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Prediction Intervals for Expert-Adjusted Forecasts*

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Abstract

This paper proposes a simple method to compute prediction intervals for expert-adjusted forecasts in case the analyst does not have the underlying model forecasts and thus has to create own approximate model forecasts, based on data available to the analyst. An illustration to airline revenues data shows that experts can substantially reduce forecast uncertainty.

Keywords: Prediction intervals, expert-adjusted forecasts, approximate model forecasts, forecast uncertainty, airline revenues.

JEL: C22, C52, C53.

1. Introduction

Many business forecasts are partly based on statistical models and partly based on managerial (expert) judgment. Recently some databases have become available which include model forecasts and expert-adjusted forecasts, see Fildes et al. (2009) and Franses (2014), thus allowing to analyze what experts could have possibly done and to what extent their judgmental adjustment improved forecast accuracy. However, in many situations spreadsheets with the final business forecasts do not come with underlying model forecasts, and then the analysis of the experts' contributions is less straightforward.

One potential way out for the analyst who has to evaluate the business forecasts is to create an own approximate model for the data at hand, using publicly available information as well as own business data as explanatory variables. Comparing the forecasts from this approximate model with the expert-adjusted forecasts can to some extent facilitate the evaluation of the accuracy of expert-adjusted forecasts.

An outstanding issue in the evaluation and use of experts' business forecasts concerns their prediction intervals. That is, usually the expert-adjusted forecasts are point forecasts and they rarely come with confidence bounds. When forecasts are uniquely based on statistical (or, econometric) models, then prediction intervals can be derived from the properties of these models, see Chatfield (1993) for a general outline, and Franses, van Dijk and Opschoor (2014) for a discussion concerning econometric time series models.

When final business forecasts are an unknown combination of a model forecast and expert adjustment, where potentially the model forecast is also unavailable, then matters become more complicated.

In this paper I propose a possibly useful solution, which again draws on the idea that an analyst creates an approximate model. This model gives a model forecast and together with an estimate of the size and sign of expert adjustment, it is possible to derive approximate prediction intervals of the expert-adjusted forecasts. Such estimated prediction intervals can then be used in practice, also to see if expert adjustment really leads to improved final forecasts.

The outline of this paper is as follows. Section 2 deals with the methodology. Section 3 illustrates this methodology to airline revenue forecasts. For this particular case it is found that the experts' adjusted forecasts substantially reduce forecast uncertainty. Section 4 concludes with suggestions for further work.

2. Methodology

Suppose there is a variable y_t, with t = 1,2,.., T, which can be sales, revenues or any other business variable, and assume that there are some variables summarized in X_t, with data information available to the analyst. When these variables are linked via a standard linear regression model

$$y_t = X_t\beta + \varepsilon_t$$

with ε_t is an error term with variance σ_ε^2, the one-step-ahead model-based (M) forecast from origin T (with a "hat" indicating estimate) is

$$\hat{y}^M_{T+1|T} = \hat{X}_{T+1|T}\hat{\beta}$$

The one-step-ahead forecast error is then equal to ε_{T+1}

One way to understand the expert adjustment of model-based forecasts, whether the model is a regression model or any other statistical tool, is to assume that an expert has some foresight information about the one-step-ahead forecast error, see Franses (2014). Denoting the added judgment of the expert as $A_{T+1|T}$, meaning the information that the expert has at time T concerning the forecast horizon T+1, then one could thus assume that

$$\varepsilon_{T+1} = A_{T+1|T} + v_{T+1}$$

where v_{T+1} is a random term with variance σ_v^2. The resultant expert-adjusted forecast is then given by

$$\hat{y}^{E}_{T+1|T} = \hat{X}_{T+1|T}\hat{\beta} + A_{T+1|T}$$

This entails that the one-step-ahead forecast error of the expert-adjusted forecast is v_{T+1}, and using its variance σ_v^2, the analyst can compute the prediction intervals. Assuming normality, the 95% confidence bounds would be $\hat{y}^{E}_{T+1|T} - 2\hat{\sigma}_v$ and $\hat{y}^{E}_{T+1|T} + 2\hat{\sigma}_v$. Naturally, when σ_v^2 is smaller than σ_ε^2, one may conclude that the expert adjustment leads to narrower confidence bounds and hence the expert apparently knows how to reduce forecast uncertainty, relative to the uncertainty associated with the model forecast.

