Predicting Significant Operating Deficits in Municipalities Using Economic Indicators

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This study investigates economic activity associated with the operating results of municipalities surrounding and including the great recession of 2007-2009. The model hypothesizes that poor operating performance, as measured by a significant operating deficit, is related to four primary drivers of a local economy--employment, investment, industrial output and wealth. The findings indicate that municipalities with significant operating deficits have (statistically speaking) significantly lower job growth (employment) and GDP growth (industrial output) and marginally fewer housing permits issued (investment). The ensuing model was able to correctly predict up to 84% of the municipalities as either having significant budget deficits or not.

Keywords: operating performance, municipalities, economic indicators, adversity index

INTRODUCTION

Municipal governments provide invaluable services to the citizenry, which include fire, police, water, sewer, parks, and recreation. These municipalities also provide a wide array of public and social services, and contribute to the quality of community life. The citizenry count on municipalities to respond in times of trouble and to help maintain the quality of life; however, municipalities can do this only if they avoid poor operating performance, such as significant operating deficits (also called "budget deficits"). Thus, a municipality's ability to avoid poor operating performance directly affects its ability to sustain its current level of services. Also, the operating performance of a municipality is closely tied to the local economy. This study investigates economic activity associated with the operating performance of municipalities surrounding and including the great recession of 2007-2009. The model hypothesizes that the operating performance of a municipality is related to four primary drivers of a local economy--employment, investment, industrial output and wealth.

A municipality can continue to provide important public services only if it can avoid, poor operating performance, defined in this study as a significant operating deficit. The purpose of this study is to develop a model based on four primary factors of the local economy that can be used to predict significant operating deficits in municipalities. The model will develop and compare the economic profiles of US municipalities that have operating deficits versus those that do not. This study is important because fiscal distress is on the rise since the great recession. For example, the city administrators of Harrisburg, the capital of Pennsylvania, declared bankruptcy following the great recession.

Poor operating performance, such as significant operating deficits, occurs when there is an imbalance between the needs and resources of the people and the resources of the municipality. Such problems are an intergovernmental problem. It can make state governments unstable, threaten the bond-ratings of state and local governments, and put pressure on state governments to intervene in delivering services when municipalities can no longer do so (Honadle 2003). These problems can also impair the willingness of businesses to move into local areas, since business decisions are often based on local taxes, services, infrastructure, and fees (Honadle 2003).

I examine the operating performance of a municipality as it is related to the local economy. This issue is of broad interest, as both scholars and professionals are interested in the topic of municipal operating performance. This study conveys important implications for future research and practice related to municipalities. The resultant model is used to develop early warning systems of significant operating deficits.

The model uses proxy measures for four primary drivers of a local economy, as utilized by Moody's Analytics—employment, investment, industrial output and wealth. Using logistical regression, these drivers are used to predict significant operating deficits. I find municipalities with significant operating deficits have (statistically speaking) significantly lower job growth (the proxy for employment) and GDP growth (industrial output), with marginally fewer housing permits (investment). However, changes in housing prices (wealth) were not statistically significant in the model. The model correctly predicts up to 84% of the municipalities as either having significant operating deficits or not. Municipalities looking to improve their operating results should first look to increase job growth, as the results indicate that such growth has the biggest impact. This model may be used by state and local government administrators in mitigating significant operating deficits, bond investors in evaluating default risk, auditors in analyzing going-concern, and others.

The remainder of the paper is organized as follows: The next section gives a background by describing the extant literature on operating results in municipalities. The section after next discusses the economic factors associated with operating results. The empirical testing the operating results model are analyzed in the next to last section, and the last section concludes the paper.

BACKGROUND ON MUNICIPAL OPERATING PERFORMANCE

Shortly after the spate of municipal emergencies in the late 1970s and early 1980s, academic and other researchers began to study the causes and measures of poor financial performance, in particular, and fiscal assessment, in general. In November 1985, the U.S. Advisory Commission on Intergovernmental Relations (ACIR) issued a widely-recognized report on fiscal health (ACIR 1985b). In this report, the ACIR purports that poor fiscal health is caused by cyclical or structural forces. Cyclical forces are short-term conditions that usually correspond to business cycles. Structural forces are long-term changes in the economy that are beyond the control of the state or local government. The ACIR (1985b) added that poor fiscal health is often the result of a complex array of economic conditions (such as unemployment rates), socioeconomic conditions (such as poverty levels), physical conditions (such as the condition of infrastructure assets), and financial factors (such as dependence on intergovernmental revenue). The primary focus of the present study is on the economic conditions associated with operating results.

