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Comparative Analysis of Travel Demand Forecasting Models[1]

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ABSTRACT

Forecasting accuracy is examined in the context of Michigan travel demand. Eight different annual models are used to forecast up to two years ahead, and nine different quarterly models up to four quarters. In the evaluation of annual models' performance, multiple regression performed better than the other methods in both the one year and two year forecasts. For quarterly models, Winters' exponential smoothing and the Box - Jenkins method performed better than naive 1 s in the first quarter ahead, but these methods in the second, third, and fourth quarters ahead performed worse than naive 1 s. The sophisticated models did not outperform simpler models in producing quarterly forecasts. The best model, multiple regression, performed slightly better when fitted to quarterly rather than annual data; however, it is not possible to strongly recommend quarterly over annual models since the improvement in performance was slight in the case of multiple regression and inconsistent across the other models. As one would expect, accuracy declines as the forecasting time horizon is lengthened in the case of annual models, but the accuracy of quarterly models did not confirm this result.

Key words: Forecasting accuracy, annual models, quarterly models, forecasting time horizon.

要 約

미국 미시간주의 旅行需要를 豫測하기 위하여 사용되어진 여러 모델들의 豫測正確性이 검토되었다. 8가지의 連年모델들은 2년까지 예측하는데 그리고 9가지의 分期모델들은 4分期까지 예측하는데 사용되어졌다. 連年모델의 豫測正確性 評價에서, 重回歸모델은 1년과 2년을 豫測하는데 있어 다른 방법들보다 더 正確했다. 分期모델에 있어서는, Winters' exponential smoothing와 Box - Jenkins 방법이 1分期豫測에 있어 naive 1 s보다 더 正確했으나 2分期, 3分期, 4分期를 豫測하는데 이 方法들은 naive 1 s 보다 正確하지 않았다. 精巧한 모델들은 分期別 豫測을 하는데 있어서 單純한 모델들보다 더 正確하지 않았다. 連年모델과 分期모델을 이용한 1年間 豫測比較에서, 重回歸模型은 年間資料보다 分期資料에 適用할 때 더 좋은 結果를 얻었으나 그 差異가 微弱하며 다른 모델들은 一貫性있게 좋은 結果를 갖지 않으므로 連年모델보다 分期모델을 사용하도록 강력하게 권장할 수 없다. 連年모델은 期待하였던 것처럼 豫測期間이 길어짐으로서 豫測正確性이 減少하였으나 分期모델은 이같은 結果를 나타내지 않았다.

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INTRODUCTION

An important element in the process of planning and management within the travel industry is accurate travel demand forecasting. Archer(1987) pointed out that "In the tourism industry, in common with most other service sectors, the need to forecast accurately is especially acute because of the perishable nature of product. Unfilled airline seats and unused hotel rooms can't be stockpiled and demand must be anticipated and even manipulated".

Travel is a major source as a generator of income, tax collections, employment, and fore - ign exchange earnings in countries and regions. Statewide annual travel activities in Michigan have increased in terms of traffic volume, tax collections, and number of foreign traveler arrivals in Michigan. During the period of 1986 - 1990, adjusted sales tax collections, adjusted use tax collections, and the sum of adjusted sales and use tax collections of hotels, tourist courts, and motels increased at an average annual rate of 12.4%, 3.7%, and 7.7% respec - tively(Spotts, 1991). The amount of combined sales and use tax collections are closely related to the number of tourists, their length of stay, and their expenditures. The sum of sales tax and use tax collections data may be more reliable indicators of travel activity than tourists' expenditure or arrival data in Michigan because no system for estimating either of the latter is currently in place.

In this study, sales and use tax collections are used as comprehensive indicators of travel activity in Michigan since these are closely related to the number of tourists, their length of stay, and their expenditures.

The purpose of this study is to evaluate the relative accuracy of various approaches to fore - casting travel demand in Michigan using the combined sales and use tax collections of hotels and motels as indicators of tourism demand.

