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Modeling the Louisiana Local Government Fiscal Module in a Disequilibrium Environment: A Modified COMPAS Model Approach

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Abstract. The objective of this study is to assess and measure the relative forecasting performance of local government expenditures in Community Policy Analysis Models (COMPAS) during periods of supply/demand disequilibrium. We evaluate whether a fiscal module under the COMPAS framework (an equilibrium model) fits better under a disequilibrium economic environment. We find that both a simple naïve model with one year lagged expenditure and a lagged expenditure model with revenue capacity variables significantly increased forecasting performance relative to the traditional supply/demand equilibrium model of the public sector. We also found weak evidence suggesting that in cases where the equilibrium model is used in a cross-sectional setting, quantile regression may improve forecasting performance given the heterogeneity in the quantity and quality of preferences in public services.

1. Introduction

Most of the public service expenditure models under the community policy analysis system (COMPAS) are structured under an equilibrium condition assumption, i.e., supply equals demand (Johnson, Otto, and Deller, 2006). Based on Inman (1978), the expenditure equations tend to describe the equilibrium of public expenditure demand and supply. First, the demand side is explained, determining how revenue is raised to pay for goods and services and/or how the goods and services will be produced. Second, the supply (production) side is explained by the process of transforming inputs to outputs. These models have rarely been tested in an environment where the public sector may be argued to operate in a disequilibrium environment.

The primary objective of this study is to assess whether the forecasting performance of the public sector expenditure under a COMPAS fiscal module (an equilibrium model) fits reasonably well under a disequilibrium environment. Conceptually, the fiscal module under a COMPAS framework represents an equilibrium concept, and this equilibrium is operationalized by demand shifters modeled empirically. These shifters, however, may not work well in a disequilibrium environment, where exogenous shocks push the public sector into an intermediate period (or long-term period) where local government public sector supply in less sensitive to traditional demand curve shifting conditions. In such cases, one should consider alternative models for forecasting local government revenues and expenditures during the period of supply-demand disequilibrium. This study is focused on evaluating the conceptual framework for modern day local government revenue and expenditure forecasting along with the strengths and weaknesses of such modeling in terms of empirical specification. We compare the traditional COMPAS model with a modified COMPAS model and analyze the forecasting performance of several indicators under disequilibrium conditions. The study evaluates forecasting performance during the time frame of proposed disequilibrium, where the data represents a period of time of major exogenous shocks (Hurricanes Katrina, Rita, and Gustav)[1] to local government.

A traditional equilibrium public service model is tested against a naïve model (that incorporates dynamics with inclusion of a lagged dependent variable) where we evaluate public service expenditure forecasting in a disequilibrium environment. The naïve model (lagged dependent variable) then is tested against the "naïve plus" model (an inclusion of revenue capacity variables in the naïve model) and a "modified naïve" model (a hybrid model that includes the naïve plus model as well as demand shifter co-variates from the traditional COMPAS empirical specification). In addition, a comparatively newer approach (quantile regression) is also introduced to evaluate its performance among existing single year cross-sectional data-based COMPAS estimators.

The remainder of the study begins with a section that presents a historical background of local fiscal modeling. We explain the theoretical and conceptual background of local public service modeling in terms of COMPAS frameworks and alternative frameworks in this section. This will be followed by the empirical specification of the fiscal module, where we set forth the empirical model with revenue capacity and expenditure equations. The succeeding section describes the data and methodology used for the analysis. We will then analyze the data, discuss the results and key findings of the regressions and the performance comparison of different estimators from various underlying models, and compare the models based on their relative forecasting performance. Finally, we conclude the study by pointing out some limitations of the study and future opportunities for research.

2. Literature on local fiscal modeling

There have been several studies focused on the construction and evaluation of fiscal modules by local governments to determine the level of public services provided to its residents. In the 1960s and most of 1970s, ad hoc expenditure models dominated the modeling issues of the local public sector. Other models developed during these periods with the concept of modeling public services were concentrated on empirical analysis and mostly were lacking a conceptual framework. We present a snapshot of some of these studies built on the empirical frameworks used to model local public service delivery in Table 1.

The introduction of IMPLAN (Alward et al., 1989) created a revolution in regional economics for studying impact analysis starting in the 1980s. IMPLAN was a major modeling accomplishment through its creation of local input-output models based on secondary data that could be updated annually, as compared to other models dependent on primary data for construction that were for typically larger regions and costly to construct and update (Johnson, Otto, and Deller, 2006). Unfortunately, despite IMPLAN's success at generating contribution and impact projections for community-wide current account variables such as output, value-added, labor income, and employment, it was less effective in providing valuable information for a community's public sector.

Consequently, researchers then focused on building models that could cater to the customized needs of communities for public sector impacts and forecasting based on secondary data. In an effort to develop advanced fiscal models for local communities, the regional rural development centers and the Rural Policy Research Institute (RUPRI) supported several rural studies that intended to generate an empirically tractable approach to local public sector modeling (RUPRI, 1995). RUPRI then extended its help and support for conducting multistate interdisciplinary research by building an outreach network, known as the community policy analysis network (CPAN) (Scott and Johnson, 1998). The network comprised a group of social scientists who attend periodic meetings to develop new models and support tools on emerging issues that were important to rural communities. Their efforts began by developing a stylized model that was originally intended as a true general equilibrium-type fiscal model where one could formally model separately local public sector demand and supply. In an effort to explore a model that accounts for both the empirical as well as the conceptual framework and could be customized based on the needs of local public supply and demand, they developed what is today known as the community policy analysis system (COMPAS) models (Johnson, Otto, and Deller, 2006). These models originated from mostly CPAN researchers from Midwestern states developing models for rural counties in their respective states where these regions were quite homogenous and equilibrium assumptions held during the slow steady growth of these rural regions in the 1990s. They were

[1] Hurricanes Katrina and Rita made landfall in Louisiana in 2005, and Hurricane Gustav made landfall in Louisiana in 2008.

developed, as their name implies, to focus on evaluating local community policies on labor markets and local governments; however, as their development and use evolved, modelers began applying these empirical tools to assist local governments with general forecasting.

Table 1. Summary of determinants of local public service expenditures in 1960s and 1970s.

Author (Year)	Model Used	Objectives of the Study	Dependent Variables	Major Regressors	Major Findings
Fisher (1961)	Simple linear regression	Estimate per capita expenditure of state and local government	Per capita expenditure of state and local government	Population, Population density, Per capita income	Income positive and significant, population density negative and significant
Sacks and Harris (1964)	Ordinary least squares	Analyze total direct expenditures on several categories of local government	Total direct expenditures, health and hospital, education and other expenditures	Population, Federal and state aids, Per capita income, % urban	Income and federal and state aids significantly describe local government expenditures
Barr and Davis (1966)	Simple and multiple regression	Analyze determinants of several expenditure categories of Pennsylvania counties	General government expenditure, Highways expenditure, Judicial expenditure, and other expenditure	Property holdings, Median income, Median education, Voting preferences	Differences in preferences for expenditures significantly explains several local government expenditure
Bahl and Saunders (1966)	Ordinary least squares, Non-linear regression	Analyze the temporal pattern of determinants of state and local government expenditures	State and local government expenditures	Per capita federal grant, Per capita income, Population, % urban	Per capita federal grant, income, population density and % urban were all positive and significant
McMahon (1970)	Ordinary least squares	Analyze determinants of public primary and secondary education expenditures by cross-sectional and time series data	Public primary and secondary education expenditures	Pupil per teacher, Assessed value, Federal and state aids, Personal income, Population	Federal and state aids, pupil enrollment over time significantly explain growth of public primary and secondary education expenditures
Bergstrom and Goodman (1973)	Ordinary least squares	Estimate demand functions for municipal public services	General expenditures, police expenditures, parks and recreation expenditures	Tax share, Population change, Crowding parameter, Income	Expenditures on different categories depends on locality. Income plays major role in most localities

