MGT 6203 Group Project Final Report

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BACKGROUND AND APPLICATIONS:

Counties across the United States are subject to the booms and busts of the economy. One of the vehicles counties use to raise funds is bonds. Like credit scores for individuals, counties must have a good bond rating to issue bonds (get loans) to fund infrastructure and improvement projects. The key benefits of estimating leading indicators are twofold: (a) It could help counties better prepare for the future and (b) serve as a business intelligence tool for businesses to make decisions on business expansion.

This research project examines the relationship between general obligation bond ratings and economic outcomes for counties in the United States. We focus on general obligation bonds because these represent the direct obligation of repayment of debt through the use of a county's general fund. Using data from counties from across the country, we investigate whether counties with higher bond ratings experience better economic outcomes than those with lower ratings. Our analysis includes a range of indicators, such as income, economic factors, public health, and immigration among others. We use a combination of statistical methods, including logistic regression and performance metrics such as ROC AUC and pseudo R^2, to assess the strength and significance of the relationship between bond ratings and economic outcomes.

We expect that business leaders could use this tool to make decisions about location intelligence. For example, suppose I ran a chain of small grocery stores and I am looking to expand into suitable markets with positive forward-looking economic prospects. Using our tool, I could select counties with low probabilities of a reduced bond rating. While other factors may play into their location selections, such as market demographics, our tool could help avoid economically problematic areas.

Additional use cases involve institutional investors such as insurance companies, banks, money management firms, and government entities who invest and are holding a large amount of investments in municipal bonds. Our analysis potentially can add value in assessing impacts to investment values in the case of a future ratings drop. For example, a municipal bond backed by Shelby county Tennessee which has AA+ rating, if it were to see a ratings drop to say AA or worse, the value of the investments would substantially drop as well, impacting the bond portfolios of institutional investors. Using our tool, investors could identify potential municipal bonds they own that could see reduced ratings in the future and potentially eliminate risk to their bond portfolio's value.

PROBLEM STATEMENT:

Municipalities across the United States experience economic headwinds (i.e., recession, fiscal insolvency, etc.) to varying degrees across different regions and economic strata. Because counties rely on bonds to secure funding for infrastructure and public works projects, maintaining a good bond rating is paramount. However, policymakers lack a forward-looking economic indicator of these future headwinds.

HYPOTHESES AND RESEARCH QUESTIONS:

Our primary research question focuses on the intersection of publicly available data and the relationship to bond ratings from that data. Specifically, we ask whether we can estimate the probability of a reduced bond rating for a given county using public data? To support this question, we ask the following supporting research questions. We also developed hypotheses to each of these questions:

- Leading Indicators:
    - Question: Are bond ratings a sufficient leading indicator of future economic headwinds?
    - Hypothesis: We expect bond ratings to relate to economic outcomes empirically.
- Local Sentiment:
    - Question: Does degrading sentiment about a county indicate a reduced bond rating?
    - Hypothesis: We expect sentiment has a moderate impact on predicting economic status.
- Public Health:
    - Question: How do public health indicators contribute to economic viability?
    - Hypothesis: We expect that public health has a positive relationship with economic outcomes.
- Demographics:
    - Question: How do migration patterns contribute to the economic outlook of a county?
    - Hypothesis: We expect that migration patterns have a positive impact on economic outcomes.

When considering these research questions in conjunction, we expect that positive sentiment, good public health outcomes, positive migration patterns, and supporting financial data to correspond with positive economic outcomes. Because bond ratings are designed to represent the creditworthiness of a geography at a point in time, our model will use recent bond data and historic predictors to predict bond ratings as a leading indicator. We hypothesize that future economic statuses can be predicted using bond ratings as a proxy.