The specific research objectives are:

1. To compare the relative accuracy of the most common methods for forecasting travel demand when applied to annual and quarterly Michigan tax collections data.
2. To compare the forecasting accuracy of annual and quarterly models in terms of one year ahead forecasts.
3. To examine the consistency of accuracy of forecasts over time.

Several forecasting techniques were used in this study to develop forecasts of sales and use tax collections for Michigan's hotel and motel industry. Eight different techniques were used to develop annual forecasts, and nine techniques were used to develop quarterly forecasts.

Annual models were fitted for the period of 1976 - 1988, 1976 - 1989, and 1976 - 1990, and quarterly models for 1976Q1 - 1989Q4 and 1976Q1 - 1990Q4. In this study, forecasting techniques were used to forecast up to two years ahead using annual models and four quarters ahead for quarterly models. More - over, the forecasting performance of the alternative annual and quarterly models were evaluated using one year ahead as the common benchmark for comparisons.

All models' forecasting abilities were evaluat - ed on the basis of the mean absolute percentage error(MAPE).

FORECASTING METHODS

Selection of the individual methods to be studied was guided by the goal to cover a spectrum of possibilities ranging from simple mechanical methods to more complex methods. The annual models developed for evaluation were labeled: (1) naive 1, (2) naive 2, (3) simple mov - ing averages, (4) single exponential smoothing, (5) Brown's one parameter linear exponential smoothing, (6) Holt's two parameter linear exponential smoothing, (7) simple linear trend, and (8) multiple regression model. The quarterly models developed for evaluation were labeled: (1) "naive 1 s", (2) "naive 2 s", (3) simple moving averages, (4) single exponential smoothing, (5) Brown's one parameter linear exponential smooth - ing, (6) Holt's two parameter linear exponential smoothing, (7) Winters' exponential smoothing, (8) Box - Jenkins method, and (9) multiple regres

-sion model. A detailed description of forecasting methods ultimately selected is provided below.

Naive 1 and Naive 1 S—(Naive 1 applied only to annual data; naive 1 s only to quarterly data)

The simplest approach to forecasting, referred to as naive 1 by some authors, is to equate the current actual and forecast values for a specified variable. This method can be described in algebraic form, as follows:

$$P_{t+1} = X_t \quad (1)$$

Where, P_{t+1} represents the forecast value for time t+1, and Xt represents the current actual value for time period t.

The quarterly sum of hotel/motel sales and use tax collections contains a distinct seasonal pattern. The naive 1 model, if applied to quarterly data in the same way as annual model, would not perform well. A version of the naive 1 model labeled "naive 1 s" was developed to account for seasonality in the quarterly data series. The method considers any quarter value for the current period(year) as an estimate for the corresponding quarter value of the next period. In this study, the naive 1 s method can be described in algebraic form, as follows:

$$P_{t+q} = X_t \quad (2)$$

Where, X_t represents any specific quarter (q) of the current year, P_{t+q} represents an estimate for the corresponding quarter (q) of the next years (t).

Naive 2 and Naive 2 S—(Naive 2 applied only to annual data; naive 2 s only to quarterly data)

This method assumes that the forecast for the next time period is equal to the actual value registered in the current period multiplied by the growth rate over the previous period. In general algebraic terms the model becomes :

$$P_{t+1} = X_t\left(1 + \frac{X_t - X_{t-1}}{X_{t-1}}\right) \quad (3)$$

Where, P_{t+1} represents the forecast value for time t+1, and X_t represents the observed value for time period t.

X_{t-1} is the actual observation at period t−1.

The naive 2 method does not perform well when applied to quarterly data because it ignores the seasonality inherent in such data. Thus, a quarterly version of the naive 2 model labeled, "naive 2 s" was also developed. Naive 2 S's forecast for any future quarter is equal to actual sales and use tax collections in that quarter in the current year multiplied by the growth rate for that quarter over the previous two years. The basic equation for Naive 2 S is as follows:

$$P_{t+q} = X_q\left(1 + \frac{X_q - X_{t-q}}{X_{t-q}}\right) \quad (4)$$

Where,

X_q represents any quarter (q) value for the current year.

