Using Fiscal Ratios to Predict Local Fiscal Distress

Evgenia Gorina, Marc Joffe,
and Craig Maher

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Abstract

Municipal fiscal distress experienced by cities such as Detroit, Michigan; San Bernardino, California; and Harrisburg, Pennsylvania, has generated an impressive body of work by researchers seeking to understand underlying factors in an effort to prevent future distress. Recent research has been informative and appears to be coalescing around a handful of predictive factors such as reserves and debt; however, the generalizability of the findings is limited because the research has focused on case studies or within-state analyses. This study draws from a large national sample of local governments in the United States over a 10-year period and incorporates robust methodology for rare events analysis. Consistent with previous research on local fiscal distress, we find evidence that unreserved general fund balances, unrestricted net assets, long-term obligations, and local unemployment are statistically associated with municipal defaults and bankruptcies.

JEL codes: H74, C35, R51

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Author Affiliation and Contact Information

Evgenia Gorina
Assistant Professor, University of Texas at Dallas
egorina@utdallas.edu

Marc Joffe
Senior Policy Analyst, Reason Foundation
marc.joffe@reason.org

Craig Maher
Professor, University of Nebraska at Omaha
csmaher@unomaha.edu

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Using Fiscal Ratios to Predict Local Fiscal Distress

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Introduction

The Great Recession (2007–2009) put extraordinary pressure on many local governments throughout the United States and plunged some into a state of severe fiscal distress. The recession also inspired a body of work that has sought to identify fiscally struggling communities and understand the determinants of that distress in hopes of keeping other communities from reaching the point of excessive fiscal strain. The purpose of this paper is to build on the existing research by developing a model that identifies the fiscal and economic attributes most closely associated with fiscal distress and by creating a local government fiscal condition scoring system that can help differentiate distressed from non-distressed cities and counties to help predict financial emergencies.

The literature on fiscally distressed communities has been consistent in defining "distressed" through the actions of filing for bankruptcy or defaulting on a loan payment (ACIR 1985; Stone et al. 2015; McDonald 2017). At the same time, researchers have recognized that fiscal health is more of a continuum than a binary state; they have therefore proposed composite numerical scores of fiscal health to capture the intensity of fiscal pressure (Brown 1993; Kloha, Weissert, and Kleine 2005; Wang, Dennis, and Tu 2007). The external validity of these scores and indices, however, has been disputed, with the main criticisms being that the indices do not actually reflect the intensity of fiscal pressure and do not capture some aspects of local fiscal space that, for example, limit revenue generation or prevent the government from scaling back spending quickly in response to a revenue decline (Clark 2015; Hendrick 2004; Stone et al.

2015). The main source of the vulnerability of the proposed scoring systems, however, has been researchers' inability to validate the systems against actual fiscal performance; up until the Great Recession, city and county defaults were extremely rare.

Another challenge for empirical fiscal health research is limited data availability. Recent studies have focused on specific cases like Detroit (Stone et al. 2015; Watson, Handley, and Hassett 2005), municipalities within a given state (Clark 2015), or local governments within a few states (Gorina, Maher, and Joffe 2017). As a result, generalizations about local government fiscal distress remain insufficiently grounded in observational data. The goal of this project is to work with a large national sample to offer additional evidence of the fiscal ratios that best predict fiscal distress and, through this, to either corroborate or dispute previously identified associations. Our sample includes over 1,500 local debt issuers and covers 10 years of financial data, giving us an opportunity to examine the extent to which fiscal emergencies may be predicted from past fiscal performance and local economic environments.

Literature Review

Fiscal distress is but one segment on a spectrum of what can be called financial condition. Given the complexity of attempting to identify a metric or set of metrics that determine where a community lies on a fiscal condition continuum (e.g., Brown 1993), a handful of studies have focused on predictors of fiscal distress, which, once identified, could then be extrapolated to measure fiscal condition more broadly (how close or far a community is from fiscal distress). Thus, while there is an extensive body of work on fiscal condition measurement (for recent reviews, see Gorina et al. 2017; Stone et al. 2015), we focus on those works that emphasize the analysis of factors that affected fiscally distressed communities.

The Advisory Commission on Intergovernmental Relations (ACIR) produced a series of reports that are quite helpful in understanding fiscal relations between state and local governments (ACIR 1971, 1979, 1981, 1988, and 1989). Most important for the purposes of this project is ACIR's analysis of local bankruptcies and loan payment defaults from 1972 to 1983 (ACIR 1985). The research focused on entities—general-purpose governments, school districts, special districts, and other entities—that defaulted on bond payments or filed for bankruptcy. The report authors identified several financial predictors of fiscal distress: operating expenditures exceeding revenues over time, current liabilities in excess of current assets, outstanding short-term loans, increases in property tax delinquency, decreased assessed valuation, and unfunded pension liabilities (ACIR 1985). Thus, fiscal distress was caused by a depressed economy (property tax delinquencies and lower assessed property valuation) that led to an erosion of the revenue structure incapable of sustaining operating expenditures and debt payments.

More recent studies appear to confirm many of the ACIR findings. For instance, Watson, Handley, and Hassett's (2005) content analysis of the 1999 bankruptcy filing of Prichard, Alabama, focuses on the longer-term social economic conditions that precipitated the filing. The authors find that population declines, civic distrust, and structural changes to the economic base coupled with poor financial management were the primary causes of Prichard's fiscal distress (the city filed a second bankruptcy petition in 2009). Using a similar approach to examine the 2012 bankruptcy filing of San Bernardino, California, a George Mason University study identifies a history of economic and demographic changes, coupled with a political culture that made it difficult for San Bernardino to avoid a fiscal crisis (Shafroth and Lawson 2013). Callahan and Pisano's (2014) case study of the city and county of San Bernardino comes to a similar conclusion: the city's bankruptcy filing was the result of a leadership void during a period of economic decline.

Stone, Singla, Comeaux, and Kirschner's (2015) case study of Detroit is methodologically distinct from ACIR (1985) and Watson, Handley, and Hassett (2005), but their findings are generally consistent. First, the city's filing was the result of a longer period of demographic and economic change that was exacerbated, though not caused, by the Great Recession. Focusing on fiscal metrics, Stone and his coauthors (2015) find that operating solvency (revenues as a percentage of expenditures, surpluses, and fund balances), assets and liabilities (e.g., long-term liabilities and assets relative to liabilities—both restricted and unrestricted), and business-type activities are most closely associated with Detroit's fiscal distress. The Watson, Handley, and Hassett study highlights the importance of fund transfers from enterprise to operating funds for the purpose of sustaining operations—a method akin to ACIR's finding that short-term borrowing was an important indicator of fiscal distress.

Holian and Joffe (2013), in a report for the California Debt and Investment Advisory Commission, studied bond defaults and constructed a set of models to predict the probability of a municipal default. The authors analyzed data from the Great Depression to the Great Recession. The project includes case study analysis of specific bankruptcies in California (e.g., San Bernardino, Stockton, Vallejo, and Mammoth Lakes) and regression modeling to predict the probability of a community defaulting on a bond payment. The modeling is consistent with previous work: demographic and economic changes (population change and average household income), operating solvency (change in operating revenues), liabilities (interest and pension payments relative to general fund revenues), and general fund balances are effective in predicting defaults.

McDonald's (2017) recent piece is one of the few studies that examine cities across states. Relying on the Lincoln Land Institute's "fiscally standardized cities," McDonald examines data from 1977 to 2012 for 150 cities, both to evaluate several existing approaches to studying fiscal condition (Brown 1983; Wang, Dennis, and Tu 2007) and to apply event history analysis to test models that predict the likelihood that a community will file for bankruptcy. McDonald (2017) finds that his composite fiscal condition score is ineffective in predicting municipal bankruptcies. Interestingly, the financial variables most associated with municipal bankruptcies are cash solvency (the more cash and cash equivalents relative to current liabilities, the lower the probability of bankruptcy), long-run solvency (long-term liabilities divided by total assets), and service-level solvency (taxes per capita, revenues per capita, and expenditures per capita). In addition, several political variables (e.g., the party of the governor) and demographic variables (e.g., the age and ethnic composition of the city) are also associated with city bankruptcies in McDonald's work. Inability to derive a satisfactory distress model may be related to the limited number of fiscally standardized cities, which excludes Vallejo, Harrisburg, and Central Falls. It may also be related to the database's reliance on census measures rather than audited financial data.

Using a different measure of fiscal distress—actions taken as a result of fiscal distress—and expanding the analysis beyond a case study or within-state analysis, Gorina, Maher, and Joffe (2017) present intuitive and consistent findings. The analysis of close to 300 cities and counties in California, Michigan, and Pennsylvania from 2007 to 2012 shows that the strongest predictors of fiscal distress were general fund balance as a percentage of expenditures, total debt as a percentage of revenues, and property taxes as a percentage of own-source revenues.

Despite the extent of the academic and professional literature and the increasingly widespread use of metrics of fiscal condition in modern management practices (for a review, see Stone et al. 2015), fiscal condition measurement issues are yet to be resolved, and empirical methodologies for predicting fiscal distress are yet to be developed. Importantly, there is a growing understanding that indicators of fiscal condition need to be validated against some objective reality of whether a government is experiencing fiscal prosperity or distress (Clark 2015; Gorina et al. 2017; Maher and Deller 2011; Stone et al. 2015).