DATA SOURCES:

We pulled state financial data for years 2010 to 2020 from Census.gov. We compiled 10 years of state level economic data by pulling down the two excel documents corresponding to a specific year as well as the states. Next, we merged each of the datafiles into one common excel document with some basic cleaning of non-essential information. Lastly, we melted the data into individual observations corresponding to the year and state for simplicity in reading it into our model. State Financials

County level health data is published annually. Each data set consists of two rankings (health outcomes and health factors), quartile ranking for all counties (~3.1K) across the US. We filtered the dataset of relevant columns and added a year column for each set. Data clean up will involve dropping all rows with NR columns. These are counties for which there is no ranking. A quick analysis of data suggests that around 2% of data exists with NR values. The final consolidated data set will consist of Year, State, County, number of ranked counties, health outcomes rank and health factors rank: County Health Rankings

We pulled the American Community Survey (ACS) for the years between 2010 & 2021 (2020 was not available on the Census website). We downloaded the individual datasets and then merged them all together to create one dataset for all years combined. We then selected the relevant columns and did some string manipulation to extract county identification. That will be used in conjunction with the year information to join this dataset with the rest of the datasets. Finally we used shift function to calculate year-on-year population change for the county, in-state, out-of-state, and foreign residents. Foreign Census Bureau Tables

Bond rating data comes courtesy of Moody's, a ratings agency that assigns a creditworthiness rating to many kinds of financial instruments. For this project, we used a recent snapshot of ratings (Aaa, Aa, etc.) from urbanized counties across the United States. The ratings correspond with the relative risk for *General Obligation* bonds. These are common financial instruments used to raise funding for a wide variety of purposes for counties. They are also *relatively* comparable where other kinds of bonds vary from state-to-state. For example, Texas issues bonds to raise funds for school districts, however, these bonds are backed by the state. The rating assigned to a Texas school bond may not represent the financial wellbeing of a locality because the state provides a strong amount of support. This backing structure may not be present in other states in the US. Therefore, we used Moody's ratings for a recent subset of general obligation bonds. You can learn more about how Moody's computes ratings by visiting the *Appendix* section and reviewing Figure 4. Likewise, you can view the rank ordering of ratings for bonds by reviewing Figure 5. Moody's Ratings

DATA MERGING AND PREPARATION:

Putting together the final master dataset for our model implied the following steps for each data source:

1. Reading individual yearly files and consolidating each dataset into one R dataframe.
2. Using the dplyr package in R for merging the data together.

In the case of Immigration data (gathered from the Foreign Census Bureau Tables) and the County Health Rankings, we could merge them by FIPS (unique identifier for United States county) and year, which were the unique identifiers for the observations in both data sources. We added State Financials by merging it to the intermediate dataframe by State and year. Finally, the Moody's Ratings were added by FIPS. We then filtered the data so that the difference between the ratings year and the predicting variables year was 4 years.

ENGINEERED FEATURES AND PREDICTORS:

We considered a wide variety of features from our original dataset to build our model. While some features available to us were not useful for predicting our dependent variable, several variables seemed promising. Of the variables present in our training data, we narrowed the list to sixteen possible predictors:

- Region: the US region the county is located in
- Debt offsets: the amount of offsets to debt liabilities in a fiscal budget
- Debt to income: the ratio of debt to expenditures in a fiscal budget
- Bond funds: the amount of funding from bonds entering a fiscal budget
- Outstanding debt: the amount of debt in a fiscal budget
- Long debt: the amount of long-term (more than one year) debt in a fiscal budget
- Population: the population of a county
- In state: the number of county residents born in-state
- Out-of-state: the number of county residents born out-of-state
- Foreign: the number of county residents born internationally

- YoY population: change in overall population from the previous year
- YoY in-state: change in in-state born population from the previous year
- YoY out-of-state: change in out-of-state born population from the previous year
- YoY foreign: change in foreign born population from the previous year
- Health outcomes: An inter-state ranking of health outcomes for a county[1]
- Health factors: An inter-state ranking of health factors for a county[2]

Many of the variables listed above suffer from the long-tail problem. Most observations fall within a sensible range (for example, a debt to income ratio between 0 and 1). However, a subset of counties possess values well beyond the normal working range. Had our dataset been larger, we would be more likely to use an outlier detection method to remove problematic data points. We originally considered using Cook's distance or removing points more than 2-3 standard deviations from the mean.

However, because our final filtered dataset only contains 490 records, we were hesitant to remove observations. Instead, we controlled for the long tails primarily through log-transformation. We used log transformation on bond funds, outstanding debt, long debt, population, in-state, out-of-state, and foreign predictor variables. This reduces the need for outlier removal and makes the distributions more normal.