X_{t-q} represents the corresponding quarter (q) value for the previous year.

P_{t+q} is any quarter (q) value for the next years.

Simple Moving Averages—(Applied to both quarterly and annual data)

The time series technique known as moving averages consists of taking a set of observed values, finding the average of those values, then using that average as the forecast for the next period. The mathematical expression for this model is:

$$P_{t+1} = \frac{1}{n} \cdot \sum_{i=t-N+1}^{t} X_i \quad (5)$$

Where,

P_{t+1} represents the forecast value for time t+1,

X_i represents actual value at time i

N represents the number of values to be averaged

Single Exponential smoothing—(Applied to both quarterly and annual data)

Single exponential smoothing is properly employed when there is no trend or seasonality present in the data. The single exponential smoothing model is expressed in the following manner:

$$F_{t+1} = \alpha X_t + (1-\alpha)F_t \quad (6)$$

where,

F_{t+1} is the forecast value for period t+1

α is the smoothing constant ($0 < \alpha < 1$)

X_t is the actual value now (in period t)

F_t is the forecast (i.e., smoothed) value for period t

Brown's One - Parameter Linear Exponential Smoothing—(Applied to both quarterly and annual data)

The double exponential smoothing method, also known as Brown's linear exponential smoothing, estimates and smoothes a linear trend in non - stationary data. The difference between the single and double smoothed values can be added to the single smoothed values and adjusted for the trend. Brown's linear exponential smoothing model is described by the following set of equations:

$$F_{t+n} = a_t + b_t(n) \quad (7)$$

$$a_t = S'_t + (S'_t - S''_t) = 2S'_t - S''_t \quad (8)$$

$$b_t = \frac{\alpha}{1-\alpha}(S'_t - S''_t) \quad (9)$$

$$S'_t = \alpha X_t + (1-\alpha)S'_{t-1} \quad (10)$$

$$S''_t = \alpha S'_t + (1-\alpha)S''_{t-1} \quad (11)$$

where

F_{t+n} is the Brown's forecast for n periods into future,

S'_t is the single exponential smoothing forecast one period into the future from period t,

S''_t is the double exponential smoothing forecast for the same period,

α is a constant between 0 and 1.

Holt's Two - Parameter Linear Exponential Smoothing—(Applied to both quarterly and annual data)

Holt's linear exponential smoothing is best used when the data show some linear trend but little or no seasonality. Holt's two—parameter exponential smoothing method is an extension of simple exponential smoothing; it adds a growth factor(or trend factor) to the smoothing equation as a way of adjusting for the trend. Three equations and two smoothing constants (with values between 0 and 1) are used in the model.

$$F_{t+1} = \alpha X_t + (1-\alpha)(F_t + T_t) \quad (12)$$

$$T_{t+1} = \beta(F_{t+1} - F_t) + (1-\beta)T_t \quad (13)$$

$$H_{t-n} = F_{t-1} + nT_{t+1} \quad (14)$$

where:

F_{t+1} is the smoothed value for the period t+1,

α is the smoothing constant for the data ($0 < \alpha < 1$),

X_t is the actual value now (in period t),

F_t is the forecast (i.e., smoothed) value for the time period t,

T_{t-1} is the trend estimate,

β is the smoothing constant for the trend estimate ($0 < \beta < 1$),

H_{t-n} is the Holt's forecast value for period t+n.

Winters' Exponential Smoothing—(Applied to only quarterly data)

Winters' method is a sophisticated exponential smoothing model that allows both seasonal and trend influences to be incorporated into the forecast. Winters' exponential smoothing is used for data that exhibit both trend and seasonality. Winters' method is based on three smoothing equations - one for stationarity, one for trend, and one for seasonality.