Maher and Deller (2011) show that practitioner views on their jurisdiction's fiscal condition tend to be problematic as a measure because they are weakly related to actual trends in the government's financial indicators. Clark (2015) offers a full-fledged criticism of research that relies on a single composite indicator of fiscal condition or arbitrarily picked indicators as measures of fiscal condition. Following Rivenbark, Roenigk, and Allison (2010), Clark (2015) recognizes that "aggregate scores may hide a particular area of weakness shown by an individual indicator" (73) and that some indicators may not be valid as measures of fiscal condition when compared against actual government performance. Echoing Clark's (2015) concerns, Stone and his coauthors (2015) attempt to validate existing metrics of financial condition by focusing on a single case study of Detroit. They offer a descriptive analysis of a variety of Detroit's fiscal indicators over a decade, including the indicators proposed by Kloha, Weissert, and Kleine (2005). Stone et al. (2015) view the city's bankruptcy as an unequivocal expression of a poor fiscal condition and, as already mentioned above, show that asset and liability ratios, operating solvency, and business-type activity ratios work as the most useful indicators of distress. Because a single case study cannot be generalized, more empirical work is needed to validate existing indicators of financial condition against actual government performance and to identify measures that can be used as predictors of fiscal crises.

In sum, current literature offers a variety of indicators and scoring systems of fiscal health, but it lacks sufficient evidence about which set of indicators can best forecast extreme episodes of fiscal distress. The purpose of this study is to develop an empirical model that predicts fiscal distress and that can be used to create a fiscal scoring system for identifying communities in fiscal distress.

Why a Composite Scoring System?

Hendrick (2004) argues that a single composite score masks important details about a government's fiscal condition and thus renders the assessment of fiscal health inaccurate. A rich qualitative inquiry certainly provides for a more detailed understanding of fiscal condition, whereas any type of quantitative modeling necessitates tradeoffs by focusing only on key characteristics of the subject of study at the expense of others. But we believe that there is a practical need for a numerical composite score of government creditworthiness, given the modern fiscal environment in which governments operate as debt issuers. Specifically, when bond investors or vendors extend credit to a local government, they implicitly or explicitly make an assumption about the likelihood of default. As a result, public-sector entities face different bond coupon rates and varying willingness on the part of suppliers to provide goods and services in advance of payment. For example, a government that is perceived to have a high risk of default can expect to pay higher interest rates on bonds and may have to pay vendors cash up front. A low-risk entity can issue debt at lower rates and can expect favorable payment terms from vendors. Those who extend credit to governments often look to credit ratings to estimate the risk they face. Credit ratings are intended to incorporate multiple credit considerations into ordinal measures expressed as alphanumeric symbols. Since rating methodologies are not fully transparent and are subject to criticism, especially following the Great Recession, alternative metrics would help investors, governments themselves, and other stakeholders estimate the chances of government default relative to other governments.

Credit scoring models are common in the corporate sector but have received far less attention in government finance. Beaver's (1966) study of the predictive power of individual ratios ends with a suggestion that "multiratio analysis" could provide better insight. Altman (1968) uses discriminant analysis to correctly predict most corporate bankruptcies in his sample with only five fiscal ratios.[1] Another influential study from the corporate finance literature by Merton (1974) uses a predictive model to assess the probability of a corporate default and proposes a model for pricing corporate debt based on equity prices and their volatility.

In contrast to the research in corporate finance, the modeling of creditworthiness of government entities is relatively undeveloped. This is not particularly surprising, given that government defaults have been historically rare since the Great Depression and that governments, unlike individuals and businesses, can typically use their taxing power to generate additional financial resources to meet operating needs. However, over the past decade, the number of bankruptcies and defaults of general local governments has increased. At the same time, the complexity of government operations and the fiscal tools to finance these operations have changed drastically, making many local governments more dependent on private-sector contractors in service provision and on consultants in the issuance and management of debt. Political incentives for maintaining fiscally sustainable, long-term trajectories for governments

[1] Commercial descendants of Altman's Z-Score model include Moody's RiskCalc index, which relies on ordered probit and logit models to model corporate defaults (Falkenstein, Boral, and Carty 2000).

have also evolved with the increased complexity and decentralization of government operations. As a result, governments vary in how they manage their finances and how much risk they assume in fiscal decisions. In such an environment of increased experimentation, it is only logical to expect increased variation in the outcomes of local financial management. In this context, the ability to assess government financial standing and predict a fiscal crisis before it occurs has taken on greater relevance.

Data Sources

To examine predictors of fiscal distress, we used Bloomberg data from comprehensive annual financial reports (CAFRs) of general-purpose governments that incurred debt from 2007 to 2016 and complemented these data with socioeconomic variables from the Bureau of Labor Statistics, Zillow, and the US Census Bureau. Bloomberg's Municipal Fundamentals database offers financial statistics for over 13,000 debt-issuing governments and is one of the largest repositories of CAFR data to date. We used the listing of all municipal entities in the Municipal Fundamentals database as the sampling frame. The original intent was to work with a panel of 21,000 observations (2,100 entities multiplied by 10 years). To select the sample, we pooled 10 years of data for each of the 18 entities that defaulted on debt or declared bankruptcy between 2007 and 2016 (see the entity listing in table 1, page 28). Then we pooled 10 years of data for the remaining 2,082 government entities that we had randomly selected from the sampling frame. Since some entities had incomplete records for some variables of interest, our tests and models use samples of different size, depending on the type of analysis and variables analyzed.

Our fiscal distress variable is a dichotomous measure equal to 1 if a government declared bankruptcy or defaulted or continued to be in bankruptcy or in default in a given year; it is otherwise equal to 0. Table 1 (page 28) shows the list of the general-purpose governments that experienced defaults or bankruptcies and describes the types of fiscal distress episodes that happened.

Several governments that filed for bankruptcy (Gould, Arkansas; Westfall Township, Pennsylvania; Moffett, Oklahoma) or defaulted (Brighton, Alabama; Hercules, California) over the observation period were not present in the Bloomberg dataset. In addition to the measure of distress that is based on the fact of a bankruptcy or default, we also created a more conservative measure of distress based on the qualitative analysis of the distress events in table 1. After a close examination of all governments that we originally considered to be in distress because they had defaulted on debt or declared bankruptcy, we excluded episodes of distress that were not related to the financial condition of the general government. Starting with 18 government defaults and bankruptcies over the 10-year span (2007–2016), we ended up with 11 observations in the "general-government distress" category. Excluded entities defaulted on bonds that supported business-type activities or filed for bankruptcy after losing a lawsuit. The results of the multivariate analyses based on this more conservative measure largely align with the main findings.

We began the analysis of financial condition by creating financial indicators. We quickly learned that not all of the financial indicators could be successfully constructed for all years of analysis. Some data elements were missing for one or more years. Table 2 (page 30) presents descriptive statistics and frequencies of all variables that we originally considered for inclusion in the models. Some of the variables from CAFRs were commonly reported by governments and were readily available for statistical analysis, whereas others were not reported as often.

Among the financial ratios, we distinguish between government-wide measures, governmental funds measures, and general fund measures. The ratios include the following:

- liquidity ratios (government-wide cash ratio and current ratio)

- operating ratios (government-wide revenues to spending, governmental funds revenues to spending, and general fund revenues to spending)
- measures of longer-term obligations (total long-term debt, pension obligations, other postemployment benefit estimates, and a variable for the sum of these three types of longer-term obligations)
- measures of fiscal reserves (total general fund balance as a share of general fund spending, general fund unreserved balance [unrestricted after Governmental Accounting Standards Board (GASB) Statement Number 54] as a share of general fund spending, total governmental funds balance as a share of governmental fund spending, and governmental funds unreserved balance [unrestricted after GASB 54] as a share of governmental funds spending)
- government-wide measures of net assets and unrestricted net assets as well as measures of the relative burden of longer-term obligations on the operating budget (percentage of spending that is paid as interest on debt and as pension contributions)

These financial variables were supplemented with two local economic characteristics: home price data from Zillow Research and local unemployment rates from the Bureau of Labor Statistics (BLS). Zillow and BLS had data for a majority of the Bloomberg entities. When these supplemental data sources did not have a precise entity match, we selected the geographically closest entity available. To determine the nearest entity, we began by geocoding all entities in the Bloomberg sample and in the BLS and Zillow universes. We then compared the derived coordinates to find those pairs that were separated by the shortest distance. Overall, we imputed the home price and unemployment rate for 21 percent of the original sample. More information on geocoding is available from the authors upon request.

Modeling

The empirical analysis proceeded as follows. First, we examined bivariate associations of all candidate predictors using correlation analysis (table 3, page 33) and bivariate associations between the candidate predictors and the fiscal distress status using t-tests (table 4, page 34). We then selected variables for inclusion into multivariate models. We made it a point to choose variables that represent each of the three measurable dimensions of solvency, as conceptualized in the seminal International City/County Management Association publication on the measurement of fiscal condition (Nollenberger et al. 2003): cash solvency, operating solvency, and long-term solvency. A major advantage of the dataset was that it allowed us to examine three types of ratios: government-wide measures, governmental fund measures, and general fund measures. After selecting the variables for inclusion, we ran multivariate logistic regressions that predict the odds and hazards of fiscal distress.