When only the expert forecasts $\hat{y}^{E}_{T+1|T}$ are available, the analyst somehow has to estimate the value of $A_{T+1|T}$. As is indicated in Franses (2014), the optimal situation would be that

$$A_{T+1|T} = \hat{y}^{E}_{T+1|T} - \hat{y}^{M}_{T+1|T}$$

where $A_{T+1|T}$ is orthogonal to and independent from $\hat{y}^{M}_{T+1|T}$. As such, the adjustment can simply be computed as the differences between the expert-adjusted forecast and the model forecast. In practice, however, it seems to occur that the optimal situation is not often encountered, and that usually

$$A_{T+1|T} = \hat{y}^{E}_{T+1|T} - \lambda\hat{y}^{M}_{T+1|T}$$

with λ unequal to 1. For example, Franses and Legerstee (2009) document for a large database with more than 30000 cases that λ seems on average to be equal to 0.4. Hence, the analyst may also want to estimate this parameter using actual data. In case $A_{T+1|T}$ is orthogonal to and independent from $\hat{y}^{M}_{T+1|T}$, the parameter can be estimated using Ordinary Least Squares to give $\hat{\lambda}^{OLS}$. In case the independence does not hold, one has to resort to Instrumental Variables to give $\hat{\lambda}^{IV}$.

3. Illustration

To illustrate the methodology proposed in the previous section, consider a database which contains the monthly airline revenues data spanning April 2004 to and including December 2008 for KLM Royal Dutch Airlines for seven distinct regions and for the world. These data have also been considered in Franses (2014). The regions are Europe, Middle East, Africa, North America, Middle and South America, Asia Pacific and India. There are one-month-ahead forecasts for these revenue data. The forecasts are all made by experts, who state that they base their final forecasts on input from model forecasts, but unfortunately these model forecasts are not available to the analyst. Figure 1 displays the revenues for Africa and the one-step-ahead forecasts.

[Figure 1 here]

To create approximate model forecasts, the analyst can consider using the following explanatory variables for the dependent variable which is the natural log of the revenues, see also Franses (2014). First, an intercept is included, and then the harmonic regressors $cos\frac{2\pi t}{12}$ and $sin\frac{2\pi t}{12}$, the exchange rate of the US Dollar versus the Euro (at time t-1), the natural log of USA Industrial Production Index (at time t-1), the natural log of oil price (West Texas crude) (at time t-1) and the unemployment rate in the USA (at time t-1), although of course other variables could have been considered as well.

[Table 1 and Figure 2 here]

Table 1 presents for the total revenues data the estimates of $\hat{\sigma}_\varepsilon$ and of $\hat{\sigma}_v$, where the last is computed in three ways (using λ = 1, $\hat{\lambda}^{OLS}$ and $\hat{\lambda}^{IV}$, respectively. Figure 2 depicts the actual data and the approximate model forecasts and the true expert-adjusted forecasts. It is clear that the expert-adjusted forecasts amount to substantially narrower confidence intervals, and hence that forecast uncertainty delivered by the experts is about 60% smaller than for the model forecasts.

[Table 2 here]

Table 2 zooms in on the same percentages, now for each of the seven regions. Again, for about all methods of setting λ, and across all regions, the confidence bounds of the expert-adjusted forecasts are much smaller than those associated with the model.

4. Conclusion

This paper has proposed a simple method to compute prediction intervals for expert-adjusted forecasts in case the analyst does not have the underlying model forecasts and thus has to create own approximate model forecasts, based on data available to the analyst. An illustration to airline revenues data showed that experts can substantially reduce forecast uncertainty.

Further applications shall reveal whether expert-adjusted forecasts generally amount to smaller confidence intervals. Further theoretical research is needed to design methods to test whether confidence intervals are statistically different. More insights into how confidence intervals should be constructed for multiple-steps-ahead forecasts will also be relevant.