2.1. COMPAS modeling framework

The COMPAS model is an effective tool for estimating the fiscal impacts on a region of different policy/development scenarios (Scott and Johnson, 1997). COMPAS models are regional economic models that combine two different approaches (typically input-output and parametric econometric modeling) to build an integrated, or conjoined, model of rural economic structure (Johnson, Otto, and Deller, 2006). These models are mostly used to evaluate the impacts within a small city, region, or county. COMPAS models typically treat employment demand as an exogenous driver of changes in the labor market which ultimately impact the fiscal sector. The fiscal module in this research is an extension to the module used by Fannin et al. (2008) and Adhikari and Fannin (2010).

COMPAS models incorporate statistically estimated relationships to forecast changes in demographic, economic, and fiscal conditions under exogenous changes in economic activity. The model includes a system of cross-sectional econometrically estimated equations estimated for communities in respective states (Johnson, Otto, and Deller, 2006). These estimates, though in some cases statistically significant, might not perform well in terms of forecasting performance. These equilibrium COMPAS estimators could be tested under disequilibrium conditions in order to compare the relative forecasting performance based on multiple quantitative evaluation methods. The block recursive diagram of the COMPAS model is displayed in Figure 1.

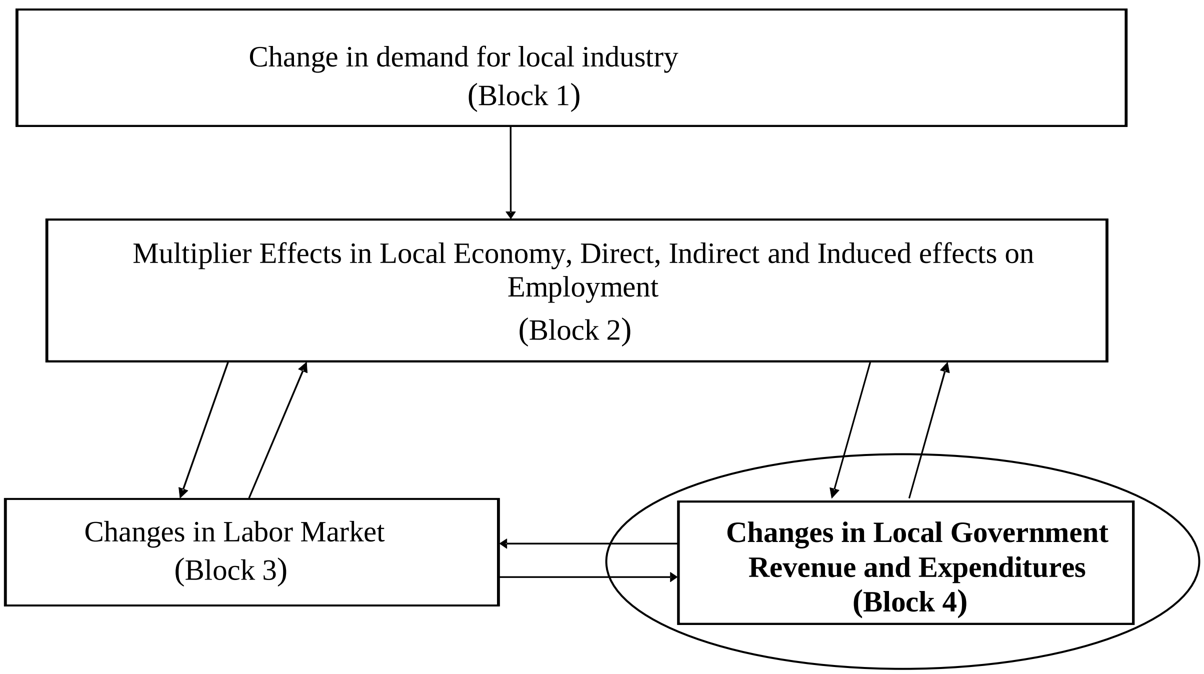

Figure 1. Block Recursive Diagram showing the components of COMPAS model.
Source: Fannin et al.; 2008, Adhikari and Fannin; 2010

The median voter model was introduced to develop the conceptual framework of public sector demand and supply based on the early voter theory of Black (1958). This median voter theory was used extensively to model the local public sector, since the service demands of median voters were addressed by the political parties in order to carry elections. As stated earlier, the local government's fiscal behavior is demand driven (for public goods and services). Under situations of majority rule, a median voter model has been used in many instances to analyze the fiscal behavior of a region. This approach of the median voter[2] was initially developed by Barr and Davis (1966) but then was applied by several scholars to replace the then-popular ad hoc expenditure model. Median income levels, population, tax prices of public goods, and consumer's tastes and preferences at the local level are assumed to determine the level of demand for local public goods and services. Any elected official approving government spending far from the median will be driven out of office by an opposition that proposes an expenditure level closer to the demands of the median voter.

[2] See Shaffer et al. (2004) for detailed explanation for median voter model, where the author has compared the median voter and Hotelling models by using a beach vendor example.

There are a few limitations which could hinder the effectiveness of the model. Some of the factors that limit the supply/demand equilibrium in the traditional conceptual framework are, but are not limited to, downward sloping supply curves, the nature of private and public goods, and the non-excludability and non-rivalrous nature of public goods (Buchanan, 1965). Hence, applied researchers interested in providing local stakeholders valuable research tools developed an alternative framework that simply attempts to forecast the movement of public expenditure between equilibrium points over time (Johnson, Otto, and Deller, 2006).

In particular, they described an equilibrium point where structural demand meets structural supply. We can thus estimate a set of equations that models these equilibrium points as proposed by Johnson, Otto, and Deller (2006):

$$e = \beta_1 + \beta_2\varphi + \beta_3 N + \beta_4 I + \sum_{i=5}^{n}\beta_i Z, \tag{1}$$

where e is the expenditure (spending) of local governments, β are the regression coefficients to be estimated, φ is the tax share of median voter, N is the population of local government jurisdictions, I is income, and Z is a vector of exogenous variables in the model.

A plethora of studies were then developed based on these empirical applications of modern COMPAS modeling built on the conceptual foundations of the median voter model. A comprehensive fiscal impact model for Virginia counties was estimated by Swallow and Johnson (1987) where they developed a model to forecast the economic, demographic, and fiscal impacts of regional economic shocks. The entire analysis was carried out by estimating sets of local government revenue capacity and local government expenditure equations. An extension and a slight modification of this work was presented by Shields (1998), where he estimated different sectors of the local economy using two revenue capacity equations, six expenditure equations, and two housing market equations. A seemingly unrelated regression (SUR) model was then used to estimate the local government expenditures on a per capita basis on the health sector, government administration, public safety, public works, and other amenities. His findings showed that local government expenditures were significantly impacted by variables such as income, assessed property values, and property taxes.

