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Decomposition of time-series by level and change

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ABSTRACT

This article examines whether decomposing time series data into two parts – level and change – produces forecasts that are more accurate than those from forecasting the aggregate directly. Prior research found that, in general, decomposition reduced forecasting errors by 35%. An earlier study on decomposition into level and change found a forecast error reduction of 23%. The current study found that nowcasts consisting of a simple average of estimates from preliminary surveys and econometric models of the U.S. lodging market, improved the accuracy of final estimates of levels. Forecasts of change from an econometric model and the improved nowcasts reduced forecast errors by 29% when compared to direct forecasts of the aggregate. Forecasts of change from an extrapolation model and the improved nowcasts reduced forecast errors by 45%. On average then, the error reduction for this study was 37%.

1. Introduction

Decomposition for forecasting involves breaking a problem into pieces, forecasting each piece, and then reassembling the forecast pieces. Decomposition allows a forecaster to use different methods and data for each component. Decomposition can be multiplicative, such as forecasting sales by forecasting market size and market share, then multiplying the two components. It can also be additive such as to decompose a sales forecast by region, forecast each region, and then add the regional forecasts.

A meta-analysis by Armstrong, Green and Graefe (2015–in this issue) found 16 studies prior to this current study that examined reduction in forecast error due to of decomposition. In all studies, decomposition led to improved accuracy. In the eight studies that assessed the amount of improvement, the average error reduction was 35%. This article examines the additive decomposition of time-series data by level and change. Little comparative research has been done on this type of decomposition.

2. Prior research on decomposition by level and change

Forecasters have long been aware that errors in estimating current levels are common. Morganstern (1963) describes the problems that economists face in assessing current levels. The errors in estimating current levels are often substantial. Runkle (1998) analyzes deviations between current and revised estimates of quarterly GDP growth from 1961 to 1996. There were upward revisions of as much as 7.5% and downward revisions of as much as 6.2%. Obviously, the errors in estimating levels affect the forecasts. For example, Zarnowitz (1967) reports that about 20% of the error in predicting the next year's GNP in the U.S. arose from errors in estimating the current U.S. GNP figure. Cole (1969) estimated that 40% of the errors for one-year ahead U.S. GNP forecasts are due to errors in estimating the starting levels.

Given the concern over the introduction of error due to poor estimation of the current levels, interest in how to improve the estimates – referred to as “nowcasting” – is strong. A Google Scholar search for “nowcasting” in March 2015 found almost 1700 hits.

One approach for dealing with errors caused by poor estimation of the current status is to make adjustments. Mechanical adjustments, such as adding one-half of the most recent forecast error to the estimate of current level, is a simple, low cost, and objective approach. Another approach is to use judgmental adjustments as they can include recent information that is not already incorporated into the data, such as recent stock-outs for a product. While McNees (1990) found that judgmental and mechanical adjustments each tend to improve accuracy of economic forecasts, the improvements were modest. Moreover, judgmental adjustments are risky as they increase the likelihood that biases would be introduced.

A search for studies that assessed the performance of decomposition forecasting using nowcasting-plus-trend found only one such study, Armstrong (1970). That study analyzed annual sales of photographic equipment averaged over 1955–1960 data for 17 countries by using a cross-sectional regression model. The econometric estimates were

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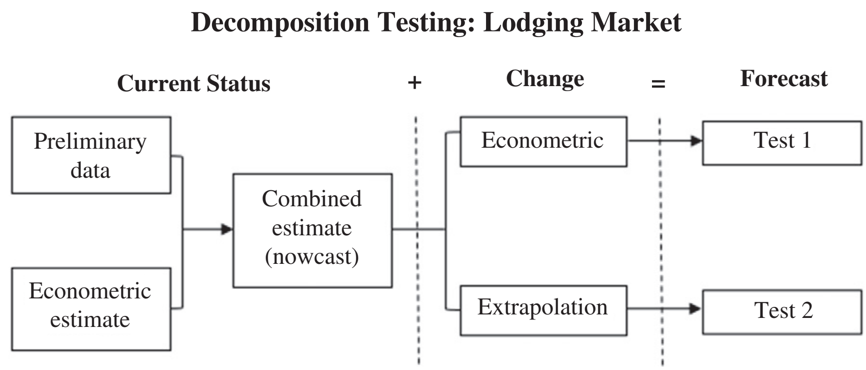

Fig. 1. Decomposition testing: lodging market.