Our multivariate analysis focuses on binary logistic regressions with cluster-robust standard errors at the government level. Since the number of defaults and bankruptcies is very small, we cannot use fixed effects or rely on conventionally estimated standard errors. We run models using relogit, an estimation approach that produces unbiased and efficient estimates of population parameters on samples with rare events as the dependent variable (King and Zeng 2001a, 2001b). Fitting conventional logit models on data with binary dependent variables with rare frequencies is often problematic because maximum likelihood estimates of the parameters tend to approach infinity. The relogit model adjusts the estimated coefficients by true frequencies of the events in the population of data, which reduces mean square errors for rare event samples, compared to conventional logistic regression (King and Zeng 2001a, 2001b).[1] The next section provides more details on our descriptive and multivariate findings.

Results

The analysis of bivariate correlations shows that several variables are highly correlated and cannot be included in the regression models at the same time. Table 3 (page 33) presents a correlation matrix, which captures the strength of these associations.[2] We observe that the cash ratio and the current ratio are highly correlated (r = 0.83); so are the general fund total balance and the general fund unreserved balance (r = 0.90) as well as the total and the unreserved balance in governmental funds (r = 0.69). To choose between the correlated candidate predictors, we examine all pairs with correlations above r = 0.60 and include one of the correlated predictors with the higher frequency into the models. In addition, we make choices about the predictors based on the results of t-tests, which demonstrate statistically significant differences in means between distressed and non-distressed entities.

Table 4 (page 34) reports the results of t-tests for all candidate predictors. The table presents two-tail t-tests with the unequal variances assumption for two samples: the full sample with the maximum number of observations available and a smaller sample with only those observations for which we were able to obtain US Census demographic information. The results of the t-tests are quite similar across the two samples. We observe that distressed governments

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[1] Relogit also corrects for potential bias in the intercept due to sample selection on the dependent variable. In our data, this bias may be present because we began sample selection by including all observations for the entities that experienced distress and a less-than-full population of non-defaulting entities. Specifically, we used 100 percent of the defaulting population (34 events) and about 11 percent of Bloomberg's non-defaulting population (14,534 observations out of 130,000 observations). As a result, the analytical sample has nine times the default ratio of the overall population (34/14,568 = 0.0023 percent, compared to the true population default ratio of 34/130,000 = 0.00026 percent). We use the true population proportion of "distress" in the *relogit* models, equal to 0.00026 percent, to adjust the estimates for selection on Y.

[2] The correlation matrix is based on data for governments with nonmissing values for all variables.

tend to have lower cash ratios, lower current ratios, and higher debt (as measured by both long-term liabilities and total liabilities that include pensions and other postemployment benefits). Also, distressed localities have lower unrestricted net assets and higher unemployment rates. Since we have low frequencies of the distressed events, t-statistics and statistically significant differences detected by the t-tests may be biased upward (the denominator is affected mostly by the variance of the larger sample, while the difference in means in the numerator is determined mostly by the smaller sample).[3]

Multivariate Results

Based on the analysis above, the general multivariate model that we fit to different samples includes the following measures: a measure of current assets (current assets divided by current liabilities), a measure of fiscal reserves (general fund unreserved balance divided by general fund expenditures), a measure of government-wide operating ratio (revenues divided by expenditures), a measure of government-wide net asset position (unrestricted net assets), and a measure of long-term obligations that includes long-term debt as well as postemployment obligations (total long-term liabilities divided by total revenues). In addition, we use the unemployment rate and changes in home prices as predictors of fiscal crises. In the models for a subsample of governments for which we have data from the US Census Bureau, we also include demographic controls such as population, median household income, and occupancy rate.

Similar to Gorina et al. (2017), we prefer the current ratio to the cash ratio. Take, for example, a government with short-term investments that are convertible into cash to address

[3] In table 7 (page 37), we present Wilcoxon rank-sum tests and median tests for the differences between distressed and non-distressed observations. The findings are consistent across the t-tests in table 4 (page 34) and these non-parametric tests.

fiscal needs. Such a government's capacity would be underestimated with a cash ratio alone, since a cash ratio does not include short-term investments and receivables. In the choice between the correlated measures of total general fund balance and unreserved general fund balance,[4] we prefer the unreserved portion of the general balance, recognizing that other components of the total general fund balance are often dedicated to other spending needs. Given the choice between long-term capital debt and total long-term liabilities including pension obligations and other postemployment benefits, we pick the latter as our measure because it provides a more comprehensive representation of total government long-term commitments than can be provided by long-term capital debt alone. As for net assets and unrestricted net assets, which are moderately correlated (r = 0.48) and equally frequent, we select unrestricted net assets because they show statistically significant differences between non-distressed and distressed entities in the t-test (table 4). Interest on debt and annual pension contributions do not make it into the final empirical models because of their relatively low frequencies and lack of statistically significant differences in univariate analysis.

In sum, the models include predictors of fiscal distress that represent different dimensions of financial solvency, are not highly correlated with the other predictors, and are available for the maximum number of observations in the data. We expect to see that higher levels of fiscal resources (higher current ratio, higher fiscal reserves, higher operating ratios, and higher unrestricted net assets) will reduce the odds of distress, whereas higher levels of liabilities (long-term obligations) will increase the odds of distress. More prosperous economic environments (unemployment rates, incomes, and occupancy rates) will be associated with distress negatively.

[4] We use the name "unreserved general fund balance" throughout the paper for consistency. This variable includes unrestricted general fund balance after the implementation of GASB 54 in 2011.

Table 5 (page 36) presents the multivariate models that predict the log odds of fiscal distress using rare event logistic regression with cluster-robust standard errors. The first four columns present estimates for the full sample, and the next four columns present estimates for a smaller sample with demographic controls. When we merge Bloomberg fiscal data with the Census Bureau socioeconomic indicators, we lose observations that are not matched across the two data sources; yet we still retain close to 65 percent of the original observations. We do not know of any discernible patterns in the unmatched observations other than sample variability. Since the small sample still includes close to 13,000 observations, a systematic bias in the data is unlikely.

The models include financial ratios, the unemployment rate, and the home price change in the full sample as well as three additional demographic controls in the smaller sample. The first column for each sample in table 5 shows models that predict the likelihood of any episode of fiscal distress. The second column estimates the probability of distress using a more conservative definition of fiscal distress that excludes municipal defaults that occurred because of business-type activity defaults and failed lawsuits. Next, we recognize that some states do not authorize municipal bankruptcy; we therefore re-run the multivariate models on the sample of municipalities from the states that have either unconditional or conditional bankruptcy authorization (for a detailed listing of the states, see Moldogaziev, Kioko, and Hildreth 2017, 51). The third column for each sample presents the models on data from only those states that authorize bankruptcy. Finally, the fourth model estimates the probability of only general government distress for only those states that authorize bankruptcy. In addition to the relogit models in table 5 that adjust the estimates for rare event frequency and selection on Y, we present the same models estimated with conventional logistic regression with cluster-robust standard errors in table 8 (page 39). The findings of the logit models and relogit models align in the direction of the effects, with the standard errors being smaller in the relogit models, as expected. Since relogit models do not report measures of fit (King and Zeng 2001b), goodness-of-fit measures for logistic regression models such as the log likelihood chi square can be used to approximate it.

We observe that the unreserved general fund balance and the unrestricted net assets decrease the odds of distress, whereas total liabilities increase the odds of distress. Contrary to expectations, the government-wide operating ratio is positively associated with fiscal distress, suggesting that the balance between revenues and expenditures of a government in the year of distress is higher than that of a non-distressed government. This finding may reflect government actions to counteract fiscal pressure, including fire sales of equipment, short-term debt issuance, and other actions that boost the revenue side of the balance sheet. All models also consistently indicate the importance of unemployment.

Discussion

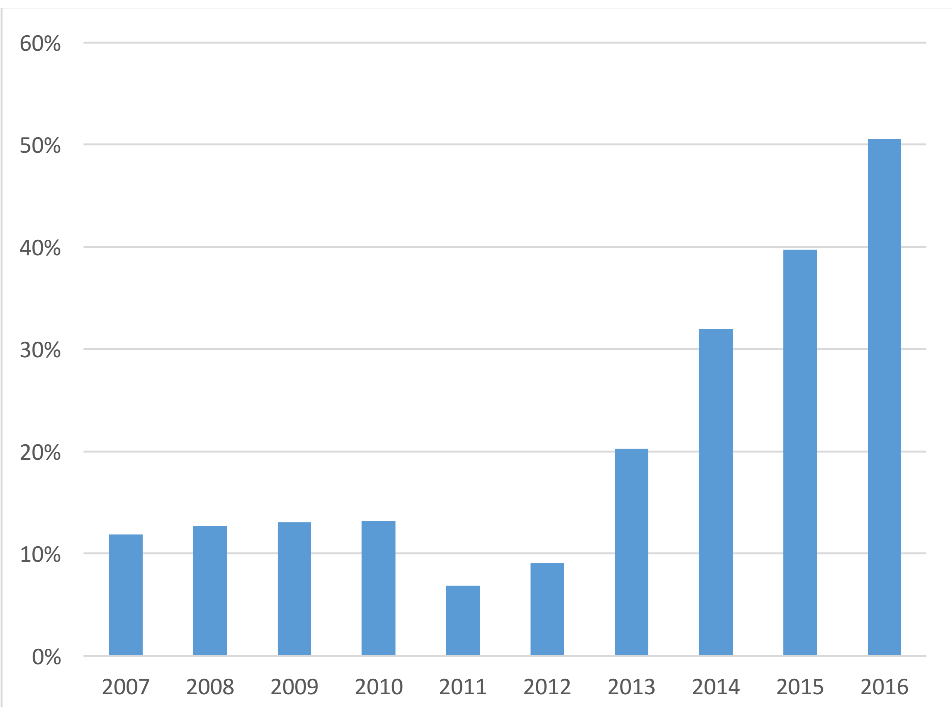
A local government's decision to file for bankruptcy tends to take one of three general forms: a response to a longer period of fiscal distress wherein reserves are depleted and debt is no longer manageable; a prolonged period of fiscal distress exacerbated by an event that pushes the entity into bankruptcy; or the loss of a lawsuit that drives an entity to file for bankruptcy. The following are graphical depictions of each of the three scenarios described above for Stockton, California; Harrisburg, Pennsylvania; and Boise County, Idaho. The analysis of fund balances and debt in the case of the first two entities largely corroborates the results of our statistical analysis. The third government that filed for bankruptcy because of the loss of a lawsuit tells a different story, and cases like this one are likely to account for the noise in the predictive power of our models.