We also used rescaling on the health ranking variables for health outcomes and health factors. These variables represent the public health ranking within a state. For example, these variables range from 1-24 for the state of Maryland because Maryland only contains 24 counties. However, in the state of Texas the range is from 1-254. In this case, the counties are ranked by health outcomes in descending order. That is, a county with rank 1 is the healthiest in the state whereas a county with rank 24 would be the least healthy in the state of Maryland, but still be in the top 10% for Texas! To get around this problem, we scaled each state's rankings between 0-1. This way, the healthiest county in each state has a value of 0 and the least healthiest county in each state has a ranking of 1.

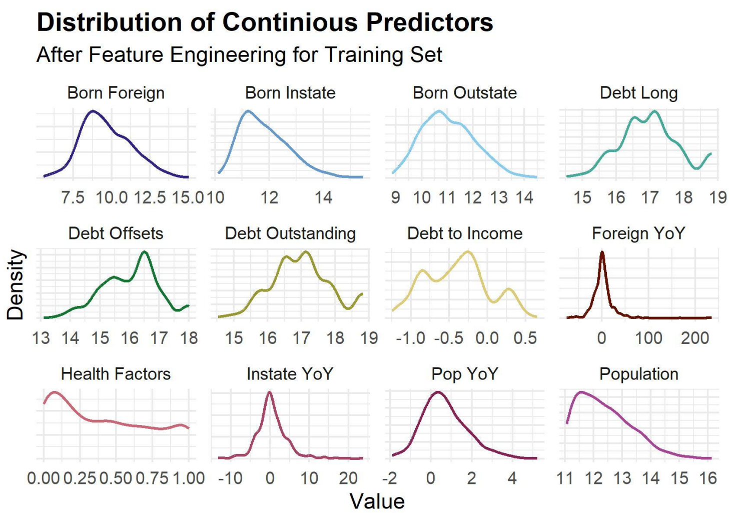
The figure below details the transformed distributions of our continuous predictors. All model predictors, apart from region, are continuous for all estimation trials. We attempted to coerce normality using log transformations where applicable. In addition, our predictors in our *final model* are uncorrelated with one another apart from two population variables. More on this in the *Model Selection and Validation* section.

[1] **Health outcomes** tell us how long people live on average within a community, and how much physical and mental health people experience in a community while they are alive. These include

- Length of Life,including premature death, life expectancy and infant mortality.
- Quality of Life,including self-reported physical and mental wellness

[2] **Health factors** represent those things we can improve to live longer and healthier lives. They are indicators of the future health of our communities. The County health rankings data used in this project highlight the opportunities for improvement by ranking the health across four factors (Healthy behaviors, Clinical Care, Social and Economic Factors, Physical Environment).

Figure 1. Feature Distributions for Training Set



MODELING METHODOLOGIES:

We weighed several classification models for our project but landed on logistic regression for several key reasons. Logistic regression is a concept discussed in this course and we wanted to deploy what we learned in practice. Moreover, members of our team have experience with this modeling technique from outside of this course. Beyond personal motivations, logistic regression provides several practical benefits for our problem. First, logistic regression produces a table of coefficients, errors, and p-values. This allows for an isolated interpretation of coefficients, a p-value assessment, and allows the model to be deployed in a lightweight manner (for example, as part of our web application). Plus, R provides good support for logistic regression models using functions from the stats package, namely GLM. Our model is structured as follows:

$$p(X) = 1 - \frac{e^{Xb}}{1 + e^{Xb}}$$

Our dependent variable is whether a county has an Aaa rating (the highest possible rating) for their general obligation bonds, as determined by Moody's Analytics. To predict the probability of economic headwinds, we take *1 minus* the probability. In the equation above, *Xb* refers to the log-odds of a county having an Aaa rating according to our model coefficients.

Note: We initially expected to predict the probability of a recent rating downgrade. That is, the probability that a county would move from a higher to a lower rating (e.g., Aaa to Aa). However, this proved problematic due to challenges related to data collection. This challenge is discussed in more detail in the *Challenges and Future Research* section further down in this document.

