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A comparison of forecasting accuracy of several quantitative forecasting methods: Application to lodging sales tax and use tax collections in Michigan

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A COMPARISON OF FORECASTING ACCURACY OF SEVERAL QUANTITATIVE FORECASTING METHODS: APPLICATION TO LODGING SALES TAX AND USE TAX COLLECTIONS IN MICHIGAN

By

Jong Ho Kim

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ABSTRACT

A COMPARISON OF FORECASTING ACCURACY OF SEVERAL QUANTITATIVE FORECASTING METHODS: APPLICATION TO LODGING SALES AND USE TAX COLLECTIONS IN MICHIGAN

By

Jong Ho Kim

The primary objective of this study was to evaluate the relative accuracy of various forecasting methods for forecasting travel demand when applied to annual and quarterly Michigan sales and use tax collections data.

Eight different techniques (naive 1, naive 2, simple moving averages, simple exponential smoothing, Brown's exponential smoothing, Holt's exponential smoothing, simple linear trend, and multiple regression) were used to develop annual forecasts up to two years ahead. Quarterly forecasts were developed using these eight less simple linear trend plus Box-Jenkins and Winters' exponential smoothing. All models' forecasting performance were evaluated on the basis of the mean absolute percentage error (MAPE).

In the evaluation of annual models' performance, multiple regression performed better than the other methods in both the one year and two year forecasts. Forecast accuracy in the annual models was found to increase with increasing information, but the quarterly models' performance did not confirm this result. 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.

Multiple regression models were developed using annual and quarterly data. Eight potential explanatory variables were evaluated. The following three variables were selected for the annual regression model using the step-wise regression technique: personal disposable income per capita, unemployment rate in the U.S., and motor gasoline prices. For the quarterly models, four explanatory variables (average temperature in Michigan, personal disposable income per capita, motor gasoline prices, and unemployment rate in the U.S.) were chosen again using step-wise regression. For both the annual and quarterly models, all variable coefficients have the expected sign and are statistically significant at the 5% probability level.

DEDICATION

This dissertation is dedicated to my parents, Seok Kwon Kim and Hee Soon Seo, in gratitude for their support and encouragement throughout my studies.

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Without the assistance of a number of people, the completion of my doctoral degree would not have been possible. I would like to express my sincere appreciation to Professor Donald F. Holecek, my major adviser, for providing continuous guidance, help, and financial assistance, throughout my graduate studies at Michigan State University. I would like to extend my sincere gratitude to my committee members; Dr. Joseph Fridgen, Dr. Larry A. Leefers, and Dr. J. Michael Vasievich for their help and guidance during my graduate course work and through this study and critical assessment of my dissertation. In addition, sincere thanks are extended to Mrs. Carolyn Koenigsknecht., professor Holecek's secretary, for special kindness during my stay in the United States.

My largest debt is to my family; I owe my greatest thanks to my father (Seok Kwon Kim) and my mother (Hee Soon Seo) who supported and encouraged me to continue my studies for many long years. Finally, I would like thank my wife, Jeong Mi Lee, who has had to sacrifice during the course of this study so I could earn the doctorate degree.

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CHAPTER I

INTRODUCTION

Problem Statement

An important element in the process of planning and management within the travel industry is accurate travel demand forecasting. Trustworthy forecasts are essential for matching supply and demand in order to avoid shortages or costly oversupply (Calantone *et al.*, 1988). Most organizations must make a variety of projections as part of planning, management, and decision making, and a manager must plan for the future in order to minimize the risk of failure or, more optimistically, to maximize the possibilities of success (Archer, 1987). It is important to select an appropriate forecasting method in order to get more precise forecasting results, since accurate travel forecasts are needed for marketing, production, and financial planning.

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 and generator of income, tax collections, employment, and foreign exchange earnings in countries and regions. Statewide annual travel activities in Michigan have increased in terms of traffic volume, 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% respectively (Spotts, 1991). Williams and Spotts (1992) noted that "hotel/motel sales tax collections and use tax collections are not comprehensive indicators of travel activity since much travel activity takes place on day trips, and much overnight travel involves lodging in friends' or relatives' homes, and campgrounds". However, the amount of combined sales and use tax collections are closely related to the number of tourists, their length of stay, and their expenditures. Most studies of tourism demand focus on the number of tourist visits as tourist expenditure data by visitors is less reliable than visitation data. The sum of sales tax and use tax collections data may be a more reliable indicator of travel acivity than tourists' expenditure or arrival data in Michigan because no system for estimating either of the latter is currently in place. Tax collection data also are superior indicators of travel activity because they are complete and consistent measures whereas arrivals and traveler expenditures are only estimates subject to a wide range of sampling errors and variations in sampling design.

Accuracy is one of the factors the manager takes into account when choosing a forecasting technique (Archer, 1987). The ability to forecast travel demand accurately in the face of a changing environment can be very beneficial in this decision making process.

The need for improved tourism research and accurate tourism forecasting has been recognized by tourism professionals for some time. Forecasting accuracy can be assessed in various ways such as error magnitude, direction of change error, and trend change error. However, Hatjoullis and Wood (1979) stressed that "there is no absolute yardstick against which forecasting performance can be judged." Makridakis (1986) also argued that "no study has shown a clear superiority of one method over another"; different empirical studies have reached different conclusions as to the performance of various methods.

Of course, it would be inappropriate to apply the results of relative forecasting from other industries to the tourism sector. However, the amount and scope of existing research on travel is very limited.

Moreover, there has not been any research at all regarding travel forecasting in Michigan specifically. Therefore, it is very important to conduct a study of relative forecasting accuracy which is applied to Michigan travel data.

In this study, sales and use tax collections are used as a comprehensive indicator of travel activity in Michigan. Holecek (1991) stressed that "developing a reliable composite overview of travel in Michigan is a major research undertaking".

The focus of this study will be to evaluate the relative forecasting accuracy of selected common forecasting approaches when applied to projecting sales and use tax collections from Michigan's lodging industry. All forecasting in this study was conducted as *ex ante* (forecasts beyond the period of model fit), and forecasting accuracy was evaluated on the basis of mean absolute error (MAPE).

Study Objectives

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

One objective of this dissertation is to attempt to identify the best forecasting methods from among alternative techniques in *ex ante* forecasting of sales and use tax collections in Michigan using both annual and quarterly models for use by practitioners in the context of travel demand in Michigan. The selection of a particular forecasting method is an important decision since the results can vary greatly with the forecasting method selected. The other objective is to examine the consistency of accuracy over time. It is important to identify a model which will consistently produce the most accurate forecasts of these indicators of travel demand. The third objective is to develop a set of multiple regression models in order to examine the nature of travel demand in Michigan (that is, the understanding of the relationships between sales and use tax collections and selected possible causal variables), as well as forecasting travel demand in Michigan. The last objective is to compare the relative forecasting accuracy of annual and quarterly models in terms of one year ahead forecasts. The results of this study will help practitioners in government, regional tourism organizations, and private companies to select a tourism forecasting model and to judge its reliability.

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 develop a set of multiple regression models to identify relationships between a number of independent explanatory variables and the following dependent indicators of travel demand: sales and use tax collections.
3. To compare the forecasting accuracy of annual and quarterly models in terms of one year ahead forecasts.
4. To examine the consistency of accuracy of forecasts over time.

Importance of the Study

Tourism is an important source of income for many states. Travel activity is affected by many diverse factors such as climate, personal disposable income per capita, gasoline price, unemployment rate, and many other factors. Accurate travel forecasting is an important element in travel planning and management. More accurate forecasts would reduce economic losses. Makridakis *et al.* (1983) suggested that forecasting is an integral part of the decision making process.

According to the "General and Use Specific Sale and Use Tax Rules", issued by the Michigan Department of Treasury Sales and Use Tax Division (1992), "all tangible personal property purchased by a hotel or motel operator is subject to sales or use tax" (Michigan Department of Treasury, 1992). Michigan imposes a 4 percent sales tax on the sales of gifts and restaurant meals. A 4 percent use tax is also imposed on the rental of hotel or motel rooms. There can be no doubt as to the importance of travel in Michigan. According to the Spotts (1991), Michigan ranks 12th in state tax revenues directly generated by domestic travel expenditures and ranks 14th in terms of travel generated employment. Thus, tourism in Michigan is a major source of tax collections, and income for Michigan residents. It is a generator of employment and foreign exchange earnings. In the long term, tourism can be an effective generator of new money into a destination area as well as a source of employment opportunities.

Summary of Procedures

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. The annual models developed for evaluation were labeled: (1) naive 1, (2) naive 2, (3) simple moving 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 smoothing, (6) Holt's two-parameter linear exponential smoothing, (7) Winters' exponential smoothing, (8) Box-Jenkins method, and (9) multiple regression model. Each of these models is described in detail in Chapter three.

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. Moreover, 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 ability were evaluated on the basis of the mean absolute percentage error (MAPE). MAPE is defined as follows: the absolute error between each actual value and its corresponding forecasts, divided by the actual value for each time period multiplied by 100%, then these results are summed and divided by the number of the forecast periods used.

Overview of the Dissertation

This study is divided into five chapters. The first chapter provides an introduction which includes: a statement of the problem, study objectives, the importance of the study, procedures, and an overview of the study. The second chapter reviews the literature relevant to tourism forecasting research. The third chapter describes the methods employed in this study which includes data sources, variable definitions, and a theoretical review of different forecasting techniques used in this study. The fourth chapter presents the results. These include the forecasting results and an assessment of the forecasting performance of alternative approaches using both annual and quarterly data. Finally, the fifth chapter summarizes the evaluation of annual and quarterly forecast results from application of alternative techniques and suggests needed future research.

CHAPTER II

LITERATURE REVIEW

This chapter reviews the literature that is directly related to the present study. First, articles related to general forecasting methods and measurement of forecasting accuracy are discussed. Second, the forecasting literature as it applies to travel and tourism in particular is examined. It includes a comprehensive discussion of different forecasting techniques and comparisons of alternative methods of forecasting accuracy that have appeared in the travel and tourism related literature.

Approaches to Forecasting: General

There are many forecasting techniques which vary from simple approaches such as the naive 1 (naive no change extrapolation model), to complicated mathematical and statistical computerized models. Authors commonly divide these forecasting methods into the following categories: (1) qualitative methods, (2) time series analysis and projection, and (3) causal methods. In this study, the literature is reviewed mainly in terms of quantitative models. The quantitative models have typically been grouped according to two types, time series and causal.

Since accuracy plays a vital role in assessing forecasting techniques, many studies have attempted to find the best way to measure accuracy. However, none of these studies has resulted in a single universally accepted accuracy measurement instrument (Makridakis *et al.*, 1983).

A comprehensive summary of accuracy is provided by Makridakis *et al.*(1982). The authors conducted empirical experiments to test the performance of numerous methods of forecasting based on several accuracy measures. Makridakis *et al.*(1982) used 24 methods for 111 time series and 21 methods for 1001 time series to examine the accuracy of various forecasting methods. In their study, the Box-Jenkins technique was used to examine the results of a comprehensive empirical study comparing the forecasting ability of various time series techniques. They note that the forecasting performance of various methods differ depending upon the accuracy measure being used. They also state that "no study has proven the superiority of one method over another." Five accuracy measures are used in their study: "mean average percentage error (MAPE), mean squared error (MSE), average ranking (AR), medians of absolute percentage error (MdAPE) and percentage better (PB)."

As a forecasting measure, some authors (Gardner,

1983) prefer to use the mean absolute percentage error (MAPE) or the median absolute percentage error (MdAPE) because of the problems inherent in the MSE measure (e.g., in this approach large variations are penalized more than smaller variations because the errors are squared). Other authors have also used forecast measures such as a mean percentage error (MPE), Theil's U statistic, the root mean squared error (RMSE), and the mean absolute deviation (MAD) (Makridakis and Hibon, 1979).

Makridakis and Hibon (1991) investigated the effects of various initial values and loss functions on the post-sample forecasting accuracy of three forecasting models--Single, Holt's and Dampened exponential smoothing. Exponential smoothing methods have been widely used in many industrial applications including production planning and production (Gardner, 1985; Winter, 1960; Makridakis and Wheelwright, 1989; Martin and Witt, 1989).

Many studies investigated the performance of combining quantitative techniques (Newbold and Granger, 1974; Makridakis *et al.*, 1982, 1984; Winkler and Makridakis, 1983; Makridakis and Winkler, 1983). Such studies have found that the combined approach provides better accuracy. Winkler and Makridakis (1983) investigated the accuracy of combined forecasts consisting of the weighted averages of forecasts from individual methods. When the accuracy of weighted averages was compared with the accuracy of a simple average, they found that the combination of forecasts improves forecasting accuracy.

Newbold and Granger (1974) compared forecasting performance of three methods-- Box-Jenkins, Holt-Winters and stepwise autoregression over a large sample of economic time series, and the possibility of combining individual forecasts in the production of an overall forecast was also explored. They obtained an improvement in forecasting accuracy by considering a combination of all three types of forecast methods.

Approach to Forecasting: Tourism

Tourism is a major source of revenue and employment in many countries and regions. The need for forecast accuracy in tourism is especially acute because of the perishable nature of product. There are many studies which seek to explain the demand for travel and/or tourism, and several studies compare the forecasting ability of different techniques. However, in general, single models have been developed, and, while their fit to existing data is discussed, they have rarely been evaluated for their forecasting accuracy.

The demand for international tourism has been examined by many authors (Loeb, 1982; Martin and Witt, 1987, 1988; Witt and Martin, 1987). Such models are not generally evaluated in terms of their forecasting accuracy although these studies often suggest that the econometric models developed may be used for forecasting purposes. Econometric models are generally used to measure cause and effect relationships among variables. Archer (1987) notes that four of the most important variables influencing demand for travel are the following: 1) the income of the potential tourist, 2) the cost of the travel, 3) consumer price indexes, and 4) the currency exchange rate.

Martin and Witt (1988) have developed econometric models to explain tourism flows from four major tourist generating countries to six destinations using annual data. They attempt to incorporate substitute prices into a single equation econometric model of the demand for international tourism. They concluded that there is no single substitute price variable or set of variables applicable to all origin-destination pairs, whereas travel costs to substitute destinations influence demand in five out of six cases. Smeral (1988) also used econometric methods to estimate how tourism demand reacts to increased economic growth. His study attempts to quantify certain important influencing factors, and it illustrates how tourism demand reacts to a rise in economic growth and to a change in tourism prices.

Loeb (1982) used multiple regression techniques to investigate the effects of real per capita income, exchange rates, and relative prices on the exports of travel services from the United Kingdom, France, Canada, Italy, and Mexico. He also analyzed the effects of real per capita income, exchange rates, and relative prices on the exports of travel services from the United States to seven foreign countries. In his study, the variables income, exchange rates and relative prices proved to have a significant effect on the demand for travel originating in the U.S. The income variable was found to be significant and positive for all countries evaluated. The coefficients associated with relative price variables were generally negative and significant for the demand model, indicating the importance of price.

Morgan (1986) developed a model for examining the impact of the energy crisis and rising gasoline costs on national park visits and in particular visits to Grand Canyon National Park. His results demonstrate that the energy crisis effect is modest but significant for all U.S. park visits, and is much stronger for visits to Grand Canyon.

Uysal and Crompton (1984) identified those factors which most influence international tourist flows to Turkey. They found that "the variables of income, price, and exchange rate were consistently significant factors in the determination of international tourist flows to Turkey for all the tourist-generating countries." Summary (1987) evaluated the usefulness of multivariable regression analysis in identifying factors which influence tourists' decisions to visit Kenya. She reported that "typical multivariate demand functions estimated by ordinary least squares regression may not represent the optimal technique to use in all tourism demand studies."

Christensen and Yoesting (1976) examined the use of stepwise regression to order independent variables in leisure behavior. They suggested the use of partial correlation or, similarly, a partial F-test as alternatives to stepwise regression.

The Box-Jenkins (1970) univariate forecasting method is the most sophisticated and complex time series method and is rather more difficult to employ than the other techniques considered in this study. Nevertheless, it has been used in various studies that have appeared in the tourism forecasting literature. The Canadian Government Office of Tourism (1977) applied the Box-Jenkins technique to monthly data on tourists entering Canada from the U.S.A. and other countries by car, plane, and other modes of transportation; and to quarterly data on payments and receipts to and from the U.S.A., and all other countries. Monthly forecasts were made for up to 18 periods ahead and quarterly forecasts up to 11 periods ahead.

Calantone *et al.* (1988) states that accuracy is an important factor in travel demand forecasting. In the few existing comparative studies, comparisons have seldom included more than two methods across very limited data series (Witt and Witt, 1992). Van Doorn (1982) pointed out that "despite the growing file of reports on tourism forecasting, surprisingly little attention is paid to the comparison of actual data with the corresponding forecast." Choy (1984) and Fritz *et al.*(1984) compared only two competing methods, and Fujii and Mak (1980, 1981) and Geurts (1982) compared three. For example, Choy (1984) examined model fit of a naive forecast and a simple time-series regression using mean absolute percentage error (MAPE) as a measure of forecasting accuracy but did not address out-of-sample forecasting ability.

The Box-Jenkins technique and exponential smoothing model were applied by Geurts and Ibrahim (1975) to compare the two techniques using Hawaii tourist arrival data. They indicated that the exponential smoothing technique was preferable to the Box-Jenkins technique because of its lower costs, although the accuracy was not superior. Wandner and Van Erden (1980) used a Box-Jenkins transfer function model to project monthly tourism demand for Puerto Rico from 1977 to 1978. They determined that the technique was difficult to use and may not have been worth the additional work and expense. They also found evidence that exponential smoothing, when carefully applied, can be a particularly good way of obtaining longer-term forecasts.