Previous research addresses the issue of measuring and assessing fiscal health, which is a broader concept than just operating performance. Groves et al. (1981) use a set of financial indicators to assess the fiscal health of 24 cities. Their indicators include environmental factors such as changes in population growth, personal income levels, property values, unemployment rates, and business activity, as well as regional inflation rates. They also consider intergovernmental constraints (e.g., the extent of grants-in-aid, tax restrictions, and federal/state mandates), legislative policies and managerial practices. They develop a theoretical model, which captures all these external factors with several basic financial indicators, and they develop financial ratios for each factor. In the end, the model includes six broad categories--revenues, expenditures, earnings, debt structure, unfunded liabilities, and condition of capital plant –and approximately 30 related financial ratios. This model, developed by Groves and Valente (1994) and published by the International City/County Management Association, is a widely accepted financial monitoring tool for municipalities. The model was not tested on a large sample of municipalities.

There are other financial assessment tools, such as Brown's 10-point test to conduct a trend analysis (1993), Ammons' (1995) attempt to establish municipal benchmarks, and Kleine et al.'s (2003) 10-point scale for Michigan. There have been several other studies of fiscal health in municipalities (e.g., Brown 1996; Campbell 1990; Honadle 1998; Stevens and LaPlante 1987; Weinberg 1984).

The great recession of 2007-2009 caused a major shift in the analysis of fiscal health of municipalities. Wallace et al. (2018), for example, discuss how the recession impacted the structure, function and regulation of the municipal bond market. Following the crisis of those years, many changes were made to primary market issuance and secondary market trading practices and to bond ownership composition, bond structures, products, processes, and market participants. Murphy et al. (2018) summarize how such changes impact the future default risk of municipal bonds. These studies imply the need for predictive models of fiscal health, such as the presence of significant operating deficits.

Most of the research prior to 2009 was descriptive and not predictive in nature. The main focus was to describe the nature of fiscal issues in municipalities, not to predict the fiscal problems. Following the great recession of 2007-2009, the need arose for the models to be more predictive in nature, allowing for an early warning system for analysts. Trussel and Patrick (2009) changed the tenor of the studies to focus on the predictive ability models of fiscal issues. They use financial factors, including revenue concentration, debt usage, administrative expenditures and entity resources, to develop a model to predict fiscal health in Pennsylvania. These authors subsequently made modifications to their initial study, including expanding to municipalities in all states (Trussel and Patrick, 2012), testing special district governments (Trussel and Patrick, 2013), using only county governments (Patrick and Trussel, 2013), applying alternative statistical methods (Trussel and Patrick, 2013) and addressing socio-demographic data (Trussel and Patrick, 2014). This paper expands upon these studies by focusing on economic factors and their relationship to the significant operating deficits.

MODEL DEVELOPMENT

Moody's Analytics, a subsidiary of the Moody's Corporation that offers research for credit, economic and financial risk management, gauges the economic health of metropolitan areas in the US on a monthly basis (Dedman, 2009). The company's analysis is based on four measures of economic activity--changes in employment, housing starts, industrial production and housing prices. Moody's uses a complex method of weighting each component to come up with an overall financial rating, called the "Adversity Index." The ratings are in one of four discrete categories, either in recession, at risk of recession, recovering from recession, or expanding. The company does not have a specific method of testing the appropriateness of the classifications. That is, they have no external validation of their defined status. Dedman (2009) notes, "Components that commonly show sporadic movement are weighted less, while smoother measures are given a higher weight. The weighting is different for each metro area." The index is developed using weights developed from the economic data itself with no independent method of defining the actual fiscal status of the underlying governmental entity.

I adopt Moody's method of using these four economic factors to develop a model predicting significant operating deficits by using a statistically valid method of weighing the four factors, while testing the reliability of the resultant classifications. I use an external (independent of the four factors) definition of municipal operating performance, namely, significant operating deficits to develop the weights on the four variables and to validate the model. As with the Moody's index, I focus on metropolitan statistical areas (MSA).

