Forecasting is very difficult, especially if it is about the future.

—Niels Bohr, Physicist, Nobel Prize winner, 1922
Financial forecasting, which defines a government's financial parameters, is one of the finance officer's most important tasks. Accurate forecasting also forewarns a government about financial imbalances, allowing it to take action before a potential imbalance becomes a crisis, and forecasts can promote discussion about the future and how the organization might develop long-term plans and strategies.

This article describes a step-by-step approach to conducting revenue forecasts in local governments. As Bohr said, forecasting is not easy — but a structured approach can help forecasters ask the right questions, given the environment and audience; use the most appropriate techniques; and apply the lessons from one round of forecasting to future rounds. Structuring the forecasting process provides the following potential advantages:

- Forecasting is easier to replicate each year, leading to greater organizational learning.
- The process is transparent and relatively easy to explain to others, which should make it easier to get others to accept the forecasts.
- Because a structured process encourages the forecaster to adhere to forecasting best practices more diligently than an unstructured method would, the results should be more accurate.

The GFOA has adapted the following forecasting approach from the advice of leading forecast scientists and the experiences of public finance practitioners and academic researchers. It involves the following steps:

1. **Define the Problem.** What issues affect the forecast and presentation?
2. **Gather Information.** Obtain statistical data, along with accumulated judgment and expertise, to support forecasting.
3. **Conduct a Preliminary/Exploratory Analysis.** Examine data to identify major drivers and important trends. This establishes basic familiarity with the revenue being forecast.
4. **Select Methods.** Determine the most appropriate quantitative and qualitative methods.
5. **Implement Methods.** Use the selected methods to make the long-range forecast.

**STEP 1: DEFINE THE PROBLEM**

The first step in the forecasting process is to define the fundamental issues affecting the forecast, providing insight into which forecasting methods are most appropriate and how the forecast is analyzed, as well as providing a common understanding as to the goals of the forecasting process. It will also help the forecasters think about what their audience might be interested in. While each local government will have distinct issues to consider, there are three key questions that all governments should consider as part of Step 1.

**What is the Time Horizon of the Forecast?** The time horizon affects the techniques and approach the forecaster will use. For example, short- and medium-term forecasts demand higher levels of accuracy because they will be used for detailed budgeting decisions. Longer-term forecasts are used for more general planning, not detailed appropriations. Also, some forecasting techniques lend themselves better to shorter-than-longer-term forecasting, and vice versa. Longer-term forecasts will benefit from presentation techniques that emphasize the degree of uncertainty inherent in the forecast and the choices decision makers face.

**Is Our Forecasting Policy Conservative or Objective?** An organization can adopt one of two basic policies on how forecasting will be conducted. A “conservative” approach systematically underestimates revenues to reduce the danger of budgeting more spending than actual revenues will be able to support. An “objective” approach estimates revenues as accurately as possible.

Some public officials prefer conservative forecasts, which reduce the risk of a revenue shortfall. But this kind of forecast can also cause unnecessary fiscal stress during the budget process as the organization closes a fictitious revenue gap. At best, the government will incur opportunity costs, losing out on the benefits that could have been realized from programs and projects not undertaken. At worst, this approach could lead to unnecessary layoffs or other disruptive cuts. Further, overly conservative estimates could lead to lost credibility as budgeting personnel become increasingly weary of the pseudo-financial stress.

The downside of an objective approach is a greater chance of experiencing an actual revenue shortfall during the year...
and, thus, incurring actual fiscal stress during the course of the year, as the budget has to be adjusted. Organizations that pursue an objective policy of revenue estimating should develop policies and practices to guard against these risks, such as budgetary reserve policies and contingency plans.

**Are We in a High or Low Growth Environment?** Land uses underpin the fiscal health of local governments. Forecasters should consider if their community is experiencing:

- High growth and development — the rate of population growth is increasing each year.
- Moderate growth — there is growth, but the rate is declining.
- Low growth — population is declining or flat, or the rate of growth is negligible.