Geurts (1982) compared three forecasting techniques; Box-Jenkins, exponential smoothing, and "Data Modified Exponential Double Smoothing" (an exponential model using a series of data modified to take out the effect of atypical events) in terms of Theil's U statistic using monthly data on tourists visiting Hawaii for the period of 1952-1971, and he found data modified exponential double smoothing to be the superior forecasting method.

Witt, Newbould, and Watkins (1992) compared three forecasting methods across multiple forecasts in terms of MAPE using monthly data on Las Vegas visitors and concluded that exponential smoothing generates forecasts with a lower error magnitude than the naive 1 (no change model) and the naive 2 (constant rate of change) models.

Many comprehensive studies on the comparison of forecast accuracy in the travel and tourism area have been conducted by Witt and Witt (1991), Martin and Witt (1989). Witt and Witt (1991) have assessed the performance of seven forecasting methods (naive 1, naive 2, exponential smoothing, trend curve analysis, gompertz, stepwise autoregression, and econometrics) in the context of flows of international tourist visits using annual data. They assessed the forecasting accuracy in various ways such as error magnitude, direction of change error, and trend change error. They concluded that the naive 1 "no change" extrapolation model outperforms all other forecasting methods for all origin countries in terms of error magnitude. However, in terms of the percentage of trend changes for one year time horizons they concluded that: "exponential smoothing and autoregression outperform naive 1 for three origins and underperforms for 1, and econometrics outperforms naive 1 for two origins and underperforms for 1." When the ranking of the various forecasting methods is averaged over the four origin countries (France, Germany, U.K., and U.S.A.) in terms of both the percentage of trend changes and direction of change error, exponential smoothing was found to be the most accurate among all forecasting methods examined.

Trend and seasonal patterns of monthly tourism-related employment in Michigan between January 1974 and December 1984 were identified by Chen (1988). He also developed alternative short-term forecasting models for predicting monthly tourism-related employment and compared them at both state and regional levels. He concluded that structural and time series models have the same seasonal component but different trend components (i.e., either a structural or a time series trend component). He also found that the performance of each model depends primarily on its trend component.

Within sample forecasts, that is, forecasting ability on the basis of model fit, were examined by Kunst and Neusser (1986). Out of sample forecasting, which represents the situation faced by the forecaster, has been attempted by Witt and Witt (1991) and Martin and Witt (1989). Their models were used to generate forecasts of tourist flows for each study region for one and two years into the future.

For comparing forecasting accuracy, mean absolute percentage error (MAPE) and root mean square percentage error (RMSPE) measured in unit free terms has been used by several authors (Witt and Witt, 1991; Martin and Witt, 1989). Although many authors (Lawrence, Edmundson, and O'Connor, 1985; Witt and Witt, 1991; Martin and Witt, 1989) support the use of MAPE, other authors (Meade and Smith, 1985) stress that squared errors are often more appropriate than absolute errors as an accuracy criterion.

Fritz *et al.* (1984) have examined the effects of combining forecasts produced using Box-Jenkins stochastic time-series and econometric forecasts of air arrivals into the State of Florida in terms of mean square errors. Their paper presents parsimonious methods of improving forecast accuracy by combining techniques. Fujii and Mak (1980, 1981) used three different methods of estimating an econometric model-OLS, generalized least square (GLS) and ridge regression, and they used root mean squared error (RMSE) and Theil's U test (Theil, 1966) to evaluate forecast accuracy.

Calantone *et al.* (1988) examined the use of combined forecasts as a method of forecasting tourism demand using data on tourism in Florida, and they concluded that combining forecasting models was more accurate than any single method both in terms of predictive power and accuracy as well as usefulness as a diagnostic (explanatory) tool.

Witt and Witt (1992) pointed out that: "Many studies present the value for the accuracy measures relating to the different forecasting techniques considered. However, others apply statistical tests to arrive at a conclusion with regard to how the performance of a technique compared with another." Lawrence *et al.* (1985) and Smyth (1983) carried out a t test to test for significant differences. Huss (1985) and Schnaars (1986) use Tukey's t to control for multiple comparisons. Lawrence *et al.* (1985), and Makridakis *et al.* (1982) used ANOVA techniques to test for statistical differences among a number of techniques. Makridakis *et al.* (1982) and Smyth (1983) used Spearman's rank correlation and Kendall's tau as non-parametric tests of ranking based on the accuracy measure.

Since results relating to the relative performance of different forecasting techniques from other industries may not be relevant to the travel industry and the existing travel industry research is very limited, it is necessary to carry out a study such as this which focuses on the relative accuracy of various forecasting methods using travel demand data.

In conclusion, the travel demand forecasting literature is limited and, that which exists, sheds little light on the relative accuracy of alternative models for forecasting. The literature contains no studies of travel demand forecasting for the State of Michigan, and existing circumstances in this state likely vary from those studies for which have been conducted. Thus, the results from this study will contribute to the overall body of knowledge on travel forecasting and will provide unique insights on travel demand forecasting in Michigan.

CHAPTER III

METHODOLOGY

This chapter presents the research methods used to achieve the objectives of this study. It is divided into five main sections. First, it explains the rationale for choosing the travel related variables used and identifies the sources of the data on which this study is based. Second, it describes the general forecasting methodology that was employed. Third, the various forecasting methods used for the comparison of forecast performance are discussed. Fourth, various methods for the evaluation of forecast accuracy are compared. Finally, within-sample and out-of-sample forecasts are presented and reviewed.

In developing forecasting models for hotel/motel sales and use tax collections in Michigan, eight annual forecasting models and nine quarterly models were used. The annual models selected for evaluation in this study are: 1) naive 1, 2) naive 2, 3) simple moving 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. The quarterly models used included: 1) naive 1 s 2) naive 2 s, 3) simple moving averages, 4) single exponential smoothing, 5) Brown's one-parameter linear exponential smoothing, 6) Holt's two-parameter linear exponential smoothing, 7) Winters' exponential smoothing, 8) multiple regression, and 9) Box-Jenkins.

Formal forecasting as practiced today is accomplished using both qualitative and quantitative techniques. However, the forecasting techniques which are used in this study are restricted to the quantitative approach.

SELECTION OF VARIABLES AND DATA SOURCES

Annual and quarterly data are used in the study. Models are developed to forecast combined sales and use tax collections by Michigan's lodging industry. These models are used to examine the model's forecasting ability for sales and use tax collections up to two years ahead using annual models and up to four quarters ahead using quarterly models.

In this study, data are used to construct multiple regression models. Unlike all of the other models which only deal with the sales and use tax collections data series, multiple regression models seek to determine the relationships between a number of explanatory variables and one dependent variable (i.e., sales and use tax collections). In this study, combined sales and use tax collections is the dependent variable; personal disposable income per capita, gasoline price, the unemployment rate of civilian workers in the U.S., index of foreign currency price of the U.S. dollar, index of consumer expectations, three month treasury bill rate, average temperature in Michigan, and average precipitation in Michigan, were evaluated as possible explanatory variables. While the latter two independent variables are expected to be significantly related to the dependent variable, weather forecasting is problematic, hence the weather variables may not be useful in directly forecasting tax collections. However, one can use a fitted regression model with a weather related independent variables in exploring a range of forecasts under differencing weather scenarios. For example, "what if" analysis can be performed assuming: 1) normal/average temperature and precipitation, 2) 10% above normal values for temperature and precipitation, and 3) 10% below normal for temperatures and precipitation.

Selection of the Variables

In this section, the rationale for choosing the variables used in this study is presented. The data used in this study consist of empirical time series. Multiple regression models were used to assess the relationships between sales and use tax collections and other explanatory variables. Since the bulk of

Michigan travel is generated from within Michigan and adjacent states, variables included in a multiple regression model would ideally reflect changing conditions in Michigan's prime travel market area. For many variables, such regional data were not available, and national data were used for lack of a better alternative.

Dependent Variable

Combined Sales and Use Tax Collections - Combined sales and use tax collection data was selected as the dependent variable because it is a comprehensive indicator of travel activity in Michigan. According to "General and Specific Sales and Use Tax Rules" (1992), issued by the Michigan Department of Treasury Sales and Use Tax Division, "all tangible personal property purchased by a hotel and motel operator is subject to sales or use tax." "Tangible personal property means goods that can be possessed and exchanged, with the exception of real property" (Spotts, 1991). Michigan imposes a four percent sales tax on the sales of gifts and restaurant meals. For example, "all prepared food and drink items sold by eating and drinking places are subject to the sales tax" (Spotts, 1991). Michigan also imposes a four percent tax on the rental of hotel and motel rooms. A four percent room use tax is imposed on "rental receipts from rooms or lodging furnished by hotel keepers, motel operators and other personal furnishing accommodations that are available to the public on the basis of a commercial and business enterprise, irrespective of whether membership is required for use of the accommodations" (Michigan Department of Treasury, 1992). "As used in the act, "hotel" or "motel" means a building or group of buildings in which the public may obtain accommodations for a consideration, including, without limitation, such establishments as inns, motels, tourist homes, tourist houses or units, lodging houses, apartment hotels, rooming houses, camps, resort lodges and cabins and any other building or group of buildings in which accommodations are available to the public" (Michigan Department of Treasury, 1992). The hotel/motel sales and use tax collections data for the annual and quarterly models presented in this study are aggregations of monthly data which were provided by the Michigan Department of Treasury.

Explanatory Variables

Personal Disposable Income per Capita - It has long been recognized that income is an important determinant of travel demand (Witt and Witt, 1992; Summary, 1987; Loeb, 1982; Witt and Martin, 1987; Johnson and Suits, 1983). This is likely to be the most appropriate form of the explanatory variable. Travel is a superior good, and thus an increase in personal disposable income per capita is expected to increase travel demand. For most recreational activity, as income increases, people are normally able to spend and buy more. It is hypothesized that the higher the personal income the higher the volume of travel activity.

Motor Gasoline Prices - It has also been recognized that travel cost is an important determinant of travel demand (Witt and Witt, 1992; Uysal and Crompton, 1984; Witt and Martin, 1987; Johnson and Suits, 1983; Morgan, 1986). Travel costs clearly play an important role in determining travel demand. Transportation costs can be measured using motor gasoline prices, since the retail price of gasoline is an indicator of travel costs and approximately 90% of Michigan travelers arrive by personal vehicle. Changes in the retail price of gasoline are expected to influence frequency of travel and length of stay. Thus, an increase in motor gasoline prices would be expected to negatively relate to the travel and tourism demand. All things being equal, people would travel less and spend less in hotels and motels when gasoline prices increase. It is hypothesized that the higher the retail price of gasoline the lower the volume of travel activity.

The Unemployment Rate of Civilian Workers in the U.S. - Unemployment rate was used as an explanatory variable in travel demand functions. The increase in the unemployment rate in the U.S. would be expected to be negatively related to the travel and tourism industry; people travel less and spend less as the unemployment rate rises. It is reasonable to hypothesize that the higher the unemployment rate in the U.S. the lower the level of travel activity.

Average Temperature in Michigan - In this study, statewide weighted average temperature was used. It is "derived from the divisional values by weighting each division by its percentage of the total state area" (U.S. Department Of Commerce, 1988). For most recreation activities, the increase in average temperature is normally positively related to the travel and tourism industry; people travel more as temperature rises. It is hypothesized that the higher the temperature in Michigan the higher the volume of travel activity.

Average Precipitation in Michigan - In this study, the statewide average weighted precipitation was used. It was "derived from the divisional values by weighting each division by its percentage of the total state area" (U.S. Department Of Commerce, 1988).

Precipitation plays an important role in determining travel demand. For most recreational activities, the increase in average precipitation is normally negatively related to the travel and tourism industry, people travel less as precipitation levels rise. It is hypothesized that the higher the precipitation in Michigan the lower the volume of travel activity.

Index of Foreign Currency Price of the U.S. Dollar - It has been found that the exchange rate has a significant effect on the amount of travel activity between the U.S. and other countries (Witt and Witt, 1992; Leob, 1982; Uysal and Crompton, 1984; Witt and Martin, 1987). The index of the foreign currency price of the U.S. dollar used in this study is a trade weighted average of 10 foreign currencies.[1] It is hypothesized that a decline in the index of the foreign currency price of the U.S. dollar will likely stimulate foreign travelers to demand more U.S. travel, other things being equal.

The Index of Consumer Expectations - "The Index of Consumer Expectations (ICE) includes three questions: how consumers view prospects for their own financial situation, how they view prospects for the general economy over the near term, and their view of prospects

[1] The 10 countries included in the index are: Belgium, Canada, France, Germany, Italy, Japan, Netherlands, Sweden, Switzerland, and the United Kingdom.

for the economy over the long term" (University of Michigan, 1993). Since the ICE captures consumers perceptions of prospects for the financial situation and the economy over the near term and long term, it would likely be an appropriate form of the explanatory variable desired to approximate consumer sentiment. An increase of ICE would be expected to positively affect the demand for travel. It is hypothesized that the higher the ICE the higher the volume of travel activity.

Three Month U.S. Treasury Bills - The prevailing interest rate may influence demand for travel since high rates are an incentive to save (defer current consumption) as well as a disincentive to borrowing to finance travel. High rates function to increase travel costs. These effects are offset partially by the income boost high rates provide to those with accumulated wealth such as, for example, retirees. Three month U.S. treasury bills are likely to be the appropriate form of the explanatory variable. An increase in interest on three month U.S. treasury bills is expected to decrease travel demand. If the interest on the three month U.S. treasury bills increases, people are more likely to save money in the bank rather than spend on travel plus they will face overall higher travel costs. Conceptually, increases in interest rates on three month U.S. treasury bills are likely to cause people to travel less and spend less. It is hypothesized that the higher the interest on three month U.S. treasury bills the lower the volume of travel activity.

Data Sources

Secondary data sources were used exclusively in this study. The sales and use tax data were obtained from *Travel and Tourism in Michigan: A Statistical Profile*, Travel, Tourism, and Recreation Resource Center, Michigan State University (Spotts, 1991 and 1986). Personal disposable income per capita was obtained from the *Economic Report of the President* (1977-1993). The retail price of unleaded regular gasoline was obtained from the *Monthly Energy Review* (Energy Information Administration, 1977-1993). Unemployment rates of civilian workers in U.S. was obtained from *Employment and Earnings*, Bureau of Labor of Statistics (U.S. Department of Labor, 1977-1993). The average temperature in Michigan and the average precipitation in Michigan were obtained from the *National Climatic Data Center* (U.S. Department of Commerce, 1977-1993). Index of foreign currency price of the U.S. dollar was obtained from the *Economic Report of the President* (1978-1993). The index of consumer expectations was obtained from the *Survey of Consumers*, The Survey Research Center, (The University of Michigan, 1976-1993). Finally, three month U.S. treasury bill rates were obtained from the *Economic Report of the President* (1978-1993).

FORECASTING METHODS

General Forecasting Methods

Forecasting methods are usually divided into qualitative and quantitative techniques. In the quantitative approach, forecasters use statistical methods in examining data to find underlying patterns and relationships. The quantitative approach has two subcategories-- time series, and causal methods. In most time series analyses, historical data of the series being projected are used for developing a forecast.

The purpose of all time series methods is to examine historical data and isolate the trends or patterns in them (Moore, 1989). For example, a time series analysis consists of statistical techniques applied to consecutive sales and use tax collections data over time. However, time series methods do not provide any rigorous explanations of the factors that influence the series being projected. That is, they do not deal with causality.

Causal models express mathematically the hypothesized relevant cause and effect relationships among sales and use tax collections and other factors such as economic and social forces. These are the most sophisticated sales and use tax collections forecasting tools and are appropriate only when historical data are available and when enough prior analysis has been conducted to make explicit the inherent causal relationships. The causal approach has certain advantages over time series analyses. It provides statistical evidence that specific variables relate to the data series being forecasted via a mathematical expression of that relationship. Forecasts are made by calculating the impact on demand for predicted change in causal factors such as income levels, relative prices, and the cost of travel (Archer, 1987).

Qualitative methods of forecasting are characterized by the use of accumulated experience of individual experts or groups of people assembled together, to predict the likely outcome of events. This approach is particularly appropriate where past data are insufficient or inappropriate for processing or where changes of a previously inexperienced dimension make numerical analyses of past data inappropriate. The qualitative category of forecasting techniques also has two subcategories-- technological and judgmental.

Technological methods are used to project future products and innovations. In this area, past data are not useful because each new product or innovation is unique. As a result, expert opinion rather than statistical techniques provide the driving force behind a projection. The best known qualitative forecasting technique is the Delphi method.

Judgmental methods also emphasize the intuition, experience, and expertise of individuals. They are more applicable to everyday forecasting situations such as product sales than are technological methods. However, neither judgmental tools nor technological methods use rigorous statistical analyses (Moore, 1989).

Model Specification

In developing models for hotel/motel sales and use tax collections in Michigan, eight quantitative methods were used as annual models, and nine quantitative methods were used as quarterly models. Considerably more forecasting methods appear in the literature, but it was not feasible to include all possibilities because of data limitations and/or limited resources available for this study. 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 forecasting literature and data expected to be available were considered in selecting those methods appearing to offer the best prospects for forecasting hotel/motel sales and use tax collections.

A detailed description of forecasting methods ultimately selected is provided bellow.

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 (Makridakis and Wheelwright, 1989). The simplest example is the assumption that whatever happens in one time period will also happen in the next time period. This method can be described in algebraic form, as follows:

$$\hat{X}_{t+1} = X_t \tag{3.1}$$

Where $\hat{X}_{t+1}$ represents the forecast value for time t+1, and X_t represents the current actual value for time period t.