Stockton, California

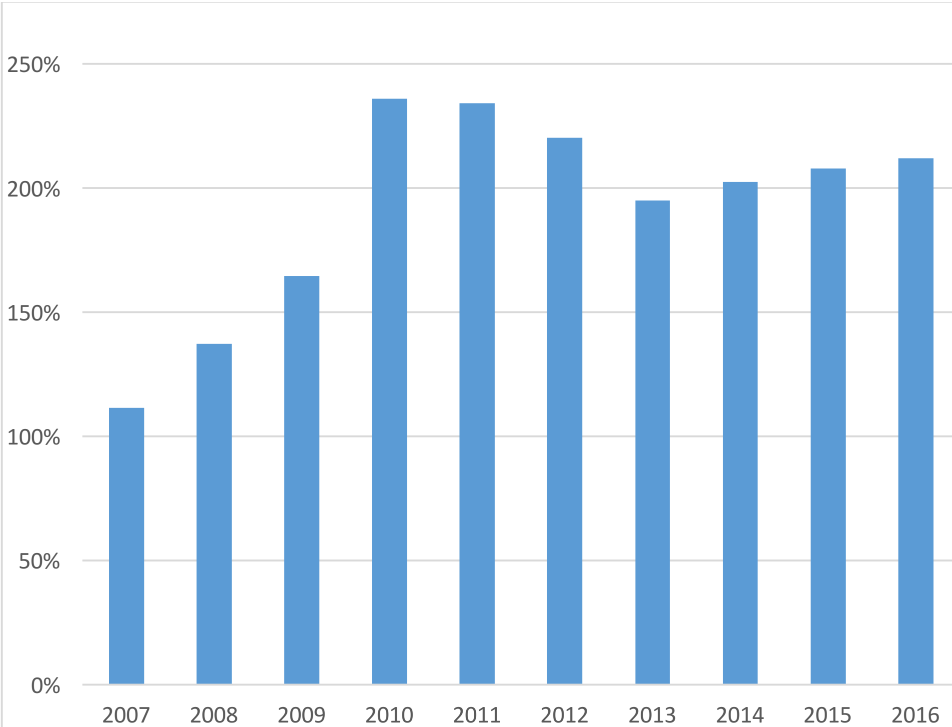
The city filed for bankruptcy protection in 2012, and based on the data in figure 1, it is not too difficult to understand why. Between 2007 and 2011, the city was operating with low fund balances (in 2011, Stockton's unreserved general fund balance was less than 7 percent of expenditures) and growing debt. The city's government-wide long-term liabilities peaked in 2010 at 236 percent of total revenues and only dipped slightly in 2011 (234 percent). Following bankruptcy filing, the city's reserves grew, but its debt has remained a challenge.

Figure 1. Fiscal Condition Indicators in Stockton, California, 2007–2016

Panel A. General Fund Balance as a Percentage of General Fund Expenditures



Panel B. Government-Wide Long-Term Liabilities as a Percentage of Total Revenue

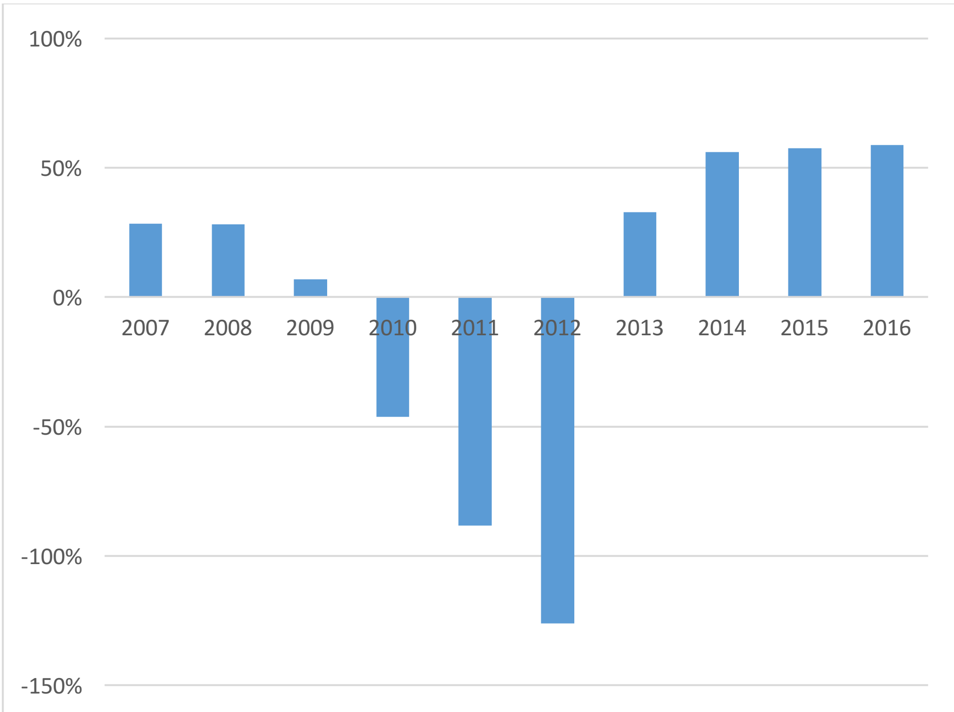


Harrisburg, Pennsylvania

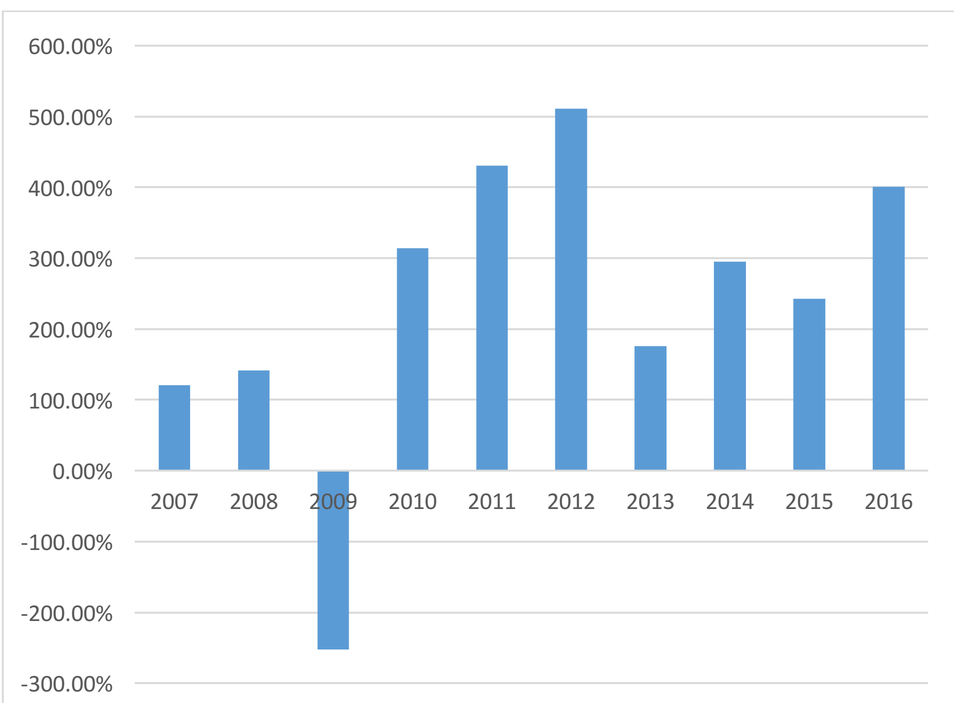
The trend in Harrisburg's general reserves was a concern even before city officials filed for bankruptcy protection in 2011. As figure 2 shows, Harrisburg's general fund balance was 28 percent of expenditures in 2007; it dropped to 7 percent of expenditures in 2009 and –46 percent in 2010. At the same time Harrisburg's reserves were dropping, the city was taking on more debt. Government-wide debt jumped from 121 percent of total revenues in 2007 to 314 percent of total revenues in 2010. Depleted reserves and insurmountable debt from the purchase of an incinerator pushed Harrisburg to file for bankruptcy in 2011. The bankruptcy filing, however, was dismissed by the state.

