METHODS for LOCAL GOVERNMENT REVENUE FORECASTING

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Ⅰ. Introduction

The United States has over 25,000 local governments including 3,093 counties, 5,455 urban places of 5000 or more population, approximately 15,500 school districts, and 111 outlying areas.[1] Among the public goods and services that these governments provide are public safety (police, fire, and emergency medical services); solid waste collection and disposal; water treatment and distribution; sewage treatment; road construction, maintenance, and plowing; public health; social welfare services; primary and secondary education; land use planning and zoning; economic development; and recreation facilities and programs. In 1986, local governments collected $288 billion as taxes and fees (exclusive of intergovernmental transfers), 6.8% of the nation's GNP, to finance these and other services.[2] Each local government independently carries out an annual budget development process to plan expenditures and allocate budgets to administrative and operating units. A central component of this process is revenue forecasting for the coming budget year and, in many local governments, for horizons of three to five years for policy-level planning. The total revenue

1) Not included in this count are special districts such as sewer and water districts.

2) Government Finances, Series GF 86, No. 5, U.S. Bureau of the Census, 1985-86.

forecast places an upper limit on budget expenditures and can determine, for example, if cutbacks are needed in existing or planned services and if tax or fee increases are needed for the current or future budget cycles. Sizeable revenue forecast errors in either direction can have severe consequences (e.g., see Bretschneider and Gorr 1987, Shkurti and Winefordner 1989).

Officials in large cities and corresponding urban counties forecast revenues using time series data and objective forecast methods (univariate extrapolative methods and multiple regression models) in addition to judgmental methods (e.g., see Bretschneider and Schroeder 1988, Bahl et al. 1981a–1981c, Downs and Rocke 1983). Officials in small local governments, however, use and incremental approach and judgmental methods, the "percentage increase" method (e.g., see Larkey and Smith 1989). This parallels the well–known incremental approach to estimating expenditures (e.g., Davis, Dempster, and Wildavsky 1966 and Crecine 1970) widely used in governmental budgeting. It involves 1) developing and approximate sense for current growth rates or computing the most recent or past few growth rates in tax collections (either in multiplicative factor or additive first difference terms), 2) extrapolating a base case by increasing the most recent year's revenue collections by the growth rate determined in step 1, and 3) making judgmental adjustments for changing conditions.[3] Thus many practitioners neither use time series forecasting methods nor even time series data.

There are two major reasons why more sophisticated methods are not commonly used by local government officials. Frist, local economies have event–driven changes in time series patterns ("special event") due to plant closings, shopping mall openings, property reassessments, etc. that decrease the extrapolative value of historical data. Thus the annual revenue time series available to forecasters have discontinuous patterns not easily handled by conventional time series methods (e.g., see Figures 1 and 2 below.) Second, even if it were possible to make conventional methods applicable to the local government environment, public officials and their staff generally do not have the requisite training in statistics and time series analysis necessary for use and interpretation of such methods.

Given these limitations, we propose to use a decision support approach (Keen and Scott Morton, 1978, p. 2) to increasing the accuracy and accountability of local government forecasting. We develop an approach and methods to enhance current judgmental practices rather than attempting to

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3) Bahl et al. (1981a–1981d) found that even large municipal governments use percentage increase revenue forecasts. We interviewed approximately a dozen school district managers and local government consultants to determine forecasting methods used. In two instances we carried out concurrent verbal protocol analyses using a local government forecasting case to get detailed information on forecasting procedures. These investigations, while limited in numbers, confirmed the predominance of the percentage increase method in local government.

replace them completely with objective methods. The proposed approach is thus and enhancement of the "percentage increase method" with objective time series extrapolation[4] and informed judgmental predictions for special event impacts. It inclueds: 1) decomposition of annual revenue time series data into "pattern steady states," segments of a time series separated by special events that are easily extrapolated with simple time series techniques; 2) objective extrapolation of the current steady state using simple time series methods; and 3) judgmental adjustment of the extrapolative forecast for future special events using a "special event database" (Gorr 1986a, 1986b and Makridakis and Wheelwright 1989).

This paper focuses on the evaluation of the extrapolative forecasting component of the proposed approach. Two post sample forecast experiments are carried out. The first uses annual revenue data from a random sample of 25 small cities in Pennsylvania to determine the comparative forecast accuracy of the simplest time series methods (simple averages and average first differences) versus more sophisticated (but still simple) time series methods−time regression and Holt exponential smoothing. These experiments also explicitly address the effect of sample size on forecast accuracy, over a range of sample sizes used to estimate forecast models from 2 to 23 years. Only a few papers deal with annual forecast accuracy (Makridakis et al. 1982 and Schnaars 1986). We can find only two papers that test for the effect of sample size; namely, Makridakis and Hibon (1979) and Schnarrs (1984). We can find no papers that empirically test extrapolative methods for short time series, as we do here. we note that Files (1989), in an editorial statement, recently drew attention to the dearth of research on forecasting short time series.

The second experiment uses annual revenue time series data and actual budget forecasts by practitioners from 42 school districts in Allegheny County, Pennsylvania. These experiments compare forecast accuracy of the best time series methods from the first experiment to that achieved by practitioners through their judgmental methods. Objective approaches to forecasting have performed as well or better than judgmental forecasts as measured by predictive accuracy in hundreds of studies. See Dawes (1979), Hogarth and Makridakis (1981), and Armstrong (1985, pp. 393−402) for extensive reviews. Much of the difficulty in obtaining accurate judgmental forecasts has

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4) We limit objective forecasting to simple time series techniques and do not consider sophisticated time series techniques nor econometric methods. Makridakis and Hibon(1979) and Makridaks et al. (1982), in extensive empirical studies, found simple time series methods to be as accurate as more sophisticated ones. Also, there is a large literature comparing time series and econometric methods. Fildes (1985) and Armstrong (f1985, ch. 15) provide extensive reviews. On balance, there is no difference between these two approaches in the short run however econometric methods are superior in the long run.

been attributed to biasing heuristics used in judgmental assessments—anchoring, representativeness, and availability—introduced by Tversky and Kahneman(1974). In the revenue forecasting literature there is a growing stream of research showing that practitioners bias forecasts for managerial and political reasons (e.g., Larkey and Smith 1989 and Cassidy et al. 1989). Past studies comparing the forecast accuracy of time series versus judgmental forecasts, such as Carbone et al. (1983) and Carbone and Gorr (1985), used time series data sets of sufficient length (exceeding n=36) to permit accurate estimation of sophisticated time series methods. New in this paper are conditions more favorable to judgmental methods—short time series and very simple time series techniques.

Section 2 describes the local government forecasting problem in more detail and Section 3 presents our proposed forecasting approach and methods. Section 4 describes the data and post sample experimental designs for the two experiments and Section 5 presents analyses of results. Section 6 briefly concludes the paper.