Before estimating models, we divided our data into training and testing. We performed this task using the rsample package, a new package in R from the tidymodels suite of packages. Because of our relatively small sample size, we used a ⅔ to ⅓ split for training and testing respectively. This ensures that validation results over the testing set are not diminished because of a small sample size. We first estimated a model using all practical predictors.

Our next set of models attempts to isolate the predictive power of each data source by estimating sub-models. Namely, we estimated models predicting an Aaa rating. These models are called *Demographics*, *Finance*, and *Health* and are discussed in more detail in the next section. Each sub-component introduces predictive lift and improves rank ordering capability. We reviewed the coefficients, and subsequent significance values, from each sub-model before assembling a set of final predictors for our candidate model.

MODEL SELECTION AND VALIDATION:

To select our final model, we performed robust model validation over each candidate model. We developed a framework for model selection which considers (a) rank ordering capability using ROC AUC, (b) pseudo-R^2 using McNemar's Method, and (c) significance of predictors. We also considered parsimony while selecting our final model and preferred models which achieve good results with fewer predictors, though this often corresponds with our significance criteria and a reduction in correlation between predictors. Lets review each model under this framework in turn.

First, the *Baseline* model considers all predictors listed in the *Engineered Features and Predictors* section. This model has arguably the best ROC AUC as shown in the plot below. However, it suffers from several critical flaws. First, nearly all predictors are insignificant, likely because many of the sub predictors are correlated with one another and collinearity is pervasive. Second, with sixteen predictors we wanted to achieve a more parsimonious result. It has an R-Squared of 0.39.

Next, we estimated the *Demographics* model. This model performs well on ROC AUC. However, because it uses many population growth variables which are collinear it suffers from many insignificant predictors. All predictors in our training data have correlation coefficients of less than 0.2 with one another except for demographic variables. We pulled a subset of variables from this model for the final candidate model which minimize the correlation coefficients of predictors. We pulled the population variables from this model for our final estimation. It has an R-Squared of 0.22.

Third, we estimated the *Health* model using the variables health outcomes and health rankings. This model performs surprisingly well on ROC AUC and significance levels and represents a meaningful lift over other candidate models such as the *Finance* model, especially considering this model includes only two predictors. We pulled the heath factors variable from this model for our final estimation. It has an R-Squared of 0.16.

Fourth, we estimated the finance model which considers a range of state-level finance details including debt offsets, bond funding, debt outstanding, and the state debt to income ratio. Because data for this model comes from the highest level of aggregation, it performs the poorest of all candidate models. This is a key limitation of this data source. While we aimed to have county-level finance data, it was omitted for several reasons discussed further in the *Challenges and Future Research* section. Nearly all variables are insignificant, though we did lift debt-to-income for the final model. It has an R-Squared for just 0.03.

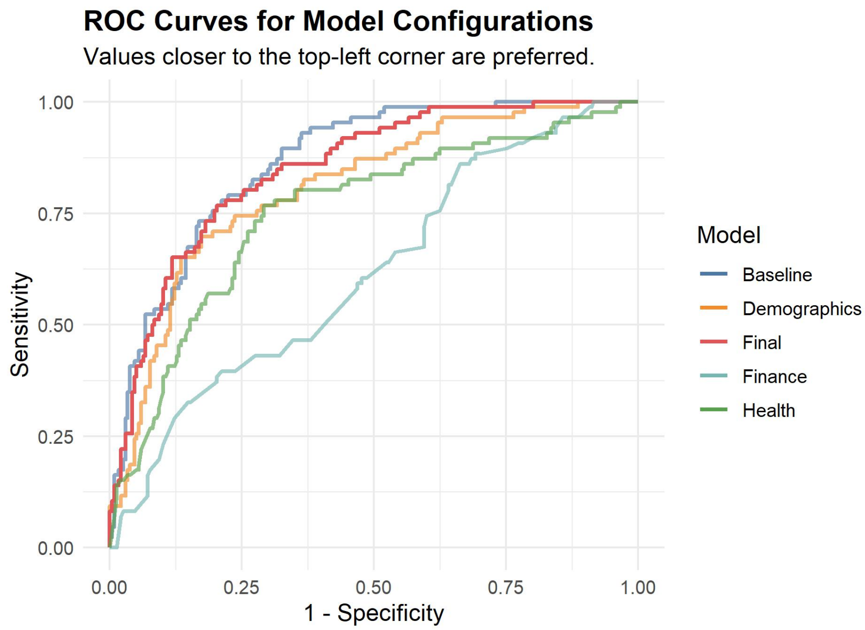
The final model pulls variable research from each of the sub models and has a ROC AUC of nearly the same as the baseline model. All variables are significant apart from debt-to-income (DTI) which has a p-value of 0.06. We expect this is because DTI is computed at a state-level of aggregation as discussed above. We also include a parameter which states whether a county is located in the midwest as midwestern and rust-belt counties tend to have lower ratings. It has an R-Squared of 0.34. The model parameters are as follows:

Table 1. Final Model Specifications; Logistic Regression Predicting Aaa Rating

Metric:	*Intercept*	*DTI*	*Midwest*	*Population*	*In-State*	*Out-State*	*Foreign*	*Health*
Coef:	-3.75	-0.79	-1.01	-6.83	3.77	2.63	1.38	-9.57
P-Val:	0.35	0.00	0.01	0.06	0.00	0.00	0.00	0.00

Data source colors are **state finance**, **Census demographics**, and **health rankings**. The **Final** model contains variables from each source. The **Baseline** model contains all variables from all sources.

Figure 2. ROC Curves for Model Formulas at Estimation



WEB APPLICATION:

We [developed an R Shiny web application hosted on shinyapps.io](), a free hosting service, to showcase our model. It allows users to view the predicted results from our model at a US county level. While not every county is included (see data limitations in *Challenges and Future Research*), this provides a high level overview of which counties are expected to face challenges in the future and which counties are expected to perform into the future, at least from the perspective of bond ratings.

We include more detailed documentation in the REAMDE within our code repository under *Visualization*, however the following is a brief description of the libraries used to build this application. First, R Shiny is an R package which acts as a front-end web framework controlled entirely through R. This means developers can create interesting visualizations and reports all while remaining within the R ecosystem. We extend our framework to use a subset of packages from the tidyverse and CRAN at large. Namely, we use dplyr, sf, and leaflet to manipulate data frames, work with geospatial files, and visualize maps respectively.

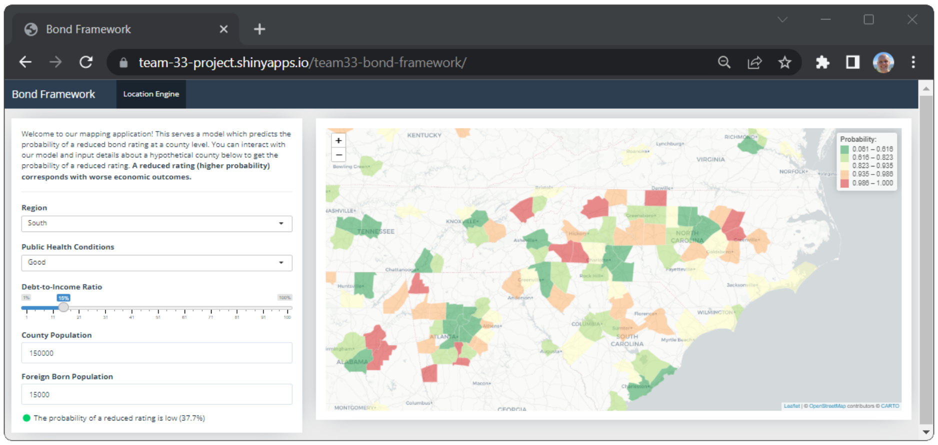
The application is bundled with a few key data sources. First, we host county shapefiles provided by the Census on our map. Second, we include a data set which converts FIPS codes (at the county level) to provide state names for a given county. This allows us to provide more useful tooltips to the user as they hover over the counties on the map. Finally, we include our training data which is used to predict the probabilities of a sub-Aaa rating on the map which generates the choropleth elements seen on the map of the United States.