When a data series contains a seasonal pattern such as that present in quarterly sales and use tax collections data, the method described as naive 1 will not perform very well because it ignores the seasonal component. 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. For example, the forecasted value for the first quarter 1991's sales and use tax collections is simply the amount of first quarter sales and use tax collections in 1990. In this study, the naive 1 S method can be described in algebraic form, as follows:

$$\hat{X}_{t+q} = X_q \tag{3.2}$$

Where,

X_q represents any specific quarter (q) of the current year,

$\hat{X}_{t+q}$ represents an estimate for the corresponding quarter (q) of the next year's (t).

The naive 1 model was fitted only to annual data while naive 1 S was applied only to quarterly data.

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 (Witt and Witt, 1992). In general algebraic terms the model becomes :

$$\hat{X}_{t+1} = X_t\left[1 + \frac{X_t - X_{t-1}}{X_{t-1}}\right] \qquad (3.3)$$

Where,

$\hat{X}_{t+1}$ 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. For example, the forecast for the first quarter of 1991 would be actual 1990's first quarter tax collections multiplied by the rate of change in tax collections between 1990's first quarter and 1989's first quarter. The basic equation for naive 2 s is as follows:

$$\hat{X}_{t+q} = X_q\left[1 + \frac{X_q - X_{t-q}}{X_{t-q}}\right] \qquad (3.4)$$

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.

X_{t+q} is any quarter (q) value for the next year.

Naive 2 was applied only to annual data, but naive 2 s was applied only to quarterly data.

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. Moving average models are also frequently called "smoothing" techniques, since they level out the distortions caused by occasional random fluctuations (Makridakis *et al.*, 1983). The mathematical expression for this model is:

$$\hat{X}_{t+1} = \frac{X_t + X_{t-1} + .. X_{t-N+1}}{N} = \frac{1}{n} \sum_{i=t-N+1}^{t} X_i \qquad (3.5)$$

Where,

$\hat{X}_{t+1}$ represents the forecast value for time t+1,

X_i represents actual value at time i,

i represents any given time period,

N represents the number of values to be averaged.

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

Single exponential smoothing, like moving averages, uses only past values of a time series to forecast future values of the same series and is properly employed when there is no trend or seasonality present in the data (Makridakis and Wheelwright, 1989). While this suggests the model is not suited to quarterly data series, it was decided to apply it in this study to both annual and quarterly data since the modeling significance of the seasonal component in the latter merits exploration. Exponential smoothing gives more weight to the recent observations and less to the older observations (Wilson and Keating, 1990).

The basic premise of exponential smoothing is that the values of the variables in more recent time periods have more impact on forecasts and, therefore, should be given more weight. Also, because the calculations require only the most recent data, the problem of data storage is greatly lessened. The single exponential smoothing model is expressed in the following manner:

$$F_{t+1} = \alpha X_t + (1-\alpha)F_t \qquad (3.6)$$

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.

The alpha (α) term is the smoothing constant and must be assigned a value between 0 and 1. The larger its value (closer to 1), the more weight is given to recent data (Kress, 1985).

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

Single exponential smoothing is only applicable to stationary data series. Exponential smoothing, like simple moving averages, has a major drawback; it always trails a trend in actual data. To overcome this shortcoming, the forecaster can use Brown's (1963) linear exponential smoothing (Kress, 1985). Brown's linear exponential smoothing technique is based on the same premise as that used in the double moving average model since both the single and double smoothed values lag the actual data when a trend exists. The difference between the single and double smoothed values is added to the single smoothed value, with an additional adjustment for its b value. Brown's linear exponential smoothing model is described by the following set of equations:

$$F_{t+n} = a_t + b_t(n) \qquad (3.7)$$

where $$a_t = S_t' + (S_t' - S_t'') = 2S_t' - S_t'' \qquad (3.8)$$

$$b_t = \frac{\alpha}{1-\alpha}(S_t' - S_t'') \qquad (3.9)$$

$$S_t' = \alpha X_t + (1-\alpha)S_{t-1}' \qquad (3.10)$$

$$S_t'' = \alpha S_t' + (1-\alpha)S_{t-1}'' \qquad (3.11)$$

and

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

n is the number of periods ahead to be forecast,

S'_t is the single exponential smoothed value

S''_t is the double exponential smoothed value

α is a constant between 0 and 1.

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

The method of single exponential smoothing is theoretically appropriate when the data series contains a horizontal pattern. Holt's linear exponential smoothing is best used when the data show some linear trend but little or no seasonality (Makridakis and Wheelwright, 1989).

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.

$$F_{t+1} = \alpha X_t + (1-\alpha)(F_t + T_t) \qquad (3.12)$$

$$T_{t+1} = \beta(F_{t+1} - F_t) + (1-\beta)T_t \qquad (3.13)$$

$$H_{t+n} = F_{t+1} + nT_{t+1} \qquad (3.14)$$

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 ($0 < \beta < 1$),

n is the number of periods ahead to be forecast,

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

Equation 3.12 adjusts F_{t+1} for the growth of the previous period, T_t, by adding T_t to the smoothed value of the previous period, F_t. The trend estimate is calculated in Equation 3.13, where the difference of the last two smoothed values is calculated. Because these two values have already been smoothed, the difference between them is assumed to be an estimate of the trend in the data. The second smoothing constant, β in Equation 3.13 is arrived at by using the same principle employed in simple exponential smoothing. The most recent trend ($F_{t+1} - F_t$), is weighted by β and the last previous smoothed trend, T_t, is weighted by $(1 - \beta)$. The sum of the weighted values is the new smoothed trend value T_{t+1}.

Equation 3.14 is used to forecast n periods into the future by adding the product of the trend component, T_{t+1}, and the number of periods to forecast, n, to the current value of the smoothed data F_{t+1}. This method accurately accounts for any linear trend in the data.

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

The basic exponential smoothing model enables the forecaster to assign greater weight (the alpha value in equation 3.6) to more recent data, allowing the model to compensate for recent changes. But, even with the use of weights, basic exponential smoothing models cannot effectively account for seasonal variations. Winters' method is a sophisticated exponential smoothing model that allows both seasonal and trend influences to be incorporated into the forecast. Since Winters' exponential smoothing method enables the forecaster to incorporate both trend and seasonality, it is usually a more effective forecasting technique than either exponential smoothing or moving averages for those variables that are affected significantly by seasonality and trend. 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. It is similar to

Holt's method, with one additional equation to deal with seasonality (Makridakis and Wheelwright, 1983). The four equations necessary for Winters' model are as follows:

$$F_t = \alpha \frac{X_t}{S_{t-p}} + (1-\alpha)(F_{t-1} + T_{t-1}) \qquad (3.15)$$

$$S_t = \beta \frac{X_t}{F_t} + (1-\beta) S_{t-p} \qquad (3.16)$$

$$T_t = \gamma(F_t - F_{t-1}) + (1-\gamma) T_{t-1} \qquad (3.17)$$

$$W_{t+n} = (F_t + nT_t) S_{t-p+n} \qquad (3.18)$$

F_t = Smoothed value for period t,

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

X_t = Actual value now (in period t),

F_{t-1} = Average experience of series smoothed to period t-1,

T_t= Trend estimate,

S_t = Seasonality estimate,

β = Smoothing constant for seasonality estimate,

γ = Smoothing constant for trend estimate,

n = Number of periods in the forecast lead period,

P = Number of periods in the seasonal cycle,

W_{t+n} = Winters' forecast for n periods into future.

Equation 3.15 updates the smoothed series for both trend and seasonality. In Equation 3.15, X_t is divided by S_{t-p} to adjust for seasonality; this operation deseasonalizes the data or removes any seasonal effects left in the data. Equation 3.16 is comparable to a seasonal index. That index is found as the ratio of the current value of the series X_t, divided by the current smoothed value of the series F_t. The ratio of X_t/F_t tells us something about the level of seasonality in the data. To smooth this seasonality, equation 3.16 weights the newly computed seasonal factor (X_t/F_t) with β and the most recent seasonal number corresponding to the same season S_{t-p} with $(1-\beta)$.

Equation 3.17 smooths the trend since it weights the incremental trend (F_t-F_{t-1}) with γ and the previous trend value T_{t-1} with $(1-\gamma)$. This is done in exactly the same way as in Holt's linear exponential smoothing (see Equation 3.13). Equation 3.18 is used to compute the forecast for n periods into the future; the procedure is almost identical to that in Holt's model.

Simple Linear Trend - (Applied only to annual data)

This technique fits a trend line to the data in such a way as to ensure that the sum of the squared deviation (the distance between each observation and the trend line) is at a minimum. It is sometimes possible to make reasonably good forecasts on the basis of a simple linear trend. This procedure uses the equation for a straight line (Y=a+bX) as the basis for its computations. Using a least squares analysis requires that the values for a (the intercept) and b (the slope) be identified and incorporated into the formula. When the least squares method is used with time series data, the time periods are used as the independent variables (X in the equation).

A visual inspection of the data can be helpful in deciding whether an annual model or quarterly model would be appropriate. A scattergram of Figure 1 (see Chapter 4) shows a positive trend in annual sales and use tax collections over time. A linear time trend fits the annual data reasonably well since all 16 points fall along a relatively single straight line. This method was not applied to quarterly model since quarterly data exhibit seasonality and all 64 points do not fall on a single straight line (see Figure 2 in Chapter 4).

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 (X_1, X_2, $X_3, .., X_n$). The sales and use tax collections regression model may be written as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + ... + \beta_n X_n + \varepsilon \qquad (3.19)$$

Where β_0 is the intercept and other β_i's are the slope terms associated with the respective independent variables (i.e., the X_i's). In this model, ε represents the population error term, which is the difference between the actual Y and ($\hat{Y}$) predicted by the regression model.

If combined sales and use tax collections is the dependent variable to be forecast, several factors such as the personal disposable income per capita, motor gasoline prices, the unemployment rate of civilian workers in the U.S., the average temperature in Michigan, the average precipitation in Michigan, the index of foreign currency price of the U.S. dollar, the index of consumer expectations, and three month U.S. treasury bills rates represent the possible explanatory variables. If it is found that these variables do influence the level of sales and use tax collections, they, with the exceptions of the two weather related variables, can be used to predict future values of sales and use tax collections.

There are three things which should be considered when one looks at any regression results. The first thing one should do in reviewing regression results is to verify that the signs on the coefficients are as would be expected based upon theory and prior empirical results. The second thing to examine is whether or not the results are statistically significant at the desired level of confidence. The third part of a quick check of regression results involves an evaluation of the coefficient of determination, which measures the percentage of the variation in the dependent variable that is explained by the regression model. In evaluating multiple regression equations, we should always consider the adjusted R^2 value. To get meaningful changes in R^2, an adjustment is made to account for a decrease in the number of degrees of freedom.

In looking at the regression output, we often see an F statistic (Wilson and Keating, 1990). The F statistic examines the equation's explained variance as a ratio of its unexplained variance. The F value measures the significance of the total equation. This statistic can be used to test the following hypothesis:

H_0: $B_1 = B_2 = B_3 = \ldots B_n = 0$

(i.e., all slope terms are simultaneously equal to zero)

H_1: All slope terms are not simultaneously equal to zero.

If the null hypothesis is true, it follows that none of the variation in the dependent variable would be explained by the regression model.

In multiple regression analyses, one of the assumptions that is made is that the independent variables are not highly correlated with each other. When this assumption isn't met, the modeler must deal with the problem technically referred to as multicollinearity. The cause(s) of the multicollinearity can be identified by looking at a correlation matrix of the independent variables. When multicollinearity exits, it is generally recommended that all but one of the highly correlated variables be dropped.

One of the assumptions of the ordinary least squares regression model is that error terms are independent and normally distributed with a mean of zero and constant variance. Autocorrelation results when there is a significant pattern in the error terms of a regression analysis that violates the assumption that the errors are independent over time. A test involving comparisons between table values of the Durbin-Watson statistic and the calculated Durbin-Watson statistic is used to detect autocorrelation.

Box-Jenkins Method - (Applied only to quarterly 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 modeler. The autoregressive integrated moving average (ARIMA) approach to time series analysis and forecasting is often called the Box-Jenkins approach.

The Box-Jenkins method is based on the assumption that the data series being modeled is stationary or that it may be reduced to a stationary series by differencing it an appropriate number of times. Stationary means that the expected value of any observation is the same, that is, there is no trend line present (Kennedy, 1992).

The Box-Jenkins analysis begins by transforming a variable, Y, to ensure that it is stationary, namely that its stochastic properties are invariant with respect to time (i.e., that the mean of Y_t, its variance, and its covariance with other Y values, say Y_{t-k}, do not depend on t). This is checked in a rather casual way, by visual inspection of an estimated correlogram, a graph that plots the estimated k th-order coefficient, ρ_k, as a function k. (ρ_k is the covariance between Y_t and Y_{t-k}, normalized by dividing it by the variance Y). For a stationary variable the correlogram should show autocorrelations that die out fairly quickly as k becomes larger. Although many scientific data are stationary, most economic time series data are trending (i.e., the mean changes over time) and thus clearly cannot be stationary. Box-Jenkins claimed that most economic time series data could be made stationary by differencing (perhaps after taking logs to remove heteroskedasticity), and found that usually only one or two differencing operations are required. This creates a new data series, Y^*, which becomes the input for the Box-Jenkins analysis.

The general model for Y^* is written as

$$Y_t^* = \phi_1 Y_{t-1}^* + \phi_2 Y_{t-2}^* + \ldots + \phi_p Y_{t-p}^* + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q} \qquad (3.20)$$

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 (Kennedy, 1992).

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. The principle of parsimony is adapted; most stationary time series can be modeled using very low values of p and q.

(2) Estimation: The θ and ϕ parameters must be estimated, usually by employing a least squares approximation to the maximum likelihood estimator.

(3) Diagnostic checking: The estimated model must be checked for its adequacy and revised if necessary, implying that this entire process may have to be repeated until a satisfactory model is found.

(4) Forecasting: An actual forecast using the chosen model is made. If the previous tests indicate that both model form and its parameters are appropriate, some short-term forecasts are made.

The Box-Jenkins method is most useful for those situations where forecasts are to be made and an unusual pattern exists in the past data. To analyze these unusual patterns effectively, at least 50 to 70 periods of past data are needed. This means that this method is not really appropriate for annual data and works best with weekly, monthly, or quarterly data. A major strength of the Box-Jenkins method is that it provides a statistical test for determining the adequacy of the fitted model along with confidence intervals for the resulting forecasts (Kress, 1985).

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).

Five common measures of accuracy include: error, mean absolute deviation (MAD), mean squared errors (MSE), mean absolute percentage error (MAPE), and root mean squared error (RMSE). Each is discussed below.

Error

Error is calculated from the difference between the actual data and the corresponding forecasts. Error is calculated as

$$e_t = A_t - F_t \tag{3.21}$$

where: e_t = the forecast error in period t

F_t = the forecast value in period t

A_t = the actual value in period t

Calculation of error is illustrated in Table 1.

Mean Absolute Deviation (MAD)/Mean Absolute Error (MAE)

The mean absolute deviation (MAD) or mean absolute error (MAE) is the average of the difference between the predicted values and actual data values over a number of forecasting periods greater than 1. This is a measure of overall accuracy which gives an indication of the degree of spread, where all errors are assigned equal weight

(Witt and Witt, 1992). Good forecast models should exhibit a low mean absolute error value. For perfect forecasts, mean absolute error should equal zero. Mean absolute error is calculated as

$$\text{MAD or MAE}=\frac{1}{n}\sum_{t=1}^{n}\left|e_t\right| \qquad (3.22)$$

where $\left|e_t\right|$ denotes the absolute value of the error and n denotes the number of forecasts. (See Table 1 for an illustration of how MAD is calculated)

Mean Squared Error (MSE)

The mean squared error (MSE) penalizes large variations more than smaller variations because the errors are squared. The mean squared error is also a measure of overall accuracy which gives an indication of the degree of spread, but larger errors are given additional weight (Witt and Witt, 1992). Mean squared error is calculated as

$$\text{MSE}=\frac{1}{n}\sum_{t=1}^{n}e_t^2 \qquad (3.23)$$

(See Table 1 for an illustration of how MSE is calculated)

Mean Absolute Percentage Error (MAPE):

The MAPE is obtained by computing the absolute error for each time period, dividing the absolute error by the corresponding actual value, and multiplying by 100%; then these are summed and divided by the number of forecast periods used. Lawrence *et al.* (1985) also noted that MAPE is a common measure used to assess relative accuracy since it is independent of scale, which enables a comparison to be made between different time series. Because of the above problems inherent in the MSE measure, some forecasters prefer to use the mean absolute percentage error (MAPE). MAPE is calculated as

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

Where, X_t = the actual value
(See Table 1 for an illustration of how MAPE is calculated)

Root Mean Squared Error (RMSE)

Root mean squared error is the root squared of the average of the squared differences between the predicted values and the actual data values. This method avoids the problem of sign by squaring the error. It has the further advantage of penalizing extreme deviations more heavily than it does small ones. Taking the square root provides an estimate in the original units of measurement. Forecasting models producing the lowest RMSE are considered to be the best models. Root mean squared error is defined as (Wilson and Keating, 1990):

$$\text{RMSE}=\sqrt{\frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n}} \tag{3.25}$$

(See Table 1 for an illustration of how RMSE is calculated)

Table 1. Measuring Accuracy.