Each of these categories has different implications for the forecast. For example, high-growth communities need to carefully consider the costs and benefits of potential new development, while low-growth communities are usually more concerned with modeling the financial impact of maintaining an aging infrastructure.

**STEP 2: GATHER INFORMATION**

The next step is to gather information supporting the forecasting process, including statistical data and the accumulated expertise of individuals inside and, perhaps, outside the organization.

**Take Stock of Economic Measures.** Economic measures help provide context and might be directly useful in developing revenue assumptions. But first, you’ll need to understand the role of economic measures in forecasting for your community. The foremost question is whether relevant indicators are available. For example, small communities might not match up perfectly with an indicator for a large geographic area — unemployment, for instance. In this case, the indicator could provide context, but it probably wouldn’t be used in forecasting equations.

For other governments, the geographic area covered by the indicator will match the jurisdiction well enough for direct use in forecasting. In this case, consider the quality of the forecast for the indicator. Are credible, reliable future values available? For example, Fairfax County, Virginia, gets estimates of future employment in the area from a third-party economic analysis firm. State and federal government agencies and universities will also often provide estimates of future values for select indicators. The Association for Budgeting and Financial Management maintains a database of state and local economic and financial indicators that can be accessed by the general public.

**Gather Inside and Outside Special Expertise.** The finance officer should access special expertise from both inside and outside of the organization to improve forecasting. People who are not part of the organization can provide technical skills or resources that aren’t available in-house or aren’t economical to maintain, or they can simply provide an outside perspective. One of the most common sources of external expertise is, of course, consultants, which can help with technical skills such as forecasting techniques, computer programs, or even cleaning and preparing historical data. Many governments also find that consultants bring additional credibility to the forecast as impartial, outside experts, and they can help by raising issues that might not be difficult to talk about, otherwise.

Practitioners and researchers advise caution, however, when using consultants. Outside consultants almost never understand the jurisdiction’s unique political and economic circumstances as well as staff does, and this kind of understanding generally leads to the best forecasts. In addition, some consultants specialize in a particular forecasting technique and tend to apply it to all forecasting problems, but the best technique depends on the particulars of the situation. Finally, if a consultant’s technique is too complex for staff to use on their own, staff might not be able to update the forecast on time or adequately explain how the forecast was produced, diminishing credibility.

Staff outside the finance department has information and perspectives that can supplement the forecast, so start accessing this accumulated expertise by holding regular internal meetings to review relevant indicators of economic and revenue. Participants can discuss whether the indicators are important or not, along with the trends shown by the indicators and their potential impact on forecasts.
Keep in mind that group interaction also has certain disadvantages, including the potential for participants to reinforce shared biases or for a dominant participant to take over the proceedings, excluding other points of view. To mitigate these problems, you can survey the people who have relevant expertise to supplement group interactions. The City of Dayton, Ohio, uses a survey to help forecast income tax revenue. Participants receive eight years of historical data, including the percentage change from year to year, and then are asked to estimate final revenues for the current year and the next year. Dayton uses these estimates to supplement other forecasting methods.

**Gather Historical Revenue Data.** Good historical data are essential to good forecasting because past revenue patterns provide clues to future behavior. The first step is to compile revenue data for as many years back as is practical. This will often require scrubbing the data to remove the impact of historical events that reduce their predictive value. For example, Fairfax County factored out a state-provided amnesty period for sales tax evaders that had brought in an additional $1.7 million in revenue. Only the data for the most important revenues need be scrubbed in this manner, and the scrubbed data can be kept in a separate system (a spreadsheet is fine), as modifying data directly in the general ledger would obviously cause problems.

Monthly data are best for mid-term (one to two years) and long-range (three to five years) forecasting. They are essentially for short-term forecasting because monthly data show trends more precisely, whereas more aggregated data such as annual figures can obscure important trends that occur within the year. Also, monthly data show seasonal variation, which is essential for short-term forecasting. If monthly data are not available, quarterly data can be used.