This application includes a user interface on the left side of the application which allows users to input details about a hypothetical county. This is useful for business leaders and county officials because they can take details about their county and perform *what-if* analyses to see if the economic outlook changes for their county if a given event or characteristic changes. Users can modify the following settings:

- Region: is the county in the South, Midwest, West, or Northeast?
- Public Health: is the public health outlook good, fair, or poor (i.e., obesity levels and access to care)?
- Debt-to-Income: what is the ratio of debt to income for a county?
- Population: what is the population of a given county?
- Foreign Born Population: what is the population size of foreign born residents?

Modifying these settings will invoke a refresh of our logistic regression. Each time a user changes settings, we provide an updated probability of a reduced rating (sub Aaa rating) where higher values correspond to worse rankings. When the probability of a reduced rating is less than 50%, we say the economic outlook is good and display a green light. However, if the probability of a reduced rating rises to 50-75% we say the economic outlook is fair whereas values above 75% correspond with poor outlooks.

Figure 3. Screenshot of our Web Application



CHALLENGES AND FUTURE RESEARCH:

We faced several challenges throughout this research project. Fortunately, all key challenges are related to data access. We expect that given enough time, we could find the appropriate data sources to extend our research. Additionally, these challenges have spurred several future research questions to consider. Our first key challenge is related to county-level finance data. Because Moody's assess ratings at the county-level based on the financials of a given county, we expected county financials to be a key component of our training data. Unfortunately, the county level finance data was extremely granular and represented only a single snapshot in time. We would have preferred to use at-time county finance data which spanned different years. Instead, we relied more heavily on state-level finance data. While state-level data is preferable to no financial inputs, financial inputs were not as strong of a rank-ordering predictor as we originally expected. Future research could include (a) gathering county level financial data at the appropriate level of granularity and time and (b) estimating our model using a more representative subset of variables used by Moody's to build general obligation bond ratings.

Our second key challenge was related to our dependent variable. Originally, we had planned to estimate the probability of a county bond rating dropping to a more pessimistic outlook (e.g., Aaa to Aa). Unfortunately, we were unable to obtain general obligation bond ratings over-time for counties in our sample. We instead were able to obtain ratings for a subset of US counties from recent years (primarily 2022). We pivoted our model to estimate the probability of a Aaa rating and used 1 minus the probability to estimate pessimistic economic outcomes. While this model structure is still a viable approach which produces useful results, we could expand our research to revisit the original question about a *reduced* rating over time instead of a *reduced rating* where reduced in this context means non-Aaa (where Aaa is the best rating).

Our final key challenge is related to overall data coverage. Not all data sources include data for all US counties. Where there are 3,143 counties in the United States (and we expected a point-in-time snapshot over a decade or more to create a dataset of 30,000+ records) we were only able to obtain data across multiple data sources for a small subset of counties (around 400). This, combined with the fact that we only have data from one point in time snapshot, meant our dataset was considerably smaller than originally expected. This is a byproduct of combining data from 4+ disparate sources. However, we were able to maintain good coverage of

US urban centers. One point of future research is to gather data from additional sources to fill in the gaps and build the larger training data we originally planned to use.

One additional future research opportunity results from the time lag between data sources. When we refer to the time lag, new health data for a prior year comes out around January while new census data comes out around april. On the other hand, county and state financial data, which back many of the rating agencies' own algorithms for assigning credit scores, typically come out much later, closer to August and September of the following year. This is mainly due to a government's official year end date for audited financials being June 30th. While our model from this project showed better results using health data vs financial data, future research with more data could point to health (and even census) data as a potential leading indicator of future ratings drops in the current year. The gap here would be approximately 3-7 months, and could be extremely useful to institutional investors of municipal bonds.

LITERATURE REVIEW:

“State Fiscal Institutions and the U.S. Municipal Bond Market” by James M. Poterba and Kim S. Rueben. This paper presents new evidence on the effect of state fiscal institutions, particularly balanced-budget rules and restrictions on state debt issuance, on the yields on state general obligation bonds. The authors find that states with more stringent balanced-budget rules have lower yields on their general obligation bonds, while states with more restrictions on debt issuance have higher yields. The paper also finds that the effect of these fiscal institutions is stronger for bonds with longer maturities. This provides evidence for the inclusion of financial data in our model whether it is at the state-aggregate level or county-level directly. We consider a balanced budget to include appropriate spending on essential county functions (such as infrastructure maintenance), managed debt obligations, adequate cash reserves, and balanced extraneous expenses.