Ⅱ. The Forecasting Problem

Table 1 provides information on the distribution of revenues collected by counties, municipalities, townships, school districts, and special districts. All except special districts depend most heavily on property taxes, which make up 32.7 to 78.4% or total collections. Special districts, such as sewer and water districts, rely most heavily on user charges, which make up 56.1% of their collections. In addition, user fees is the second most important revenue source for the other types of local governments included in Table 1. Sales and income taxes, interest earnings, and licenses are important, but provide proportionally less revenues.

The local government revenue forecasting problem requires annual time series data and forecast horizone of one to three years. The first-year-ahead forecast is important, being the budget forecast. Forecasts must be made a month or more before the start of a fiscal year to allow time for budget and tax policy decision making. Thus the last month or so of the current year's data must be estimated prior to making the annual forecasts. We assume that this estimate is easily made without much consequence to forecast accuracy and concentrate on the annual forecasts. Forecasts made for two and three years ahead are used in planning future expenditure patterns and tax rates (Schroeder 1982).

If we denote the forecast origin (i.e., the last historical data poing) as t, then the general form of relationship to be forecasted is as follows:

$$(\text{Revenue Receipts})_{t+\triangle} = (\text{Rate})_t \times (\text{Base})_{t+\triangle}. \quad (1)$$

$$(\triangle = 1, 2, \cdots)$$

This shows that the fee or tax rate is a decision variable set prior to the end of year t; however, the base (e.g., total sales or earned income)is exogenous and occurs in future year $t+\triangle$. Thus the quantity to forecast is the base.[5]

The property tax forecasting problem follows the same general form as (1), but has more components to consider:

$$(\text{Property tax Receipts})_{t+\triangle} =$$

$$(\text{Tax Lavy})_{t+\triangle} \times (\text{Property Tax Annual Change Factor})_{t+\triangle} \quad (2)$$

where

$$(\text{Market Value})_{t+\triangle} \text{ and}$$

$$(\text{Property Tax Annual Change Factor})_{t+\triangle} = (\text{Collection Rate}) \times$$

$$(\text{Annual Change in Market Value})_{t+\triangle}. \quad (3)$$

There is one major decision variable, the tax rate (or "millage"), which is increased periodically (e.g., on the order of every two to three years in Allegheny County, Pennsylvania) to keep up with inflation and changing expense needs.[6] The assessment ratio is a factor between zero and one that changes infrequently; for example, in the 15 years of school district data used below, it changed only once(and as part of a court case decision), from 0.50 to 0.25. The tax base is the total market value of real properties, and this changes only at discrete points in time, every two to four years, when properties are reassessed. The product of the market value and assessment ratio yields the "assessed value."

The total market value established at time t remains in effect during $t+1$, because property reassessment is a lengthy process and property tax bills are sent out early in the fiscal year. Thus $(\text{Market Value})_{t+\triangle}$ is known for $\triangle=1$ but must be forecasted for $\triangle>1$ with $\triangle-1$ step-ahead forecast. Properties may go severdal years without reassessment, so the forecast here is "lumpy," either no change or a step jump in level. For example, Figure 1 shows the assessed value for the Avonworth School District which is on the Ohio River just west of Pittsburgh, Pennsylvania. This is a residential district with no major industries. It had reassessments roughly every three years over

5) Note that the rate set at t may vary with $\triangle$. Also, the base may be treated as a policy variable. Its definition can be changed according to policies.

6) Again, this policy variables may vary with $\triangle$.

the past 15 years, as have the remaining 41 school districts and 132 municipalities in this area.

Besides changes in the market value due to major reassessments, there can be annual changes during t+1 and more distant years as new properties are added, existing properties are taken off the taxable base, properties are reassessed upon their sale, or taxes are reduced by owner challenges to the accuracy of assessments. These changes, which we have expressed as a multiplicative factor (near 1.0 in value), need to be forecasted. Another factor that needs to be forecasted is the collection rate for the coming year and beyond. A few percent of levied taxes will be in arrearage, the complement of which, expressed as a fraction, is the collection rate. Data on the product of this and the previous factor to be forecasted; i.e., the Property Tax Annual Change Factor, are easily obtained by dividing actual tax collections by the corresponding levy. This is the only quantity to forecast for the budget forecast of one year ahead.

An important aspect of local government revenue forecasting is that the scale of local economies is small enough that discrete events can drastically impact the time series to be forecasted. For example, Figure 2 is plot of sales tax collections from Wood River, Illinois between 1978 and 1986.[7] In 1981 a new shopping center opened, causing an economic boom (during a national recession). Unfortunately the town's largest employer, an AMOCO refinery, closed in 1983, causing a bust (during a period of national economic recovery). Note the diamonds to the right of dashed lines in this figure are counter-factual forecasts for the year of special events, made by the method of average first differences described below, showing what would have happened had there been no special events. Also shown as plus signs are the actual budget forecasts for 1982 through 1986. A consultant made the very accurate 1983 forecast. After 1983 local officials apparently forecasted conservatively in the face of economic uncertainty.

Ⅲ. Proposed Forecasting Approach and Methods

This section provides a decomposition of local government revenue time series into two parts: time series extrapolations and event-driven predictions. This is followed by a discussion of time series techniques appropriate for the resulting short time series of pattern steady states.

3.1 Decomposition of the Forecasting Problem

We define a pattern steady state to be a time interval for a time series during which a level or smooth time trend exists. The underlying pattern can be a constant, straight line, or a monotonic co-

7) The author is indebted to Professor Dennis Hostetler of Southern Illinois University for providing these data.

nvex/concave curve. When a turning point, discontinuity, or distinct change in slope occurs a new pattern steady state arises. We define an outlier to be anomalous data point which departs temporally from a pattern steady state; i.e., the the time series resumes the trend of the pattern steady state after one or more outliers occur. Examples of outliers are windfall, one time tax collections due to unusual business transactions, or for water user fees, an unusually dry summer leading to abnormally high water consumption and water bills.

Local government officials are able to become experts on their economies. Local economies have relatively few major firms and other organizations large enough to change a pattern state. Many special events have "leading indicators" such as construction for a new office complex or layoffs prior to a plant closing. In some cases local governments negotiate the timing of future special events, such as a delayed and staged decline in assessed property values for closed plants. An example is in Figure 2, where Wood River, Illinois officials knew in 1982 that the Amoco refinery would close in 1983 and then made an accurate forecast for 1983. Thus, practitioners can accurately predict the persistence or change of a pattern steady state for the one-year-ahead budget forecast. Moreover, they can describe the qualitative effect of a given future special event on tax collections (e.g., step jump increase or decrease in time trend slope). For longer horizons of one to two years, we believe that practitioners can readily generate scenarios relevant for policy analyses.