The four equations necessary for Winters' model are as follows:

$$F_t = \alpha\frac{X_t}{S_{t-p}} + (F_{t-1} + T_{t-1}) \quad (15)$$

$$S_t = \beta\frac{X_t}{F_t} + (1-\beta)S_{t-p} \quad (16)$$

$$T_t = \gamma(F_t - F_{t-1}) + (1-\gamma)T_{t-1} \quad (17)$$

$$W_{t+n} = (F_t + nT_t)S_{t-p-n} \quad (18)$$

Where:

F_t = Smoothed value for period t,

α = Smoothing constant for the data ($0 < \alpha < 1$),

X_t = Actual value now (in period t),

T_t = Trend estimate

S_t = Seasonality estimate,

β = Smoothing constant for seasonality estimate,
γ = Smoothing constant for trend estimate,
P = Number of periods in the seasonal cycle,
W_{t-n} = Winters' forecast for n periods into future.

Simple Linear Trend–(Applied only to annual data)

This procedure uses the equation for a straight line(Y=a+bX) as the basis for its computations. When the least squares method is used with time series data, the time periods are used as the independent variables(X in the equation).

Multiple Regression Model–(Applied to both quarterly and annual data)

Multiple regression is a statistical procedure in which a dependent variable (Y) is modeled as a function of more than one independent variable (X1, X2, X3,.., Xn). The sales and use tax collections regression model may be written as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots\ldots + \beta_n X_n + \varepsilon \quad (19)$$

Where β_0 is the intercept and other β_i's are the slope terms associated with the respective independent variables(i.e., the Xi's). In this model, ε represents the population error term.

Box-Jenkins Method–(Applied only to quar-terly data)

The Box-Jenkins (1970) model incorporates autoregressive and moving average terms, and the method involves identifying the most suitable form of the model for analyzing the data. The Box-Jenkins modeling approach can provide relatively accurate forecasts, but it involves complex mathematical and statistical algorithms, together with subjective judgments on the part of the modelers.

The general model for autoregressive integrat-ed moving average is written as

$$Y_t^* = \phi_1 Y_{t-1}^* + \phi_2 Y_{t-2}^* + \cdots + \phi_p Y_{t-p}^* + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \quad (20)$$

Where the ϕ and θ are unknown parameters and ε are independent and identically distributed normal errors with a zero mean. This model expresses Y^* in terms only of its own past values along with current and past errors. This general model is called an ARIMA(p, d, q) model for Y. Here p is the number of the lagged value of Y^*, representing the order of the autoregressive(AR) dimension of the model, d is the number of times Y is differenced to produce Y^*, and q is the number of lagged values of error terms, representing the order of the moving average(MA) dimension of the model.

The Box-Jenkins methodology used in ARIMA modeling consists of the following four stages: identification, estimation, diagnostic checking, and forecasting.

(1) Identification/model selection: The value of p, d, and q must be determined.
(2) Estimation: The θ and ϕ parameters must be estimated.
(3) Diagnostic checking: The estimated model must be checked for its adequacy and revised if necessary.
(4) Forecasting: An actual forecast using the chosen model is made.

EVALUATION OF ACCURACY MEASURES

Accuracy is generally treated as the supreme criterion for selection of a forecasting method. Since accuracy plays a vital role in assessing forecasting techniques, many studies have attempted to find the best way to measure how accurate the forecasting model is. One of the difficulties in dealing with the criterion of accuracy in forecasting is the absence of a universal measure (Makridakis, Wheelwright, and McGee, 1983).

Error, mean absolute deviation(MAD), mean squared errors(MSE), mean absolute percentage error(MAPE), and root mean squared error (RMSE) are generally used as measures of forecast accuracy. MAPE in this study was selected for the following reasons; first, it is less affected than squared measures by extreme error, second, the metric of accuracy measure is independent of scale, and last, it enables a comparison of forecasts to be made between different time series.

The MAPE is obtained by computing the absolute error for each time period, dividing the absolute error by corresponding actual value, and multiplying by 100%; then these are summed and divided by the number of forecast periods used. MAPE is calculated as

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|e_t|}{X_t}*100 \qquad (3.24)$$

Where, $|e_t|$ denotes the absolute value of the error, X_t denotes the actual value, n is the number of forecast periods.