“Municipal Bonds, State Politics, and Economic Outcomes” by Andriy Bodnaruk and Eugene N. White. This paper examines how political factors affect municipal bond markets and economic outcomes. The authors find that political factors such as political polarization and corruption can lead to higher borrowing costs for municipalities. We do not expect this to manifest in counties where political affiliations are strongly established (for example, Los Angeles has a strong democratic leaning and Oklahoma City has a strong republican leaning), however in cities and states where political affiliations are changing as regions age and or urbanize.

“Aging and public financing costs: Evidence from U.S. municipal bond markets” by Yilin Hou, David C. Ling, and Andy Naranjo. This paper examines how demographic changes affect public financing costs in U.S. municipal bond markets. The authors find that an aging population can lead to higher borrowing costs for municipalities. We can consider this for our research because different parts of the country represent different age demographics. For example, Georgia has a median age of approximately 36 years of age whereas Maine has a median age of 44 years of age. This may not manifest in our bond ratings data directly, however it may be a subfactor which manifests in other economic indicators over time. This can also be considered for alternative approaches to a leading economic indicator other than bond ratings.

APPENDIX:

Figure 4. Scorecard Framework for Moody's Analytics

Scorecard Framework

The scorecard in this rating methodology is composed of four factors, most of which comprise sub-factors. The scorecard also includes five notching factors, which may result in upward or downward adjustments in half-notch or whole-notch increments to the preliminary outcome.

EXHIBIT 1
US Cities and Counties Scorecard Overview

Factor	Factor Weighting*	Sub-factor	Sub-factor Weighting
Economy	30%	Resident Income (MHI Adjusted for RPP / US MHI)†	10%
		Full Value per Capita (Full Valuation of Tax Base / Population)	10%
		Economic Growth (Difference Between Five-Year Compound Annual Growth in Real GDP and Five-Year CAGR in Real US GDP) ‡	10%
Financial Performance	30%	Available Fund Balance Ratio (Available Fund Balance + Net Current Assets / Revenue)	20%
		Liquidity Ratio (Unrestricted Cash / Revenue)	10%
Institutional Framework	10%	-- **	10%
Leverage	30%	Long-term Liabilities Ratio ((Debt + ANPL + Adjusted Net OPEB + Other Long-Term Liabilities) / Revenue)††	20%
		Fixed-Costs Ratio (Adjusted Fixed Costs / Revenue)	10%
Total	**100%**		**100%**

Preliminary Outcome

Notching Factor	Notching Range
Additional Strength in Local Resources	0 to +2
Limited Scale of Operations	–1 to 0
Financial Disclosures	–2 to 0
Potential Cost Shift to or from the State	–1 to +1
Potential for Significant Change in Leverage	–2 to +1.5

Scorecard-Indicated Outcome

* Factor weights shown in this table reflect standard weights. As described in Appendix A, we apply overweighting when scores are low.
† MHI stands for median household income. RPP stands for regional price parity.
‡ CAGR stands for compound annual growth rate.
** This factor has no sub-factors.
†† ANPL stands for adjusted net pension liabilities. OPEB stands for other post-employment benefit liabilities.
Source: Moody's Investors Service

Figure 5. Rating Agency Levels from High to Low

Standard & Poor's	AAA	AA+	AA	AA-	A+	A	A-		
Moody's	Aaa	Aa1	Aa2	Aa3	A1	A2	A3		
Fitch IBCA	AAA	AA+	AA	AA-	A+	A	A-		
Standard & Poor's	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-
Moody's	Baa1	Baa2	Baa3	Ba1	Ba2	Ba3	B1	B2	B3
Fitch IBCA	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-
Standard & Poor's	CCC+	CCC	CCC-	CC	C	D			
Moody's	Caa1	Caa2	Caa3	Ca	C				
Fitch IBCA	CCC+	CCC	CCC-	CC	C	D			

Source: Bank for International Settlements, "Long-term Rating Scales Comparison," http://www.bis.org/bcbs/qis/qisrating.htm.

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