Figure 2. Fiscal Condition Indicators in Harrisburg, Pennsylvania, 2007–2016

Panel A. General Fund Balance as a Percentage of General Fund Expenditures



Panel B. Government-Wide Long-Term Liabilities as a Percentage of Total Revenue

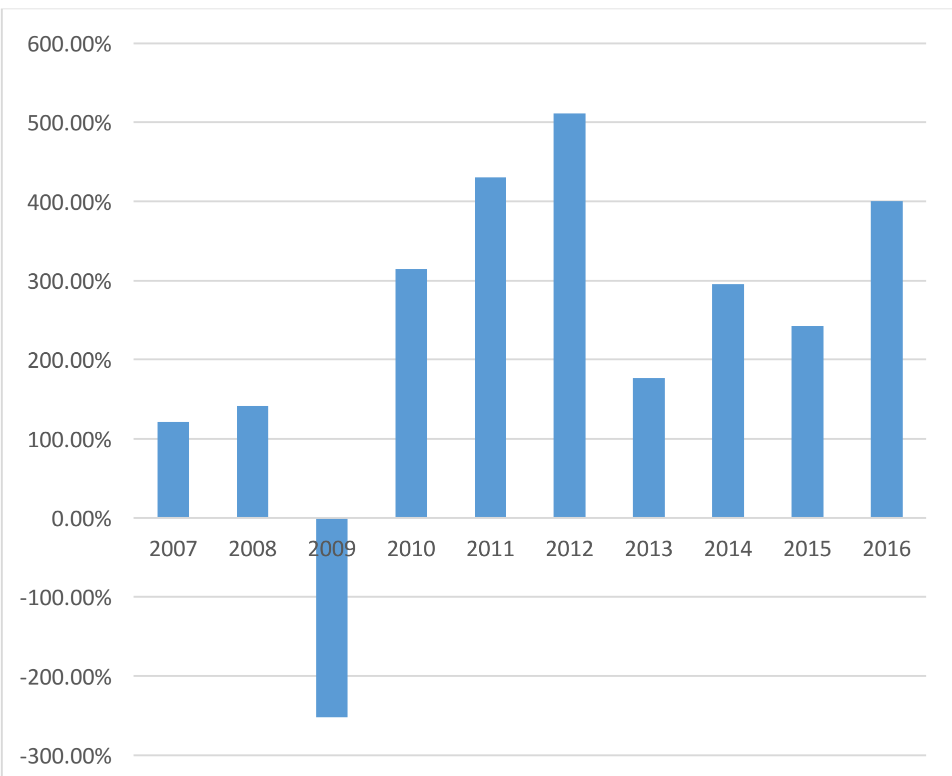


Boise County, Idaho

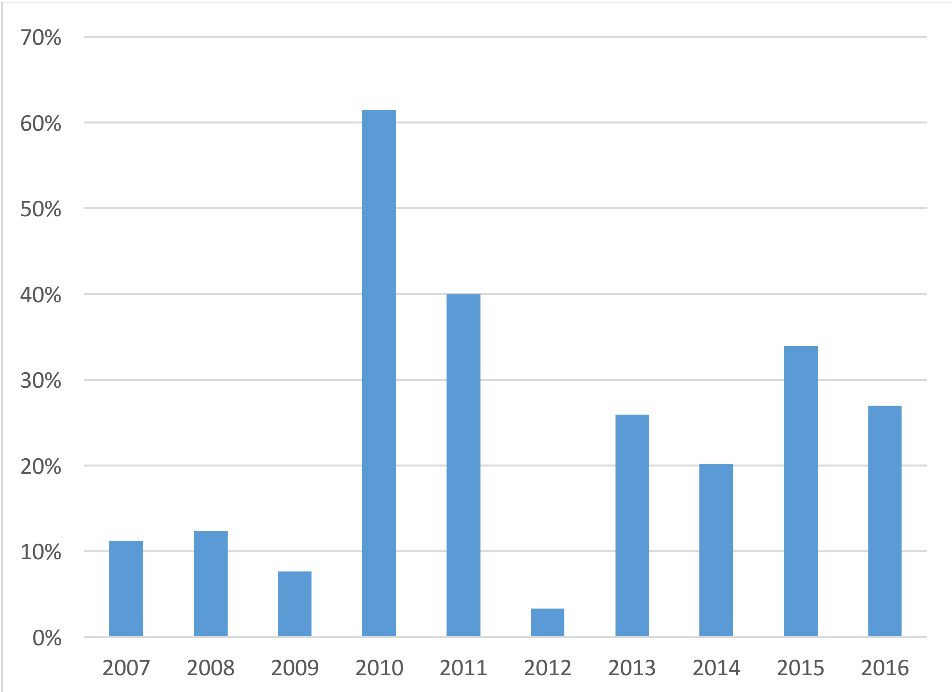
County officials filed for bankruptcy in 2011 after it was ruled that county officials violated the federal Fair Housing Act by trying to prevent the construction of a teen treatment facility. The developer was awarded $4 million in damages, and the county had to pay an additional $1.4 million in attorneys' fees. A federal judge denied the bankruptcy filing, given the country's strong fiscal position—strong reserves and manageable debt. Figure 3 below suggests that the city's financial ratios are likely to muddy the waters in the estimation of the probability of fiscal distress when Boise County is designated as distressed.

Figure 3. Fiscal Condition Indicators in Boise County, Idaho, 2007–2016

Panel A. General Fund Balance as a Percentage of General Fund Expenditures



Panel B. Government-Wide Long-Term Liabilities as a Percentage of Total Revenue



Composite Fiscal Scoring System

Next, we use predicted probabilities of distress from the relogit model above for the full sample to identify observations (i.e., government-years) at the highest risk of distress. We examine the upper tail of the distribution of the predicted probabilities, which includes 60 observations with z-scores above 3 standard deviations from the mean. These observations with the highest predicted probabilities of distress are presented in table 6 (page 37). They include 21 distinct governmental entities, of which 7 are municipalities that defaulted on debt or filed for bankruptcy. The other 14 entities with the highest predicted probabilities of distress may be viewed as false positives—had the elected and appointed officials reacted differently, these cases of fiscal distress could have resulted in a bankruptcy or default. Circumstances of several municipalities on this list suggest extreme financial distress. For example, Compton, California, declared a fiscal emergency in 2012 (DeBord 2012); Pontiac, Michigan, was placed under a state-appointed financial manager in 2009 (Michigan Department of Treasury 2009); Maywood, Illinois, suffered the withdrawal of its Moody's credit rating in 2011 (Moody's Investors Service 2011); and Philadelphia, Pennsylvania, has been in a "quiet" crisis owing to the mounting costs of its retirement obligations (Barret and Greene 2008).

Conclusion

The generalizability of empirical research is critical for the development of new knowledge. The field of government financial condition analysis has long been characterized by operationalization debates that have too frequently been limited in their generalizability. In recent years, the field appears to be coalescing toward a set of metrics that capture government fiscal slack, long-term liabilities, assets, and some local economic attributes (e.g., unemployment) as predictors of distress. Several recent studies in particular have helped to move the fiscal distress research forward (Clark 2015; Stone et al. 2015; Gorina et al. 2017) but remain limited in their generalizability. This study offers an important contribution both in terms of the methodological approach and the scope. The study draws conclusions from a large national sample of local governments in the United States over a 10-year period and incorporates robust methodology for rare events analysis.

Consistent with previous research on local fiscal distress, we find evidence that unreserved general fund balances, unrestricted net assets, long-term obligations, and local unemployment are statistically associated with municipal defaults and bankruptcies. Based on the findings of multivariate logistic regressions that take into account the relative contribution of predictors to the overall likelihood of distress, we use predicted probabilities to identify municipalities in the sample that are at the greatest risk of fiscal distress. The intuitive appeal of the findings, coupled with their consistency relative to the previous research, should enable local officials to engage their communities in a conversation about how best to prevent fiscal distress. These conversations should include the development or reexamination of policies related to appropriate levels of reserves and debt. The same applies to states that have local government monitoring systems and need to decide when and how to intervene, based on assessments of local reserves and debt levels.

Government-provided (and underprovided) services have opportunity costs and may be associated with fiscal risk. As awareness of this risk grows, the valuation of fiscal monitoring of governments is likely to grow as well, especially in this age of big data. Models of fiscal monitoring are likely to continue evolving. Analytical work in this area is critically dependent on the financial data available to analysts. Today, Bloomberg is one of a small number of data aggregators that have compiled a critical mass of audited public finance data; normally this data is available only to institutional bond investors at substantial cost. Academic researchers and policymakers could obtain better access to the massive government finance data if comprehensive annual financial reports were provided in a machine-readable format rather than PDF files. Although US state and local governments are neither required nor even encouraged to file machine-readable financial reports, the corporate sector in the United States and some governments in other countries have already transitioned to structured text disclosure. So, for example, the Spanish central government began collecting local government financial disclosures in eXtensible Business Reporting Language (XBRL) in 2006 (Amelivia 2009). By 2008, 80 percent of Spanish provinces and cities had embraced the new format (Roberts 2010). It is also noteworthy that between 2009 and 2012, the Securities and Exchange Commission phased in an XBRL filing mandate for quarterly and annual financial statements of all US public corporations (SEC 2009). Applying a machine-readable financial reporting standard such as XBRL to US municipal financial reports holds promise not only for increasing the speed and success of academics working to model and detect fiscal trouble but also for increasing the speed and success of those working to address it.