Period	Actual	Forecast	Error	Absolute Error	Squared Error	Absolute Percentage Error
1989	10.0	11.0	-1.0	1.0	1.0	10.0%
1990	20.0	16.0	4.0	4.0	16.0	20.0%
1991	15.0	18.0	-3.0	3.0	9.0	20.0%
		Sum	0.0	8.0	26.0	50.0%

Mean Absolute Error: 8.0/3=2.67

Mean Squared Error: 26.0/3=8.67

Mean Absolute percentage Error: 50.0/3=16.67

Root Mean Squared Error: $\sqrt{8.67}$=2.89

The Comparison of Accuracy Measures

In order to examine the accuracy of the forecasting methods under consideration, it is necessary to select a particular measure of accuracy. There are several criteria which a forecaster may require a forecast to meet. These criteria will vary between forecasters according to the various purposes for which the forecasts are used. There are many methods of measuring the magnitude of error, such as error, mean absolute deviation (MAD)/mean absolute error (MAE), mean squared error (MSE), mean absolute percentage error (MAPE), and root mean squared error (RMSE).

Although some authors (Lawrence *et al.*, 1985; Choy, 1984; Witt and Witt, 1989, 1991, and 1992; Winkler and Makridakis, 1983; Kunst and Neusser, 1986) have supported mean absolute percentage error (MAPE), many authors (Meade and Smith, 1985; Wright *et al.*, 1986; Witt & Witt, 1989, 1991, and 1992) note that an accuracy criterion specified in terms of squared errors is often more appropriate than one in terms of absolute errors. Mean squared error (MSE) is also the most common measure of forecasting accuracy. Lewis (1982), Makridakis and Hibon (1979), Thomopoulos (1980), Firth (1977), and Sunders *et al.* (1987) note that the MSE is preferred when more weight is given to larger errors.

If the forecaster wants a model that provides reasonable accuracy for each period, MAD or MAPE will be best for comparisons to each model. Or, if the forecaster wants a model that minimizes the possibility of a major forecasting error in any given period, MSE should be used to select the model (Kress, 1985). Most previous studies which examine forecasting accuracy have concentrated on MAPE or MSE/RMSE as measures of 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, and it provides a good relative measure for comparisons among techniques.

Within-Sample/Out-of-Sample Forecasts

Before comparing the different measures of forecasting accuracy, it is necessary to consider the approach to be followed in generating a forecast. The ultimate test of any forecasting model is how well that model forecasts into the future. The basic measure for comparing the accuracy of a model is the difference between actual data for certain periods and the model's forecast for those periods. There are within-sample forecasts and out-of-sample forecasts for comparing forecast accuracy.

Out-of-sample forecasting represents the reality of the situation faced by forecasters. In time series situations such as that involved in this study, out-of-sample forecasting involves the use of some portion of the available data to fit the model(s) and then exercising it (them) to develop forecasts for comparison to actual data not employed in fitting the model. The forecasts generated by annual models and quarterly models consist of *ex ante* forecasts. In this study, each annual model is estimated over the period 1976-1988, 1976-1989, and 1976-1990 and the results are then used to generate forecasts for the next year (i.e., 1989, 1990, and 1991). Each quarterly model is estimated over the period 1976Q1-1989Q4, and 1976Q1-1990Q4 and used to generate forecasts for the periods 1990Q1-1990Q4 and 1991Q1-1991Q4.

Some authors examine forecasting ability on the basis of model fit, that is, within sample forecasts which are calculated individually (Kunst and Neusser, 1986). For example, each type of model will be estimated using data for the period 1976-1991 up to the present time. Each resulting model will be applied to predict dependent variables for each year and each quarter in the period either 1976-1991 or 1989-1991 to see how well they match the actual value of each of those years and that of each of those quarters. Some authors refer to this as *ex post* forecasting, but most refer to this purely in terms of evaluating model fit.

This study is conducted using out-of-sample forecasts for all models to be evaluated. That is, all forecasts in this study are conducted as *ex ante* forecasts (forecasts beyond the period of fit).

Finally, the following four software packages were used in this study: Lotus 1-2-3, SYSTAT DOS 5.03, SORITEC Version 2.01, and ITSM Version 3.0.

CHAPTER IV

RESULTS

This chapter contains the results of the data analyses performed in this study. It is divided into three main sections. The first section describes the characteristics of the data for hotel/motel sales and use tax collections in Michigan. The second section describes the model fitting process and the forms of each model used in this study. Each model was fitted to annual data over the periods 1976-1988, 1976-1989, and 1976-1990, and quarterly data over the periods 1976Q1-1989Q4 and 1976Q1-1990Q4. Forecasts were made for 1989, 1990, and 1991 using annual models, and 1990 and 1991 for quarterly models. Eight different annual models are used to forecast up to two years ahead, nine different quarterly models for up to four quarters, and forecasts are compared to actual sales and use tax collections in these time periods. In the third section, actual forecasts and differences between actual and forecast values are provided along with comparisons of the forecasting accuracy of each annual and quarterly model. In terms of one year ahead forecasts, the forecasting accuracy of both annual and quarterly models are compared. Forecasting performance in this study was evaluated using Mean Absolute Percentage Error (MAPE).

TRENDS IN COMBINED SALES AND USE TAX COLLECTIONS

Trends in the sum of sales and use tax collections of hotels, motels, and tourist courts in Michigan over the period of 1976-1991 are shown in Figures 1 and 2. Figure 1 shows the continual rise in sum of annual sales and use tax collections from 1976 to 1990, followed by the slight drop between 1990 and 1991.

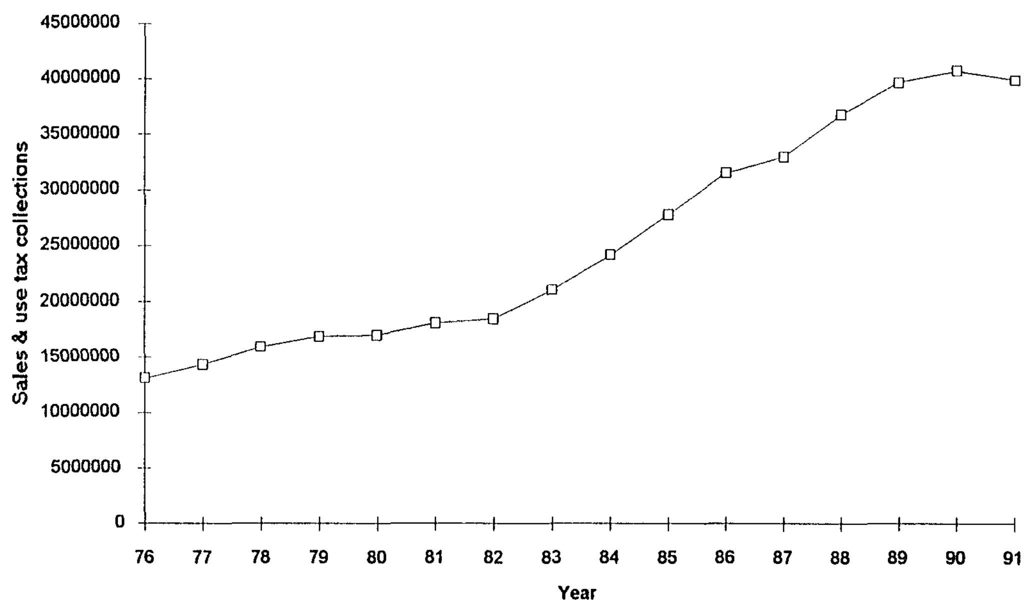


Figure 1. Annual Hotel/Motel Sales and Use Tax Collections in Michigan, 1976-1991.

Figure 2 shows the quarterly fluctuations and almost continual rise in sum of quarterly sales and use tax collections when the same quarters are compared between 1976 and 1991. Typically, the sum of hotel/motel sales and use tax collections peaks in the third quarter, are second highest in the second quarter, reach their third level in the fourth quarter, and reach their lowest levels in the first quarter. The only exceptions to the steady rise between any given quarter and that same quarter the next year occurred in 1991 when first and second quarter tax collections dipped below the levels registered in 1990. Since hotel/motel sales and use tax collections are largest in the third quarter, it is concluded that overall recreational travel activities in Michigan peaks in the third quarter period.

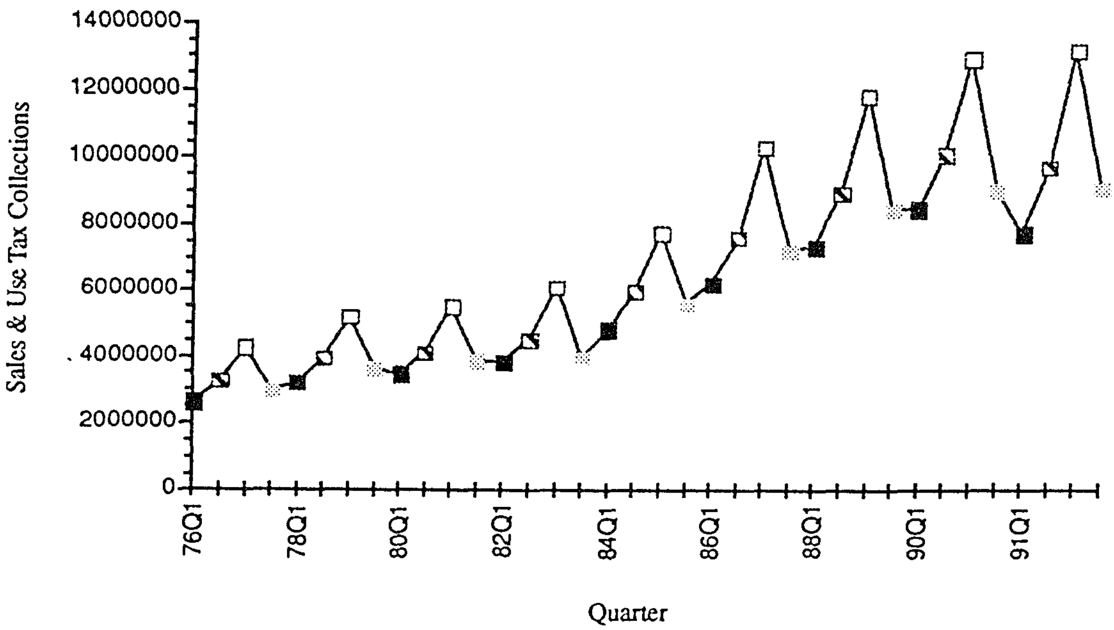


Figure 2. Michigan quarterly Hotel/Motel Sales and Use Tax Collections, 1976-1991.

FITTING THE MODELS TO THE DATA

Annual Models

Naive 1 - The naive 1 model which was used as an annual model in this study considers the current actual sum of sales and use tax collections as the forecast for the next period. In this study, annual models were exercised to generate forecasts for one and two years ahead. For example, if forecasts are desired for 1990 (one year ahead) and 1991 (two years ahead), one would apply this model by taking the level of sales and use tax actually collected in 1989 as the forecast level for both 1990 and 1991.

Naive 2 - The naive 2 method as applied to annual data in this study considers the forecast for the preceding year's sales and use tax collections as being equal to the sales and use tax collections of the current year multiplied by the growth rate registered between the current and prior year. An example will illustrate how naive 2 was applied in this study. To arrive at a one year ahead forecast for 1991, the level of sales and use tax registered in 1990 was adjusted up or down by the rate of change registered between 1989 and 1990. If the latter was found to be +5%, then the forecast for 1991 would be the level of collections registered in 1990 multiplied by 1.05. A two year ahead forecast for 1991, would be generated by applying the rate of change between 1989 and 1990 to the 1990 level of collections for two iterations. Thus, the two year ahead forecast for 1991 would be the level of forecasted sales and use tax collections in 1990 multiplied by the growth rate over the one year ahead forecast value in 1990 and the actual value in 1989.

Simple Moving Averages - The simple moving averages used as an annual model in this study considers the forecasts for next year's sales and use tax collections to be the average of the previous two years. The two year moving average was chosen because it proved to be more accurate than any other combination (e.g., 3, 4, or 5 year moving average).

Single Exponential Smoothing - The single exponential smoothing method gives more weight to recent values and less to the older values. The simple moving average gives equal weights to the all values included in each average.

The smoothing parameter was estimated by selecting the value that minimized the mean absolute percentage error over the time period examined. In this study, the best α was 0.999 for the periods 1976-1990, 1976-1989, and 1976-1988.

The alpha (α) term is the smoothing constant and must be assigned a value between 0 and 1. The larger its value (closer to 1), the more weight is given to recent sales and use tax collections data. A large alpha places greatest emphasis on the most recent data and will respond more quickly to recent changes. Thus, a large alpha is better suited to data going through some form of consistent growth or decline.

Single exponential smoothing with a high smoothing constant (α=.999) yields almost the same result as the naive 1 method. Exponential smoothing using a smoothing constant of 1.0 is in fact equivalent to the naive 1 method.

Single exponential smoothing can be forecasted by using equation (3.6). For example, the sales and use tax collections forecast for period 1991 when α = .999 is computed as follows:

$F_{1991} = \alpha X_{1990} + (1 - \alpha) F_{1990}$

$= (.999)(40669019) + (.001)(39648117) = 40667998$

Brown's One-Parameter Linear Exponential Smoothing - The double exponential smoothing method, also known as Brown's linear exponential smoothing, estimates and smoothes a linear trend in non-stationary data. First, a single exponentially smoothed line is developed. This line is adjusted by the difference between the single and double exponentially smoothed lines. Finally, a second adjustment adds a portion of the difference between the single and double exponentially smoothed lines. Each forecast for Brown's linear exponential smoothing in the annual model was tested for error, and the best alpha value was determined on the basis of the lowest mean absolute percentage error. These have the values of α=0.791 for the period 1976-1990,

α=0.795 for the period 1976-1989, and α=0.80 for the period 1976-1988.

Holt's Two-Parameter Linear Exponential Smoothing - Holt's linear exponential smoothing method is an extension of simple exponential smoothing. It adds a trend factor to the smoothing equation as a way of adjusting for any trend present in the data set. Holt's linear exponential smoothing takes trend into account but not seasonality. This technique is a two-parameter method that calculates a weighted trend component of the series in addition to a weighted average of past observations, and generates forecast values using the weighted trend and baseline fitted value. Each forecast for Holt's exponential smoothing in the annual model is tested for error and the values of alpha (the smoothing constant for the data) and beta (the smoothing constant for the trend estimate) are chosen on the basis of the lowest mean absolute percentage error. Two starting values are needed: one for the first smoothed value and another for the first trend value. The two smoothing constants derived for the annual model are α=0.999 and β= 0.524 for the period of 1976-1990, α=0.945 and β=0.646 for the period of 1976-1989, and α=0.960 and β=0.624 for the period of 1976-1988.

Simple Linear Trend - In the application of simple regression, it is assumed that a relationship exits between the variable to be forecasted (the dependent variable) and other variables (the independent variables). The first step in the regression process is to plot both sets of data on a graph to determine the general type of association that exits between the two variables. Figure 1 indicates a linear relationship between the sum of sales and use tax collections, and year.

The fact that sales and use tax collections increase over time can be expressed in a general mathematical form as follows:

Sales and use tax collections = f (time) (4-1)

Equation (4-1) implies that the level of sales and use tax collections is influenced by changes in time. This general relationship becomes $Y = a + bX$ when expressed in terms of a simple regression model.

The fitted regression equations for the annual model is Y (sales and use tax collections) = -4089310000 + 2074563.407 X (year), $R^2 = 0.942$, t = 14.576***, F = 212.455*** for the period 1976-1990, Y (sales and use tax collections) = -3985250000 + 2022020.532 X (year), $R^2 = 0.930$, t = 12.593***, F = 158.576*** for the period 1976-1989, and Y (sales and use tax collections) = -3748740000 + 1902567.28 X (year), $R^2 = 0.92$, t = 11.236***, F = 126.244*** for the period 1976-1988. Where, *** indicates significance at the 0.001 level. The coefficient of determination (R^2) is 0.942 for the estimation period of 1976-1990 (0.930 for 1976-1989 and 0.92 for 1976-1988), which tells us that 94.2 percent of the variation in sales and use tax collections for the estimation period of 1976-1990 (93 percent for 1976-1989 and 92 percent for 1976-1988) is explained by variations in the year. There are strong positive relationships between sales and use tax collections and year as shown in the above equations. For example, the slope term for 1976-1990 tells us that on average, sales and use tax collections increased by 2,074,563.407 (dollars) per year.

Multiple Regression Model - In general, multiple regression models seek to determine the relationships between a number of explanatory variables and one or more dependent variables. Underlying this model is the assumption that what has happened in the past will continue in the future. Multiple regression in this study was used to identify and quantify variables to be used in developing the sales and use tax collections forecasting model, to develop a sales and use tax collections forecasting model, and to generate forecasts for sales and use tax collections.

Stepwise regression was used in order to obtain the best set of independent variables to be used as a predictor of sales and use tax collections. One of the first items provided by a stepwise model is the correlation matrix. This matrix identifies the correlation coefficient (r values) between each independent variable and sales and use tax collections. In addition, the correlation matrix also identifies the degree of correlation among the independent variables. When a high degree of correlation is found between two independent variables, the problem of multicollinearity is said to exist. The literature suggests that correlations between independent variables that are greater than 0.7 in absolute value are problematic in multiple regression models. It further suggests that the best thing to do when multicollinearity exists is to drop all but one of the highly correlated variables.

The stepwise regression procedure includes backward elimination and forward selection. Forward selection begins with no variables in the equation. It enters the most significant predictor as the first step, and continues adding and deleting variables until none can significantly improve the fit. Backward elimination begins with all candidate variables, removes the least significant predictor in the first step, and continues until no significant variables remain.