Significant Operating Deficits

The purpose of this paper is to develop a model to predict significant operating deficits of municipalities using lagged economic factors as inputs. In order to achieve this goal, a definition of the operating performance of a municipality is needed. Measuring operating performance, including analyzing fiscal health in general, has been addressed in the literature using several different methods.

The Government Accountability Office (GAO) defines a poorly performing municipality as one "in which residents bear substantially higher tax burdens in order to obtain levels of public services comparable to better-off communities" (GAO 1990). DeSanto et al. (1991) define poor fiscal performance as "a persistent shortfall in cash flows…resulting from an imbalance between revenues and expenditures for given service levels" (p. 7). Kloha et al. (2005a) define poor operating performance as "a failure to meet standards in the areas of operating position, debt, and community needs and resources over successive years" (p. 314). A variety of methods have been utilized in attempt to operationalize these constructs. Raman (1982) identifies poor performing entities using bond ratings from Moody's. Trussel and Patrick (2012, 2013a, 2013b, 2014) using either a decline in spending on public services or an operating deficit to operationalize the operating performance of a municipality. Their conceptual definition is that a municipality is performing poorly if there is an imbalance between revenues and expenditures. This imbalance is best captured by the operating margin, revenues less expenditures scaled by revenues. If revenues exceed expenditures, then the municipality has an "operating surplus." When expenditures exceed revenues, an "operating deficit" occurs.

Following Trussel and Patrick (2009, 2012, 2013a) and Patrick and Trussel (2011), I define a poorly performing municipality as one that experiences a significant imbalance between revenues and expenditures. I operationalize this imbalance as a significant operating deficit. I use data from the US Census Bureau to measure a significant operating deficit for the principal municipality in the MSA. An MSA typically consists of a principal city (the largest in the area) and several smaller ones. Since the fiscal health of the smaller cities is tied to the largest city, I use the principal city in the MSA to measure the operating surplus or deficit. The annual operating margin, revenues less expenditures scaled by revenues, is used by many researchers to reflect the overall operating performance of a municipality (e.g., Trussel and Patrick, 2009). Researchers argue that a deficit must be significant for a municipality to be considered as fiscally imbalanced. Following the recommendations of Pennsylvania's Department of Economic Development (DCED, 2001), I classify a municipality as poorly performing if the annual operating deficit is significant, greater than five percent of revenues. In other words, if the municipality has an operating margin of less than negative five percent, then it is considered to be performing poorly. I provide robustness tests of other definitions of fiscal performance later.

Economic Factors

Following Moody's Analytics, I identify proxy measures of the four primary drivers of a local economy—employment, investment, industrial output and wealth. The data sources are explained below and summarized in Table 1.

Employment

I use employment data from US Bureau of Labor Statistics to measure the annual percentage change in the total number of jobs (JOBS) in a Metropolitan Statistical Area (MSA). I hypothesize that the percentage change in the number of jobs is directly related to the operating performance of the MSA, meaning that if employment increases, then the likelihood of significant operating deficits should decrease.

Investment

As a proxy for investment, I use housing construction permit data from the US Census Bureau to measure the percentage change in the annual number of new privately owned housing units (PERMITS) authorized in an MSA. I hypothesize that the percentage change in the number of permits is directly related to the operating performance of the MSA, meaning that if housing permits increase, then the likelihood of significant operating deficits should decrease.

Industrial Output

I use data from the US Bureau of Economic Analysis to measure the percentage change in gross domestic product (GDP) in an MSA. I hypothesize that the percentage change in GDP is directly related to the operating performance of the MSA, meaning that if GDP increases, then the likelihood of significant operating deficits should decrease.

Wealth

As a proxy for wealth, I use data from the Federal Housing Finance Agency to measure the year end housing price index (PRICES) for an MSA. This index is a measure of housing prices indexed to a base year. I hypothesis that the housing price index is directly related to the operating performance of the MSA, meaning that if housing prices increase, then the likelihood of significant operating deficits should decrease.