Practitioners, however, cannot readily predict the magnitude of a special event's impact on tax or fee collections. Besides the direct impact of an event (e.g., direct loss of jobs or property tax base), there are indirect, multiplier effects and other complications. Hence, we propose to construct special event databases describing historical events and their timing (Gorr 1986a and 1986b, Makridakis and Wheelwright 1989) and to build models isolating and quantifying their impacts (e.g., tax dollars lost per year per job lost or tax dollars added per year per 1000 square feet of retail showroom space added). These will be regional databases with data collection across several similar local governments, such as school districts, to permit adequate special event sample sizes. A future paper will report on our efforts on this endeavor.

3.2 Forecast Methods

As is common in empirical research on forecasting, we include random walk forecasts (in which the last available non-outlier data point is taken as the forecast over the entire forecast horizon) as a benchmark. For a time series method to be acceptable, its forecast performance has to be significantly better than this benchmark.

Methods using first differences provide one the simplest approaches for forecasting time series with a trend. One rationale for such methods here comes from the observation that the residuals within pattern steady states are generally small compared to the trend component. This suggests that it may not be important to have forecasts "depart" from an estimate of the mean time trend. Instead, it may be sufficient to use the last data point as the basis of a forecast and add to it the appropriate multiple of a slope estimate for a corresponding forecast. This motivates a family of first difference estimators that use the differences of adjacent data points in any relevant steady states as observations of the slope. Variations possible, in addition to average first differences, are smoothed first differences (which use automatic simple exponential smoothing on the time series of first differences)and the "last first difference" (which used the last observed first difference as the slope estimate). Except for not having a judgmental adjustment step, the last first difference method is representative of the "percentage increase" method used by many local government practitioners.

Complex, data intensive techniques such as the Box−Jenkins family of models or Bayesian forecasting methods (Harrison and Stevens 1971) are clearly inappropriate for the local government context. Instead, very simple methods are appropriate because sample sizes are very limited (e.g. five to ten years in a pattern steady state) and the decomposed forecasting problem is simple. We thus propose linear time trend regression estimated via ordinary least squares and automatic Holt exponential smoothing (using a grid search over the level and slope smoothing factor space to optimize the mean squared one−step−ahead forecast errors). These two methods represent the spectrum from long−memory methods that weight each data point equally and to short−memory methods that weight recent data more heavily. For time series without a trend, we propose simple arithmetic averages.

Ⅳ. Experimental Designs

This paper has two experiments conducted in sequence, each with its own independent data set. The first has the purpose of determining 1) the most accurate time series methods for extrapolating pattern steady states and 2) the effect sample size has on forecast accuracy. Extrapolative forecasts are necessary both when the current pattern steady state is forecasted to persist and when a state change is forecasted as the counterfactual basis for making judgmental adjustments. The second experiment's purpose is to compare the forecast accuracy of the best time series methods of the first experiment with real budget forecasts made in practice. This makes good use of the two datasets that we have collected: the first has long time series but no actual budget forecasts and the second has shorter series but also budget forecasts. Moreover, it provides a simple and compelling contrast of best time series methods versus practitioners' actual budget forecasts using paired comparisons. The second experiment also replicates tests on the effect of sample size on forecast accuracy, albeit over a shorter range of sample sizes.

In order to obtain sufficient sample sizes of annual forecast errors, it is necessary to use cross-sectional time series data from several governments. Fortunately local governments (e.g., cities and school districts) in the same state are often bound by the same set of statutes and rules on financial data reporting, so it is readily possible to obtain consistent and comparable data from hundreds of separate entities. For example, the school district data used in this study is based on a common chart of accounts and is sent annually by school districts to the Pennsylvania Department of Education in audited reports where we collected it.

4.1 The Frist Experiment

A rolling horizon design is used with forecasts made in parallel using the following methods:

1. Random Walk (RW),
2. Simple Arithmetic Average (AVE),
3. Last First Difference (LFD),
4. Average First Differences (AFD),
5. Linear Time Regression (TR), and
6. Automatic Holt (HLT).

For a given pattern steady state and forecast orign, models are estimated with the data existing at and prior to the origin. Then forecasts are made and compared to actual values from hold-out samples. Note that any hold-out sample in the experiment has data points that are members of the same pattern steady state as the historical data used in making the forecasts.

Starting with two or three as the minimum number of data points, depending on the type of series being forecasted, all models are estimated and annual forecasts are made in parallel over a three year horizon. Then an additional data point is added to the end of the historical series, models are re-estimated, and three new forecasts made over the rolled-forward horizon. This process is continued until there are no more data left for a hold out sample (the minimum holdout sample is one). For each forecast made, an ex ante error is computed by subtracting the forecast from the actual value of the time series. This process is used on each pattern steady state in the sample.[8] Note that outliers are excluded from the historical data but included in hold-out samples. We recommend screening the historical data and excluding outliers prior to model extimation.

Data were collected for a random sample of 25 small cities (under 50,000 population in 1961) in Pennsylvania over a 26 year period (1961−1985).[9] Two quantities were chosen for forecasting: earned income tax collections and the property tax annual change factor, equation (3). The first generally has an increasing trend and the second fluctuates around a mean with some drifting. Earned income tax rates have been nearly constant in Pennsylvania due to fixed state ceilings; thus, the earned income tax data are representative of the tax base.

No special event data were collected on assignable causes of pattern steady state changes. Instead we had three judges independently identify pattern steady states and outliers based on visual inspection of the time series plots. This was straightforward because pattern steady state changes are large. Ambiguous transitional data points were left unclassified for purposes of these experiments. This process resulted in 52 pattern steady states with 15 outliers for the earned income tax and 26 pattern steady states and no outliers for the annual property tax change (i.e., no state changes were detected for the latter variable). The 25% fractile, median, and 75% fractile lengths of steady states for the earned income tax are 7.0, 10.5, and 15 years respectively.

4.2 The Second Experiment

This experiment investigates one−year−ahead budget forecasts for earned income tax receipts, the property tax annual change factor, and an aggregate of other local revenue sources using data obtained from the Pennsylvania Department of Education. We collected 15 years of annual tax revenue data (1972−1986) for the 42 school districts of Allegheny County, Pennsylvania, excluding the large City of Pittsburgh School District. For the last five years of these series (1982−1986), we also collected the budget forecasts for each revenue source actually used in budgeting. Two school districts had missing data for the budget forecasts, so there are 200 budget forecasts in total.

8) Another design would yield more observations on sample size relative to forecast accuracy, but at the expense of introducing complex forms of serial correlation. This alternative would make multiple forecasts from the same forecast origin, varying the number of historical data points by iteratively dropping the earliest data points until the minimum size historical data set of two or three was reached. We rejected this design in favor of the simple rolling horizon experiment because we can easily use generalized least squares regression analysis to control for the latter's serial correlation.