An appraisal of a multiple regression analysis usually considers criteria such as correct coefficient signs, goodness of fit, the statistical significance of the coefficients, the significance of the total model as measured by the F value, and the lack of autocorrelation. Selection of the best subset of variables in this study is based on the combination of using the best prediction possible and keeping the model as parsimonious as possible.

The adjusted R^2 value in this study was used in evaluating multiple regression equations. To get meaningful changes in R^2, an adjustment is made to account for a decrease in the number of degrees of freedom. The reason for the adjustment is that adding another independent variable will always increase R^2 even if the variable has no meaningful relation to the dependent variable.

In both annual and quarterly models, combined sales and use tax collections is the dependent variable. Personal disposable income per capita, motor gasoline prices, the unemployment rate of civilian workers in the U.S., the average temperature in Michigan, the average precipitation in Michigan, the index of foreign currency prices with respect to the U.S. dollar, the index of consumer expectations, and three month U.S. treasury bill rates are the possible explanatory variables.

In the annual model, the factors influencing sales and use tax collections in Michigan were analyzed by using stepwise multiple regression techniques. Annual data covering the periods of 1976-1988, 1976-1989, and 1976-1990 were used for the regression model to produce forecasts for the periods of 1989, 1990 and 1991. A model may work well for a within-sample period but not work nearly so well in forecasting. Thus, it is usually best to focus on MAPE for actual forecasts. A single best model was identified for each data set on the basis of the lowest out-of-sample MAPE. Adjusted R^2 relates to the within-sample period; i.e., to the past. The models selected for the forward forecasting process for the periods of 1976-1988, 1976-1989, and 1976-1990 were:

Model 1 (for the period of 1976-1988):

$$SAUTAX = 4504891.892 + \underset{(39.021)^{***}}{2845.935}\ DISPIPC - \underset{(-7.734)^{***}}{70068.810}\ GASOLINE - \underset{(-3.116)^{*}}{527527.447}\ UNEMRATE$$

Adjusted R^2 = 0.994   F = 683.645***   DW = 2.106

Model 2 (for the period of 1976-1989):

$$SAUTAX = 4700747.599 + \underset{(36.314)^{***}}{2897.970}\ DISPIPC - \underset{(-6.693)^{***}}{70447.750}\ GASOLINE - \underset{(-3.191)^{**}}{610655.581}\ UNEMRATE$$

Adjusted R^2 = 0.994   F = 707.233***   DW = 1.723

Model 3 (for the period of 1976-1990):

$$SAUTAX = 4694540.236 + \underset{(38.292)^{***}}{2914.018}\ DISPIPC - \underset{(-6.753)^{***}}{69663.687}\ GASOLINE - \underset{(-3.459)^{**}}{639853.662}\ UNEMRATE$$

Adjusted R^2 = 0.995   F = 933.683***   DW = 1.673

( ) = The figures in parentheses are t values,
*** = Significant at the 0.001 level,
** = Significant at the 0.01 level,
* = Significant at the 0.05 level.

Where:
SAUTAX = sum of hotel/motel sales and use tax collections in Michigan,
DISPIPC = personal disposable income per capita,
GASOLINE = motor gasoline retail prices,
UNEMRATE = the unemployment rate of civilian workers in the U.S.

Based on the combination of the best prediction possible and keeping the model parsimonious, three independent variables out of eight were chosen using the forward stepwise regression selection process. These independent variables are personal disposable income per capita, motor gasoline retail prices, the unemployment rate of civilian workers in the U.S. for the estimation periods of 1976-1990, 1976-1989, and 1976-1988. All coefficients of the variables have the expected sign and are statistically significant at the 5% probability level. The personal disposable income per capita variable had a positive sign, motor gasoline prices and the unemployment rate of civilian workers in the U.S. each had a negative sign. In the case of the period 1976-1990, the slope terms indicate that for every one unit increase in DISPIPC (i.e., $1) SAUTAX would increase by 2,914.018 (dollars), for every one unit increase in GASOLINE (i.e., 1 cent per gallon) SAUTAX would decrease by 69,663.687 (dollars), and for every one unit increase in UNEMRATE (i.e., 1 percent) SAUTAX would decrease by 639,853.662 (dollars). The coefficients generated for all variables make sense. For most recreational activities, an increase in personal disposable income per capita is positively related to the travel and tourism industry; people are able to spend and buy more. Meanwhile, increases in the price of motor fuel and the unemployment rate of civilian workers in the U.S. are negatively related to the travel and tourism industry; people travel less and spend less when faced with higher fuel costs and when facing the prospects of being unemployed.

Results of all regression equations measuring overall impact of the selected variables based upon the F test were significant at the 0.1 percent probability level, thus these models are acceptable based on this criterion. The value of the Durbin-Watson statistic (a way to test statistically for the existence of autocorrelation) are 1.673 for the period of 1976-1990 and 1.723 for the period of 1976-1989. Since DW values fall between 0.82 and 1.75 (i.e., inconclusive region), these models are acceptable under the DW criterion. The Durbin-Watson value is 2.106 for the period 1976-1988. Since this value lies within acceptable limits indicating no autocorrelation among the three variables, it is concluded that there is no autocorrelation problem in this multiple regression model.

The goodness of fit of the model is very high. The adjusted R^2 indicates that 99.5 percent of the variation in sales and use tax collections for the estimation period 1976-1990, and 99.4 percent of the variation for the estimation periods 1976-1988 and 1976-1989 are explained by these models.

Quarterly Models

Naive 1 S - Two versions of the naive 1 model were employed in this study. The quarterly version will be referred to as naive 1 s. The naive 1 s model is the same as the annual model except that it is applied to quarterly rather than annual data. 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 data (i.e., the latest observation is the forecast for the next quarter), would not perform well. The naive 1 s model considers the possibility of seasonality in the data, thus should produce more accurate forecasts when applied to quarterly data. The naive 1 s method involves linking forecasts to corresponding prior quarters rather than to the immediately preceding quarter as would be the case in using naive 1. For example, the forecasted period's fourth quarter sales and use tax collections is simply the current period's fourth quarter sales and use tax collections.

Naive 2 S - Two versions of the naive 2 model were also employed in this study. The naive 2 method, if employed as it was to annual data, considers the forecast for the next quarter's sales and use tax collections to be equal to the sales and use tax collections in the current quarter multiplied by the growth rate over the previous two quarters. Since the sum of quarterly sales and use tax collections contains a seasonal pattern, naive 2 applied in this way to quarterly data will not do very well because it ignores the seasonal component. Thus, a seasonal version of the naive 2 model was developed which will be referred to as naive 2 s.

The naive 2 s method considers the forecast for the next quarter (for example, fourth quarter) sales and use tax collections as being equal to the sales and use tax collections in the most current corresponding quarter (fourth quarter) multiplied by the growth rate over the previous two quarters (e.g., the previous two years' fourth quarters).

Simple Moving Average - The basis of the simple moving average used as the quarterly model in this study is the average sales and use tax collections over the four quarters immediately prior to the quarter for which a forecast is desired. The four quarter moving average was chosen as the base number of periods for calculating the moving average since this procedure effectively smoothes out seasonal effects, and it provided more accurate results when tested emphirically.

Single Exponential Smoothing - The basic method of developing a quarterly model is identical to that discussed above in the annual section. Each forecast for single exponential smoothing in the quarterly model is tested for error, and the best alpha value was determined on the basis of the value that minimized the mean absolute percentage error over the time period examined. The most appropriate alpha (α) values in the quarterly model are 0.276 for the period 1976Q1-1990Q4, and 0.289 for the period of 1976Q1-1989Q4.

Brown's One-Parameter Linear Exponential Smoothing - The basic method of developing a quarterly model is identical to that discussed above in the annual section. Each forecast for Brown's linear exponential smoothing in the quarterly model is tested for error, and the most appropriate parameter was determined by selecting the value that minimized the mean absolute percentage error over the time period examined. The best values for α were found to be: α=0.06 for the period 1976Q1-1990Q4, and α=0.103 for the period 1976Q1-1989Q4.

Holt's Two-Parameter Linear Exponential Smoothing - The basic method of developing a quarterly model is identical to that discussed above in the annual model section. Each forecast for Holt's exponential smoothing in the quarterly model is tested for error, and the values of alpha (smoothing constant) and beta (trend smoothing constant) are chosen on the basis of the lowest mean absolute percentage error. The most appropriate values of alpha and beta derived for the quarterly model are α (smoothing constant)=0.102 and β(trend smoothing constant)=0.998 for 1976Q1-1990Q4 and α=0.105 and β=0.999 for 1976Q1-1989Q4.

Winters' Exponential Smoothing - The Winters' exponential smoothing method is based on three smoothing equations-one for stationarity, one for seasonality, and one for trend. The Winters' method extends exponential smoothing so as to cope with trend and seasonality. This method is well suited to the quarterly data used in this study since they exhibit both trend and seasonality. Winters' exponential smoothing is exactly the same as Holt's exponential smoothing when there is no seasonality in the data. Winters' exponential smoothing was not used as an annual model in this study since the annual data are non-seasonal.

Each forecast for Winters' exponential smoothing in the quarterly model was tested for errors, and three parameter combinations (alpha, beta, gamma) which minimize the mean absolute percentage error were determined. Three starting values are needed: one for the first smoothed value (α), another for the first seasonality value (β), and the third for the first trend value (γ). The three smoothing constants for the two forecasting periods 1976Q1-1990Q4 and 1976Q1-1989Q4 were found to be identical with α (smoothing constant)=0.600, β (season smoothing constant)=0.40, and γ (linear trend smoothing constant)=0.100 .

Multiple Regression Model - In the quarterly model, the factors influencing sales and use tax collections in Michigan were also analyzed by using stepwise multiple regression techniques. Quarterly data over the periods

1976Q1-1989Q4 and 1976Q1-1990Q4 were used to produce forecasts for 1990Q1-1990Q4 and 1991Q1-1991Q4. The best quarterly models were chosen using the same procedures as described in the above annual model section. The results of fitting regression equations to quarterly data for the periods of 1976Q1-1989Q4 and 1976Q1-1990Q4 are presented below.

Model 4 (for the period of 1976Q1-1989Q4):

$$\begin{aligned} SAUTAX = &-773453.507 + \underset{(11.048)^{***}}{58746.338}\ AVGTEMMI + \underset{(19.086)^{***}}{677.105}\ DISPIPC \\ &- \underset{(-2.654)^{*}}{12431.186}\ GASOLINE - \underset{(-2.605)^{*}}{218096.044}\ UNEMRATE \end{aligned}$$

Adjusted $R^2 = 0.928$ $F = 179.16^{***}$ $DW = 2.51$

Model 5 (for the period of 1976Q1-1990Q4):

$$\begin{aligned} SAUTAX = &-895366.984 + \underset{(11.343)^{***}}{61412.222}\ AVGTEMMI + \underset{(19.067)^{***}}{674.102}\ DISPIPC \\ &- \underset{(-2.540)^{*}}{12276.448}\ GASOLINE - \underset{(-2.507)^{*}}{216135.923}\ UNEMRATE \end{aligned}$$

Adjusted $R^2 = 0.933$ $F = 206.23^{***}$ $DW = 2.56$

( ) = The figures in parentheses are t values,
*** = Significant at the 0.001,
* = Significant at the 0.05 level.

Where: SAUTAX: sum of hotel/motel sales and use tax collections in Michigan,
AVGTEMMI: average temperature in Michigan ,
DISPIPC: personal disposable income per capita,
GASOLINE: motor gasoline retail prices,
UNEMRATE: the unemployment rate of civilian workers in the U.S.

Based upon the dual model selection criteria of seeking the best prediction possible while keeping the model as parsimonious as possible, four independent variables from the eight available for consideration were chosen in the stepwise forward selection process. These independent variables were average temperature in Michigan, personal disposable income per capita in the U.S., motor gasoline retail prices in the U.S., and the unemployment rate of civilian workers in the U.S. for the estimation periods 1976Q1-1989Q4 and 1976Q1-1990Q4. All coefficients of variables have the expected sign and are statistically significant at the 5% probability level. The calculated coefficients for average temperatures in Michigan and personal disposable income per capita have positive signs as expected, while motor gasoline retail prices and the unemployment rate of civilian workers in the U.S. have expected negative signs. In the case of the period of 1976Q1-1990Q4, the temperature coefficient indicates that for every one unit increase in AVGTEMMI (i.e., 1 degree Fahrenheit) SAUTAX would increase by 61,412.222 (dollars), for every one unit increase in DISPIPC (i.e., $1) SAUTAX would increase by 674.102 (dollars), for every one unit increase in GASOLINE (i.e., 1 cent per gallon) SAUTAX would decrease by 12,276.448 (dollars), and for every one unit increase in UNEMRATE (i.e., 1 percent) SAUTAX would decrease by 216,135.923 (dollars). The coefficients of all of these variables make sense. For most recreational activities, an increase in average temperature is positively related to the travel and tourism industry, and people travel more. There is, of course, an upper bound on this general tendency, and upper and lower bounds will vary somewhat with seasons. An increase in personal disposable income per capita is also positively correlated to travel activity; as people earn more they can afford to spend more on travel. An increase in the price of gasoline or an increase in the U.S. unemployment rate is negatively related to travel activity. People travel less and spend less when fuel costs rise and their confidence in the economy is shaken by rising unemployment.

Both regression equations, as indicated by the F test, are significant at the 0.1 percent probability level. The value of the Durbin-Watson statistic are 2.56 for the period of 1976Q1-1990Q4. Since the DW values lies between 2.27 and 2.56 (i.e., the inconclusive region), these models are acceptable in that autocorrelation is not a significant problem. The value of the Durbin-Watson statistic is 2.51 for the period of 1976Q1-1989Q4. Since this value also lies between 2.29 and 2.59 (i.e., inconclusive region), it also meets the acceptable standard for autocorrelation. The goodness of fit of the model is high. The adjusted R^2 indicates that 93.3 percent of the variation for the estimation period of 1976Q1-1990Q4 is explained by model 5, and 92.8 percent of the variation for the estimation period of 1976Q1-1989Q4 is explained by model 4.

Box-Jenkins Method - In general, the Box-Jenkins model procedure consists of four stages: data transformation, model identification, parameter estimation and diagnostic checking. Only after the diagnostic checks indicate that an adequate model has been constructed, are forecasts produced. The Box-Jenkins method requires a great deal of past data to function as an effective forecasting tool. To employ this technique effectively, at least 50 to 60 periods of past data are needed. Thus, it is not appropriate for annual data and works best with quarterly or monthly data. The Box-Jenkins method, therefore, was not used in this study as a basis for an annual data based forecasting model. The Box-Jenkins method involves considerable mathematical complexity over several iterations to arrive at a model with the best fit to the data set. While an extensive set of guidelines exist for navigating through the steps involved in the method, a degree of subjectivity is involved. Thus, it is desirable to present a detailed description of the results of each iteration employed in arriving at the best Box-Jenkins model for forecasting from the data set employed in this study. This presentation extends over the next dozen or so pages of the dissertation.

The time plot of quarterly sales and use tax collections data for the period of 1976Q1-1989Q4 are shown Figure 3. This plot indicates an upward trend and that the variability of the data increases with the level of the series. Since the data displays characteristics suggesting non-stationary tendencies (e.g., it contains trend and seasonality elements), it is necessary to make a logarithmic transformation so as to stabilize this variability.

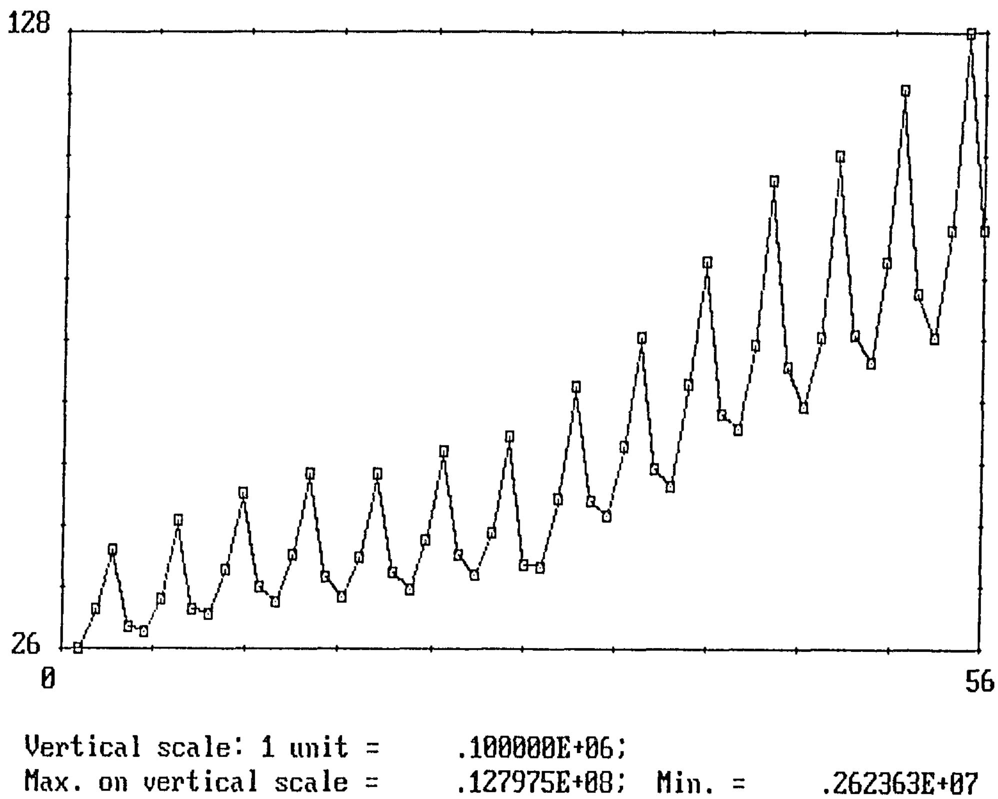


Figure 3. The time plot for the sum of quarterly sales and use tax collections for the period 1976Q1-1989Q4 before application of Box-Jenkins procedures.