TABLE 1
ECONOMIC FACTORS ASSOCIATED WITH OPERATING PERFORMANCE

Economic Factor	**Measurement**	**Source**
Employment (JOBS)	Annual percentage change in number of jobs	US Bureau of Labor Statistics
Investment (PERMITS)	Annual percentage change in number of permits for new privately owned housing units	US Census Bureau
Industrial Output (GDP)	Annual percentage change in GDP	US Bureau of Economic Analysis
Wealth (PRICES)	Annual index for housing prices	Federal Housing Finance Agency

EMPIRICAL TESTING

Sample

Financial data are used for the years 2005-2012, which are the years surrounding and including the great recession of 2007-2009. This allows me to test the model during years of expansion, recession and recovery. Due to the nature of the economic data, I focus my attention on the 384 to 397 Metropolitan Statistical Areas (MSA), which account for nearly 85% of the US population (Dedman, 2009). An MSA contains a core urban area with a population of at least 50,000. The data comes from different data sources as discussed in the previous section and summarized in Table 1. Combining the eight years, 2005-2012, to develop panel data gives a possible 3,176 MSA-years. Some data are missing to arrive at a final sample of 2,718 MSA-years, or 85.6% of all the possible available. Panel A of Table 2 summarizes the sampling procedures.

The breakdown of the final sample by operating performance and year is included in Panel B of Table 2. Nearly 34% of the cities in the final sample have significant operating deficits. Except for a slight decline in 2007, there is a gradual increase in the percentage of municipalities with significant operating deficits that climaxes in 2010 and begins to drop in 2011. Given that the economic recession began in 2007 and ended in 2009, there seems to be about a one year lag in the financial impact. Thus, the economic indicators were measured one year in advance. For example, if operating performance was measured in 2006 on Panel A of Table 2, then the economic indicators were measured in 2005. This will also allow for me to use the economic data for predictive purposes.

TABLE 2
SAMPLE SELECTION PROCEDURES

Panel A: Overall Sample

	Municipal Statistical Areas (MSA)	
	Number	Percent
Total MSA-years	3,176	100.0
Missing Data	(458)	(14.4)
Final Sample	2,718	85.6

Panel B: Sample Partitioned by Operating Performance and Year

Year	No Significant Deficits*	Significant Deficits*	Total	Percent with Significant Deficits
2005	224	96	320	30.0%
2006	200	114	314	36.3%
2007	257	107	364	29.4%
2008	225	105	330	31.8%
2009	213	129	342	37.7%
2010	186	156	342	45.6%
2011	231	111	342	32.5%
2012	262	102	364	28.0%
Total	1,798	920	2,718	33.8%

*A significant operating deficit is defined as an operating margin less than negative five-percent. Operating margins are revenues less expenditures scaled by revenues.

Descriptive Statistics

The descriptive statistics are included in Panel A of Table 3, including information about the population of the principal cities in the MSAs. MSAs are by definition large metropolitan areas with a core municipality of at least 50,000 people. As noted, the economic data are from MSAs, while the financial data are from the principal city within the MSA. The sample results indicate that cities with significant operating deficits (mean population of 187,172) have larger populations than do cities without significant budget deficits (146,520). This finding is consistent with other studies (e.g., Trussel and Patrick, 2013) that find that the size of a city is positively correlated with fiscal problems. As predicted, cities without significant operating deficits have higher job growth, issue more housing permits and report higher GDP growth. However, there is no significant difference in the housing price indices between the two groups.

Panel B of Table 3 includes the Pearson correlation coefficients among the economic factors. The largest coefficient was 0.666 between JOBS and GDP. This does not appear to cause any problems with the regression results.

TABLE 3
DESCRIPTIVE STATISTICS

Panel A: t-Tests

Variable*	Significant Deficit?**	Mean	Std. Dev.	*t*-statistic	*p*-value
JOBS	No	0.008	0.024	4.652	<0.001
	Yes	0.004	0.025		
PERMITS	No	(0.058)	0.358	3.201	0.001
	Yes	(0.106)	0.388		
GDP	No	0.041	0.050	4.558	<0.001
	Yes	0.032	0.048		
PRICES	No	177.237	34.464	0.563	0.574
	Yes	176.253	35.166		
POPULATION	No	146,520	207,719	(4.261)	<0.001
	Yes	187,172	259,955		

Panel B: Pearson Correlation Coefficients

	JOBS	PERMITS	GDP
PERMITS	0.222***		
GDP	0.666***	0.240***	
PRICES	0.200***	-0.091***	0.097***

*Variables are defined in Table 1.
** A significant operating deficit is defined as an operating margin less than negative five-percent. Operating margins are revenues less expenditures scaled by revenues.
***Pearson correlation coefficient is significant at the 0.01 level (two-tailed).