Johnson and Scott (2006) proposed the Show Me Community Policy Analysis model, where they collected data from county and city governments of Missouri to estimate the labor market and the fiscal module coefficients. The model was actually a spreadsheet-based model that was used in conjunction with the IMPLAN model. They regressed police expenditure, jail expenditure, court expenditure, road expenditure, administrative expenditure, and other expenditure with several socio-economic variables that served as demand shifters. Major results showed that demands for public services were a function of income, wealth, age, education, and a few other factors such as input and other demand conditions. Based on this conceptualized framework and data for the model, they constructed and estimated a labor force module and fiscal module for all counties of Missouri using three stage least squares. Their fiscal module included two revenue base equations, three revenue equations and six expenditure equations.

Swenson and Otto (2000) provided continuity from earlier research and estimated an economic/fiscal impact modeling system for Iowa counties, where they introduced the concept of housing market equations. The fiscal module was quite similar to the one used by Swallow and Johnson (1987), in which they included six revenue capacity equations and various sets of expenditure equations. An extension of earlier studies was proposed by Evans and Stallmann (2006), where they proposed the Small Area Fiscal Estimation Simulator for Texas counties using a two-stage least squares procedure. A labor force module and fiscal module were estimated using a 14-equation model.

Most of the empirical models rely heavily on the median voter model assumption for their empirical specification. Further, COMPAS modelers assume that local governments consider demand and provide the desired level of services at the lowest possible cost. When tax bases and demand for expenditures are known, local governments are assumed to adjust tax rates to balance their budget. Public services may be subject to increasing and/or decreasing returns to scale. Unit costs of public services could be hypothesized as a function of the level and quality of services, input and output factors, input prices, and the rate of population growth.

3. Alternative conceptual frameworks for public service delivery

The CPAN network acknowledges an alternative conceptual framework for modeling public service delivery (Deller, 2006): the bureaucratic approach

(Niskansen, 1971; Poole and Rosenthal, 1996). The bureaucratic approach to the local budget allocation decision was set forth initially by Niskansen (1971) and concentrates more on political practices than economic approaches. Bureaucrats regulate the local level budget request and allocation process and present them to elected officials. It depends on the bureaucrats whether or not to adjust budget requests taking into account the behavior of elected officials who might cut off some portions of the proposed request. A regional economic modeler must consider the political attributes in addition to the economic attributes when modeling the local public sector. The supply/demand equilibrium model that we described earlier focuses more on the economic background and thus the political aspect of decision making is ignored.

Our focus in this study is to compare the Louisiana fiscal module built in the equilibrium COMPAS modeling tradition to alternative empirical formulations argued as more consistent with a bureaucratic model in the disequilibrium environment of the period immediately preceding and following the 2005 hurricane season in Louisiana. We estimate traditional OLS regressions with the COMPAS equilibrium model and compare them to panel data and a quantile regression model. Local governments may make decisions about the total expenditures in the fiscal year under a bureaucratic model conceptual framework based on the spending that was made in the previous year plus the total revenues that would be projected as available in the current fiscal year. Our contribution would be the addition of dynamics in the model by incorporating the lagged dependent variable for different expenditure categories. We estimate the forecasting performance by several quantitative methods incorporating different indicators such as mean simulation error, mean square simulation error, root mean square simulation error, and Theil's coefficients as a benchmark for comparison.

4. Empirical specification of fiscal module

The fiscal module in a COMPAS framework is composed of two components, local government revenue and local government expenditures, that use outcomes from the labor force module as exogenous variables. The endogenous variables from the labor force module (in-commuter earnings and out-commuter earnings) serve as exogenous variables in the fiscal module that determine the factors contributing to total revenue. Local government revenue is generated by different forms of tax revenue (typically property taxes and sales taxes which are dependent on assessed property value and retail sales) as well as self-generated revenue (fees) and intergovernmental transfers (block grants from the federal and state governments, etc). Two equations, for assessed property value and retail sales, measure revenue capacity in our fiscal module[3].

$$ASDVAL = f(LNDNSTY,\ OUTCERN,\ RESEMPERN) \tag{2}$$

$$RETSALE = f(LNDNSTY,\ INCERN,\ OUTCERN,\ RESEMPERN) \tag{3}$$

Expenditure equations are explained by factors that measure the quantity of public services, quality of public services, demand conditions related to public services, and input conditions (Johnson, 1996). For this study, four expenditure equations are accounted for through regression analysis, and a total of seven explanatory variables are used. The expenditure equations are presented as:

$$GEN\_GOV = f(ASDVAL,\ RETSALE,\ TOTINC,\ LNDNSTY,\ LCLRD,\ POP) \tag{4}$$

$$HEL\_WEL = f(ASDVAL,\ RETSALE,\ TOTINC,\ PERAFAM,\ POPPLUS,\ LCLRD,\ POP) \tag{5}$$

$$PUB\_SAF = f(ASDVAL,\ RETSALE,\ TOTINC,\ PERAFAM,\ POPPLUS,\ POP) \tag{6}$$

$$PUB\_WRK = f(ASDVAL,\ RETSALE,\ TOTINC,\ PERURB,\ LNDNSTY,\ LCLRD,\ POP) \tag{7}$$

(Variable descriptions are provided in Table 2).

5. Data and methodology

An initial comparison is made by modeling each of the equations using Ordinary Least Squares (OLS) regression, panel regression, and the quantile regression approach. As an alternative approach for the COMPAS models, OLS, panel, and quantile regressions are useful in measuring forecasting performance. OLS (and to a lesser extent panel) regression has been historically applied in COMPAS fiscal modeling. The inclusion of quantile regression

[3] Other non-tax revenue such as intergovernmental transfers also make up the total public sector revenue available for spending on public services. However, many of these transfers are based on formulas that include the demand shifter covariates in the public service expenditure equations. As a result, other public revenue sources are not included as covariates in the expenditure variables.

represents an additional iteration (or sensitivity analysis) in COMPAS regression modeling.

For a distribution function $F_Y(y)$, one can determine the probability φ of occurrence for a given value of the dependent variable y. Quantiles, however, are meant to do exactly the opposite. That is, one wants to determine for a given probability φ of the sample data set the corresponding value y. In OLS, given some explanatory variable x_i, we would determine the conditional mean $E[Y \mid x_i]$ of the random variable Y. Cross-sectional data are used in the analysis process.

Quantile Regression goes beyond this and enables one to pose such a question at any quantile of the conditional distribution function. Hence, quantile regression overcomes various problems of OLS and panel models as it focuses on the interrelationship between a dependent variable and its explanatory variables for a given quantile. Frequently, error terms are not constant across a distribution, thereby violating the axiom of homoscedasticity. Also, by focusing on the mean as a measure of location, information about the tails of a distribution is lost. Also, OLS and panel regressions are sensitive to extreme outliers, which can distort the results significantly. As has been indicated in the small example of Boston Housing data (Belsley, Kuh and Welsch, 1980), sometimes a policy based on OLS might not yield the desired result, as a certain subsection of the population does not react as strongly to this policy or, even worse, responds in a negative way, which was not indicated by OLS. Finally, quantile regression addresses a specific issue of public service delivery, that is, it accounts for differences in the quantity and quality of public services based on quantiles being defined on per capita expenditure levels of the dependent variable. Historically, COMPAS models have included quantity and quality demand conditions as exogenous regressors explaining expenditure variation. However, there may be unknown demand conditions explaining public expenditure variation or factors that are not easily measurable. Quantile regression serves as an alternative in these situations.