Figure 4 shows the transformed sales and use tax collections data after taking the natural log of the observations. This plot indicates that this transformation has resulted in stabilization of variability over the period covered by the data; however, seasonal effects remain as does a general upward trend over time.

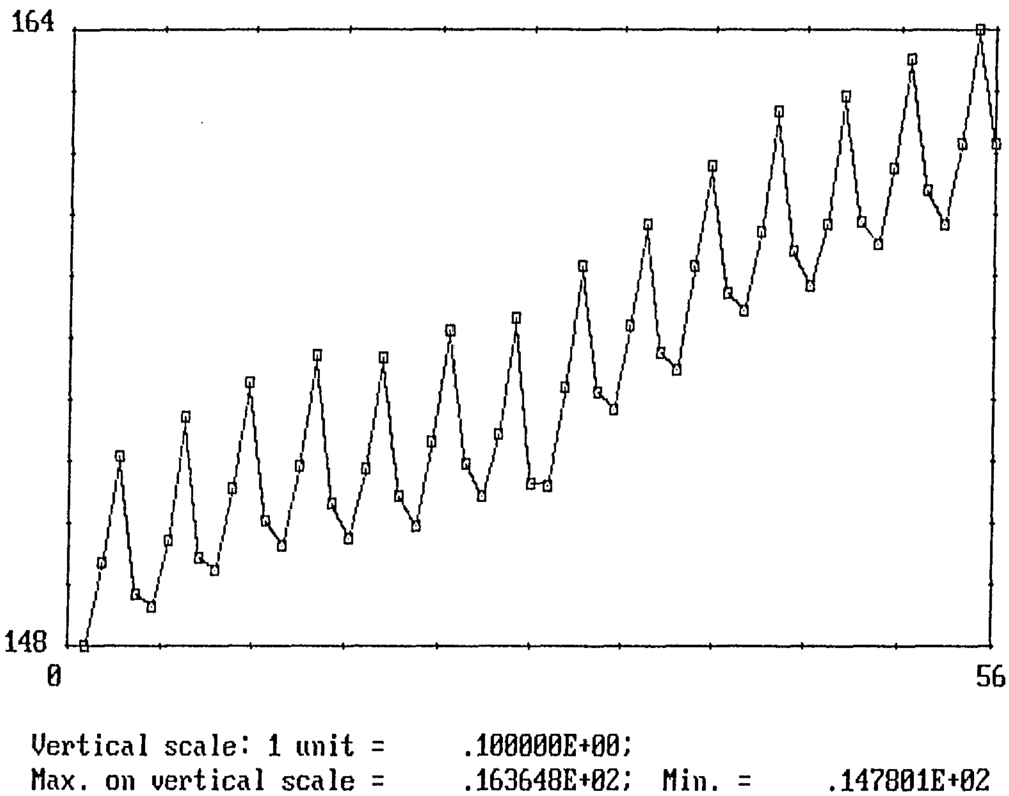


Figure 4. The natural log of the sum of sales and use tax collections for the period 1976Q1-1989Q4.

To remove these tendencies in the data, two step differencing can be used. To remove a seasonal component of period 4 from the series $\{X_t\}$, the transformed series Y_t =

$X_t - X_{t-4}$, was generated. All seasonal components of period 4 (corresponding to that quarter of the year) are eliminated by this transformation, which is called differencing at lag 4. The remaining linear trend was eliminated by further differencing at lag 1.

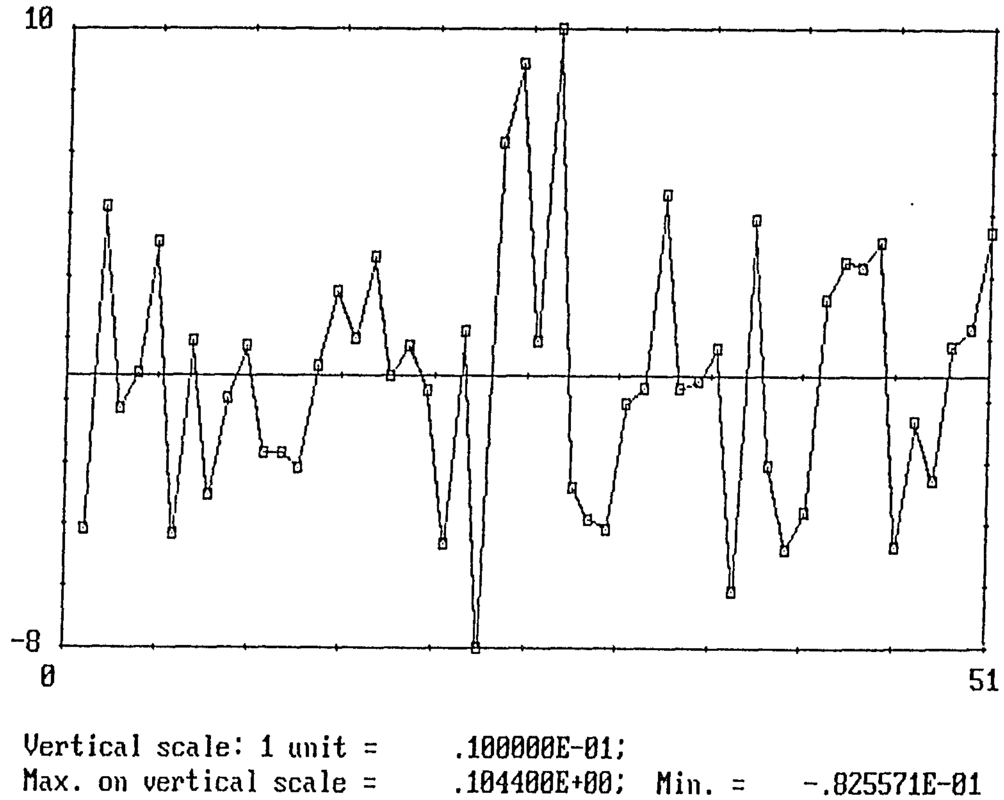
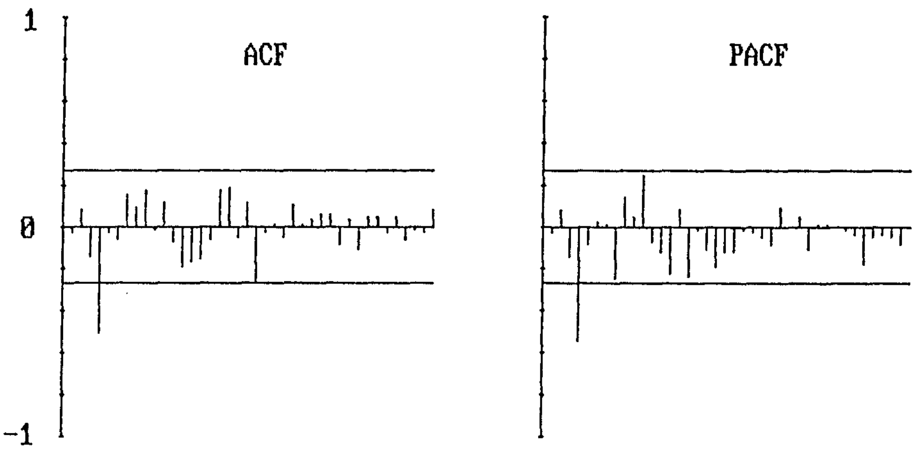


Figure 5. The natural log of the sum of sales and use tax collections after differencing at lags 4 and 1, and subtracting the mean of the transformed data for the period 1976Q1-1989Q4.

Figure 5 is a plot of sales and use tax collections for the period of 1976Q1-1989Q4 after taking logs and differencing at lags 4 and 1. This figure shows that the apparent deviations from the stationarity of the data have been reduced. To generate a series to which a zero-mean stationary model fits, the sample mean of the transformed data from each observation was subtracted.



ACF:	-.027	.085	-.139	-.510	-.029	-.065	.148	.100	.179	-.011
	.123	-.073	-.192	-.161	-.148	-.059	.175	.189	-.051	.117
	-.260	-.018	.008	-.051	.104	.014	.033	.059	.053	-.077
	.040	-.105	.047	.049	-.024	.041	-.056	-.010	-.019	.088
PACF:	-.027	.084	-.136	-.537	-.084	.021	.013	-.244	.135	.042
	.242	-.073	-.113	-.229	.087	-.238	-.010	-.104	-.186	-.119
	-.112	-.014	-.026	-.049	-.083	.095	-.005	.042	-.110	.009
	.007	-.001	-.007	-.033	-.181	-.045	-.040	-.043	-.085	-.004

Figure 6. The sample autocorrelation function (ACF) and partial autocorrelation function (PACF) of the series shown in Figure 5 for the period 1976Q1-1989Q4.

Figure 6 presents the autocorrelation function (ACF) and partial autocorrelation function (PACF) for the sales and use tax collections data after taking logarithms of the observations, differencing at lags 4 and 1 and subtracting the mean of the transformed data.

The autocorrelation function (ACF) is a measure of dependence between observations as a function of their separation along the time axis. The partial autocorrelation function (PACF) of the stationary time series $\{X_t\}$ is defined as the correlation between the residuals of X_{t+h} and X_t after linear regression on X_{t+1}, X_{t+2}, ..., X_{t+h-1}. This is a measure of the dependence between X_{t+h} and X_t after removing the effect of the intervening variables X_{t+1}, X_{t+2}, ...,X_{t+h-1}.

The ACF shows that the largest autocorrelation occurs at the fourth lag. The PACF shows that the largest partial autocorrelation occurs at the fourth lag. This graph suggests that one of the following Box-Jenkins type models might be appropriate: a moving average (MA) model of order 4 with a large number of zero coefficients, or alternatively an autoregressive (AR) model of order 4, or finally a mixed autoregressive/moving average (ARMA) model.

The next step of the Box-Jenkins analysis is to consider a variety of competing models and to select the most suitable. To use suggested model selection criteria, it is necessary to compute the value of the criteria for each possible model and then select the model which has the minimum value. A more generally applicable criterion for model selection is the information criterion of Akaike (1973), known as the AIC. In this study, a bias-corrected version of the AIC, referred to as the AICC, suggested by Hurvich and Tsai (1989) was used. The AICC criterion provides a rational criterion for choosing between competing models. Smallness of the AICC value is indicative of a good model. The best of the models considered from the point of view of AICC value is the one with non-zero coefficients at lag 4 (AICC = -196.931), that is the autoregressive model (ARMA(4, 0)) for the period 1976Q1-1989Q4. It was chosen from the point of view of the AICC value.

The forecasting form of the model selected is

$$X_t = Z_t - .523X_{t-4} \quad \{Z_t\} \sim \text{WN}(0, .0011). \qquad (4.2)$$

After the model which minimizes the AICC value has been identified, it can be checked by studying the residuals to see whether or not the model provides a good fit to the data. The histogram of residuals is illustrated in Figure 7. If the fitted model is appropriate, the histogram of residuals should have a mean close to zero and variance close to one. The mean and the variance are -0.009 and 0.9999, which is almost the same as white noise (0,1). Since the residuals for this model turned out to be compatible with white noise, it was not necessary to modify the model further.

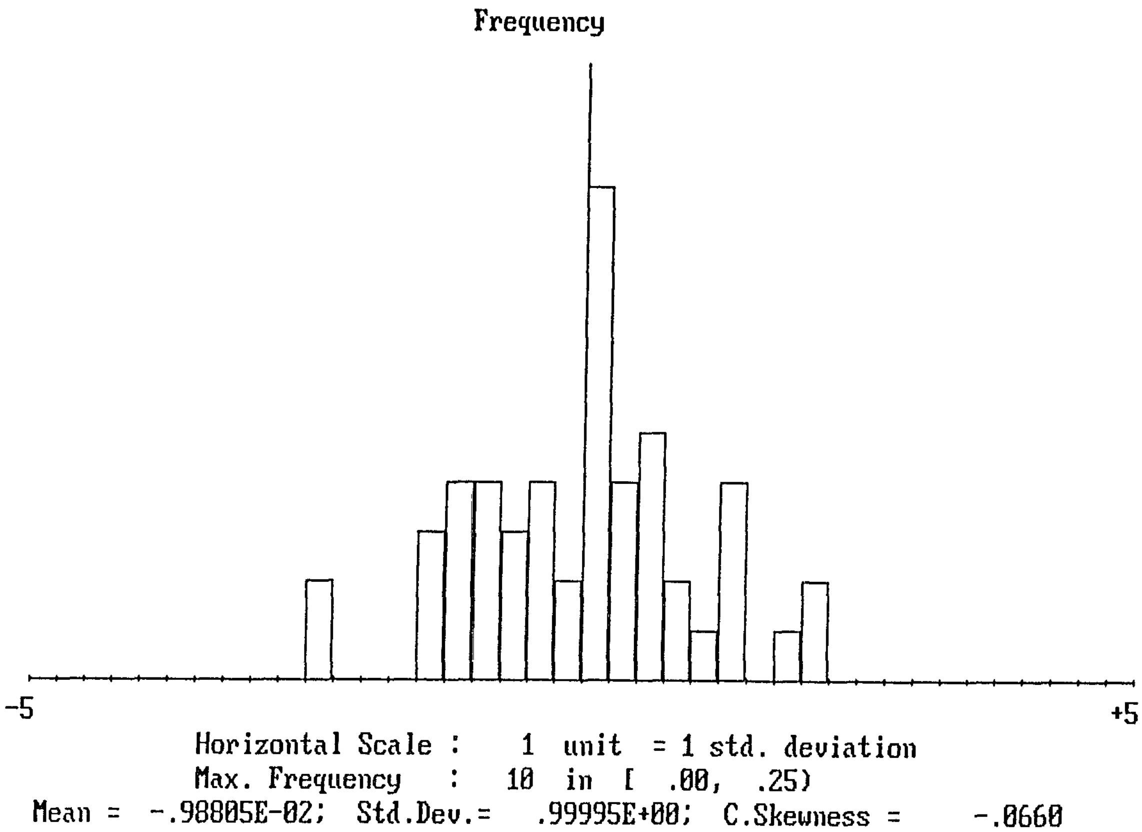
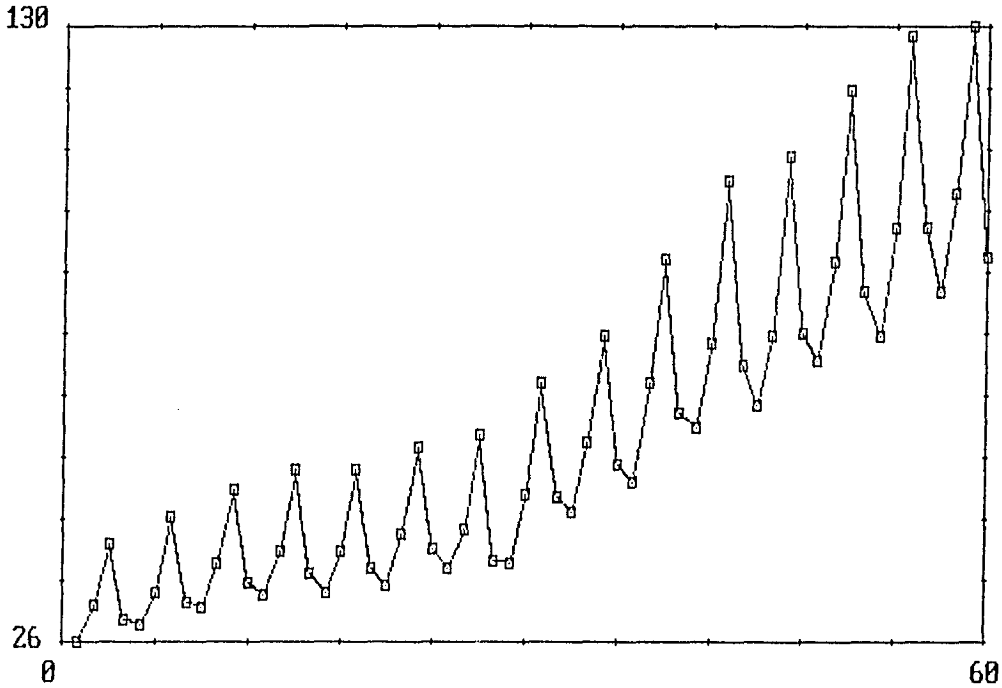


Figure 7. Histogram of the residuals from sales and use tax collections for the period 1976Q1-1989Q4.

One of the main purposes of time series modeling is the prediction of future observations. The future values are generated by the above model, and the results of first quarter to fourth quarter ahead forecasts for each quarter and the full year using the ARIMA model for 1990 are presented in Table 6.