**STEP 3: CONDUCT A PRELIMINARY/EXPLORATORY ANALYSIS**

The objective of this step is to build the forecasters’ familiarity with and feel for the data. Forecasters do better if they have insight into when and what quantitative techniques might be appropriate, and a better feel for the data can be helpful in more qualitative forms of forecasting. Forecasters look for consistent patterns or trends, such as the ones described below.

**Seasonality.** Patterns that have reliably repeated themselves are likely to continue into the future. It might also be necessary to use statistical techniques to “smooth out” seasonality and reveal a long-term trend line. Exhibit 1 shows an example of a seasonal pattern in sales taxes; Colorado Springs, Colorado, sees a jump from holiday spending and increases due to quarterly filings from smaller firms at three other points in the year.

**Business Cycles.** Does the revenue (or expenditure) tend to vary with the level of economic activity in the community, or is it independent of cycles? Sales taxes on luxury goods often vary directly with business cycles, while sales taxes on consumer essentials remain fairly even.

**Outliers.** Extreme values represent highly anomalous events that don’t add to the predictive power of the data set, and they should be scrubbed out. Or they could represent what author Nassim Nicholas Taleb has dubbed “black swan” events — highly unpredictable occurrences that can’t be forecasted but do hold lessons for the future. For instance, the “dot-com” stock market crash of 2001 may have foreshadowed the implications of the housing bust for some localities.

**How Much Is Enough?**

Generally, forecasters should make every effort to gather at least five years of monthly data for forecasting. This is the amount required to get a valid result from most statistical forecasting techniques and to give the forecaster a good sense of the historical trends behind the revenues.
Relationships between Variables. Correlation analysis is useful for determining important relationships between variables that could aid in forecasting. Forecasters use correlation analysis to compare revenues with predictive variables such as economic or demographic statistics, looking for strong relationships that can be used in quantitative forecasting or just to provide additional insight for judgmental forecasts. The most useful statistic is the correlation coefficient, often known simply as “r.” It measures the extent to which two variables move in the same or opposite directions and expresses this movement as a positive or a negative number. An r value of 1.0 is a perfect positive relationship, and -1.0 represents a perfect inverse relationship. A value of a zero indicates no relationship. Generally, an r value of more than 0.8 or less than -0.8 would indicate a relationship worth exploring further.

A limitation of the standard correlation coefficient, however, is that it might not account for a lagging relationship between two variables. For example, enrollment would be a significant driver of tuition fees at a community college. And unemployment is often thought to motivate people to go back to school, so it would presumably have an impact on enrollment, as well. However, people do not typically enroll in a college course immediately after losing a job or failing to find employment. Hence, a correlation analysis of enrollment and regional unemployment figures would probably show a weak correlation for the same time period, but comparing enrollment to unemployment figures from earlier periods might show a stronger correlation.

STEP 4: SELECT METHODS

The next step is to determine the quantitative and/or qualitative forecasting methods to be used. Forecasting research has shown that “statistically sophisticated or complex methods do not necessarily produce more accurate forecasts than simpler ones.” While complex techniques might get more accurate answers in particular cases, simpler techniques tend to perform just as well or better, on average. Also, simpler techniques require less data, less expertise on the part of the forecaster, and less overall effort to use. Further, simpler methods are easier to explain to the audience for the forecast. It makes sense to heed Einstein’s advice and make things “as simple as possible, but not simpler.”

In the spirit of Einstein’s guidance, the GFOA has adapted Exhibit 2 from the work of J. Scott Armstrong. Armstrong originally published a flow chart to guide forecasters through

Why Simple is Better — The Devil is in the Details

Why do simple methods tend to outperform more complex ones? Forecasting science luminary Spyros Makridakis believes it is because complex methods try to find patterns that aren’t really there by creating a tight statistical “fit” to historical data. These false patterns are then projected forward. Conversely, simple methods ignore such patterns and just extrapolate trends.

selecting a technique, across a comprehensive set of possible forecasting circumstances. The GFOA has modified the chart to focus on the circumstances that are most relevant to public-sector financial forecasting and the techniques that appear most practical, given the limited resources available for forecasting that government organizations typically face.