Table 1. Episodes of Fiscal Distress

Entity	Event (month and year)	Main Reason for Default or Bankruptcy	General Government Distress
Boise County, ID	Bankruptcy, March 2011–September 2011	Filed for bankruptcy because of an inability to pay a multimillion-dollar judgment against it. When the county placed restrictions on the developer of a proposed residential treatment facility, the firm sued under the federal Fair Housing Act and won a $4 million judgment plus $1.4 million in attorneys' fees. Boise County has an annual operating budget of about $9.4 million.	No
Buena Vista, VA	Default, December 2010	Defaulted on a revenue bond issued to build a golf course that turned out to be unsuccessful.	No
Central Falls, RI	Bankruptcy, August 2011–September 2012	The city was placed into receivership in 2010 under a financial stability act passed by the state legislature. The receiver filed a Chapter 9 bankruptcy petition in 2011. Central Falls had about $21 million of outstanding general-obligation bonds at the time of its filing and faced a $4.8 million budget gap for fiscal year 2012. The city continued to service its bonds in bankruptcy but raised health insurance deductibles and copayments for city employees and retirees. By altering collective bargaining agreements, the city was able to emerge from bankruptcy within a year.	Yes
Detroit, MI	Bankruptcy and default, July 2013–December 2014	Long-term population decline, political corruption, and inflexible union contracts are cited as general causes for the city's secular fiscal decline. A financial review team identified insufficient cash, eight consecutive general fund deficits, long-term liabilities including pension and OPEB obligations, and bureaucratic inflexibility as causes for the state takeover. On June 13, 2013, Detroit missed a $39.7 million payment on pension bonds, and its emergency financial manager proposed to restructure the city's debt. On July 18, 2013, the city filed a Chapter 9 bankruptcy petition.	Yes
Dolton, IL	Default, December 2016	The village failed to make a full payment of the December 1, 2016, principal and interest due on five general obligation bonds.	Yes
Harrisburg, PA	Bankruptcy and default, October 2011–March 2012	A failed incinerator project generated roughly $300 million in city-guaranteed debt, while the city relied on sewerage charges to offset a persistent general fund deficit. The city filed a Chapter 9 petition in October 2011, but the filing was dismissed because it violated a state moratorium on certain municipal bankruptcies. The city has defaulted on three general obligation bond debt service payments since March 15, 2012.	Yes
Hillview, KY	Bankruptcy, August 2015–May 2016	Filed for bankruptcy after a truck driving school won a lawsuit against the city that was related to a 2002 land dispute.	No

Jefferson County, AL	Bankruptcy, November 2011–December 2013	Declared bankruptcy after a failed deal to restructure debt. The county has a history of frequent and costly bond issuance as well as a history of corruption and fraud charges.	Yes
Mammoth Lakes, CA	Bankruptcy, June 2012–November 2012	Filed for bankruptcy after it lost a lawsuit, exhausted its appeals, and failed to convince the plaintiff to reduce the amount of the judgment. The city did not default on any bond payments and quickly exited from bankruptcy.	No
Menasha, WI	Default, September 2009	Defaulted on bond anticipation notes that were issued by the steam plant (BTA); these notes were secured by the plant's revenues and backed up by the city's appropriation pledge.	No
Prichard, AL	Bankruptcy, October 2009–August 2010	In the wake of dwindling population, persistent deficits, and unfunded pension obligations, the city declared bankruptcy to reduce pension benefits.	Yes
San Bernardino, CA	Bankruptcy and default, July 2012–June 2017	Citing the exhaustion of the city's general fund and an estimated general fund deficit of $45.8 million, San Bernardino staff recommended that the city declare bankruptcy and adopt an emergency budget that deferred debt service payments, retiree health contributions, and other items. Staff argued that these steps were necessary to meet the city's payroll.	Yes
Scranton, PA	Default, June 2012	The Scranton Parking Authority went into default after the city council turned down a request to make a loan payment from a contingency account. The city had previously raised tax rates to secure the loan. Because the city backstopped the loan, the mayor decided to not jeopardize $16 million of borrowing that Scranton needed to plug a budget deficit. Also in 2012, the city temporarily cut employee salaries to $7.25 per hour—the federal minimum wage.	Yes
Stockton, CA	Bankruptcy and default, June 2012–February 2015	The city filed for bankruptcy after it was unable to secure concessions from creditors during a mediation process. The city stopped making debt service payments on 2004 lease revenue bonds that were secured by parking garage revenues, and it discontinued other postemployment benefits for retirees.	Yes
Vadnais Heights, MN	Default, February 2013	Defaulted on debt payment on $25 million of lease-backed revenue debt issued in 2010 to finance a sports complex for which the city later cut financial support.	No
Vallejo, CA	Bankruptcy and default, May 2008–August 2011	Vallejo's bankruptcy filing was blamed on a sudden decline in property values and unsustainable labor contracts. The city also defaulted on certificates of participation (COPs). These certificates, unlike general obligation or revenue debt, are not senior claims on a city's tax revenue. Instead, they represent the investor's share in lease revenues the city agrees to pay on certain facilities. As noted in the COPs offering materials, "the city could choose to fund other services before making lease payments," and holders have limited recourse in the event of a default or bankruptcy.	Yes
Volo, IL	Default, September 2010	The landowner within a development funded by special tax bonds failed to pay the maximum parcel special taxes securing the bonds. The capital assessment delinquencies exceeded the amount available to pay from the bond and interest fund debt service payment, and accordingly there were insufficient funds to pay the interest on the bonds.	No

Warrens, WI	Default, November 2010	The village's community development authority did not pay the interest on its taxable interim community development revenue bonds.	No
Yorkville, IL	Default, January 2015	The city defaulted on the interest and principal payment on the sales tax revenue bonds that had been issued in 2007 to fund a retail facility.	Yes

Note: This table was compiled by the authors from a variety of sources, including Bond Buyer (https://www.bondbuyer.com), the Municipal Securities Rulemaking Board's Electronic Municipal Market Access system (https://emma.msrb.org), media reports, and court rulings.

Table 2. Descriptive Statistics and Data Sources (Full Sample)

Variable	Description	Obs.		Entities		Frequency
Distress	Equal 1 if defaulted or declared bankruptcy; equal 0 otherwise	20,945		18		34
Distress, General Government	Equal 1 if defaulted or declared bankruptcy; equal 0 otherwise, excluding business-type activity defaults and lawsuit-related defaults	20,945		11		27
		Obs.	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Government-Wide—Cash and Operating Solvency						
GW Cash Ratio	Government-wide cash and near cash assets divided by government-wide current liabilities	16,601	2.87	3.75	0.06	199.86
GW Current Ratio	Government-wide current assets divided by government-wide current liabilities	16,729	5.20	9.27	0.10	49.37
GW Revenues / GW Expenditures	Government-wide total revenues divided by total expenditures, in percent	17,382	107.22	16.05	10.28	292.98
General Fund—Cash and Operating Solvency						
GF Total Balance / GF Expenditures	Total general fund balance divided by general fund expenditures, in percent	17,898	43.23	44.30	–155.19	944.12*
GF Unreserved Balance / GF Expenditures	General fund unreserved balance divided by general fund expenditures, in percent (after 2011, unrestricted is coded as equivalent to unreserved)	16,681	37.10	42.02	–155.19	944.12*
GF Revenues / GF Expenditures	General fund revenues divided by general fund expenditures, in percent	18,700	105.31	20.48	9.46	299.20

All Governmental Funds—Cash and Operating Solvency						
GO Total Balance / GO Expenditures	Total balance in governmental funds divided by expenditures, in percent	11,652	60.08	48.07	−205.45	774.35*
GO Unreserved Balance / GO Expenditures	Unreserved balance in governmental funds divided by expenditures in governmental funds, in percent (after 2011, unrestricted is coded as equivalent to unreserved)	11,501	30.16	34.41	−270.89	736.20*
GO Revenues / GO Expenditures	Governmental funds revenues divided by governmental funds expenditures, in percent	12,239	95.16	14.70	11.18	227.92
Government-Wide—Long-Term Solvency						
Pension Obligations / GW Revenues	Annual pension contributions divided by government-wide revenues, in percent	2,630	27.27	36.73	−70.90	378.29
OPEBs / GW Revenues	Other postemployment benefits divided by government-wide revenues	3,616	11.91	16.90	−5.09	144.23
Long-Term Debt / GW Revenues	Long-term debt divided by government-wide revenues, in percent	16,692	97.92	82.45	−317.08	1,426.03
Total Long-Term Liabilities / GW Revenues	Total long-term liabilities (including debt, pension obligations, OPEBs) divided by government-wide revenues, in percent	16,706	124.41	94.02	−299.85	1,588.04
GW Net Assets	Total government-wide assets minus total government-wide liabilities, the difference divided by government-wide expenditures, in percent	17,163	223.18	180.75	−358.68	1,458.68
GW Unrestricted Net Assets	Unrestricted net assets divided by government-wide expenditures, in percent	17,136	25.99	61.09	−623.99	531.77
General Fund—Ability to Pay the Current Portion of Long-term Obligations						
Interest on Debt / GF Revenues	Interest payments on debt divided by general fund revenues, in percent	15,368	5.37	6.02	−0.26	59.63
Pension Contributions / GF Revenues	Annual pension contributions divided by general fund revenues, in percent	12,180	8.53	7.09	0.00	89.83
Socioeconomic Indicators						
Unemployment	Unemployment rate	20,858	6.92	2.81	0.90	30.60
Home Price	Home price in dollars	20,037	188,310	145,325	33,991	2,524,875

Change in Home Price	Change in home price, in percent	19,735	0.23	7.05	–40.60	45.06
Population	Population, linearly interpolated between 2000 and 2010 censuses and between 2010 and 2016 (ACS), in 1000s	12,884	167.032	67.843	0.083	10,170,000
Median Household Income	Median household income, linearly interpolated between 2000 and 2010 censuses and between 2010 and 2016 (ACS), in dollars	12,884	51,307	16,764	17,044	147,349
Occupancy Rate	Housing occupancy rate, linearly interpolated between 2000 and 2010 censuses and between 2010 and 2016 (ACS), in percent	12,884	89.07	6.69	33.35	98.50

Sources: Bloomberg's Municipal Fundamentals Database; US Bureau of Labor Statistics (https://www.bls.gov); Zillow Research (https://www.zillow.com/research/).