9) Pennsylvania Local Government Financial Statistics, Pennsylvania Department of Community Affairs, Harrisburg, 1961−1985. The cities are: Arnold, Beaver Falls, Bradford, Butler, Carbondale, Clairton, Connellsvile, Corry, Easton, Farrell, Greensburgh, Jeannette, Lock Haven, Lower Burrell, Meadville, Monessen, Monongahela, New Castle, New Kensington, Pottsville, Shamokin, Sharon, Titusville, Washington, and Williamsport.

We use the best time series methods determined from the first experiment: simple averages for the property tax annual change since it does not have a trend and average first differences method for the earned income tax and other revenues variables since these series do have time trends. To make a fair comparison of objective and practitioners' forecasts, it is necessary to generate rule-based objective forecasts using only "historical data." For example, if at one point in the experiment we have the simulated forecast origin (i.e., last historical data point) for a given school district at 1983 and we wish to forecast 1984's revenues, only 1983 and prior data may be used in generating the forecast.

The property tax annual change is simple because it does not have state changes. Thus we merely use all available historical data points to compute an average for a forecast. The other two variables are complicated, however, since they have numerous state changes. The rules incorporate the average first differences forecast technique and use data from steady states prior to the current one for estimating time trend slopes, if necessary to obtain at least three first differences (equivalent to four data points), under the assumption that state changes are step jumps affecting a time series's level but not slope. The rules also contain an objective means of identifying pattern steady state changes in the historical data used for estimation. The rules do not include special event adjustments for forecasts. They only extrapolate the current steady state; thus, if there is a state change in the forecast period, the forecast will be very much in error. To control for this we simply report forecast error summaries by whether or not forecasted data points are state change points. The rules were generated using only the first ten data points of the school district data (1972-1981), which do not include any hold-out sample data. See the Appendix for details.

4.3 Forecast Error Model Specification

The overall comparisons of forecast methods in terms of forecast accuracy presented below use a simple t-test or multiple comparisons of means test. A comparison including the effect of sample size, however, requires a multivariate model specification. The dependent variable for this model is the absolute percentage forecast error (APE) computed as

$$APE_t = 100x\ (X_t - F_t)\ /\ X_t \qquad (4)$$

where

X_t = actual value and

F_t = forecasted value.

This measure has the advantage of not being effected by the scale of the data, which varies substantially in the cross−sectional data of this experiment. Note that an analysis of bias, as measured say by the mean percentage error, requires model building and analysis beyond the scope of this paper (e.g., see Larkey and Smith 1989 and Cassidy et al. 1989) and so will be left to a future paper.

Rather than imposing a functonal form on the sample size term of the model (e.g., a quardratic function), we chose the more robust approach of using dummy variables. The large sample sizes available permit this, thus we use the following variables:

$$D_t = \begin{cases} 1 & \text{if sample size is } j\ (j=p,\cdots,pq) \\ 0 & \text{otherwise} \end{cases}$$

Where p is 1,2, or 3 depending on circumstance and q is as high as 10. The base case of $j>q$ is suppressed in regressions.

Two other factors are included in the model. One is randomness (Makridakis and Hibon 1979) which controls for the inherent difficulty of forecasting a series. The measure used here is LMAPE, the MAPE of the fit residuals from time based linear trend regression, estimated via ordinary least squares. This measure is computed for each forecast origin of each pattern steady state in the experiment. LMAPE is useful in specifying the scope of the experiment; i.e., if the LMAPE of a new case is within the range covered by the experiment, then the experimental results likely apply to the new case.

The second factor, also in the randomness family of indicators, is a dummy variable indicating whether or not a particular forecasted data point is an outlier, as determined by judges who classified the data:

$$OUTLIER_t = \begin{cases} 1 & \text{if } X_t \text{ is an outlier} \\ 0 & \text{otherwise.} \end{cases}$$

This variable's estimated coefficient provides the average impact of an outlier on the forecast MAPE.

In summary, the forecast error model specified in this section is:

$$APE = \beta_0 + \beta_p D_p + \beta_q D_q + \beta_{q+1}\,LMAPE + \beta_{q+1}\,OUTLIER + \varepsilon, \quad (5)$$

where ϵ is the classical disturbance term.

V. Results

5.1 The Best Time Series Methods for Pattern Steady States

Table 2 presents a multiple comparison of MAPE forecast accuracy from the first experiment, comparing alternative time series methods for forecasting pattern steady states. Each step ahead of forecast, 1−3, has separate MAPEs reported by time series method. These are arranged in increasing order from left to right with underlining indicating groups of methods significantly different from each other, but homogeneous within groups. The use of a step−down multiple stage F test maintains the overall error rate of the multiple comparisons to. 05.

All methods and series in Table 2 show the classical decrease of forecast accuracy with step ahead. Looking at the first column in this table, containing the most accurate forecasts of the experiment, we see that forecasts for the earned income tax start with a MAPE of 5.9% for the budget forecast, increase to 7.5% for the second step ahead and then 8.6% for the third. Forecast accuracy is much better for the property tax annual change, with little decrease with step ahead. It starts at 1.9%, progresses to 2.0%, and then 2.2%.

Average first differences and time regression are best for each of the three forecast horizons of the earned income tax forecasts, on the average about 25% more accurate than the next best group consisting of Holt smoothing and the random walk. The earned income tax data has an increasing time trend, thus the simple average estimates a misspecified model for this series. This explains its poor performance, with MAPEs about three times that of the best two methods. The last first difference method, closest to the practitioners' "percentage increase" method, is the worst correctly specified method. The average first differences and time regression methods are approximately 30 to 50 % more accurate than the last first difference(and significantly so), with the gap widening with the step ahead of the forecast. Apparently first differences need to be averaged to eliminate noise and accurately estimate time trend slopes. Given this finding, we expect practitioners to do poorly in comparison to the average first differences or time regression methods.

Based on these results, we recommend using average first differences for forecasting pattern steady states with time trends and LMAPEs up to 10% (the scops of this experiment). While time regression provides accuracy equivalent to average first differences in the experiments, its lacks the flexibility to readily incorporate the forecaster's judgment and data from earlier steady states of the same series.

Forecast accuracy is not as widely different across methods for the property tax annual change, which generally does not have a trend. Here the simple average does estimate a correctly-specified model and so, on a comparison of MAPE values only, is the best method. Time regression, the random walk, and average first differences, however, are not significantly less accurate. Holt smoothing and the last first difference method are significantly worse than the simple average. The simple average is typically 50% better than the last first difference.

Based on the results for the property tax annual change, we thus recommend the simple average as an objective forecast method for cases with no time trend and LMAPES up to 2.5%. The random walk may be preferable during volatile periods in the economy, say after turning points, but this determination is left for future research.