This section also develops and demonstrates a model evaluation process for community policy analysis models and highlights a number of key steps in this evaluation process. In particular, the study evaluates, via theoretical discussion and through empirical investigation, the quality of forecasts generated by one particular module, the fiscal module of the Louisiana Community Impact Model (LCIM). The base year for estimation is 2007, which is a desired time period because many parishes had measurably recovered from the serious damages caused by Hurricanes Katrina and Rita and was not impacted by another sizeable hurricane, Gustav (that made landfall in 2008). Although the base year for estimation of OLS and quantile regression estimators is 2007, the study also assesses multi-year data (from 2004 to 2009) for forecasting purposes to compare performance within and outside of the in-sample year (see Figure 2 for on- and off-sample year forecasting performance comparisons for different sets of models for the general government expenditure category).

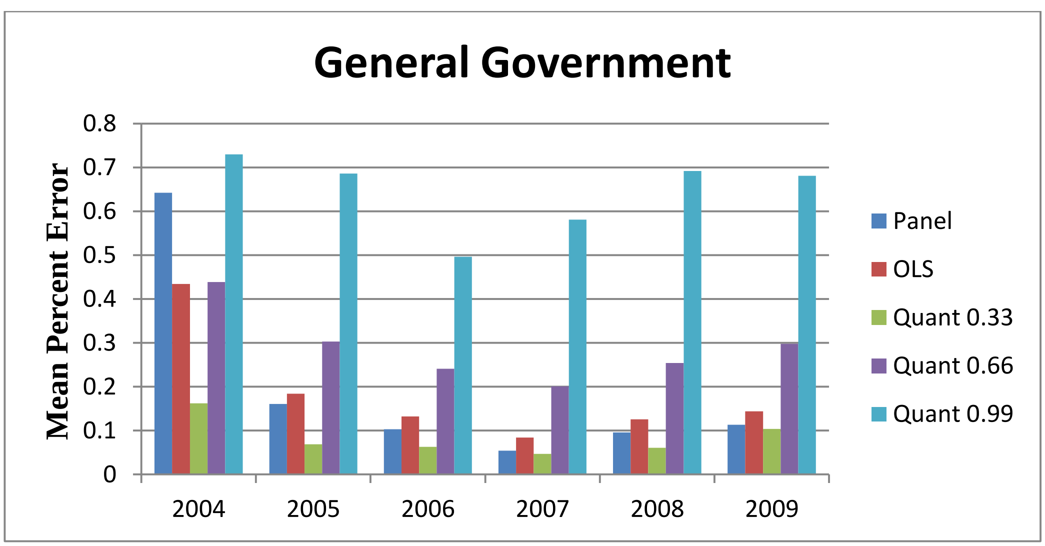

Figure 2. Bar Diagram comparing OLS, panel, and quantile estimators of COMPAS model.

The performance of estimators is compared on the basis of quantitative evaluation methods. These methods include analysis of mean simulation error (ME), mean percent simulation error (MPE), mean absolute simulation error (MAE), mean absolute percent simulation error (MAPE), mean square simulation error (MSE), root mean square simulation error (RMSE), root mean square percent simulation error (RMSPE), and Theil's U1 and U2 coefficients[4] (Kovalyova and Johnson, 2006; Pindyck and Rubinfield, 1991; Theil, 1970 and 1975).

Estimation is based on the COMPAS model for Louisiana that includes all 64 parishes, where the variables for the fiscal module were selected on the basis of Fannin et al. (2008) and were modified depending on the requirements of our model and applied geographically to all Louisiana parishes. Louisiana parish-level fiscal module data are obtained from audited financial statements of parish governments. The data collected uses a common federal accounting standard (Government Accounting Standards Board Standard 34). It has been collected annually by the Louisiana Legislative Auditor since 2004 and allows for the creation of a panel dataset of common local government expenditure categories for modeling purposes. Within the fiscal module, different expenditure equation data on public safety, public works, general government, and health and welfare sectors are estimated by a cross-section Ordinary Least Square (OLS) model as a base control, with quantile and panel data regressions also estimated. Other major data sources for the covariates include the Louisiana Department of Education, U.S. Census Bureau, and Bureau of Economic Analysis. We apply OLS regression and quantile regression using STATA. The forecasting performance is evaluated based on the procedures outlined in Johnson, Otto, and Deller (2006) and Kovalyova and Johnson (2006).

6. Results and discussion

Descriptions of variables used in the study are presented in Table 2. The average spending for a Louisiana parish was about $13 million for general government, $3 million for health and welfare, $12.5 million for public safety, and $14.5 million for public works in 2007. Assessed value and retail sales average $418 million and $901 million, respectively. Total income of the 64 Louisiana parishes average $2 billion, with measurable variation from a low of $163 million (Tensas) to $19 billion (Jefferson). Average parish population totaled just over 68,000.

The results in Table 3 show the comparison of the panel estimator, OLS estimator, and quantile estimators, divided in three quantiles (0.33, 0.66 and 0.99), for four different expenditure categories within the 64 parishes of Louisiana. Quantiles were divided base on the per capita expenditure levels of each of the dependent variables. Varying per capita expenditures highlight the differences in the quantity and/or quality of public services consumed. We might expect to see differing factors drive expenditures based on the quantity or quality of public services consumed per capita. Only three quantiles were chosen so that we could have enough degrees of freedom in each quantile. Most of the signs in the parameter estimates are as expected. In the general government category, for example, an increase in assessed value leads to an increase in the expenditure of the general government. That is, general government is a normal good given that incomes and assessed value are positively correlated, consumption of the public service increases as the assessed value increases. We see that public safety is also a normal good.

Results are mixed in identifying a superior model for forecasting when comparing panel, OLS, and quantile regressions (Table 4) in our traditional

[4] Theil (1958) recommended an accuracy measure in forecasting, widely known as U1. The value of U1 lies between 0 and 1, regardless of how data are defined. Theil's U1 normalizes RMSE with sum of root squares of actual and predicted values. A value of 0 indicates perfect prediction and the value of 1 corresponds to inequality or negative proportionality between actual and predicted values.

$$U1 = \frac{\sqrt{\frac{1}{n}\sum(\hat{Y}_t - Y_t)^2}}{\sqrt{\sum Y_t^2} + \sqrt{\sum \hat{Y}_t^2}}$$

or, $$U1 = \frac{RMSE}{\sqrt{\sum Y_t^2} + \sqrt{\sum \hat{Y}_t^2}}$$

To address the shortcomings of U1, Theil (1966) proposed another modified error measure (U2) that normalizes RMSE with the root mean square actual values. The U2 statistic is bounded below by 0, as is the case for U1, but the upper bound is lacking in this case and could thus take any value between 0 and $+\infty$. The choice of using U1 or U2 depends on the researcher and the objectives of the study. Again, a value of 0 indicates perfect prediction (the smaller the better).

$$U2 = \frac{\sqrt{\frac{1}{n}\sum(\hat{Y}_t - Y_t)^2}}{\sqrt{\frac{1}{n}\sum Y_t^2}}$$

or, $$U2 = \frac{RMSE}{\sqrt{\frac{1}{n}\sum Y_t^2}}$$

COMPAS model. In the general government category, the lowest quantile (0.33) on the quantile regression performs better than OLS and panel models in terms of mean percent simulation error, mean absolute percent simulation error, mean square percent simulation error and Theil's coefficient (U1 and U2). Higher quantiles are far higher in terms of error measures (which demonstrate poorer model fit). For the health and welfare category, again the mean percent simulation error, mean absolute percent simulation error, mean square percent simulation error, and Theil's coefficient (U1 and U2) are least in the lowest quantile (0.33) as compared to the higher quantiles and OLS and panel models. Public works and public safety categories follow a similar pattern. However, OLS has the advantage over panel regression in the cases of both public works and public safety.