The flow chart begins with the availability of historical data. If data are not available or are in poor condition, expert judgment will likely be the best alternative — generating a number based on your feel for the situation. Research suggests that this is not an ideal approach, however, and that forecasters should always at least develop an algorithm to help guide the forecast. To illustrate, user fee revenue projections would be helped immensely by developing a simple model that multiplies the estimated price per unit sold by the number of customers. A similar approach can be taken for other revenues.

In many cases, and especially for important revenue sources, historical data will be available, and cleaning it up will not be cost prohibitive. Under these circumstances, the next question is about the forecaster’s knowledge of the relationships between the item being forecast and independent variables that help explain that item’s behavior. For example, is there a significant relationship between certain economic indicators and revenue yield? Finding significant relationships can be difficult, especially in small governments, because there aren’t enough locally relevant economic indicators or because contextual events have a big impact on revenue yield. This leads to the question of whether the forecaster has good domain knowledge, or knowledge of the local financial and economic environment, which allows individual expertise to be combined with an extrapolation of historical trends. If you don’t have good domain knowledge, you will likely be better off using extrapolation techniques without judgmental adjustment.
If you do have good knowledge of the relationships between the dependent and independent variables, the next question is whether large changes are expected. In the context of government revenue forecasting, large changes are most likely to occur over a long time period, so econometric methods might be more useful for long-term forecasting. If you do not expect large changes, you are probably better off using extrapolation techniques, perhaps combined with expert judgment, if your domain knowledge is good. The choice between forecasting methods is not always clear cut, and if more than one method appears useful, the results can be combined.

Of course, accuracy is also important when selecting a forecasting method. The GFOA conducted a very basic forecasting experiment with historical sales tax data from seven local governments and income taxes from one, using relatively simple techniques to project revenues 12 months into the future. Econometric forecasting was excluded from the analysis since that technique is generally better suited to longer-term forecasts. The analysis focused on sales tax data, since sales taxes have the reputation of being volatile and, therefore, harder to predict.

Exhibit 3 summarizes the results. Single exponential smoothing, which is a relatively simple extrapolation technique, clearly appears to have the greatest accuracy. It has the lowest percentage of error, and it was tied for the number of times it was the best-performing technique, as well as being a close second in three other cases. And it was never the worst-performing technique, which means that it will often be very accurate and seldom be highly inaccurate. For the entire year, exponential smoothing predicted total revenues within 3 percent five times, and two of those times were within 1 percent. The other techniques tested had varying degrees of success. The premise behind moving average forecasting is similar to that of single exponential smoothing, so it isn’t surprising that moving average forecasting appears to be the second-best technique, overall. The results of time series regression were mixed; on one hand, it was the best-performing technique three times (tied with exponential smoothing), and it predicted annual revenues within 3 percent on three occasions, two of those within 1 percent. On the other hand, it was also the worst-performing technique twice, producing annual errors of 23 percent and 14 percent. In comparison, the worst error produced by exponential smoothing was 11 percent. Simple trending is clearly the worst technique, often producing substantial errors and rarely producing an accurate forecast (although it did produce the best results in one case).

The premise behind moving average forecasting is similar to that of single exponential smoothing, so it isn’t surprising that moving average forecasting appears to be the second-best technique, overall. The results of time series regression were mixed; on one hand, it was the best-performing technique three times (tied with exponential smoothing), and it predicted annual revenues within 3 percent on three occasions, two of those within 1 percent. On the other hand, it was also the worst-performing technique twice, producing annual errors of 23 percent and 14 percent. In comparison, the worst error produced by exponential smoothing was 11 percent. Simple trending is clearly the worst technique, often producing substantial errors and rarely producing an accurate forecast (although it did produce the best results in one case).