Table 3 presents the results of applying forecast error model (5) to the earned income tax data by time series method for first-step-ahead forecasts. Results for the second and third-step-ahead forecasts are qualitatively similar and so, given space limitations, are not reported here. The major difference is that the magnitudes of coefficients increase as the forecast horizon lengthens and forecast errors increase, but the pattern of significant coefficients remains nearly the same. Three is the minimum number of historical data points used in model estimation in this case, so $p=3$. The number of cases in the experiment with 11 historical data points, 12, etc. up to 25 is small for each sample size. Thus we made the base case to be $q>10$ historical data points, which in aggregate does have a sufficient number of data points for estimation of the intercept. The OLS or GLS estimates in Table 3 are significant, as indicated by the overall F-tests, and are free of first-order serial correlation as indicated by the Durbin-Watson test.

The randomness variable, LMAPE, is positive and significant for every time series method, indicating that indeed some series are inherently more difficult to forecast than others as indicated by randomness. Also, the OUTLIER variable is positive and significant at the .05 error rate level, indicating that outliers typically add 10 to 13 forecast MAPE percentage points. The remarkable result in this table, however, is for the D_j variables on historical data sample sizes: sample sizes of only six years or more provide optimal accuracy. Forecast MAPEs generally decrease with increasing sample size. For average first differences, a sample size of three typically yields 4.12 higher MAPE percentage points than does a sample size of 11 or more; a sample size of four yields an increase of 2.21. While both of the previous two estimates are statistically significant at conventional levels, the estimated value for β_5, 1.38, is not with a t-value of 1.48. Nevertheless, we suggest six data points as optimal for this method. Performance with varying sample sizes for the time trend regression method are quite similar to that of average first differences. The Holt method, however, needs nine or more data points, which may explain its relatively poor forecast accuracy in comparison to average first differences and time regressions. Of course, the random walk and last first difference only use one and two data points respectively for estimation and so do not have performance varying with sample size.

Table 4 presents the forecast error model results for the first-step-ahead forecast of the property tax annual change variable. Again the LMAPE and OUTLIER variables are positive and significant. The major result, however, is on sample size for the recommended method for series without a time trend, the simple average: four or more historical data points provides optimal budget forecast accuracy. For this table, we have reclassified the random walk as the simple average with a sample size of one (i.e., the case where $D_1=1$ under the simple average), and have made forecasts with the simple average using two historical data points ($D_2=1$). This provides a continuum of sample sizes of 1 to 10 years for the simple average method. The coefficient for D_1 is 1.24 and significant and the coefficients for D_2 and D_3 are 0.45 and 0.48 respectively, while not significant, have t-statistics in excess of 1.2. The results for the two and three-step-ahead forecasts are similar.

5.2 Comparison of Time Series and Actual Budget Forecasts

Table 5 contains the results of applying the rules described in the Appendix of this paper to the school district revenue time series data. The first column contains forecast MAPEs attained by the rules versus practitioners for cases where the most recent pattern steady state of the historical period persisted into the forecast period. Here we expect the rule-based forecasts to be more accurate and they are: 47%, 20%, and 39% more accurate than the practitioners' forecasts for the earned income tax, annual property change, and other revenues respectively. Furthermore, t-tests of paired differences show all of these differences to be highly statistically significant.

The second column contains the results for the cases where the forecasted data point is a state change point. Recall that the annual property tax change does not have state changes, so there are no entries for this variable in this column. Note that the MAPEs in this column are on the order of two to five times those in the first column, a pattern expected due to the large changes in the time series here. Also note that 36 out of 200 earned income tax data points (18%) are state change points and 41 out of 199 other revenue data points (21%) are state change points. So, roughly 20% of the time the practitioners faced difficult forecasting conditions of state changes for these two revenues. If the practitioners judgmentally adjusted their forecasts and did so successfully, we would then expect their forecasts to be more accurate than the rule-based forecasts. There is evidence that this is the case. The practitioners are 22% more accurate on the earned income tax forecasts and 38% so on the other revenues forecasts. These differences are statistically significant, but at lower levels than those for the persistence case.

A caveat of these results is that there are two sources of inaccuracy for the practitioners. First, they may have sizable forecast errors due to uncertainty or poor forecast procedures. Second, they may be intentionally biasing forecasts for managerial or political reasons (e.g., Cassidy et al. 1989 or Larkey and Smith 1989). A future paper will attempt to sort the effects of these two causes of poor accuracy using a forecast error model with the mean percentage forecast error as the dependent variable.

VI. Conclusion

The economies of local governments are small enough that plant closings, shopping mall openings, and other special events change the patterns of tax fee collections time series. Practitioners, with a high degree of confidence, know what special events will occur in the next year and the direction of their impacts, but need support for estimating the magnitude of impacts on revenues. Thus the local government revenue forecasting has two separable components: 1) extrapolation of the current pattern steady state and 2) prediction of adjustments to extrapolations to account for special events that are known will occur during the forecast period. This paper has focused on the first of these two components. Accurate extrapolations are valuable as counterfactuals as a basis for making special event adjustments when the forecast period is forecasted to have a special event, and they are valuable when policy makers decide to bias forecasts as the reference point for making the bias. This paper has produced the following results on local government revenue forecasting:

1) For variables that have a trend, time regression estimated via OLS or multiples of average first differences added to the last historical data point are the most accurate methods. Automatic Holt and other methods are significantly less accurate.
2) For variables that drift but do not have a trend, the simple average is the most accurate method among those tried.
3) Forecast accuracy of time series methods follows the classical pattern of decreasing as the horizon increases.
4) Only four to six historical annual data points are needed for optimum budget forecast accuracy. More data points may add slightly to forecast accuracy, but instances with fewer have

rapidly degrading forecast accuracy.

5) The simplest time series techniques (simple averages and average first differences) are 20 to 47% more accurate than practitioners's actual budget forecasts for cases where there is no pattern steady state change in the forecast period. The practitioners may have relatively large forecast errors due to either poor forecast methods or intentional biases serving managerial or political purposes.

6) The practitioners are 22 to 38% more accurate than the time series techniques when the forecast period is a state change point (e.g. is a step jump). In this event the time series forecasts provide counterfactual cases, so we have evidence that practitioners improve their forecasts with judgmental adjustments.

Plans for future research are threefold. First, we plan to adapt the Bretschneider/Gorr (1987, 1989) forecast error model from the state level to the small local government level of analysis. This research will attempt to see if political, organizational, fiscal stress, and other variables can explain variations in school district practitioners' forecast accuracy and bias. Second, we plan to write a paper on the construction of special event prediction models and a database and for the Allegheny County school districts. Third, and lastly, we plan to construct and implement a school district decision support system for revenue forecasting and evaluate it in the field.