Table 2. Variable description and summary statistics, Louisiana, 2007.

Variables (Units)	Description (Expected Sign)	Mean	Standard Deviation	Min	Max
GEN_GOV ($)	General Government Expenditure	12,907,252	37,669,961	593,955	210,722,026
HEL_WEL ($)	Health and Welfare Expenditure	3,357,312	7,399,740	5,664	13,602,439
PUB_SAF ($)	Public Safety Expenditure	12,561,498	40,169,582	232,882	189,130,903
PUB_WRK ($)	Public Works Expenditure	14,526,595	31,200,493	847,070	65,739,927
GG_LAG ($)	*GEN_GOV* lag (+)	9,097,823	25,819,736	555,209	191,462,016
HW_LAG ($)	*HEL_WEL* lag (+)	2,894,097	5,003,084	5,016	28,751,486
PS_LAG ($)	*PUB_SAF* lag (+)	11,361,581	30,625,856	178,617	17,260,2185
PW_LAG ($)	*PUB_WRK* lag (+)	12,895,400	29,179,849	685,291	20,744,981
ASDVAL ($)	Assessed Value (+)	418,151,563	553,860,439	36,056,864	3,466,560,930
RETSALE ($)	Retail Sales (+)	901,353,145	1,355,501,809	29,883,946	7,612,001,075
LNDNSTY (sq. mi.)	Arable Land Density (+)	770	431	190	2,413
LCLRD (miles)	Local Road Miles (+)	1,513	717	284	3,635
POP (#)	Population (+)	68,376	90,951	5,788	440,339
TOTINC (000 $)	Total Income (+/-)	2,447,161	3,864,120	163,901	18,996,431
PERAFAM (%)	Percent African American (+)	32	14	3	68
PERURB (%)	Percent Urban (+/-)	48	28	0	99
POPPLUS (#)	Population > 65 years of age (+/-)	8,290	10,291	660	58,362

Table 3. Parameter estimates for panel, OLS and quantile regressions, Louisiana.

Expenditure Category	Panel		OLS		Quantile Regression					
					0.33		0.66		0.99	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
GEN_GOV										
Constant	0.051	0.96	-2.049	0.28	-2.590	0.46	-2.768	0.29	0.637	0.78
ASDVAL	0.425***	0.001	0.175	0.36	0.067	0.82	0.338	0.28	0.195	0.60
RETSALE	0.252***	0.009	0.415*	0.07	0.584	0.26	0.361	0.43	0.242	0.56
TOTINC	0.213*	0.09	1.988***	0.001	2.025***	0.003	2.049***	0.01	1.239*	0.07
LNDNSTY	0.227**	0.06	0.120	0.28	0.103	0.72	0.061	0.69	0.234	0.30
LCLRD	-0.45***	0.003	-0.309*	0.06	-0.359	0.32	-0.223	0.33	-0.437*	0.09
POP	0.047	0.62	-1.98***	0.001	-0.207**	0.03	-2.201***	0.001	-0.884	0.29
HEL_WEL										
Constant	-0.488	0.84	-8.612**	0.04	-10.244	0.19	-6.966	0.18	-6.243	0.59
ASDVAL	0.494**	0.015	0.617***	0.009	0.520	0.33	0.449	0.40	0.772	0.45
RETSALE	0.410*	0.09	0.085	0.81	0.540	0.34	0.423	0.39	0.066	0.96
LCLRD	-0.580**	0.02	-0.120	0.70	-0.073	0.90	-0.260	0.61	0.209	0.79
PERAFAM	0.0006	0.99	0.279	0.12	0.104	0.63	0.169	0.56	0.059	0.91
POP	0.017	0.96	-1.946*	0.06	-1.776	0.24	-3.817**	0.02	1.230	0.68
TOTINC	-0.385	0.29	1.878**	0.02	1.647	0.26	2.311	0.13	-0.333	0.89
POPPLUS	0.705**	0.02	0.363	0.63	-0.144	0.91	1.572	0.23	-0.583	0.82
PUB_SAF										
Constant	-8.40***	0.001	-15.92***	0.001	-12.62***	0.003	-17.49***	0.001	-17.52***	0.008
ASDVAL	0.633***	0.001	0.528**	0.02	0.765*	0.09	0.454	0.28	0.247	0.31
RETSALE	0.012	0.92	0.316	0.19	-0.198	0.77	0.505	0.24	0.555	0.28
TOTINC	0.791***	0.001	3.795***	0.001	0.018	0.95	0.045	0.77	0.171	0.68
POPPLUS	-0.621*	0.06	-1.018**	0.05	-0.009	0.99	-1.546**	0.04	-2.623**	0.02
PERAFAM	0.126	0.46	0.152	0.23	3.705***	0.001	3.993***	0.001	3.289***	0.001
POP	0.406	0.25	-2.929***	0.003	-3.369**	0.02	-2.782***	0.005	-0.67*	0.09
PUB_WRK										
Constant	-0.373	0.77	-0.219	0.89	0.398	0.92	0.369	0.89	1.912	0.56
ASDVAL	0.459***	0.003	0.304	0.11	0.251	0.54	0.555	0.11	0.113	0.71
RETSALE	0.223*	0.06	0.258	0.25	0.372	0.42	-0.011	0.98	0.182	0.70
PERURB	-0.077*	0.09	-0.020	0.68	-0.014	0.86	-0.027	0.58	0.028	0.88
LCLRD	-0.28***	0.002	-0.064	0.60	-0.175	0.56	-0.226	0.20	0.035	0.90
POP	-0.42**	0.05	-0.759	0.20	-1.143	0.32	0.192	0.86	-1.268	0.29
TOTINC	0.625***	0.009	0.870*	0.09	1.063	0.30	0.180	0.82	1.486	0.19
LNDNSTY	0.110	0.35	0.194*	0.06	0.198	0.59	0.336***	0.01	0.128	0.56

Single, double, and triple asterisks indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 4. Average performance estimation measures for different categories of expenditure.

