

Notes: 1-year lead RD estimates with year fixed effects for recession years using the joint running variable. Columns report per-pupil RD estimates with robust standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.