Given these results, it would appear that revenue forecasters should always at least consider using single exponential smoothing, which puts a heavier weighting on recent periods; this probably explains its superior performance. Moving averages might present a reasonable secondary option, if single exponential smoothing is too complex to use, for example. Time series regression is also worth considering, but it assumes a linear relation between time and revenue yields, so you must be certain that this assumption holds. It’s also possible that larger governments will experience better results with time series regression, since the diversity of their revenue bases means that there is less variability in their yields, thereby making it easier to “fit” a regression equation to the historical data. Indeed, the largest four governments in the GFOA’s data set had an average error for the year of 3.7 percent, using regression, compared to 9.29 percent for all eight governments. Simple trending should

---

**Exhibit 3: Results of Forecasting Technique Accuracy Experiment**

<table>
<thead>
<tr>
<th></th>
<th>Mean Absolute Percent Error for Months</th>
<th>Average Percent Error for Entire Year</th>
<th>Number of Times It Was Best (of 8)</th>
<th>Number of Times It Was Worst (of 8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single Exponential Smoothing</td>
<td>12.38</td>
<td>4.46</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>12-Month Moving Average</td>
<td>12.68</td>
<td>5.40</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Simple Trending</td>
<td>18.47</td>
<td>13.19</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Time Series Regression</td>
<td>15.39</td>
<td>9.29</td>
<td>3</td>
<td>2</td>
</tr>
</tbody>
</table>

Good historical data are essential to good forecasting because past revenue patterns provide clues to future behavior.
probably be avoided in most cases. Although it did work well in one case, it produced substantial errors in others (more than 40 percent, in two cases).

**STEP 5: IMPLEMENT METHODS**

Once the methods have been selected, they can be used to make a forecast. This section will explain the concept of averaging forecasting methods and developing a range of possible forecast results.

**Averaging Methods.** Research shows that averaging the results of multiple forecasting methods produces better results than using any one method alone. One oft-cited study tested averages of different combinations of 14 quantitative forecast techniques, comparing the results of each technique in isolation with the averages of up to 10 of the techniques. The results showed large and consistent reductions in error across a variety of situations, some of which are displayed in Exhibit 4. Many researchers cite between four and five models as the number necessary to gain the benefits from averaging (results did continue to improve beyond that, but they were inconsequential). Averaging even two or three forecasts could reduce “noise” and better reveal the underlying pattern, as Exhibit 4 shows. In fact, these researchers found that even the technique that performed best in isolation could be improved (albeit slightly) by averaging it with just two to three other high-performing techniques.

Averaging can also work with purely judgmental forecasts. The error associated with these forecasts, much less averages of them, have not been studied in nearly as much depth as quantitative forecasts, so the guidance on how many forecasts to average is not as definitive. Leading forecast scientist Spyros Makridakis suggests five to seven contributors as a minimum to aim for, although fewer contributors are necessary if you are using a hybrid of quantitative and judgmental techniques.

**Forecast Ranges.** Forecasts are often expressed as “point forecasts” because they express future revenues as a single number, although this number is actually made up of averages — averages of historical experiences and perhaps averages of different forecasting techniques. Presenting one number obscures variability, since the possible future outcomes are many. Hence, it might be wise to develop a range of possible forecast outcomes — known in forecasting science as “prediction intervals.” Prediction intervals illustrate uncertainty in the forecast by showing a range around the baseline forecast in which the forecaster believes the actual value will fall, expressed in probabilities (e.g., the actual value is 90 percent certain to fall between X and Y). Research shows that some forecast users prefer prediction intervals over point forecasts because prediction intervals better demonstrate future uncertainties and assist in planning for alternative strategies that address the range of future outcomes. However, many members of the forecaster’s audience are probably not accustomed to thinking in terms of probabilities, so prediction intervals might take some getting used to.