combined with trade and production data from surveys of producers to provide estimates of the current levels. Backcasts (forecasting backwards in time) were then made for average annual sales in 1953–55. One approach started with the survey data and added the change over time where the change was forecast by an econometric model. Another approach used an average of the estimates from the survey data and the econometric estimates of the current level. The a priori weights – two-thirds on survey and one-third on the econometric estimate – reduced the backcast error for 14 of the 17 countries. On average, across the countries, the mean absolute percentage error (MAPE) was reduced from 30% to 23%, an error reduction of about 25%. No matter the weights, the combination was always more accurate than forecasts based on survey data alone. For a further assessment on the effects of decomposing by level and change, this current study reanalyzes data from an MBA thesis by the first author (Tessier, 1974). These data relate to the U.S. lodging market.

3. Testing decomposition using U.S. lodging market data

The data include room, food, and beverage sales in constant dollars for the U.S. lodging market – e.g. hotels and motels – for 1958 through 1970. The U.S. Department of Commerce conducted annual surveys of lodging sales and published them in the *U.S. Industrial Outlook*. The Department of Commerce used various sources to make its estimates. During 1958, 1963, and 1967, the business census was the primary source. During non-census years, sales were estimated from sample surveys, tax returns, and information from private sources. Estimates of lodging sales were made at the end of each year.

Sales estimates were revised in following years as additional data became available. For example, at the end of 1968, the Department of Commerce estimated that 1968 lodging sales were approximately $7.3 billion. In 1969, the 1968 estimate was revised to $7.6 billion. In 1970, it was revised to $7.1 billion. The most current (1971) and presumably "final" estimate of 1968 lodging sales is $6.5 billion. In this example, the preliminary estimate of $7.3 billion made in 1968 was 11.0% higher than the final estimate made in 1971. The MAPE of the Department of Commerce's preliminary estimates between 1964 and 1970 was 11.0%.

This study decomposes the Department of Commerce's sales estimates into level and change, and focuses on improvement in nowcasting. The effect that decomposition and nowcasting has on forecast accuracy is then examined. The approach is summarized in the Figure.

3.1. Developing an econometric model for nowcasting

A number of alternative approaches could be used to estimate the current level. This study uses an econometric model. Because few data on the lodging market were available for estimating the coefficients, development of the model relied primarily on estimates from prior econometric studies.

The first step in the a priori analysis was to identify the causal variables relevant to lodging sales. In broad terms, lodging demand is determined by market size, ability to buy, and needs. Given the available data, the following five variables were chosen for the model: U.S. population (market size), corporate profits and lodging rates (ability to buy), and aircraft speed and intercity passenger miles (measures of needs). The model is specified in constant dollars.

The direction of each relationship in the model is based on standard economic theory: The coefficients for corporate profits and intercity passenger miles are positive, while the coefficients for lodging rates and aircraft speed are negative. The functional form of the model is multiplicative (log–log), which assumes constant elasticities, following standard econometric practice. The effect of market size is fixed a priori at 1.0 by transforming the dependent variable values into per capita figures.

The ranges of plausible values for each of the four remaining elasticities are subjective estimates based on previous studies on similar products and services (Houthakker & Taylor, 1970). While the subjective estimates are highly uncertain, prior research shows that the accuracy of econometric models is not sensitive to magnitudes of the relationships as estimated by regression analysis. That research began at least as far back as 1971; Graefe (2015–in this issue) provides a review.

The a priori analysis yielded a range of subjective estimates of the elasticity of each variable shown here:

	A priori range
B = corporate profits per capita in constant dollars	1.0 to 2.0
M = miles of intercity passenger travel per capita	0.6 to 1.0
A = lodging rates in constant dollars	−0.5 to −0.9
S = aircraft speed in miles per hour	−0.4 to −0.7.

Data from 1958 to 1964 (see Table 1) were used to update the model. Note that only seven years of data were available. Revising the model with only seven years of data was possible only by using a priori information. The regression analysis provided an estimate of the constant and additional information on the coefficients.

A method called "conditional regression analysis" was used to update the coefficients. Wold and Jureen (1953) describe this approach. It was also called a "poor man's Bayesian regression analysis" when used in Armstrong and Grohman (1972).

The procedure was as follows: First, historical data for each independent variable (corporate profits, intercity passenger miles, rates and speed) were regressed against the dependent variable (lodging sales per capita). Second, results were examined for verification of a priori