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APPENDIX

Rule−Based Forecasts for Experiment 2

Suppose that we have a time series, $X_1, \cdots, X_T$ The *i*th pattern steady state of this series, S_i, $(i=1,\cdots)$ is a sub−series, $X_{i_o} \cdots, X_{i_f}$ where $i_o \geq 1$ and $i_f \leq T$. The intersection of all pattern steady states of a time series is the null set. Let $n_i = i_f - i_o + 1$ be the number of data points in S_i. We require $n_i \geq 2$ for S_i to be a pattern steady state. Given $X_{t-1} \in S_i$ and a forecast X^F_t determined by the rules given below, if

$|(X_t - X^F_t)/X_t| < \triangle$ then $X_t \in S_i$; otherwise, X_t is a candidate for membership in S_{i+1}. The parameter $\triangle$ is specified using expert judgment.[10)]

Suppose that t is the forecast origin (last historical data point for use in estimation) and $X_t \in S_i$.

10) The value of $\triangle$ is chosen to be 0.1 for the earned income tax time series and 0.2 for the "other" revenue time series of the school district case. These values replicate judgmental assessments of pattern steady states for the first 10 data points of the 42 series. The last five data points, used as hold−out data for forecast experiments, were not included in the selection of these values.

The one−step−ahead budget forecast model is $X^F_{t+1}=X_t+b$ where b is a time slope to be estimated by average first differences. Let $b_i=(X_{if}-X_{io})/(i_f-i_o)$ be the average first difference of S_i and $b_{it}=(X_{it}-X_{io})/n_{it}$, where $n_i=(t-i_o)$, the average first difference of data points up through t in S_i. Then for $i_f \le t \le i_o$ we have the following rules for

estimating b:

1. If $n_{it} \ge 4$ then $b=b_{it}$.
2. If $n_{it}=2$ then $b=2b_{it}/3+b_{i-1}/3$.
3. If $n_{it}=2$ and $n_{i-1}\ge 3$ then $b=b_{it}/3+2b_{i-1}/3$.
4. If $n_{it}=2$ and $n_{i-1}=2$ and S_{i-2} exists then $b=b_{it}/3+b_{i1}/3+b_{i2}/3$.
5. If $n_{it}=1$ and $n_{i-1}\ge 4$ then $b=b_{i-1}$.
6. If $n_{it}=1$ and $n_{it}=3$ then $2b_{i-1}/3+b_{i-2}/3$
7. If $n_{it}=1$ and $n_{i-1}=2$ and $n_{i-2}\ge 3$ then $b=b_{i-1}/3+2b_{i-2}/3$.
8. If $n_{it}=1$ and $n_{i-1}=2$ and $n_{i-2}=2$ and S_{i-3} exists then $b=b_{i-1}/3+b_{i-2}/3+b_{i-3}/3$.
9. If there are more than three consecutive data points at the end of the historical time series failing to belong to pattern steady states, then use a random walk forecast.
10. If none of the rules fire, then use a fandom walk forecast.

The principle behind these rules is that an estimate of b should be the average of at least three first differences. If the historical data in the current steady state number less than 4, then use weighted estimates including average first differences from prior steady states.

estimating b:

1. If $n_{it}\ge 4$ then $b=b_{it}$.
2. If $n_{it}=3$ then $b=2b_{it}/3+b_{i-1}/3$.
3. If $n_{it}=2$ and $n_{i-1}\ge 3$ then $b=b_{it}/3+2b_{i-1}/3$.
4. If $n_{it}=2$ and $n_{i-1}=2$ and S_{i-2} exists then $b=b_{it}/3+b_{i1}/3+b_{i2}/3$.
5. If $n_{it}=1$ and $n_{i-1}\ge 4$ then $b=b_{i-1}$.
6. If $n_{it}=1$ and $n_{i-1}=3$ then $2b_{i-1}/3+b_{i-2}/3$.
7. If $n_{it}=1$ and $n_{i-1}=2$ and $n_{i-2}\ge 3$ then $b=b_{i-1}/3+2b_{i-2}/3$.
8. If $n_{it}=1$ and $n_{i-1}=2$ and $n_{i-2}=2$ and S_{i-3} exists then $b=b_{i-1}/3+b_{i-2}/3+b_{i-3}/3$.
9. If there are more than three consecutive data points at the end of the historical time series

failing to belong to pattern steady states, then use a random walk forecast.

10. If none of the rules fire, then use a random walk forecast.

The principle behind these rules is that an estimate of b should be the average of at least three first differences. If the historical data in the current steady state number less than 4, then use weighted estimates including average first differences from prior steady states.

Table 1

Percentage Distribution of General Revenues Collected by Types of Local Government, 1981－82.

Revenue Source	Counties	Munici-palities	Townships	School Districts	Special Districts
Property Tax	45.9	32.7	74.6	78.4	14.6
Fees	2.5	21.0	9.2	9.5	56.1
Sales/Gross Receipts Taxes	9.5	17.1	0.2	1.0	3.4
Interest Earnings	8.2	8.5	5.7	5.9	16.1
Other	6.9	8.4	5.6	3.6	9.5
Income Tax	1.7	8.3	2.0	0.8	—
Licenses	2.3	4.0	2.8	0.8	0.3
	100.0	100.0	100.0	100.0	100.0

Source: U. S. Department of Commerce, Bureau of the Census, 1982 Census of Governments, Vol. 4, Governmental Finances, no. 5, Compendium of Governmental Finances (Washington, D. C.: GPO, 1984), p. 4.

Table 2

Multiple Comparisons of MAPE Forecast Accuracy: Random Sample of 25 Small Cities in Pennsylvania.

Earned Income Tax

Step 1	AFD	TR	RW	HLT	LFD	AVE
(n=380)	5.9	5.9	6.8	7.6	8.1	18.7
Step 2	TR	AFD	HLT	RW	LFD	AVE
(n=332)	7.5	7.5	10.2	10.6	12.7	22.2
Step 3	AFD	TR	HLT	RW	LFD	AVE
(n=282)	8.6	8.8	12.3	14.4	16.7	25.6

Property Tax Annual Change

Step 1	AVE	TR	RW	AFD	HLT	LFD
(n=486)	1.9	2.0	2.1	2.2	2.6	3.2
Step 2	AVE	RW	TR	AFD	HLT	LFD
(n=463)	2.0	2.2	2.3	2.4	3.3	4.5
Step 3	AVE	RW	TR	AFD	HLT	LFD
(n=439)	2.2	2.5	2.6	3.0	4.2	6.4

AFD = Average first differences
AVE = Simple Average
HLT = Holt Smoothing
LFD = Last First Difference
RW = Random Walk
TR = Time Regression

[1]A step-down multiple stage F test, REGWF in SAS, is used to carry the tests. The maximum experimentwise error rate is 0.05. Underlined methods are homogeneous subsets)

Table 3

Pennsylvania Sample of Small Cities Forecast Error Model Estimates: First−Step−Ahead Forecasts for Earned Income Tax, N=380

(Shown are Coefficient Estimates with t−statistics in parentheses).