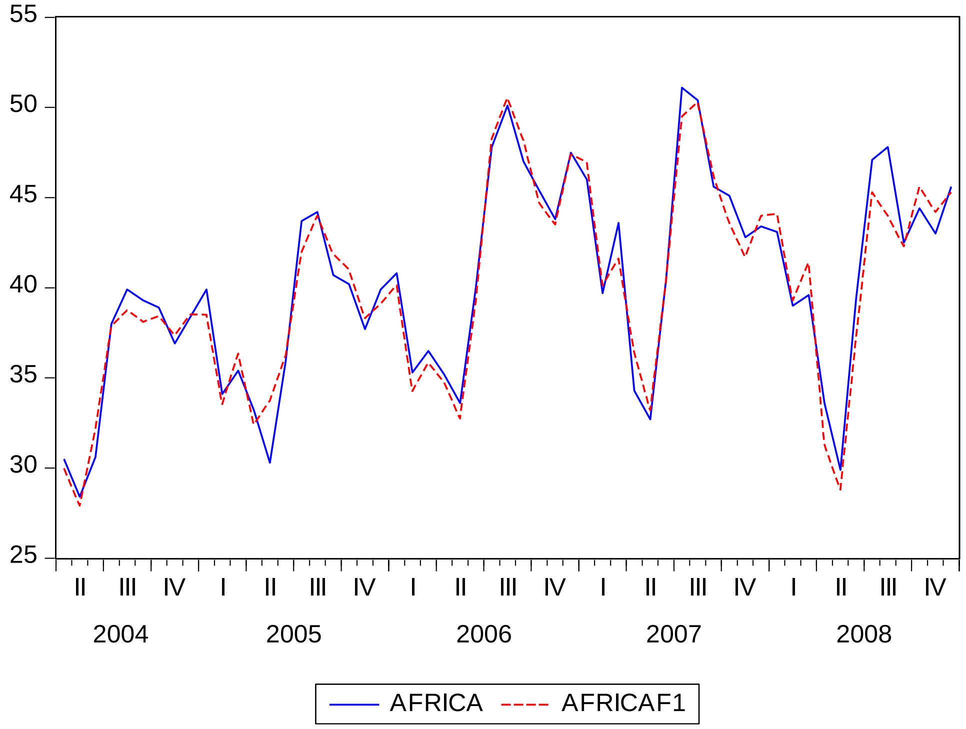

Figure 1

Airline revenues for Africa and the one-step-ahead forecasts

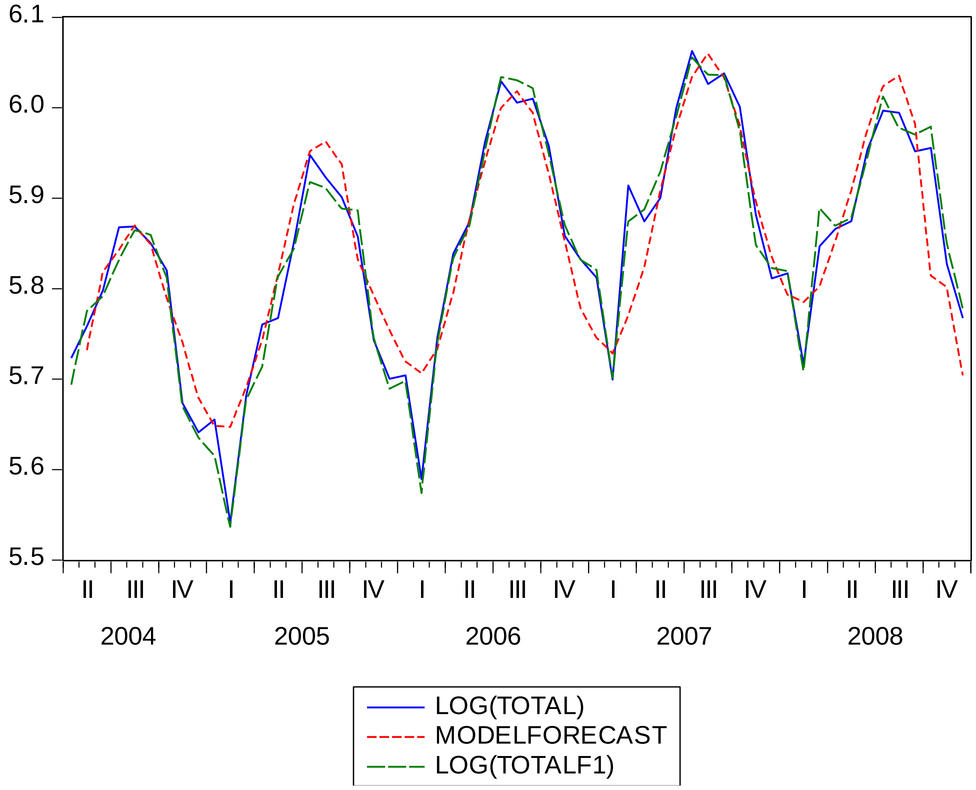

Figure 2

Forecasts using the approximate model and the expert forecasts

Table 1

Estimation results for total revenues

Method 1 computes the adjustment using $A_{T+1|T} = \hat{y}^{E}_{T+1|T} - \hat{y}^{M}_{T+1|T}$, and methods 2 and 3 estimate λ from $A_{T+1|T} = \hat{y}^{E}_{T+1|T} - \lambda\hat{y}^{M}_{T+1|T}$,

where method 2 uses OLS and method 3 uses two-stage least squares where the instruments are the three months lags of the exchange rate, the log production index the log of oil price and the USA unemployment rate. The percentage of the prediction interval (assuming normality) of the expert-adjusted forecasts relative to the approximate model-based forecasts is in the last column.

		$\hat{\sigma}_{\varepsilon}$	0.047515	
Method	1	$\hat{\sigma}_{v}$	0.019100	40.2%
	2	$\hat{\sigma}_{v}$	0.019024	40.0%
	3	$\hat{\sigma}_{v}$	0.029530	62.1%

Table 2

The percentage of the prediction interval (assuming normality) when $\hat{\sigma}_v$ is used relative to when $\hat{\sigma}_\varepsilon$ is used for three methods of computing expert adjustment (see Table 1)

Region	Methods		
	1	2	3
Europe	26.4%	26.1%	44.2%
Middle East	64.4%	64.4%	73.0%
Africa	39.3%	39.2%	43.4%
North America	76.9%	76.5%	121.1%
Middle and South America	35.0%	34.7%	40.5%
Asia Pacific	52.7%	52.1%	55.4%
India	86.9%	86.5%	88.4%

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