RESULTS

Evaluation of Annual Models' Performance

Table 1 summarizes the performance of eight annual forecasting methods examined for one year ahead and two year ahead forecasting horizons. In terms of one year ahead forecasts, multiple regression has the lowest MAPE(2.253) of all forecasting methods. The second best model was the naive 1 model(MAPE=2.274). Single exponential smoothing was the third best performer(MAPE=2.276). For one year ahead forecasts, the worst forecast was Holt's exponen-tial smoothing method. All methods except the multiple regression perform worse than the naive 1 method which simply takes last year's sales and use tax collections as the forecast for the next year.

In terms of two year ahead forecasts, multiple regression(MAPE=2.717) also performed the best of all methods as it did among the one yearahead forecasts. The simple linear trend model (MAPE=4.975) ranked second. The naive 1 (MAPE=5.129) ranked third.

The naive 2 method is the worst performer of the eight. All methods except multiple regres-sion and the simple linear trend performed worse than the simplistic naive 1.

Multiple regression outperforms all other forecasting methods in both in one year and two year ahead forecasts. This is an encouraging finding since it suggests that it may be possible to enhance forecasting ability beyond the simplistic naive 1 model via developing a multi-ple regression model around existing secondary data.

In this study, the effects of forecasting time horizons were compared as to whether forecasting methods perform differently under different time horizons. The comparisons of forecasting accuracy as the forecast horizon was extended from one year ahead to two year ahead are given from Table 1. Although multiple regression ranked best for both one year ahead and two year ahead forecasts, the value of MAPE(2.253) in one year ahead forecasts is lower than that of MAPE(2.274) in two year ahead forecasts. The naive 1 method was the second best performer overall, but its MAPE increased dramatically between one and two year ahead forecasts. This pattern of higher MAPE between one and two year ahead forecasts persisted across all eight models. Thus, on the basis of the MAPE criterion, one year ahead forecasts are more accurate than two year ahead forecasts when the forecasting method is held constant. As would be expected, this study shows that the forecasting accuracy decreases as the time horizon increases.

Table 1. Accuracy of Annual Forecasts: Average MAPE and Ranking by Forecasting Method and Forecasting Horizon

Forecasting Method	Forecasting Horizon	
	1 Year	2 Year
Naive 1	2.274 (2)	5.129 (3)
Naive 2	4.995 (6)	14.068 (8)
Moving Averages	3.447 (4)	7.210 (5)
Single Exponential	2.276 (3)	5.130 (4)
Brown's Exponential	5.885 (7)	9.956 (6)
Holt's Exponential	6.024 (8)	10.207 (7)
Simple Linear Trend	4.210 (5)	4.975 (2)
Multiple Regression	2.253 (1)	2.717 (1)

Evaluation of Quarterly Models' Performance

Table 2 summarizes the forecasting perform-ance of the nine forecasting methods in terms of MAPE from the first quarter ahead to the fourth quarter ahead forecasts.

Table 2. Accuracy of Quarterly Forecasts: Average MAPE and Ranking by Forecasting Method and Forecasting Horizon, 1990 and 1991.

Forecasting Methods	1st Quarter	2nd Quarter	3rd Quarter	4th Quarter
Naive 1 S	9.233 (3)	4.781 (2)	1.582 (1)	2.941 (1)
Naive 2 S	12.188 (4)	5.168 (5)	3.549 (2)	12.076 (7)
Moving Averages	23.781 (6)	5.790 (7)	18.326 (7)	11.500 (6)
Single Exponential	23.749 (7)	2.135 (1)	25.956 (9)	5.384 (2)
Brown's Exponential	27.517 (8)	5.583 (6)	18.593 (8)	18.806 (8)
Holt's Exponential	32.906 (9)	10.787 (9)	13.996 (6)	26.401 (9)
Winters' Exponential	5.147 (1)	4.793 (3)	5.954 (3)	8.543 (4)
Box-Jenkins	5.443 (2)	4.907 (4)	6.306 (4)	9.258 (5)
Multiple Regression	12.189 (5)	9.684 (8)	12.766 (5)	6.675 (3)