Dependent variable: APE

Method	AFD	TR	HLT	RW	LFD
Estimation	OLS	OLS	OLS	OLS	GLS
Adj. $\bar{R}^2$	0.31	0.31	0.30	0.18	0.35
F−Value	17.90	18.27	17.01	43.24	201.38
Prob.>F	0.0001	0.0001	0.0001	0.0001	0.0001
DW Statistic	1.86	2.06	1.94	1.96	2.03
Intercept	1.85	1.83	−2.53	4.90	4.54
	(2.76)	(2.72)	(−1.91)	(12.31)	(6.92)
D_3	4.12	4.26	13.66		
	(4.50)	(4.65)	(7.55)		
D_4	2.21	2.27	5.80		
	(2.43)	(2.50)	(3.22)		
D_5	1.38	2.09	3.86		
	(1.48)	(2.24)	(2.09)		
D_6	0.10	0.60	2.42		
	(0.11)	(0.61)	(1.26)		
D_7	0.10	0.68	0.56		
	(0.10)	(0.66)	(0.28)		
D_8	1.34	−0.73	2.48		
	(1.25)	(−0.68)	(1.17)		
D_9	0.25	−0.45	0.57		
	(0.23)	(−0.41)	(0.27)		
D_{10}	0.51	0.57	1.42		
	(−.45)	(0.49)	(0.62)		
LMAPE*	0.66	0.68	1.69	0.08	0.90
	(8.41)	(8.56)	(10.83)	(5.07)	(6.80)
OUTLIER**	13.02	12.74	10.17	10.91	11.08
	(9.60)	(9.37)	(3.79)	(7.59)	(6.97)

*90% interval for LMAPE is 0.6 to 9.2% with a median of 2.7%

**Mean for Outlier=0.04

Table 4
Pennsylvania Sample of Small Cities Forecest Error Model Estimates:
First－Step－Ahead Forecasts for Property Tax Collection Rate, n＝486
(Shown are Coefficient Estimates with t－statistics in Parentheses).

Dependent variable: APE

Method	AFD	TR	HLT	LFD	AVG
Estimation	OLS	OLS	GLS	OLS	OLS
Adj. $\bar{R}^2$	0.35	0.39	0.30	0.32	0.42
F－Value	26.89	31.6	18.72	115.46	30.08
Prob.＞F	0.0001	0.0001	0.0001	0.0001	0.0001
DW－stat.	1.48	2.00	2.11	1.07	1.87
Intercept	0.34	0.39	－2.72	0.33	0.24
	(1.74)	(2.28)	(－1.90)	(1.40)	(1.44)
D_1					1.24
					(3.26)
D_2					0.45
					(1.21)
D_3	0.67	0.59	13.71		0.48
	(1.52)	(1.54)	(7.33)		(1.31)
D_4	0.52	0.36	5.81		－0.11
	(1.17)	(0.93)	(3.13)		(－0.30)
D_5	0.23	0.47	3.94		-0.37
	(0.51)	(1.21)	(2.07)		(-0.98)
D_6	-0.28	-0.27	2.47		-0.50
	(-0.63)	(-0.70)	(1.25)		(-1.34)
D_7	-0.19	-0.15	-0.63		-0.23
	(-0.42)	(-0.39)	(0.30)		(-0.60)
D_8	-0.25	-0.49	2.42		-0.40
	(-0.81)	(-1.30)	(1.12)		(-1.09)
D_9	0.23	0.43	0.55		-0.28
	(0.52)	(1.09)	(0.25)		(-0.75)
D_{10}	-0.01	0.01	1.39		-0.17
	(-0.02)	(0.04)	(0.61)		(-0.46)
LMAPE*	1.52	1.21	1.73	12.69	1.31
	(11.46)	(10.42)	(10.27)	(14.15)	(11.33)
OUTLIER**	4.12	4.43	10.73	3.08	0.37
	(11.74)	(14.49)	(4.00)	(5.95)	(14.83)

* 90% interval for LMAPE is 0.2 to 2.5% with a median of 0.8%.
* * Mean for outlier＝0.08

Method	AFD	TR	HLT	LFD	AVG

Method	AFD	TR	HLT	RW	LFD

Table 5
Accuracy of Rule−Based Time Series Versus Practitioners' Forecasts:
Allegheny County School Districts' Budget Forecasts, 1982−1986.

	Pattern Steady Status	
	Persistence MAPE p−value	State Change MAPE p−value
Earned Income Tax	(n=164)	(n=36)
Rule−Based	3.3	17.6
Practitioners	6.2	13.7
Differences [1)]	−2.8 (.0001)	3.9 (0.196)
Annual Property Tax Change	(n=200)	
Averages		
Practitioners	1.6	
Differences[1]	2.0	
Other Local Revenues	−0.5 (0.003)	
Rule−Based	(n=158)	(n=41)
Practitioners	10.0	45.0
Differences[1]	16.4	28.1
	−5.8 (.0001)	17.4 (.0943)

1) Differences of matched pairs.

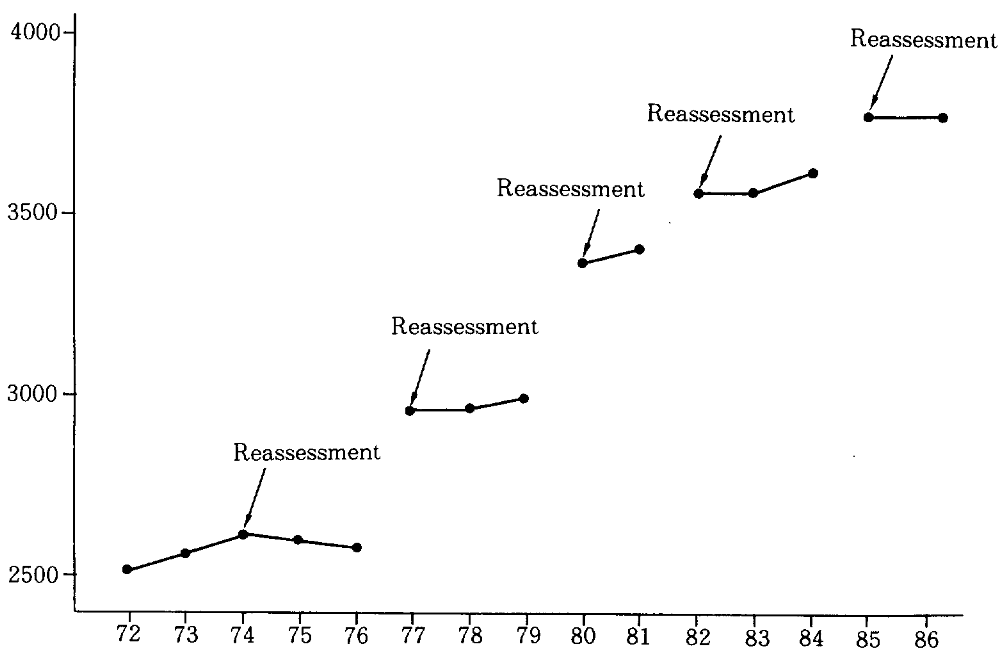

Figure 1. Annotated Time Series Plot of Assessed Froperty
Values for the Avonworth Pennsylvania School District