Logistic Regression Results

I use cross-sectional time-series (panel data) analysis to test the model of operating performance. Since the dependent variable is categorical, the significance of the multivariate model is addressed using logistic regression analysis and adjusted for autocorrelation. Using this method, the underlying latent dependent variable is the probability of significant operating deficits for municipality *i*, which is related to the observed variable, $Status_i$, through the relation:

$Status_i = 0$ if the organization does not have significant operating deficits, or
$Status_i = 1$ if the organization has significant operating deficits.

The model includes all of the independent variables from Table 1, and each is lagged by one year for predictive purposes. Recall that municipalities are classified as poorly performing if the operating deficit is greater than five-percent of annual revenues. The predicted probability of the k^{th} status for municipality *i*, $P(Status_{ik})$ is calculated as:

$$P(Status_{ik}) = \frac{1}{1+e^{-Z}} \tag{1}$$

where

$$Z_i = \alpha + \beta_1 \overline{JOBS}_{t-1} + \beta_2 \overline{PERMITS}_{t-1} + \beta_3 \overline{GDP}_{t-1} + \beta_4 \overline{PRICES}_{t-1}$$

I use data from 2005-2011 to develop the model (the estimation sample) and data from 2012 to test the model (the holdout sample). The results of the logistic regression model (adjusted for autocorrelation) are included in Table 4. JOBS and GDP are significantly related to the probability of significant operating deficits (at the 0.05 level) with the predicted negative signs. PERMITS is marginally significant at the 0.10 level with the predicted negative sign. The other economic factor, PRICES, is not statistically significant in the multivariate model, although it does have the predicted negative sign.

TABLE 4
REGRESSION RESULTS

Variable	Coefficient	Std. Error	Wald	*p*-value	*Exp(B)*	Impact
Intercept	-0.481	0.3209	2.249	0.134		
JOBS	-5.563	2.3174	5.763	0.016	0.004	-0.054
PERMITS	-0.250	0.1517	2.709	0.100	0.779	-0.002
GDP	-2.446	1.0817	5.111	0.024	0.087	-0.024
PRICES	-0.001	0.0018	0.020	0.888	1.000	<0.001

Note: See Table 2 for a description of the independent variables. The latent dependent variable equals 0 if the municipality did not have a significant operating deficit, and 1 if it did. The last column represents the impact on the predicted likelihood of a significant operating deficit due to a 0.01 increase in the value of the covariate, except for PRICES, which represents the impact due to a one-unit increase in the value.

The results of the regression analysis also allow one to address the impact of a change in an economic factor on the likelihood of significant operating deficits. In Table 4, *Exp(B)* is the odds ratio, which is the change in the odds of the event (significant operating deficits) occurring for a one-unit change in the economic factor. A one-unit change in the price index is reasonable, but a one unit change in the other factors is not possible, since they are percentage changes. Thus, the last column in Table 4 represents the impact on the predicted likelihood of significant operating deficits due to a 0.01 increase in the value of JOBS, PERMITS and GDP, and a one-unit change in PRICES. The impact is computed as $Exp(b)^{0.01} - 1$, except for PRICES, which is just $Exp(b)$-1. JOBS and GDP have the biggest influences on the likelihood of significant operating deficits. A one-percent increase in the number of jobs will decrease the predicted likelihood of significant operating deficits by 0.05, while a one-percent increase in the GDP will decrease the likelihood by 0.024. Based on the economic factors in this model, cities attempting to reduce the likelihood of significant operating deficits will have the biggest impact by increasing the number of jobs or by increasing industrial output (GDP). Changes in the housing permits has a relatively small impact, and changes in housing prices has a negligible impact.

Predicting Significant Operating Deficits

I use the results of the logistic regression analysis to test the predictive ability of the model. The observed logistic regression equation (from Table 4) for entity i at time t is:

$$P(i,t) = 1/(1+e^{-Z_i})$$

where:

$$Z_i = -0.481 - 5.563\ JOBS_{t-1} - 0.250\ PERMITS_{t-1} - 2.446\ GDP_{t-1} - 0.001\ PRICES_{t-1}$$

The predicted dependent variable, $P(i,t)$ the probability of significant operating deficits for municipality i, is computed using the actual economic indicators for each municipality in the estimation sample. The resulting probabilities are used to classify municipalities as experiencing a significant operating deficit or not. Jones (1987) suggests adjusting the cutoff probability for classifying in two ways. Following the suggestion of Jones, I first incorporate the prior probability of a significant operating deficit and then include the expected cost of misclassification.

