How to forecast for recessions and recoveries

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February 2009

Widely used methods of automated forecasting for production and inventory control tend to contribute to the severity of recessions. This is because of the assumption that causal forces support the historical trend is violated when recessions occur. We describe an approach to forecasting that should ameliorate the damage caused by business cycles.

In the early 1990s, Fred Collopy and Scott Armstrong published a series of papers in which they showed that nearly all inventory models are fallacious because they assume that the causal forces will support the historical trends. In fact, they found no practical time series where an assumption of supporting causal forces was warranted.

While the assumption of supporting causal forces is unfounded, the world often looks as though trends are supported by causal forces. Consequently, in normal times, standard extrapolation models perform adequately. However, when the historical trends are contrary to the expected causal forces—referred to as "contrary series"—the forecast errors from standard extrapolation models become very large.

To deal with this and related problems, Collopy and Armstrong developed and published a set of 99 rules as the basis of "rule-based forecasting." Although a number of RBF programs have been developed privately, there is no commercial package. While applying RBF without software is onerous, a simple and inexpensive rule can achieve much of the benefit of RBF by reducing errors when forecasting contrary series.

Here is the rule: *When a time series is identified as "contrary," do not extrapolate a trend.*

Armstrong and Collopy (1993) described five types of series: growth, decay, opposing, regressing, supporting, and unknown. They found that college students with little domain knowledge were able to quickly identify the causal forces for a wide variety of time series (for example, they used some data from the M-Competition where the descriptions of the series were quite brief). Of course, it would be better to use people who have expertise in the areas.

Once the causal forces have been identified for each series, a simple line of code can be introduced to compare the expected trend with the trend estimated by the extrapolation model. When they are contrary, set the trend forecast to zero. This rule was tested for using 26 contrary series from the widely-used M-competition (primarily economic) data. The rule was found to be more accurate than Holt's exponential smoothing; Holt's error was 1.1 times larger. Collopy and Armstrong also tested the rule on data from Chinese epidemics, unit product sales, the Weatherhead economic data (similar to the M-competition series), and data on naval manpower planning. For these tests, Holt's exponential smoothing led to errors that were larger by factors ranging from 1.22 to 1.25 for one-period-ahead forecasts, and for longer term forecasts, Holt's errors were from 1.56 to 2.2 times larger.

When a recession is anticipated (as was the case with the 2008 recession), one would expect that a large number of growth series would be re-coded as decay, thus leading many series to be reclassified as contrary. Had firms used the contrary series rule, they would have substantially reduced their forecast errors coming into the recession. Eventually, the recession will end, and here again, use of the contrary series rule will aid the firms.

Contrary series also affect the confidence intervals because their errors are asymmetric. The errors tend to be larger in the direction of the expected trend based on the causal forces. This will have an impact on setting the desired inventory levels. For a short answer to the solution, shift the prediction intervals in the direction of the causal forces. This would help to move quickly to smaller inventories in anticipation of a downturn– and a larger inventory when a recovery is expected.

This *structured* use of managers' knowledge is almost always useful to forecasting for production and inventory control. When the economy is in recession or is recovering from one, it is especially useful.

> Note: For more information on this topic, see J. Scott Armstrong & Fred Collopy, (1993), "Causal Forces: Structuring Knowledge for Time-series Extrapolation", *Journal of Forecasting*, 12, 103-115. In addition, adjustments must be made for assessing prediction intervals for contrary series. For this, see J. Scott Armstrong & Fred Collopy, (2001), "Identification of Asymmetric Prediction Intervals through Causal Forces," *Journal of Forecasting*, 20, 273-283. Full text of these papers can be obtained at ForPrin.com.