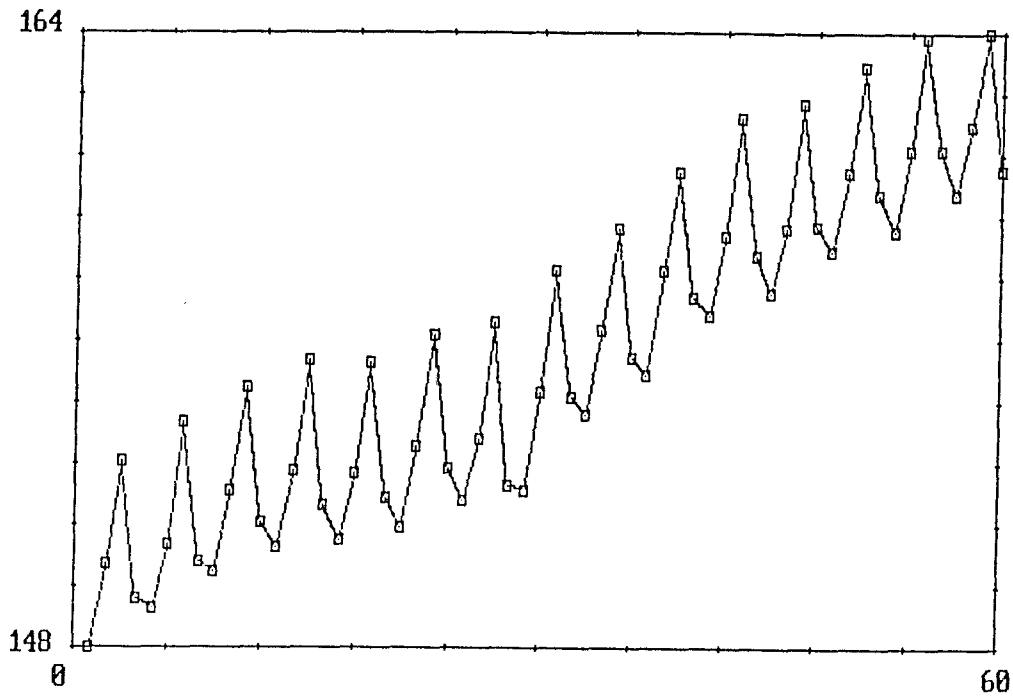
The sum of sales and use tax collections data for the period of 1976Q1-1990Q4 are shown in Figure 8, and they exhibit the same upward trend and increasing variability as seen in Figure 3 for the period 1976Q1-1989Q4.



Vertical scale: 1 unit = .100000E+06;
Max. on vertical scale = .129610E+08; Min. = .262362E+07

Figure 8. The time plot for the sum of quarterly sales and use tax collections for the period 1976Q1-1990Q4 before application of Box-Jenkins procedures.

Figure 9 illustrates the data after transformation to their natural logs to stabilize variability. Although variability of the data over time has been stabilized, a seasonal effect and upward trend are both still evident. Consequently first order differencing and quarterly differences were applied to the log-transformed data.



Vertical scale: 1 unit = .100000E+00;
Max. on vertical scale = .163775E+02; Min. = .147801E+02

Figure 9. The natural log of the sum of sales and use tax collections for the period 1976Q1-1990Q4.

A plot of sales and use tax collections for the period of 1976Q1-1990Q4 after taking logs and differencing at lags 4 and 1 is illustrated in Figure 10. This figure indicates that these transformations have created stationary in the mean. The sample mean of the transformed data from each observation was subtracted in order to generate a series which fit a zero-mean stationary model.

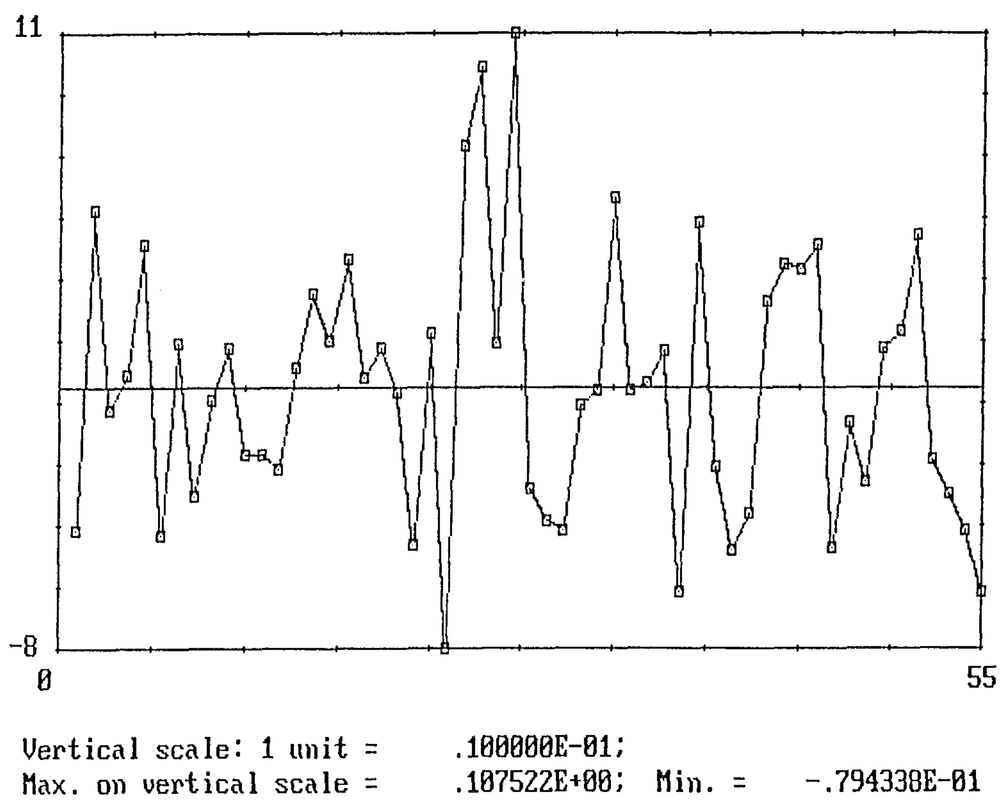
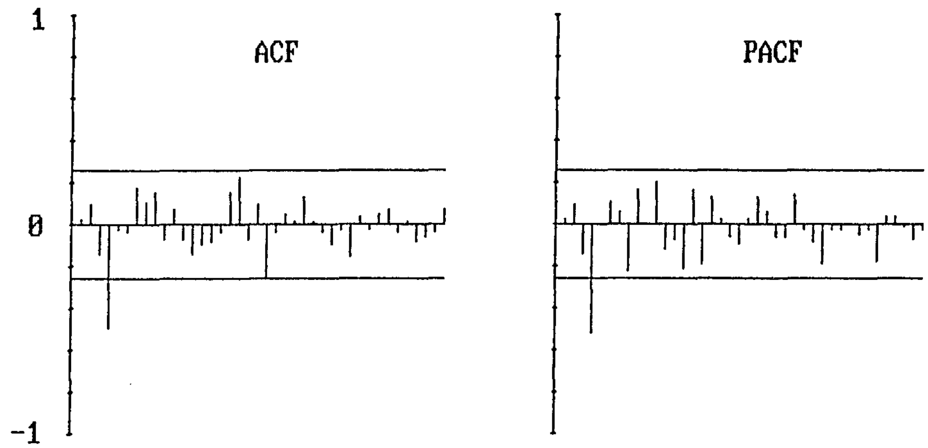


Figure 10. The natural log of the sum of sales and use tax collections after differencing at lags 4 and 1, and subtracting the mean of the transformed data for the period 1976Q1-1990Q4.

ACF and PACF for the sales and use tax collections data after taking logarithms, differencing at lags 4 and 1 and subtracting the mean of the transformed data are shown Figure 11.



ACF:	.025	.093	-.140	-.499	-.028	-.030	.173	.103	.157	-.076
	.073	-.072	-.141	-.091	-.082	-.034	.158	.218	-.065	.090
	-.257	-.037	.049	.012	.134	.016	-.035	-.090	-.018	-.151
	.031	-.027	.052	.074	-.040	.007	-.086	-.059	-.039	.072
PACF:	.025	.093	-.146	-.515	-.004	.100	.062	-.227	.162	.004
	.200	-.112	-.075	-.207	.166	-.185	.128	.020	-.055	-.095
	.023	.130	.064	-.060	-.064	.136	-.021	-.086	-.187	-.025
	-.026	-.003	-.045	-.026	-.175	.037	.032	-.012	-.071	-.028

Figure 11. The sample autocorrelation function (ACF) and partial autocorrelaiton function (PACF) of the series shown in Figure 10 for the period 1976Q1-1990Q4.

The ACF shows that the largest autocorrelation occurs at the fourth lag. The PACF shows that the largest partial autocorrelation occurs at the fourth lag. This graph suggests that the best Box-Jenkins model for these data would be a MA model of order 4 with a large number of zero coefficients, or alternatively an AR model of order 4, or finally a mixed ARMA model. The rational criterion for choosing between competing models is, as noted previously, the AICC criterion. The best of these models from the point of view of minimum AICC value is the one with non-zero coefficients at lag 4 (AICC = -216.888). Thus, the moving average model (ARMA(0,4)) is the best choice for the period 1976Q1-1990Q4.

The forecasting form of the model selected is

$$X_t = Z_t - .799Z_{t-4} \quad \{Z_t\} \sim WN(0, .00093) \qquad (4.3)$$

After the model which minimizes the AICC value has been identified, it can be checked by studying the residuals to see whether or not the model is a good fit to the data thus meeting the Box-Jenkins standard for goodness of fit. The histogram of residuals is given in Figure 12. If the fitted model is appropriate, the histogram of residuals should have a mean close to zero and variance close to one. The mean and variance are 0.1626 and 0.9933 respectively, which is almost the same as white noise (0,1). Since the residuals for this model turned out to be compatible with white noise, it was not necessary to modify the model further.

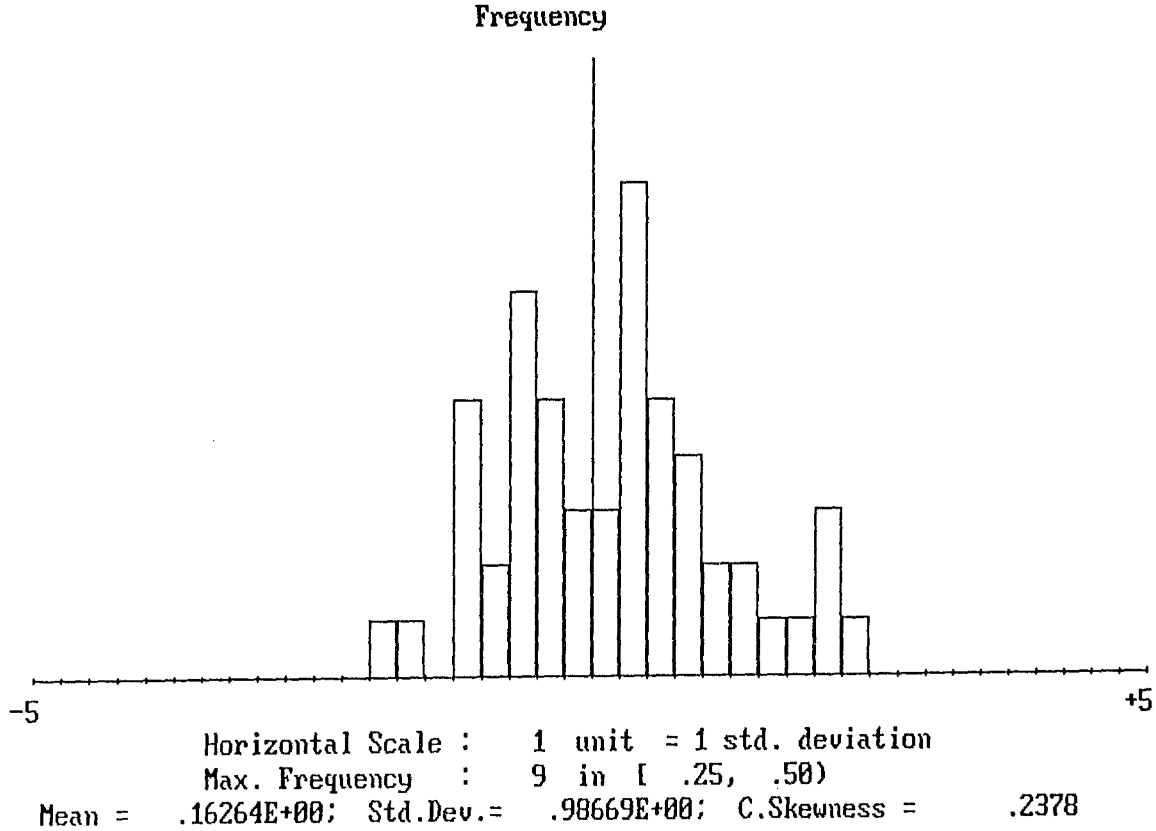


Figure 12. Histogram of the residuals from sales and use tax collections for the period 1976Q1-1990Q4

USING THE MODELS TO FORECAST AND EVALUATE THE QUALITY OF FORECASTS DERIVED

In this section, the forecasts derived using each of the models will be presented. This will be followed by an evaluation of the quality of the forecasts derived using MAPE as the evaluation criterion.

To generate out-of-sample forecasts, each model was fitted to yearly data over the periods 1976-1988, 1976-1989, and 1976-1990, and quarterly data over the periods 1976Q1-1989Q4, 1976Q1-1990Q4. Yearly forecasts were made for 1989, 1990, and 1991, and quarterly forecasts for 1990 and 1991.

One year ahead and two year ahead forecasts for 1990 and 1991 for all forecasting methods and absolute percentage error are given in Tables 2 to 5. The first quarter to fourth quarter ahead forecasts for all forecasting methods and absolute percentage error for the periods 1990 and 1991 are shown in Table 6 and 7. Highlights from each table are presented below.

One year ahead forecasts for 1990 for each model are presented in Table 2. Based on absolute percentage error magnitude, the most accurate of the one year ahead forecasts for 1990 was produced by the multiple regression model. The second best model proved to be naive 1, and the third best model was single exponential smoothing. The moving average model yielded the least accurate forecast with considerably greater absolute percentage error than produced by other models.

Table 2. Annual Forecasts: One Year Ahead to 1990

Forecasting Method	Actual ($)	Forecast ($)	APE
Naive 1	40669019	39651068	2.503
Naive 2	40669019	42834760	5.325
Moving Averages	40669019	38177535	6.126
Single Exponential	40669019	39648117	2.510
Brown's Exponential	40669019	42719208	5.041
Holt's Exponential	40669019	42719838	5.043
Simple Linear Trend	40669019	38567303	5.168
Multiple Regression	40669019	40013783	1.611

Table 3. Annual Forecasts: One Year Ahead to 1991

Forecasting Method	Actual ($)	Forecast ($)	APE
Naive 1	39854231	40669019	2.044
Naive 2	39854231	41713103	4.664
Moving Averages	39854231	40160043	0.767
Single Exponential	39854231	40667998	2.042
Brown's Exponential	39854231	42535996	6.729
Holt's Exponential	39854231	42645552	7.004
Simple Linear Trend	39854231	41149781	3.251
Multiple Regression	39854231	41007578	2.894

One year ahead forecasts for 1991 for each model are shown in Table 3. Based on absolute percentage error magnitude, the most accurate one year ahead forecast for 1991 was produced by the moving average model which yielded the worst forecast for 1990. The second best model in forecasting 1991 tax collections was single exponential smoothing, and the third best model was the naive 1 model. Holt's exponential smoothing produced the worst forecast for 1991.

Table 4. Annual Forecasts: Two Years Ahead to 1990

Forecasting Method	Actual ($)	Forecast ($)	APE
Naive 1	40669019	36704003	9.749
Naive 2	40669019	45560687	12.028
Moving Averages	40669019	35763977	12.061
Single Exponential	40669019	36703999	9.750
Brown's Exponential	40669019	42719208	5.041
Holt's Exponential	40669019	42921684	5.539
Simple Linear Trend	40669019	37372771	8.105
Multiple Regression	40669019	39477633	2.929

Two year ahead forecasts for 1990 for each model are shown in Table 4. Based on absolute percentage error magnitude, the most accurate of the two year ahead forecasts for 1990 was produced by the multiple regression model. The second best performing model was Brown's exponential smoothing, and the third best model was Holt's exponential smoothing. Moving averages was the worst performer in forecasting two years ahead for 1990 as it was for projecting one year ahead for the same year.

Two year ahead forecasts for 1991 for each model are shown in Table 5. Based on the absolute percentage error magnitude, the most accurate two year ahead forecast for 1991 was derived using the naive 1 model. The second best model was single exponential, and the third best model was simple linear trend. The worst forecast was derived using the naive 2 model.

Table 5. Annual Forecasts: Two Years Ahead to 1991

Forecasting Method	Actual ($)	Forecast ($)	APE
Naive 1	39854231	39651068	0.509
Naive 2	39854231	46274081	16.108
Moving Average	39854231	38914301	2.358
Single Exponential	39854231	39651065	0.510
Brown's Exponential	39854231	45780988	14.871
Holt's Exponential	39854231	45782627	14.875
Simple Linear Trend	39854231	40589324	1.844
Multiple Regression	39854231	40852688	2.505

Based upon these results, no model stands out as being particularly superior or inferior in its forecasting accuracy. However, judging a model's ability based upon its performance in any given year is not especially meaningful. A more useful measure of its usefulness is its average ability to produce accurate forecasts. This will be explored later in this chapter.

The first quarter ahead to the fourth quarter ahead forecasts for 1990 for each model are shown in Table 6. Based on absolute percentage error magnitude, the most accurate first quarter ahead forecast for this year was produced by the Winters' exponential smoothing model. The second best model was the naive 2 s, and the third best model was Box-Jenkins. The worst forecast was produced by Holt's exponential smoothing method.

The most accurate second quarter ahead forecast for 1990 was produced by the naive 2 s model. The second best model was moving averages, and the third best model was single exponential smoothing. Box-Jenkins was the worst performer and produced considerably greater error in forecasts than other models.

The most accurate third quarter ahead forecast for 1990 was produced by the naive 1 s model. The second best model was naive 2 s, and the third best model was Winters' exponential smoothing. The worst forecast was produced by single exponential smoothing.