Using logit, the proportion of distressed municipalities in the sample must be the same as the proportion in the population to account for the prior probability of significant operating deficits. If the proportion is not the same, then the constant must be adjusted (Maddala 1991). This is more of a problem when a paired sample method is used, which is not the case here. Since I do not know the proportion of municipalities that had a significant operating deficit in the population of all municipalities, I assume that the proportion of municipalities in the sample is an unbiased estimator of the proportion in the population of all municipalities. Since 33.8% of the municipalities in the sample had significant operating deficit, I assume that the prior probability of significant operating deficits is 0.338.

The ratios of the cost of type I errors (incorrectly classifying municipalities with significant operating deficits as not having them–a false negative) to type II errors (incorrectly classifying municipalities that do not have significant operating deficits as have them–a false positive) also must be determined. The particular cost function is difficult to ascertain and will depend on the user of the information. For example, municipal bond investors may want to minimize losses (and thus type I errors); however, they will suffer an opportunity cost (type II error) if another bond is purchased offering a lower rate. In most cases, the cost of a type II error is likely to be much smaller than a type I error. Thus, I incorporate multiple relative cost ratios (and cutoff probabilities) into my analysis. Specifically, I include the relative costs of type I to type II errors of 1:1, 10:1, and 20:1 (Beneish 1999; Trussel 2002). Ratios beyond 20:1 were also considered, but there is no change in the classification accuracy of the model at cost ratios greater than 10:1.

The results of using the logit model to classify municipalities as either having significant operating deficits or not are included in Table 5 for both the estimation and the holdout samples. The cutoff probabilities presented are those that minimize the expected costs of misclassification. Following Beneish (1999), the expected costs of misclassification (ECM) are computed as:

$$ECM = P(FD)P_I C_I + [1 - P(FD)]P_{II} C_{II},$$

where P(FD) is the prior probability of having a significant operating deficit, P_I and P_{II} are the conditional probabilities of type I and type II errors, respectively, and C_I and C_{II} are the costs of type I and type II errors, respectively.

TABLE 5
THE PREDICTIVE ABILITY OF THE OPERATING PERFORMANCE MODEL INCLUDING THE EXPECTED COSTS OF MISCLASSIFICATION AND THE RELATIVE COSTS OF TYPE I ERROR TO TYPE II ERROR

	Ratio of the Cost of Type I to Type II Errors					
	Estimation Sample			Holdout Sample		
	1:1	10:1	20:1	1:1	10:1	20:1
Cutoff	0.360	0.100	0.100	0.360	0.100	0.100
Type I Error	0.463	0.000	0.000	0.969	0.000	0.000
Type II Error	0.000	0.524	0.524	0.041	1.000	1.000
Overall Error	0.161	0.342	0.342	0.305	0.716	0.716
ECM Model	0.157	0.347	0.347	0.355	0.662	0.662
ECM Naïve	0.338	0.662	0.662	0.338	0.662	0.662
Relative Costs	0.463	0.524	0.524	1.050	1.000	1.000
Overall Correct	0.839	0.658	0.658	0.695	0.284	0.284

Note: The cutoff is the probability of a significant operating deficit that minimizes the expected cost of misclassification, ECM. ECM is computed as $ECM = P(FD)P_I C_I + [1 - P(FD)]P_{II} C_{II}$, where P(FD) is the prior probability of a significant operating deficit (0.338), P_I and P_{II} are the conditional probabilities of Type I and Type II errors, respectively. C_I and C_{II} are the costs of type I and type II errors, respectively. The relative costs are the ECM Model divided by the ECM Naïve.

The validity of the model is tested on the holdout sample (2012 holdout data) using the same cutoff probabilities from the estimation sample. The results, displayed in Table 5, indicate that the model can identify cities with significant operating deficits with 66% (at a cost ratio greater than 1:1) to 84% (at a cost ratio of 1:1) of the entities in the estimation sample correctly classified. In the holdout sample, 29% to 70% of the entities are correctly classified.