Expenditure Category	Panel	OLS	Quantile Regression		
			0.33	**0.66**	**0.99**
GEN_GOV					
Mean Percent Simulation Error	0.054	0.084	0.047	0.201	0.581
Mean Absolute Percent Simulation Error	0.365	0.341	0.323	0.319	0.790
Mean Square Percent Simulation Error	0.211	0.201	0.148	0.211	1.321
Theil's Coeff (U1)	0.285	0.246	0.183	0.206	0.583
Theil's Coeff (U2)	0.322	0.297	0.238	0.255	0.718
HEL_WEL					
Mean Percent Simulation Error	0.443	0.276	0.271	0.524	2.097
Mean Absolute Percent Simulation Error	0.888	0.682	0.562	0.749	2.097
Mean Square Percent Simulation Error	2.354	0.846	0.645	1.305	10.934
Theil's Coeff (U1)	0.278	0.261	0.260	0.401	0.469
Theil's Coeff (U2)	0.337	0.304	0.296	0.514	0.608
PUB_SAF					
Mean Percent Simulation Error	0.281	0.414	0.264	0.387	0.422
Mean Absolute Percent Simulation Error	0.188	0.130	-0.063	0.512	2.254
Mean Square Percent Simulation Error	0.570	0.439	0.306	0.624	2.254
Theil's Coeff (U1)	0.678	0.337	0.176	0.876	0.512
Theil's Coeff (U2)	0.209	0.372	0.200	0.343	0.347
PUB_WRK					
Mean Percent Simulation Error	0.132	0.089	0.077	0.478	0.446
Mean Absolute Percent Simulation Error	0.441	0.365	0.274	0.575	0.547
Mean Square Percent Simulation Error	1.322	0.236	0.135	0.978	0.641
Theil's Coeff (U1)	0.184	0.194	0.174	0.326	0.325
Theil's Coeff (U2)	0.237	0.279	0.196	0.382	0.361

Although the lower quantiles displayed superior forecasting performance relative to other quantiles and the other two models in all four categories of expenditure, a more robust model is preferable for estimating and forecasting public sector expenditure. As suggested by Johnson, Otto, and Deller (2006), the best way to validate model performance is by comparing the forecasts with those of naïve extrapolation. As such, we applied a naïve model (cross-sectional) where all four categories of expenditures were regressed with its one year lagged value. This approach makes for a reasonable baseline because it suggests that any model estimated should forecast at least as well as simply using the information from last year's expenditure. In addition, this approach forms the basis for a bureaucratic model conceptual framework to public sector expenditure, given that local governments often make decisions on their spending for the fiscal year based on the spending that was made last year plus some adjustment for the current year. More specifically, bureaucrats use the previous year's budget as a baseline to inflate budgets constrained by the level of expected growth in revenue collections. We also add revenue capacity variables in the naïve model to develop a new model (Naïve plus) for comparing the forecasting performance that incorporates expected revenues that can be spent in the current year. We further introduce a modified naïve model which includes the original COMPAS covariates to compare with naïve and naïve plus model. The expenditure equations in the new models are now expressed as:

6.1 NAÏVE MODEL:

$$GEN\_GOV = f(GG\_LAG) \tag{8}$$

$$HEL\_WEL = f(HW\_LAG) \tag{9}$$

$$PUB\_SAF = f(PS\_LAG) \tag{10}$$

$$PUB\_WRK = f(PW\_LAG) \tag{11}$$

6.2 NAÏVE PLUS MODEL:

$$GEN\_GOV = f(GG\_LAG, ASDVAL, RETSALE) \tag{12}$$

$$HEL\_WEL = f(HW\_LAG, ASDVAL, RETSALE) \tag{13}$$

$$PUB\_SAF = f(PS\_LAG, ASDVAL, RETSALE) \tag{14}$$

$$PUB\_WRK = f(PW\_LAG, ASDVAL, RETSALE) \tag{15}$$

6.3. MODIFIED NAÏVE MODEL:

$$GEN\_GOV = f(GG\_LAG, ASDVAL, RETSALE, TOTINC, LNDNSTY, LCLRD, POP) \tag{16}$$

$$HEL\_WEL = f(HW\_LAG, ASDVAL, RETSALE, TOTINC, PERAFAM, POPPLUS, LCLRD, POP) \tag{17}$$

$$PUB\_SAF = f(PS\_LAG, ASDVAL, RETSALE, TOTINC, PERAFAM, POPPLUS, POP) \tag{18}$$

$$PUB\_WRK = f(PW\_LAG, ASDVAL, RETSALE, TOTINC, PERURB, LNDNSTY, LCLRD, POP) \tag{19}$$

Results from Table 5 compare the parameter estimates of the OLS and panel estimators of the naïve, naïve plus and modified naïve model for four different expenditure categories within the Louisiana parishes. Similarly, results from Table 6 display parameter estimates for the naïve model, naïve plus model and modified naïve model based on three quantiles (0.33, 0.66, and 0.99) via quantile regression. The results are quite similar to earlier models. However, results are superior compared to earlier COMPAS equilibrium models, as we observe the forecasting performance increases with inclusion of the lagged dependent variable (naïve model) in our earlier model. The lagged variable is highly significant for all models and for all categories of expenditure and suggests that the previous year's expenditure plays an important role in determining the future year's expenditure. Except for the public works category, assessed value is positive, which indicates that an increase in assessed value leads to an increase in the expenditure of general government, public safety, and health and welfare.

There is again a mixed result in performance between OLS and quantile regression models (Table 7). All models including the lagged dependent variable outperform the baseline COMPAS models; however, performance varies in the quantile regression with lagged dependent variables. In most of the models, lower quantiles (0.33) perform better as compared to the middle (0.66) and higher quantiles (0.99). The OLS model outperforms the panel model (except in case of public works category) in most of the expenditure categories for naïve, naïve plus, and modified naïve, as measured in terms of the aforementioned error measures. Although the naïve model is superior when compared to our earlier model, the naïve plus model displays better forecasting performance than the naïve model measured in terms of mean percent simulation error, absolute mean percent simulation error, mean square percent simulation error, and Theil's coefficient.

Table 5. Parameter estimates for Naïve Model, Naïve Plus Model, and Modified Naïve Model, OLS and Panel Data regressions.

	OLS			Panel		
	Naïve	**Naïve Plus**	**Modified Naive**	**Naïve**	**Naïve Plus**	**Modified Naive**
GEN_GOV						
Constant	-0.23	-0.45	-0.04	0.15*	-0.54***	-0.49
ASDVAL		0.08	0.11***		0.11**	0.07
RETSALE		-0.03	-0.11**		-0.03	-0.01
TOTINC			0.06			0.29***
LNDNSTY			-0.01			0.04
LCLRD			-0.03			-0.09
GG_LAG	1.02***	0.97***	0.95***	0.99***	0.93***	0.88***
POP			0.04			-0.24**
HEL_WEL						
Constant	0.004	-1.33**	-4.71***	0.40*	-1.32***	-1.06
ASDVAL		0.25***	0.22***		0.12**	0.12**
RETSALE		-0.14***	-0.16		0.03	0.06
TOTINC			0.78**			-0.007
LCLRD			-0.16**			-0.05
POPPLUS			-0.16			0.09
PERAFAM			0.19**			-0.002
HW_LAG	0.99***	0.94***	0.91***	0.97***	0.87***	0.86***
POP			-0.64			-0.10
PUB_SAF						
Constant	0.23	-1.10**	-2.84***	0.70***	-1.58***	-1.89***
ASDVAL		0.13*	0.08		0.22***	0.20**
RETSALE		-0.05	-0.01		-0.004	-0.07
TOTINC			0.64**			0.19
POPPLUS			-0.16			-0.28*
PERAFAM			0.12***			0.02
PS_LAG	0.98***	0.97***	0.90***	0.95***	0.82***	0.79***
POP			-0.46			0.20
PUB_WRK						
Constant	0.47	0.05	-1.63**	1.06**	-0.49	-0.61
ASDVAL		0.01	-0.003		-0.23***	-0.16***
RETSALE		0.05	0.15**		0.06	0.004
TOTINC			0.27*			0.35*
PERURB			0.01			-0.006
LNDNSTY			0.07*			0.07*
LCLRD			0.13**			-0.03
PW_LAG	0.98***	0.92***	0.89***	0.93***	0.66***	0.66***
POP			-0.46***			-0.24

Single, double, and triple asterisks indicate statistical significance at 10%, 5%, and 1% levels respectively.