In terms of first quarter ahead forecasts, Winters' exponential smoothing method(MAPE=5.147) ranked first among all methods, the Box-Jenkins method(MAPE=5.443) ranked second best, and naive 1 s(MAPE=9.233) ranked third best. The values of MAPE in the first quarter ahead forecasts varied over a range of a low of 5.147 to a high of 32.906. The mathematically sophisticated models, Winters' exponential smoothing and Box-Jenkins, proved to be more accurate than the simple models, naive 1 s and naive 2 s. However, multiple regression which ranked first in both one year ahead and two year ahead forecasts only ranked fourth in the first quarter ahead forecasts. All methods except Winters' exponential and Box-Jenkins performed worse than the simplistic naive 1 s model.

In terms of the second quarter ahead forecasts, the single exponential smoothing method(MAPE=2.135) ranked the best of all methods. Naive 1 s(MAPE=4.781) was second best; Winters' exponential smoothing method(MAPE=4.793) was third best; and Box-Jenkins (MAPE=4.907) was fourth best. The results indicate that the best model in the second quarter ahead forecasts is more complex than the second best model. However, the multiple regression model ranked only eighth(MAPE=9.684). Multiple regression's weak performance indicates that forecast accuracy may not increase with increasing information and model complexity in quarterly models. All methods except single exponential smoothing performed worse than the simplistic naive 1 s model. However, the more sophisticated models such as Winters' exponential and Box-Jenkins performed better than relatively simple models such as naive 2 s, Brown's exponential smoothing, simple moving averages, and Holt's exponential smoothing.

In terms of the third quarter ahead forecasts, the naive 1 s method (MAPE=1.582) ranked the best among alternative methods; the naive 2 s method(MAPE=3.549) was second best; Winters' exponential smoothing(MAPE=5.954) was third best; the Box-Jenkins method(MAPE=6.360) ranked fourth. However, multiple regression ranked only fifth(MAPE=12.766). The top ranked naive 1 s model is simpler than naive 2 s. This suggests that there is a decrease in accuracy as model complexity increases. However, the more complex models such as Winters' exponential smoothing, the Box-Jenkins method, and the multiple regression model performed better than the simple models such as Holt's exponential, simple moving averages, Brown's exponential smoothing, and single exponential smoothing.

In terms of fourth quarter ahead forecasts, the naive 1 s(MAPE=2.941) was the best performer. Single exponential smoothing(MAPE=5.384) ranked second best; multiple regression(MAPE=6.675) ranked third; Winter's exponential smoothing(MAPE=8.543) ranked fourth. All methods performed worse than the simplistic naive 1 s method. As was found for the third quarter ahead forecasts, the fourth quarter ahead forecasts generally showed a strong decrease in accuracy as model complexity increased. The top ranking naive 1 s model is simpler than single exponential smoothing which is the second best model; multiple regression which ranked third is a more complicated model than the second best performer; the Box - Jenkins method which ranked fifth is a more complicated model than Winters' exponential smoothing which ranked fourth.

In summary, in the first quarter ahead fore - casts, the more sophisticated models such as Winters' exponential smoothing and Box - Jenkins performed better than naive 1 s, and in the second quarter ahead forecasts single exponential smoothing performed the best while naive 1 s performed second best. In the third quarter ahead forecasts naive 1 s outperformed all other forecasting methods as it did in the fourth quarter ahead forecasts.

In the quarterly forecasts, the effects of forecasting time horizons also were compared to see whether forecasting methods perform differ - ently under different time horizons. The forecast accuracy of quarterly models as the forecasting horizons were extended are compared in Table 2. Winters' exponential smoothing in first quarter ahead forecasts, the single exponential smoothing in the second quarter ahead forecasts, and the naive 1 s in the third and fourth quarters ahead forecasts ranked the best of all methods. However, the value of the MAPE (5.147) for the best performing first quarter ahead forecasting model is higher than that of the best MAPE(2.135) produced in the second quarter ahead forecasts. The value of MAPE (2.135) for the single exponential smoothing in the second quarter ahead forecasts is also higher than that of MAPE(1.582) of the naive 1 s in the third quarter ahead forecasts. However, the pattern of declining MAPE does not continue into the fourth quarter ahead forecasts.