Table 3. Correlation Matrix for Candidate Predictor Variables

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	GW Cash ratio	1.00																		
2	GW Current ratio	0.83	1.00																	
3	GW Rev/Exp	0.16	0.20	1.00																
4	GF Tot Bal/Exp	0.41	0.47	0.31	1.00															
5	GF Unreserved/Exp	0.45	0.49	0.30	0.90	1.00														
6	GF Rev/Exp	0.05	0.06	0.01	0.17	0.20	1.00													
7	GO Tot Bal/Exp	0.52	0.54	0.36	0.63	0.62	−0.02	1.00												
8	GO Unreserved/Exp	0.50	0.51	0.31	0.62	0.71	0.07	0.69	1.00											
9	GO Rev/Exp	0.24	0.21	0.20	0.16	0.16	0.29	0.18	0.20	1.00										
10	GW Pension Obl/Rev	0.01	0.00	−0.19	−0.06	−0.04	0.03	−0.01	−0.04	0.07	1.00									
11	GW OPEB/Rev	−0.21	−0.25	−0.31	−0.24	−0.24	−0.06	−0.27	−0.22	−0.01	0.14	1.00								
12	GW LongT Debt/Rev	−0.20	−0.25	−0.18	−0.13	−0.13	−0.05	0.04	−0.12	−0.22	0.52	0.25	1.00							
13	GW Tot Liab/Rev	−0.24	−0.30	−0.18	−0.14	−0.14	−0.06	0.03	−0.13	−0.23	0.49	0.26	0.99	1.00						
14	GW Net Assets/Exp	0.02	0.00	0.16	−0.01	−0.01	−0.01	0.13	0.06	0.00	−0.22	−0.12	−0.02	−0.02	1.00					
15	GW Unrestr Net Ass/Exp	0.13	0.14	0.16	0.16	0.16	0.04	0.14	0.17	0.06	−0.44	−0.12	−0.38	−0.38	0.48	1.00				
16	GF Interest Debt/Rev	−0.10	−0.11	0.02	0.02	0.00	−0.09	0.18	−0.08	−0.31	−0.02	−0.10	0.55	0.56	−0.01	−0.15	1.00			
17	GF Pension Contr/Rev	−0.09	−0.03	−0.06	−0.09	−0.06	−0.09	0.01	−0.07	−0.06	0.29	0.09	0.26	0.27	0.07	−0.10	0.11	1.00		
18	Unemployment rate	−0.20	−0.19	−0.17	−0.20	−0.26	−0.01	−0.19	−0.26	0.03	−0.10	0.02	0.00	0.01	−0.02	−0.05	0.04	0.09	1.00	
19	Home price	0.15	0.09	0.05	0.05	0.04	0.06	0.08	0.07	0.10	0.13	0.01	−0.02	−0.02	0.08	−0.04	−0.10	0.01	−0.31	1.00
20	Change in home price	0.10	0.11	0.09	0.13	0.15	0.02	0.17	0.12	0.04	0.21	0.00	0.08	0.07	0.07	−0.04	−0.02	0.11	−0.27	0.19

Note: The correlation matrix is based on the data for 1,331 observations with nonmissing values for each of the 20 candidate predictor variables.

Sources: Bloomberg’s Municipal Fundamentals Database; US Bureau of Labor Statistics (https://www.bls.gov); Zillow Research (https://www.zillow.com/research/); American Community Survey (https://www.census.gov/programs-surveys/acs/).

Table 4. T-tests for Differences in Sample Means, Unequal Variances Assumed, Satterthwaite's Degrees of Freedom

	Full Sample				Small Sample with Demographic Variables			
	Non-distressed	Distressed	t-statistic		Non-distressed	Distressed	t-statistic	
Cash Solvency								
GW Cash Ratio	3.156	1.429	5.476	***	2.995	1.344	6.997	***
	n=16,548	n=34			n=10,932	n=23		
GW Current Ratio	4.626	2.372	3.828	***	4.589	2.291	6.689	***
	n=16,539	n=34			n=10,957	n=23		
GO Total Balance / GO Expenditures, percent	60.121	38.583	1.896	**	58.834	34.001	2.604	**
	n=11,602	n=34			n=7,502	n=23		
GO Unreserved Balance / GO Expenditures, percent	30.248	–2.838	3.467	**	27.936	–2.553	5.364	***
	n=11,449	n=34			n=7,422	n=23		
GF Total Balance / GF Expenditures, percent	43.31	12.721	4.222	***	40.120	4.183	3.828	**
	n=17,830	n=34			n=11,843	n=23		
GF Unreserved Balance / GF Expenditures, percent	37.174	7.90	3.944	**	33.845	1.976	3.352	*
	n=16,628	n=34			n=11,014	n=23		
Operating Solvency								
GW Revenues / GW Expenditures, percent	107.227	102.026	1.93	***	106.779	103.796	0.949	***
	n=17,350	n=34			n=11,381	n=23		
GO Revenues / GO Expenditures, percent	95.094	100.73	–2.506		95.228	98.049	–1.289	
	n=12,205	n=34			n=7,772	n=23		
GF Revenues / GF Expenditures, percent	105.307	104.306	0.419		106.125	103.453	0.942	
	n=18,666	n=34			n=12,340	n=23		
Long-Term Solvency								
GW Total Liabilities / GW Revenues, percent	124.052	303.866	–3.588	**	118.335	233.681	–3.454	**
	n=16,672	n=34			n=11,018	n=23		
GW Total Long-Term Debt / GW Revenues, percent	97.734	190.693	–2.552	**	92.63	186.873	–3.102	**
	n=16,658	n=34			n=11,015	n=23		
GW Net Assets / GW Expenditures, percent	223.32	153.816	1.517		216.847	179.918	0.708	
	n=17,129	n=34			n=11,302	n=23		
GW Unrestricted Net Assets / GW Expenditures, percent	26.194	–78.723	4.987	***	22.516	–68.852	3.925	***

	n=17,103	n=33			n=11,289	n=22		
GW Pension Obligations / GW Revenues	27.187	68.728	−1.603	*	22.217	82.023	−1.20	
	n=2,625	n=5			n=1,469	n=2		
GW OPEBs / GW Revenues	11.942	18.559	−0.874		10.947	27.376	−2.028	*
	n=3,603	n=6			n=2,435	n=4		
GF Interest on Debt / GF Revenues	5.384	8.064	−1.407	*	5.384	6.825	−1.124	
	n=14,134	n=14			n=10,508	n=10		
GF Annual Pension Contributions / GF Revenues	8.521	6.001	1.969	*	8.844	9.562	−0.355	
	n=11,247	n=11			n=8,045	n=7		
Socioeconomic and Demographic Factors								
Unemployment Rate	6.91	10.10	−6.488	***	7.26	12.92	−8.975	***
	n=20,858	n=36			n=12,799	n=23		
Home Price	188,372	152,846	3.157	**	184,253	141,511	2.9321	**
	n=20,002	n=35			n=12,314	n=22		
Change in Home Price	0.233	0.095	0.066	*	−0.409	−0.657	0.079	**
	n=19,701	n=34			n=12,133	n=21		
Population					165,880	188,221	−0.406	
					n=12,841	n=23		
Median Household Income					51,298	40,712	4.156	***
					n=12,841	n=23		
Occupancy Rate					89.086	86.881	1.447	*
					n=12,841	n=23		

Note: * indicates $p < 0.10$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Source: Author calculations.