Table 6. Parameter estimates for Naïve Model, Naïve Plus Model, and Modified Naïve Model, quantile regressions.

	Naïve			Naïve Plus			Modified Naive		
	0.33	**0.66**	**0.99**	**0.33**	**0.66**	**0.99**	**0.33**	**0.66**	**0.99**
GEN_GOV									
Constant	-0.52**	-0.19	-4.77*	-0.87***	-0.54	2.04	-0.69	-0.36	-0.94
ASDVAL				0.11***	0.14	0.22	0.10	0.12	0.17
RETSALE				0.16	-0.09	0.03	-0.05	-0.16**	-0.19
TOTINC							0.05	0.29	0.14
LNDNSTY							-0.002	-0.01	-0.10
LCLRD							-0.01	-0.02	0.14
GG_LAG	1.03***	1.02***	1.38***	0.96***	0.99***	1.13***	0.95***	0.95***	0.99***
POP							-0.01	-0.17	-0.04
HEL_WEL									
Constant	0.02	-0.11	-1.01	-1.22	-1.12	-1.52	-4.08**	-5.66***	-2.04
ASDVAL				0.25***	0.19	0.09	0.20*	0.15	0.33
RETSALE				-0.14*	-0.11	0.06	-0.09	-0.07	-0.18
TOTINC							0.26	0.94***	-0.29
LCLRD							0.25*	0.20	0.07
POPPLUS							-0.71	-0.42	0.24
PERAFAM							0.19	0.17*	0.04
HW_LAG	0.99***	1.01***	1.12***	0.95***	0.97***	0.92***	0.94***	0.92***	0.89***
POP							0.24	-0.59	0.23
PUB_SAF									
Constant	-0.01	-0.11	1.86***	-1.78	-0.31	-1.34	-1.32	-3.01**	-2.12
ASDVAL				0.20	0.02	0.24	0.004	0.04	-0.01
RETSALE				-0.09	-0.005	-0.09	0.04	0.01	0.06
TOTINC							0.31	0.79*	0.78*
POPPLUS							0.14	-0.19	-0.42
PERAFAM							0.11	0.10	0.11
PS_LAG	1.00***	1.01***	0.92***	0.96***	1.00***	0.93***	0.97***	0.93***	0.85***
POP							-0.48	-0.64	-0.14
PUB_WRK									
Constant	0.47	0.41	1.17***	0.03	-0.08	1.27	-1.13	-2.33**	0.123
ASDVAL				0.05	-0.06	-0.03	0.01	-0.06	-0.04
RETSALE				-0.0006	0.08	0.02	0.07	0.22**	0.08
TOTINC							0.53	0.29	0.02
PERURB							0.02	0.002	0.07*
LNDNSTY							0.04	0.066	0.08
LCLRD							0.03	0.16*	0.19
PW_LAG	0.97***	0.98***	0.95***	0.93***	0.99***	0.96***	0.86***	0.95***	0.89***
POP							-0.60	-0.54**	-0.12

Single, double, and triple asterisks indicate statistical significance at 10%, 5%, and 1% levels respectively.

Table 7. Average performance estimation measures for different categories of expenditure.

Error Measures	Panel Naïve	Panel Naïve Plus	Panel Mod. Naive	OLS Naive	OLS Naïve Plus	OLS Mod. Naive	QR Naive 0.33	QR Naive 0.66	QR Naive 0.99	QR Naïve Plus 0.33	QR Naïve Plus 0.66	QR Naïve Plus 0.99	QR Mod. Naive 0.33	QR Mod. Naive 0.66	QR Mod. Naive 0.99
GEN_GOV															
MPSE	0.17	0.13	0.11	0.12	0.11	0.05	-0.09	0.08	0.41	-0.06	0.06	0.32	-0.05	0.05	0.25
MAPSE	0.16	0.12	0.12	0.10	0.10	0.08	0.10	0.16	0.43	0.08	0.13	0.32	0.08	0.11	0.25
MSPSE	0.14	0.10	0.09	0.13	0.09	0.06	0.03	0.09	0.19	0.02	0.03	0.16	0.01	0.02	0.09
Theil's U1	0.11	0.09	0.07	0.06	0.04	0.04	0.05	0.08	0.31	0.03	0.07	0.21	0.03	0.07	0.20
Theil's U2	0.16	0.12	0.09	0.09	0.07	0.07	0.08	0.10	0.42	0.06	0.11	0.29	0.06	0.09	0.24
HEL_WEL															
MPSE	0.13	0.13	0.09	0.10	0.05	0.03	0.07	0.17	0.61	0.02	0.10	0.66	0.01	0.09	0.54
MAPSE	0.37	0.26	0.17	0.33	0.20	0.18	0.25	0.29	0.58	0.12	0.27	0.66	0.14	0.22	0.54
MSPSE	0.83	0.14	0.14	0.91	0.10	0.07	0.23	0.24	0.77	0.04	0.20	0.72	0.06	0.11	0.58
Theil's U1	0.26	0.19	0.16	0.23	0.17	0.12	0.18	0.29	0.23	0.06	0.18	0.18	0.08	0.16	0.17
Theil's U2	0.33	0.24	0.21	0.27	0.19	0.16	0.22	0.35	0.30	0.10	0.22	0.20	0.10	0.19	0.20
PUB_SAF															
MPSE	0.12	0.14	0.11	0.08	0.08	0.06	-0.07	0.14	0.36	-0.05	0.13	0.34	0.03	0.11	0.23
MAPSE	0.33	0.19	0.15	0.25	0.15	0.14	0.25	0.15	0.31	0.24	0.16	0.34	0.11	0.14	0.23
MSPSE	0.39	0.09	0.06	0.32	0.09	0.08	0.12	0.09	0.21	0.07	0.05	0.16	0.05	0.04	0.09
Theil's U1	0.28	0.16	0.11	0.21	0.11	0.08	0.14	0.15	0.17	0.11	0.07	0.07	0.06	0.06	0.03
Theil's U2	0.37	0.23	0.19	0.29	0.19	0.13	0.17	0.20	0.24	0.16	0.10	0.09	0.09	0.08	0.07
PUB_WRK															
MPSE	0.08	0.03	0.03	0.05	0.04	0.04	-0.05	0.13	0.33	-0.03	0.10	0.27	-0.03	0.09	0.21
MAPSE	0.21	0.11	0.09	0.16	0.14	0.12	0.12	0.17	0.31	0.10	0.18	0.27	0.08	0.13	0.21
MSPSE	0.09	0.03	0.02	0.04	0.03	0.02	0.04	0.07	0.17	0.02	0.04	0.13	0.01	0.03	0.10
Theil's U1	0.16	0.05	0.04	0.10	0.07	0.06	0.08	0.14	0.18	0.07	0.10	0.14	0.04	0.07	0.09
Theil's U2	0.22	0.12	0.10	0.15	0.11	0.09	0.10	0.18	0.27	0.10	0.16	0.20	0.07	0.10	0.11

MPSE = Mean Percent Simulation Error; MAPSE = Mean Absolute Percent Simulation Error;
MSPSE = Mean Square Percent Simulation Error

To gain a better understanding of the relative performance of these estimators, we performed a mean absolute percent simulation error comparison test in STATA, where we compared the base OLS cross-section model with the cross-section models of each of the equations that incorporated the lagged dependent variable (naïve, naïve plus, and modified naïve). These results are presented in Tables 8 –11.