The formula in Exhibit 5 shows how to calculate a prediction interval for a one-step-ahead forecast (e.g., a forecast for the period immediately following the last available actual statistics). The prediction internal (PI) is equal to the forecast plus-and-minus a constant, which is multiplied by the square root of the mean squared error. Our example uses a constant of 1.65, which produces a 90 percent interval. This constant is known as a “z score,” and the z scores necessary to produce other intervals can be easily obtained from the Internet and most statistical texts. The mean squared error is simply the average of the squared difference between the actual and forecasted value for every point in the data set. Squaring the error removes any negative sign. A square root is then taken to reduce the number back to a magnitude relevant to the data set.

While the formula for one-step-ahead prediction intervals is simple enough, a statistical calculation becomes increasingly

### Exhibit 5: Calculating a Prediction Interval

\[
PI = (\text{the forecast number}) \pm (1.65 \times \text{square root of mean squared error of historical data})
\]
complex for multiple steps ahead. This is because the mean square error statistic from Exhibit 5 is based on one-step-ahead forecasts, so it must be modified to reflect the average error in making the “n”-step-ahead forecast that the forecaster is interested in — and this must be repeated for every n value of interest. The statistical method can become tedious and complex, so researchers have offered alternatives.

You can set the prediction interval using your own judgment, but research has shown that confidence intervals set this way are usually too narrow (i.e., the forecaster is overconfident or underestimates the amount of variability), likely because the point forecast becomes an anchor from which the forecaster unconsciously hesitates to stray. Following are two ways to deal with this problem.

One way is to calculate a one-step-ahead prediction interval using the formula in Exhibit 5, since it is relatively simple to do. This might serve as a starting point, or an anchor, for judgmentally developing prediction intervals for n-step-ahead forecasts. The interval should widen as n becomes larger, since there will presumably be greater uncertainty the farther the forecast goes into the future.

Another approach is to simply widen a judgmentally set prediction interval. First decide the interval probability (e.g., 90 percent, 80 percent, etc.) and then ask a series of knowledgeable judges to estimate the range of upper and lower values that would include 90 percent (or 80 percent or whatever probability you selected) of all possible outcomes. Average all the results together to get an interval. This interval will likely be too narrow, so double it.

The second alternative to the prediction interval statistical formula uses historical data but doesn’t rely on statistical techniques. Take the difference between the largest and smallest observation in the historical data set and multiply by 1.5, although if you have very small set of data, you might need to use a multiplier as high as 2. This range is thought to be a crude estimation of a 95 percent prediction interval. You can divide the range by two and add the result to or subtract it from the forecast to get the forecast range. Again, remember that the further forecasts go into the future, the less reliable they become, so the prediction interval should widen as it moves away from the origin.

CONCLUSIONS

Revenue forecasting helps local governments better plan future service levels and anticipate financial challenges. This article has presented a structured approach to the revenue forecasting process in order to help finance officers produce a more replicable, transparent, and accurate forecast.

Forecasters do better if they have insight into when and what quantitative techniques might be appropriate, and a better feel for the data can be helpful in more qualitative forms of forecasting.

Notes

1. Particularly Principles of Forecasting by J. Scott Armstrong and Forecasting: Methods and Applications by Spyros Makridakis, et al.
2. Forecasters should also consider how the forecasts will be used and how the process should be evaluated, but those are beyond the scope of this article.
3. Rebecca M. Hendrick, author of Managing the Fiscal Metropolis, contributed to this section.
4. Quote from Spyros Makridakis and Michele Hibon, “The M3 Competition: Results, Conclusions, and Implications,” International Journal of Forecasting 16 (2000). The “M Competitions” were a series of three forecasting accuracy tests conducted over almost 20 years by Makridakis and colleagues. The results have been widely studied, replicated, and cited.
9. “Overconfidence” does not necessarily mean that the forecaster has an inflated sense of his or her abilities, but that the forecaster underestimates variability.

SHAYNE C. KAVANAGH is senior manager of research for the GFOA’s Research and Consulting Center in Chicago, Illinois. He can be reached at skavanagh@gfoa.org. CHARLES IGLEHART is a volunteer researcher for the GFOA. He recently obtained his M.S. in applied mathematics from DePaul University and is pursuing actuarial certification.