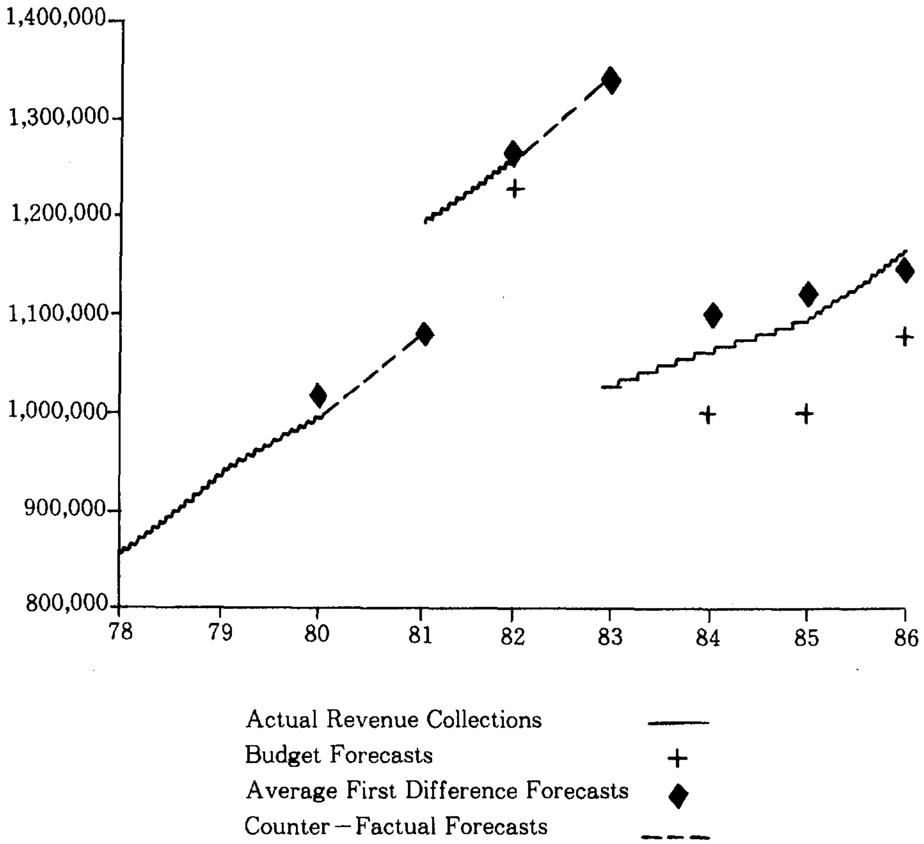

Figure 2. Annotated Time Series Plot of Sales Tax Collections for Wood River, Illinois.

New Shopping Center

Refinery Closed

<國文抄錄>

地方政府의 稅入豫測을 위한 方法

이 영 희

우리나라에서 실시를 목전에 두고 있는 地方自治制는 地方化時代의 도래와 더불어 地方財政體制에 일대변혁을 가져오게 될 것이다. 크게는 각도와 직할시, 작게는 시와 군까지 모든 地方自治團體는 현재 中央으로부터 받고있는 統制를 벗어나 자율적인 豫算編成과 稅入豫測을 하여야 할 것이다. 본 논문은 이미 地方自治가 굳건한 체계를 갖추고 있는 미국 地方政府의 稅入豫測을 위한 方法과 過程을 논하고 아울러 보다낳은 改善方案을 제시하고자 한다.

地方政府의 경제상황은 주민들의 소득, 판매 또는 부동산가액 등에 따라 많은 영향을 받는데 특히 공장폐쇄나 백화점등의 쇼핑센터 개점 등은 해당지방 당회기년도의 稅入豫算에 커다란 변화를 준다. 이러한 불규칙한 영향으로 인한 과거 시계열 자료의 不連續性(discontinuitios)은 기존의 豫測方法(forocasting method)이나, 計量經濟的 方案(econometric method)만의 사용을 불가능하게 한다.

따라서 본 논문은 地方政府의 상황, 즉 i) 資料의 불연속성 ii)짧은 時系列過去資料 iii)地方公務員의 統計 處理 能力不足을 고려하여 사용가능성이 높고 豫測誤差를 최소화 할 수있는 方法을 제시해 보고자 한다.

우선 地方政府의 稅入 時系列資料를 객관적인 豫測方法이 가능한 부문과 그렇지 못한 부분으로 분리하여 外挿法(extrapolation)을 이용한 方法과 불규칙한 변동(special event)을 豫測할 수 있는 주관적 판단으로 이분하였다. 이분된 時系列資料는 두종류의 地方政府 橫斷面的 時系列(cross-sectional time series) 稅入資料를 이용하여 검증하고 평가하였다.

첫번째 실험은 Pennsylvania州에 있는 임의의 25개 소도시를 대상으로 稅入豫測을 하여 가장 적절한 豫測方法을 선별하였고 두번째 실험은 Pennsylvania州 Allegheny County에 있는 42개의 小地方政府인 學群(School District)을 대상으로 하여 客觀的 方法에 의한 稅入豫測과 實務公務員들이 실제 豫測한 稅入을 비교분석 하였다. 그 결과는 1)가장 간단한 객관적 時系列 方法이 안정된 패턴(pattern steady state)내에서 豫測誤差가 적었고 2)최고 豫測誤差減小를 위해서는 최소한 약 4~6년의 過去資料가 時系列分析方法에 필요하였으며 3)특별한 경기 변동이 없는 상황하에서는 時系列方法을 이용한 豫測이 약 20~40%정도 실무자의 豫測보다 정확하였고 4) 불규칙한 변동이 예상되는 조건하에서는 實務公務員의 稅入豫測이 객관적 時系列 方法에 의한 豫測보다 22~38%보다 더 정확도를 나타내었다.

결론적으로 地方政府의 稅入豫測에 있어 客觀的 豫測方法이 主觀的 판단보다 豫測誤差가 훨씬적었으나 불규칙한 변동이 예상되는 경우에는 時系列方法과 실무자의 사전지식을 병합한 수정에 의한 豫測이 誤差를 최소화 할 수 있었다. 그러므로 意思決定補助시스템(Decision Support System)의 개발이 위와같은 豫測方法을 위해 바람직하다고 생각된다.