Table 5. Relogit Regression Parameter Estimates of the Log Odds of Fiscal Distress

	Full Sample				Smaller Sample with Demographic Controls			
Variables	Any distress	General government distress	Bankruptcy authorized—any distress	Bankruptcy only—general gov't. distress	Any distress	General government distress	Bankruptcy authorized—any distress	Bankruptcy only—general gov't. distress
Cash Solvency								
Current Ratio (GW)	–0.037	–0.113	–0.039	–0.133	–0.020	0.010	–0.001	0.065
	(0.123)	(0.212)	(0.127)	(0.221)	(0.164)	(0.101)	(0.152)	(0.121)
Unreserved Fund Balance (GF)	–0.017**	–0.018**	–0.016*	–0.020***	–0.012	–0.019**	–0.009	–0.015*
	(0.007)	(0.007)	(0.008)	(0.007)	(0.010)	(0.008)	(0.010)	(0.009)
Operating Solvency								
Revenues/Expenditures (GW)	0.024***	0.026***	0.026**	0.028***	0.032***	0.037***	0.032***	0.035***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)	(0.007)
Long-Term Solvency								
Unrestricted Net Assets (GW)	–0.007**	–0.009**	–0.008**	–0.007*	–0.009***	–0.008***	–0.010***	–0.009***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Total Long-term Liabilities (GW)	0.003*	0.002	0.002	0.003*	0.005*	0.006**	0.004	0.005**
	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)
Socioeconomic Variables								
Unemployment Rate (%)	0.295***	0.331***	0.281***	0.297***	0.364***	0.372***	0.341***	0.347***
	(0.051)	(0.056)	(0.054)	(0.059)	(0.064)	(0.068)	(0.067)	(0.067)
Change in Home Price (%)	0.059	0.077**	0.065	0.075	0.067	0.074	0.066	0.072
	(0.065)	(0.076)	(0.067)	(0.078)	(0.075)	(0.080)	(0.080)	(0.083)
Population (ln)					0.125	0.336	0.129	0.269
					(0.242)	(0.215)	(0.218)	(0.193)
Median Household Income (ln)					0.826	–0.449	0.445	–0.731
					(1.650)	(2.429)	(1.942)	(2.512)
Occupancy Rate (%)					0.068	6.683	0.715	7.172
					(6.581)	(6.592)	(7.329)	(6.747)
Constant	–11.16***	–11.58***	–11.30***	–11.46***	–23.88	–43.49*	–22.58	–41.39*
	(1.038)	(1.356)	(1.055)	(1.346)	(24.85)	(23.63)	(25.26)	(22.13)
Observations	14,568	14,568	10,513	10,513	9,672	9,672	7,006	7,006
Distressed Events	34	27	29	25	21	19	20	19

Notes: Estimates are corrected for selection on the dependent variable by weighting the sample by the true population proportion of distressed entities (0.00026 percent). Robust standard errors appear in parentheses, clustered at the government entity level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Source: Author calculations.

Table 6. Top 60 Municipality-Year Observations with the Highest Predicted Probabilities of Distress

City of Central Falls, RI: 2012, 2013	County of Jefferson, AL: 2009
City of Detroit, MI: 2008, 2009, 2010, 2011, 2012, 2013, 2014	City of Harrisburg, PA: 2010, 2011, 2012
City of Huntington Park, CA: 2011	County of County, TN: 2009
City of Stockton, CA: 2011, 2012	City of Philadelphia, PA: 2010, 2011
City of Webster, FL: 2011	City of Pontiac, MI: 2009, 2010, 2011, 2012
City of Muskegon, MI: 2010	City of Saginaw, MI: 2009, 2010
City of Norton Shores, MI: 2010	Village of Dolton, IL: 2014
City of Oglesby, IL: 2011, 2012, 2013,	Village of Elwood, IL: 2007, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016
City of Compton, CA: 2011, 2012, 2013, 2014	Village of Maywood, IL: 2009, 2010, 2011, 2012, 2013, 2014
County of Conecuh, AL: 2009, 2010	Village of Warrens, WI: 2009, 2010, 2011, 2012
County of Crook, OR: 2009	City of Yuma, AZ: 2010

Note: These observations are based on the relogit model for the full sample.

Table 7. Wilcoxon Rank-Sum Two-Sample Test for Equality of Distributions and a Nonparametric Test for the Difference in Medians

	Full Sample				Small Sample with Demographic Variables			
	Wilcoxon rank-sum z-score	Significance level	Median test Chi-square (continuity corrected)	Significance level	Wilcoxon rank-sum z-score	Significance level	Median test Chi-square (continuity corrected)	Significance level
Cash Solvency								
GW Cash Ratio	3.907	***	8.518	***	2.793	***	4.355	**
GW Current Ratio	4.497	***	12.995	***	3.655	***	8.539	***
GO Total Balance / GO Expenditures, percent	1.631		0.266		2.150	**	0.697	
GO Unreserved Balance / GO Expenditures, percent	5.311	***	13.005	***	6.086	***	14.126	***
GF Total Balance / GF Expenditures, percent	4.804	***	8.516	***	5.616	***	14.114	***
GF Unreserved Balance / GF Expenditures, percent	4.587	***	6.631	***	5.365	***	11.151	***

Operating Solvency								
GW Revenues / GW Expenditures, percent	2.308	**	2.387		1.186		0.697	
GO Revenues / GO Expenditures, percent	−2.533	***	2.391		−1.397		0.699	
GF Revenues / GF Expenditures, percent	0.375		0.265		0.708		0.174	
Long-Term Solvency								
GW Total Liabilities / GW Revenues, percent	−5.588	***	12.997	***	−4.377	***	−8.542	***
GW Total Long-Term Debt / GW Revenues, percent	−3.244	***	6.631	***	−3.462	***	−6.274	***
GW Net Assets / GW Expenditures, percent	1.905	*	0.029		0.608		0.175	
GW Unrestricted Net Assets / GW Expenditures, percent	6.568	***	20.524	***	5.421	***	16.438	***
GW Pension Obligations / GW Revenues	−3.342	***	3.287	*	−3.009	***	2.297	
GW OPEBs / GW Revenues	−1.505		1.572		−3.013	***	5.845	**
GF Interest on Debt / GF Revenues	−2.396	**	1.534		−1.624		0.697	
GF Annual Pension Contributions / GF Revenues	−2.290	**	1.889		−1.495		0.943	
Socioeconomic and Demographic Factors								
Unemployment Rate	−6.457	***	21.263	***	−6.888	***	21.815	***
Home Price	0.571		0.000		1.148		0.046	
Change in Home Price	0.003		0.029		0.333		0.000	
Population					−1.601		1.568	
Median Household Income					3.105	***	4.356	**
Occupancy Rate					1.833	*	0.174	

Note: Wilcoxon H0: the nondistressed and distressed populations are equally distributed. Median test H0: the nondistressed and distressed population medians are equal.

Source: Author calculations.

Table 8. Logit Regression Parameter Estimates of the Log Odds of Fiscal Distress

	Full Sample				Smaller Sample with Demographic Controls			
Variables	**Any distress**	**General government distress**	**Bankruptcy authorized—any distress**	**Bankruptcy only—general gov't. distress**	**Any distress**	**General government distress**	**Bankruptcy authorized—any distress**	**Bankruptcy only—general gov't. distress**
Cash Solvency								
Current Ratio (GW)	–0.073	–0.234	–0.073	–0.245	–0.331	–0.116	–0.311	–0.184
	(0.141)	(0.299)	(0.144)	(0.293)	(0.346)	(0.292)	(0.326)	(0.343)
Unreserved Fund Balance (GF)	–0.013	–0.025	–0.011	–0.027*	–0.023	–0.080**	–0.024	–0.080*
	(0.014)	(0.017)	(0.016)	(0.016)	(0.034)	(0.038)	(0.039)	(0.047)
Operating Solvency								
Revenues / Expenditures (GW)	0.024***	0.032***	0.027***	0.034***	0.039***	0.061***	0.042**	0.065**
	(0.009)	(0.010)	(0.009)	(0.009)	(0.012)	(0.022)	(0.017)	(0.031)
Long-Term Solvency								
Unrestricted Net Assets (GW)	–0.007*	–0.008*	–0.008**	–0.007*	–0.005	0.002	–0.004	0.004
	(0.004)	(0.005)	(0.004)	(0.004)	(0.007)	(0.008)	(0.010)	(0.010)
Total Long-Term Liabilities (GW)	0.006***	0.006*	0.005*	0.007**	0.007*	0.009*	0.007	0.010
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.005)	(0.006)
Socioeconomic Variables								
Unemployment Rate (%)	0.236***	0.232***	0.216***	0.209***	0.249**	0.143	0.215*	0.124
	(0.057)	(0.082)	(0.069)	(0.077)	(0.103)	(0.106)	(0.122)	(0.120)
Change in Home Price (%)	0.034	0.042	0.037	0.040	0.030	0.0362	0.027	0.035
	(0.057)	(0.067)	(0.060)	(0.066)	(0.060)	(0.057)	(0.060)	(0.057)
Population (ln)					–0.049	0.715	0.012	0.582
					(0.385)	(0.544)	(0.366)	(0.557)
Median Household Income (ln)					–1.125	–4.684*	–1.589	–4.959
					(1.602)	(2.706)	(2.146)	(3.102)
Occupancy Rate (%)					–4.995	1.103	–7.036	2.147
					(4.177)	(13.69)	(5.057)	(15.61)
Constant	–14.89***	–16.34***	–14.79***	–15.80***	17.36	15.45	30.70*	15.02
	(1.636)	(2.224)	(1.695)	(2.168)	(17.24)	(48.71)	(16.27)	(55.25)
Standard Errors	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust
Observations	14,568	14,568	10,513	10,513	9,672	9,672	7,006	7,006
Distressed Events	34	27	29	25	21	19	20	19
Wald X Squared	71.31	61.71	39.36	61.23	419.52	681.55	448.17	468.27
–2 Log Likelihood	–143.14	–95.73	–123.97	–91.66	–81.89	–63.68	–72.69	–62.08

Note: Robust standard errors appear in parentheses, clustered at the government entity level. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Author calculations.

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