Table 8. Mean Absolute Percent Simulation Error Comparison Test based on OLS model for general government expenditure.

	Base	Naïve		Naïve Plus		Modified Naive	
		Magnitude	t-stat	Magnitude	t-stat	Magnitude	t-stat
Base		0.209	6.01***	0.223	6.55***	0.261	6.92***
Naive				0.014	1.38*	0.052	1.75**
Naïve Plus						0.038	0.69
Modified Naive							

Single, double, and triple asterisks indicate statistical significance at 10%, 5%, and 1% levels respectively.

Table 9. Mean Absolute Percent Simulation Error Comparison Test based on OLS model for public safety expenditure.

	Base	Naïve		Naïve Plus		Modified Naive	
		Magnitude	t-stat	Magnitude	t-stat	Magnitude	t-stat
Base		0.189	2.32**	0.289	5.50***	0.299	6.19***
Naive				0.102	1.54*	0.112	1.79**
Naïve Plus						0.010	1.04
Modified Naive							

Single, double, and triple asterisks indicate statistical significance at 10%, 5%, and 1% levels respectively.

Table 10. Mean Absolute Percent Simulation Error Comparison Test based on OLS model for health and welfare expenditure.

	Base	Naïve		Naïve Plus		Modified Naive	
		Magnitude	t-stat	Magnitude	t-stat	Magnitude	t-stat
Base		0.352	1.38*	0.482	5.54***	0.502	5.84***
Naive				0.130	1.53*	0.150	1.68**
Naïve Plus						0.021	1.17
Modified Naive							

Single, double, and triple asterisks indicate statistical significance at 10%, 5%, and 1% levels respectively.

Table 11. Mean Absolute Percent Simulation Error Comparison Test based on OLS model for public works expenditure.

	Base	Naïve		Naïve Plus		Modified Naive	
		Magnitude	t-stat	Magnitude	t-stat	Magnitude	t-stat
Base		0.205	4.81***	0.225	5.12***	0.245	5.38***
Naive				0.023	1.21	0.041	1.57*
Naïve Plus						0.020	0.90
Modified Naive							

Single, double, and triple asterisks indicate statistical significance at 10%, 5%, and 1% levels respectively.

In considering only the lowest magnitudes (highest forecasting performance), the modified naïve model displayed superior results as compared to the naïve and naïve plus model, if measured in terms of absolute mean percent error. Overall, results from Tables 8-11 suggested that lagged models are significantly lower in terms of error measures as compared to the base OLS model in all four categories of expenditure. However, the modified naïve model is not always significantly lower (in terms of absolute mean percent error) than the naïve and naïve plus models, and thus one should not infer that modified naïve model outperforms the other lagged dependent variable models. In Table 8, one can statistically observe that the modified naïve model displays better forecasting performance as compared to the base OLS model and naïve model, but there is no significant difference between the naïve plus and the modified naïve model. Also, the naïve plus model displays significantly better performance compared to the base OLS and naïve model. For the public safety and health and welfare categories of expenditure, test results show a similar pattern (Table 9 and 10). In the case of public works (Table 11), the modified naïve model performs significantly better than the base OLS and naïve models, but not the naïve plus model. These results suggest that during this period, Louisiana parish governments were driven more by bureaucratic forces than equilibrium based supply and demand factors.

7. Conclusion

In this study, we evaluated whether the forecasting performance of public sector expenditure models under traditional COMPAS supply/demand equilibrium assumptions fit reasonably well in a disequilibrium environment. This study focused on evaluating the conceptual framework for modern day local government revenue and expenditure forecasting along with the strengths and weaknesses of such modeling in terms of empirical specification. We compared the traditional COMPAS model with a modified COMPAS model and analyzed the forecasting performance of several indicators under disequilibrium conditions. The study evaluated forecasting performance during a time frame of supply/demand disequilibrium, a period of major exogenous shocks (Hurricanes Katrina, Rita, and Gustav) to local government operations. Different models were compared parametrically using cross-sectional OLS, panel data, and quantile regressions.

Most of the original COMPAS models were developed in Midwestern states where there was measurable homogeneity in economic and fiscal structure of rural regions (the focus of many of these models) during the period of their original creation. Our results showed that newer alternative methods such as quantile regression have potential statistical advantages over traditional COMPAS model OLS and panel regression in improving model performance (as evidenced by our original model particularly in the lowest quantile). Consequently, Quantile regressions are proposed as another COMPAS estimator alternative since they apply varying parameter estimates in forecasting depending on a county's relative position within the distribution of all counties in a state for a given public expenditure category. While early COMPAS models may have segmented based on rural/urban, these results suggest that segmentation may also occur on spending levels which may or may not always follow population size.

Further, results indicated that a bureaucratic model may have been a more appropriate conceptual framework during this public service delivery period of Louisiana local government history. However, these results are limited in that one cannot infer that the bureaucratic model is superior in all disequilibrium environments. In particular, due to data limitations one cannot evaluate the pre-Katrina/Rita forecasting performance between traditional COMPAS models and the bureaucratic model. The panel dataset starts from the year 2004, the first year in which there were quality comparable public sector data across all parish jurisdictions. That is, Louisiana parish public sector spending may have followed a more bureaucratic model prior to the disequilibrium period brought about by the storms.

There are some additional limitations. The largest is the tradeoff of forecasting performance for potential reduced policy analysis. From a modeling perspective, the magnitude of the parameters that serve as demand shifters in the public service equation are measurably reduced in the modified naïve model (with lagged dependent variable) in Table 6 as compared to the base models in Table 3. Since the demand shift variables are typically the variables through which proposed policies are incorporated into COMPAS, reducing their influence on expenditure projections through the addition of a lagged dependent variable may be problematic for those interested in using COMPAS models for policy analysis. Since most COMPAS policy analysis includes evaluating the policy effect through the difference between baseline expenditure and policy enacted expenditure projections, much of the forecasting error is likely to drop out in the difference between the two. The second limitation is that states with small numbers of counties will be limited in using the quantile regression approach because an insufficient number of counties would exist for generating statistically reliable results for each quantile subset.

An evaluation of the alternative methods performed in this study is expected to give regional economic modelers better information from which to construct models projecting local public sector expenditures. Using data from different sources, this study developed a model to forecast different categories of expenditure in the fiscal module using OLS, panel, and quantile regression. Future research should focus on a further narrowing of the confidence interval around these forecasts. As more and higher quality public sector data become available due to compulsory reporting requirements, researchers should be able to construct models with increasing forecast reliability that can be used by analyst-deficient local governments for more informed public sector decision making.

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