Unlike in the annual models, forecasting accuracy in a quarterly model does not decrease as the forecasting horizons are extended, in fact, there is no consistent pattern evident across the models in the forecasting accuracy as the forecast time horizon is lengthened.

Comparison of the Forecasting Performance of Annual and Quarterly Models in One Year Ahead Forecasts

Table 3 compares the forecasting performance of the annual and quarterly models in terms of one year ahead forecasts. In order to compare the forecasting performance between an annual model and a quarterly model, quarterly forecasts were converted into one year ahead forecasts by the summing the forecast values from the first through the fourth quarter. The values of MAPE for the annual models are the same as those shown in Table 1. The MAPE in terms of the one year ahead forecasts for the quarterly model were calculated by averaging the sum of the quarters in 1989 and 1990.

Table 3 shows that the quarterly models are generally better than the annual models in terms of one year ahead forecasts. The multiple regression model with a MAPE of 2.182 is the best of the nine quarterly forecasting methods, and the multiple regression model with a MAPE of 2.253 is the best of the eight annual forecasting methods. The MAPE of the quarterly multiple regression model is lower than that of the annual multiple regression model, but the difference in performance is negligible.

Table 3. Comparison of Forecasting Performance based on Average MAPE and Rank - ing of Annual and Quarterly Models in One Year Ahead Forecasts

Forecasting Methods	Annual: 1990 – 1991 (1 Year Avearge)	Quarterly: (Sum of Qaurters: 1 Year Average)
Naive 1	2.274 (2)	–
Naive 2	4.995 (6)	–
Moving Averages	3.447 (4)	2.809 (4)
Single Exponential	2.276 (3)	2.776 (3)
Brown's Exponential	5.885 (7)	5.084 (5)
Holt's Exponential	6.024 (8)	10.645 (9)
Multiple Regression	2.253 (1)	2.182 (1)
Simple Linear Trend	4.210 (5)	–
Naive 1 (Seasonal)	–	2.274 (2)
Naive 2 (Seasonal)	–	5.165 (6)
Winters' Exponential	–	6.033 (7)
Box – Jenkins	–	6.103 (8)

In summary, the comparison of forecasting performances of various models fitted to annual or quarterly data yielded mixed and sometimes contradictory results. The models fitted to quarterly data did not consistently yield more accurate forecasts as one might expect from the advantage offered by an enriched data base although models fitted to quarterly data appeared to have a slight edge. As one would expect, accuracy declined as the forecasting time horizon was lengthened in the case of the annual models, but the quarterly models' performance did not confirm this result. Finally a more data rich model such as multiple regression slightly outperformed the naive models, but mathematically complex models such as Box-Jenkins and Winters' exponential smoothing did not outperform simple models when forecasting one year ahead.

CONCLUSION

The comparison of forecasting accuracy of various models fitted to annual or quarterly data yielded mixed and sometimes contradictory results. Forecast accuracy in the annual models increased with increasing information, but the quarterly models' performance did not confirm this result. The selection of different time horizons did play an important role in choosing the different forecasting methods. For quarterly models, Winters' exponential smoothing and the Box-Jenkins method performed better than naive 1 s in the first quarter ahead, but these methods in the second, third, and fourth quarters ahead performed worse than naive 1 s. More complex or statistically sophisticated methods did not outperform simpler methods when forecasting quarterly data. When forecasting performances of annual and quarterly models were compared in terms of one year ahead forecasts, the quarterly multiple regression model produced superior forecasts. However, the models fitted to quarterly data, despite an enriched data base, did not consistently yield more accurate forecasts than models fitted to annual data. Forecast accuracy declined as the forecasting time horizon was lengthened in the case of the annual models, but the accuracy of the quarterly models did not decrease as the horizons were extended.

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