To test the usefulness of the model, I compare these results to a naïve strategy. This strategy classifies all municipalities as having a significant operating deficit (or not) when the ratio of relative costs is greater than (or less than or equal to) the prior probability of having a significant operating deficit (0.338). This switch in strategy between classifying all organizations as not having a significant operating deficit to classifying all of them as having one occurs at relative cost ratios of just below 3:1 (i.e., 1 / 0.338).

If all municipalities are classified as having a significant operating deficit (not having one), then the naïve strategy makes no type I (type II) errors. In this case, P_I (P_{II}) is zero, and P_{II} (P_I) is one. The expected cost of misclassification for the naïve strategy of classifying all municipalities as not having one (having one) reduces to $0.662C_{II}$ ($0.338C_I$).

In both panels of Table 5, I also report the relative costs, which is the ratio of the ECM for my model to the ECM for the naïve strategy. Relative costs below 1.0 indicate a cost-effective model. For the estimation sample, my model consistently has a much lower ECM than the naïve strategy. In fact, the relative costs are below 53% for all levels of type I to type II errors. These results provide evidence to suggest that the classification model is extremely cost-effective in relation to a naïve strategy for all ranges of the costs of type I and type II errors. However, the results are not as good for the holdout sample with the model about the same as the naïve model.

Applying the Prediction Model

I use one of the municipalities from the sample to illustrate the model. The model allows one to predict the status of the municipality as having a significant operating deficit or not. From the results of the logistic regression, the probability of a significant operating deficit for municipality *i* at time *t*, *P(i,t)* is:

$$P(i,t) = \frac{1}{1+e^{-zi}} \tag{2}$$

where

$$Z_i = -0.481 - 5.563\ JOBS_{t-1} - 0.250\ PERMITS_{t-1} - 2.446\ GDP_{t-1} - 0.001\ PRICES_{t-1}$$

Substituting the actual variables from the example entity (in parentheses), I obtain:

$$Z_i = -0.481 - 5.563\ (-0.031) - 0.250\ (0.493) - 2.446\ (-0.018) - 0.001\ (137.16)$$
$$Z_i = -0.422$$
$$P = 1 / (1+e^{0.422})$$
$$P = 0.396.$$

Table 5, Panel A, shows that the selected municipality is predicted to have a significant operating deficit, since the actual probability (0.396) is greater than the cutoff at all levels of the ratio of type I to type II errors. The entity actually experienced a significant operating deficit. Thus, the model correctly predicted the operating performance of this municipality.

Robustness Tests

I made several assumptions when developing and testing my model and test these assumptions for robustness. For example, I defined a municipality as having a significant operating deficit if the organization has operating deficits greater than five-percent of annual revenues. I also test my model by using any decline in the operating margin (i.e., more than zero percent) and declines of more than 10% and 20% in the operating deficit. For these versions of the model, the tenor of my results does not change.

I also assumed the prior probability of a significant operating deficit in developing my prediction model. I assumed that the prior probability was 0.338 because 33.8% of the municipalities in the initial sample had a significant operating deficit. I evaluated the sensitivity of the model to other assumptions of the prior probability by using prior probabilities of 0.10, 0.20 and 0.50. These assumptions do not alter the results significantly.

CONCLUSION

Municipalities provide important public services. They provide the first level of response when it comes to public services such as safety, water, sewer, streets, parks, and recreation. Municipalities also play a large role in the quality of community life by providing a wide variety of public and social services; however, they can sustain these services only if they avoid significant operating deficits. Significant operating deficits threaten the ability of municipalities to continue to serve the citizenry and maintain essential public functions. Economic factors, such as job growth and GDP impact a municipality's operating performance. This study explicitly links four primary economic factors related to a municipality's job growth, investment, industrial output and wealth to its operating performance.

Using logistical regression, I find that municipalities with operating deficits exceeding five-percent of annual revenues, have (statistically speaking) significantly lower job growth and GDP and marginally fewer new housing permits. However, housing prices were not statistically significant in the model. I was able to correctly predict up to 84% of the municipalities as either having a significant operating deficit or not. Municipalities looking to improve their operating performance should first look to improve its job growth.

These results should interest state and municipal administrators in mitigating poor operating performance, bond investors in evaluating default risk, auditors in analyzing going-concern, and others. Further research is needed to apply this model to smaller municipalities across the US and other countries and to different time periods.

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