The most accurate fourth quarter ahead forecast for

Table 6. Quarterly Forecasts (Dollars), 1990

Forecasting Method	1st Quarter	2nd Quarter	3rd Quarter	4th Quarter	Year (Sum of Quarters)
Actual	8502283	10136516	12960986	9069234	40669019
Naive 1 S	7742075	9557917	12797516	9553560	39651068
(APE)	8.941	5.708	1.261	5.340	2.503
Naive 2 S	8154096	10156284	13796871	10753167	42860418
(APE)	4.095	0.195	6.449	18.568	5.388
Moving Averages	9912767	10455440	10679820	10150396	41198423
(APE)	16.589	3.146	17.600	11.921	1.302
Single Exponential	9911677	9808216	9734646	9682329	39136868
(APE)	16.577	3.239	24.893	6.760	3.767
Brown's Exponential	10341722	10515159	10688595	10862032	42407508
(APE)	21.635	3.735	17.533	19.768	4.275
Holt's Exponential	10514938	10851555	11188172	11524789	44079454
(APE)	23.672	7.054	13.678	27.076	8.386
Winters' Exponential	8694426	10670669	14264888	10181628	43811611
(APE)	2.260	5.270	10.060	12.266	7.727
Box-Jenkins	8863922	10898110	14488995	10581312	44832339
(APE)	4.253	7.513	11.789	16.673	10.237
Multiple Regression	9256027	10796243	11330470	9578794	40961534
(APE)	8.865	6.508	12.580	5.619	0.719

1990 was produced by the naive 1 s model. The second best model was found to be multiple regression, and the third best model was single exponential smoothing. Holt's exponential smoothing for the second time was found to be the worst performer.

In the one year ahead forecasts for 1990 which were calculated by summing the first quarter ahead to the fourth quarter ahead forecasts are shown in Table 6. The most accurate forecast was produced by the multiple regression model. The second best model was simple moving averages, and the third best model was naive 1 s. The worst forecast was produced by the Box-Jenkins method.

The first quarter ahead to the fourth quarter ahead forecasts for 1991 for each model are shown in Table 7. Based on the absolute percentage error magnitude, the most accurate first quarter ahead forecast for 1991 was produced by the Box-Jenkins method. The second best model was Winters' exponential smoothing, and the third best model was naive 1 s. The worst forecast was produced by Holt's exponential smoothing method.

The most accurate second quarter ahead forecast for 1991 was produced by the single exponential smoothing method. The second best model was Box-Jenkins, and the third best model was naive 1 s. The worst forecast again came from Holt's exponential smoothing method.

The most accurate forecast of the third quarter ahead for 1991 was produced by the naive 2 s model. The second best model was Box-Jenkins, and the third best model was Winters' exponential smoothing. The worst forecast was produced by the single exponential smoothing method.

The most accurate fourth quarter ahead forecast for 1991 was produced by the naive 1 s model. The second best

Table 7. Quarterly Forecasts (Dollars), 1991

Forecasting Method	1st Quarter	2nd Quarter	3rd Quarter	4th Quarter	Year (Sum of Quarters)
Actual	7762826	9760408	13212342	9118655	39854231
Naive 1 S	8502283	10136516	12960986	9069234	40669019
(APE)	9.526	3.853	1.902	0.542	2.044
Naive 2 S	9337137	10750141	13126544	8609461	41823283
(APE)	20.280	10.140	0.649	5.584	4.941
Moving Averages	10167254	10583497	10695243	10128807	41574801
(APE)	30.974	8.433	19.051	11.078	4.317
Single Exponential	10163214	9861114	9642439	9484150	39150917
(APE)	30.922	1.032	27.019	4.008	1.765
Brown's Exponential	10355599	10485691	10615782	10745874	42202946
(APE)	33.400	7.431	19.653	17.845	5.893
Holt's Exponential	11034042	11177527	11321012	11464497	44997078
(APE)	42.139	14.519	14.315	25.726	12.904
Winters' Exponential	8386575	10181798	13456552	9558136	41583061
(APE)	8.035	4.317	1.848	4.820	4.338
Box-Jenkins	8277901	9985054	13089225	9286757	40638937
(APE)	6.635	2.302	0.932	1.843	1.969
Multiple Regression	8967141	11015724	11501021	9823535	41307421
(APE)	15.514	12.861	12.952	7.730	3.646

model was Box-Jenkins, and the third best model was single exponential smoothing. Holt's exponential smoothing for the third time had the worst performance.

The one year ahead forecasts for 1991 resulting from summing the first through the fourth quarter ahead forecasts are also given in Table 7. The most accurate forecast for

1991 was produced by the single exponential smoothing model. The second best model was Box-Jenkins, and the third best model was naive 1 s. Holt's exponential smoothing was the worst performer in this instance.

Up to this point, the forecasting performance of the annual and the quarterly models were compared in terms of the one year ahead forecasts for a single year. In the following three sections, their forecasting consistency over multiple time periods are evaluated. Annual model forecasts and quarterly model forecasts which were converted into one year ahead forecasts are compared in terms of a MAPE. In this study, the criterion used to assess forecast accuracy and compare techniques was the mean absolute percentage error (MAPE). The reason for choosing this technique was already explained in Chapter 3. The results of forecasting accuracy are presented in Table 8 for the annual models and in Table 9 for the quarterly models. Table 10 shows the comparison of the forecasting performance of the annual and quarterly models in terms of a one year ahead forecasting horizon.

Evaluation of Annual Models' Performance

Table 8 summarizes the performance of the eight annual forecasting methods examined for one year ahead and two year ahead forecasting horizons.

Table 8. 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)

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 which produced a MAPE of 2.274. Single exponential smoothing was the third best performer with a MAPE of 2.276. For the one year ahead forecasts, the worst performer was Holt's exponential smoothing method. All methods except 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 the two year ahead forecasts, multiple regression which has a MAPE of 2.717 also performed the best of all methods as it did among the one year ahead forecasts.

The simple linear trend model with a MAPE of 4.975 ranked second. The naive 1 model with a MAPE of 5.129 ranked third, and single exponential smoothing which has a MAPE of 5.130 ranked fourth. The naive 2 method was the worst performer of the eight. All methods except multiple regression and the simple linear trend performed worse than the simplistic naive 1 model.

Multiple regression outperformed all other forecasting methods in both the 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 multiple regression model around existing secondary data.

In this study, the effects of forecasting time horizons were compared as to whether the eight 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 in Table 8. Although multiple regression ranked best for both one year ahead and two year ahead forecasts, the value of MAPE (2.253) for the one year ahead forecasts is lower than that of the MAPE (2.274) for two year ahead forecasts. The naive 1 method was the second best performer overall, but its MAPE increased dramatically between the one and two 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 forecasting accuracy decreases as the time horizon increases.

Evaluation of Quarterly Models' Performance

Each type of quarterly model was estimated using data from the periods of 1976Q1-1989Q4, 1976Q1-1990Q4, and was used to generate an *ex ante* forecasts over the periods 1990Q1-1990Q4 and 1991Q1-1991Q4, respectively. Table 9 summarizes the forecasting performance of the nine forecasting methods in terms of MAPE from the first quarter

Table 9. 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)	6.360 (4)	9.258 (5)
Multiple Regression	12.189 (5)	9.684 (8)	12.766 (5)	6.675 (3)

ahead to the fourth quarter ahead forecasts.

In terms of first quarter ahead forecasts, Winters' exponential smoothing method with a MAPE of 5.147 ranked first among all methods, the Box-Jenkins method with a MAPE of 5.443 ranked second best, and naive 1 s with a MAPE of 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 with a MAPE of 2.135 ranked the best of all methods. Naive 1 s with a MAPE of 4.781 was second best; Winters' exponential smoothing method with a MAPE of 4.793 was third best; and Box-Jenkins with a MAPE of 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 with a MAPE of 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 with a MAPE of 1.582 ranked the best among alternative methods; the naive 2 s method with a MAPE of 3.549 was second best; Winters' exponential smoothing with a MAPE of 5.954 was third best; the Box-Jenkins method with a MAPE of 6.360 ranked fourth. However, multiple regression ranked only fifth with a MAPE of 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 with a MAPE of 2.941 was the best performer. Single exponential smoothing with a MAPE of 5.384 ranked second best; multiple regression with a MAPE of 6.675 ranked third; Winter's exponential smoothing with a MAPE of 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 forecasts, 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 differently under different time horizons. The forecast accuracy of quarterly models as the forecasting horizons were extended are compared in Table 9. 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 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 Forecasting Performance of Annual and Quarterly Models in One Year Ahead Forecasts

Table 10 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. One year ahead forecasts are compared in terms of MAPE. The values of MAPE for the annual models are the same as those shown in Table 8. The MAPE in terms of the one year ahead forecasts for the quarterly model were calculated by averaging the sum of the quarters in Tables 6 and 7.

Table 10. Comparison of Forecasting Performance based on Average MAPE and Ranking of Annual and Quarterly Models in One Year Ahead Forecasts

Forecasting Methods	Annual: 1990-1991 (1 Year Average)	Quarterly: (Sum of Quarters: 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)	2.766 (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)

Table 10 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.

In summary, the comparision 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.

CHAPTER V

SUMMARY AND CONCLUSIONS

SUMMARY OF THE STUDY

The primary objective of this study was to evaluate the relative accuracy of various forecasting methods using annual and quarterly data for the sum of sale and use tax collections of hotels, motels, and tourist courts in Michigan as an indicator of tourism demand in Michigan. The second objective was to develop a multiple regression model in order to examine the nature of the travel demand in Michigan. The third objective was to compare the relative forecasting accuracy of annual and quarterly models in terms of one year ahead forecasts. The last objective was to examine the consistency of forecasting accuracy of the models developed over time.

Several forecasting techniques were used 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. The annual models developed for the evaluation were: (1) naive 1, (2) naive 2, (3) simple moving 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. The quarterly models developed for evaluation were: (1) naive 1 s, (2) naive 2 s, (3) simple moving averages, (4) single exponential smoothing, (5) Brown's one-parameter linear exponential smoothing, (6) Holt's two-parameter linear exponential smoothing, (7) Winters' exponential smoothing, (8) Box-Jenkins, and (9) multiple regression.

Annual models were fitted to data over the periods of 1976-1988, 1976-1989, and 1976-1990, and quarterly models for 1976Q1-1989Q4 and 1976Q1-1990Q4. Forecasting techniques were used to forecast up to two years ahead using annual models and four quarters ahead for quarterly models.

All models' forecasting ability were evaluated on the basis of the mean absolute percentage error (MAPE).

Evaluation of Annual Models' Performance

In terms of the one year ahead forecasts, multiple regression performed the best of all methods; the second best model was the naive 1; and single exponential smoothing ranked third. For the two years ahead forecasts, multiple regression also performed the best of all methods; the simple linear trend model ranked second; and naive 1 ranked third. Multiple regression performed better than the other methods in both the one year and two year ahead forecasts. Multiple regression's best performance indicates that forecast accuracy, in this case, increases with increasing information and model complexity in annual models.

When the effects of forecasting time horizons were compared to the eight forecasting methods, they performed differently under different time horizons. The one year ahead forecasts were more accurate than the two year ahead forecasts using the same models. As would be expected, this study shows that forecasting accuracy usually decreases as the time horizon increases.

Evaluation of Quarterly Models' Performance

In terms of the first quarter ahead forecasts, the mathematically sophisticated models, Winters' exponential smoothing which ranked first and the Box-Jenkins method which ranked second best, proved to be more accurate than the simple model, naive 1 s which ranked third. In terms of the second quarter ahead forecasts, the single exponential method ranked the best of all methods; naive 1 s was the second best; Winters' exponential smoothing method was third best. In terms of the third quarter ahead forecasts, the naive 1 s method ranked the best among alternative methods; the naive 2 s method was the second best; Winters' exponential smoothing was the third best. This suggests that there is a decrease in accuracy as model complexity increases. In terms of the fourth quarter ahead forecasts, naive 1 s was the best performer. Single exponential smoothing ranked second, multiple regression ranked third. The fourth quarter ahead forecasts generally exhibited a strong decrease in accuracy with increased model complexity.

Unlike in the annual models, forecasting accuracy in the quarterly models does not decrease as the forecasting horizons are extended.

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

The forecasting accuracy of annual and quarterly models were compared in terms of one year ahead 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.

Multiple Regression Model

In the annual model, three independent variables out of eight were chosen using the stepwise forward selection process. These independent variables were: personal disposable income per capita in the U.S., motor gasoline retail prices in the U.S., and the unemployment rate of civilian workers in the U.S. for the estimated periods of 1976-1988, 1976-1989, and 1976-1990. All coefficients of the variables selected have the expected sign and are statistically significant at the 5% probability level. The personal disposable income per capita variable had a positive sign, motor gasoline retail prices and the unemployment rate of civilian workers in the U.S. had a negative sign. For most recreational activities, an increase in personal disposable income per capita is positively related to the travel and tourism industry; people are able to spend and buy more. Meanwhile, the increase in the price of motor fuel and the unemployment rate of civilian workers in the U.S. are negatively related to the travel and tourism industry; people travel less and spend less when faced with higher fuel costs and when facing the prospects of being unemployed.

In the quarterly model, four independent variables of the eight available for consideration were chosen in the stepwise forward selection process. These independent variables were: average temperature in Michigan, personal disposable income per capita in the U.S., motor gasoline retail prices in the U.S., and the unemployment rate of civilian workers in the U.S. for the estimation periods 1976Q1-1989Q4 and 1976Q1-1990Q4. All coefficients of these variables have the expected sign and are statistically significant at the 5% probability level. The calculated coefficients for average temperature in Michigan and personal disposable income per capita had positive signs as expected, while motor gasoline retail prices and the unemployment rate of civilian workers in the U.S. had the expected negative signs. For most recreational activities, the increase in average temperature is positively related to travel activity, and people travel more. An increase in personal disposable income per capita is also positively correlated to travel activity; as people earn more they can afford to spend more on travel. An increase in the price of gasoline or an increase in the U.S. unemployment rate is negatively related to travel activity. People travel less, and spend less when fuel cost rises and when their confidence in the economy is shaken by rising unemployment.

CONCLUSIONS AND RECOMMENDATIONS

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.

In annual models, the slightly better performance of the multiple regression model is an encouraging finding for advocates of quantitative models. However, the difference between the regression model's performance and naive 1 is ever so slight, and the latter did outperform the other six model types. Thus, the findings of this study are generally in line with international model findings from Witt and Witt (1991); as noted by Witt and Witt, the naive models can be strong performers, in their case the very best among models they evaluated. The one year ahead forecasts are more accurate than the two year ahead forecasts, thus supporting Witt and Witt's (1992) contention that "both RMSPE and MAPE one-year-ahead forecasts are significantly more accurate than two-year-ahead forecasts at the 95% confidence level (p. 120)".

The effects of forecasting time horizons for annual models were compared up to two years ahead and those for quarterly models were compared up to the fourth quarters ahead. In order to compare the effects of forecasting time horizons, future research should extend forecasting time horizons beyond the two year outer limit examined in this study. Data series in this study were confined to annual and quarterly. Future research should evaluate monthly data series if such are available. Actual forecasts using annual, quarterly, and monthly data should be developed for practitioners in government, regional tourism organizations, and private companies. Eight quantitative methods as annual models and nine quantitative methods as quarterly models were used as forecasting methods. Still more quantitative models exist for evaluation in future studies, and qualitative techniques such as expert opinion should be considered for inclusion in future studies of this type. Construction of multiple regression models for this study relied upon a pool of variables selected as those most likely to possess a relationship with sales and use tax collections. Further research should examine the benefit of possibly better models and predictions resulting from the inclusion of other variables.

It should also be noted that actual values for independent variables were used in developing forecasts and calculating MAPE. In a real world forecasting situations, it is necessary to forecast the values of the independent variables before calculating the forecast value of the dependent variable. The approach used in this study, necessitated by lack of a simple scheme for selecting forecast values for independent variables, clearly removes some uncertainty from developing regression model based forecasts, thereby giving it an advantage not available in actual forecasting circumstances.

Finally, it is important to note that results obtained in this study would not necessarily apply in other states or regions unless their underlying data bases exhibit similar tendencies to those exhibited for Michigan over the time period covered in this study.

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APPENDIX

DATA USED IN ANALYSES

DATA USED IN ANALYSES

A listing of the data for selected variables used in the analyses is given below.

Annual Data, 1976-1991

YEAR	SAUTAX	DISPIPC	GASOLINE	UNEMRATE	AVGTEMMI
1976	13137319	5796	61.4	7.7	43.6
1977	14364074	6316	65.6	7.1	44.9
1978	15946530	7042	67.0	6.1	43.3
1979	16891575	7787	90.3	5.8	43.2
1980	16978451	8576	124.5	7.1	43.6
1981	18088936	9455	137.8	7.6	44.7
1982	18493546	9989	129.6	9.7	43.9
1983	21054210	10642	124.1	9.6	45.5
1984	24150750	11673	121.2	7.5	45.0
1985	27783968	12339	120.2	7.2	44.2
1986	31441770	13010	92.7	7.0	45.2
1987	32943900	13545	94.8	6.2	47.5
1988	36704003	14477	94.6	5.5	45.1
1989	39651068	15307	102.1	5.3	43.2
1990	40669019	16174	116.4	5.5	46.2
1991	39854231	16658	114.0	6.7	46.4

YEAR	AVGPREMI	IOFCPOUS	IOCONEX	NINETB
1976	28.16	105.7	83.03	4.989
1977	33.77	103.4	81.30	5.265
1978	31.14	92.4	69.30	7.221
1979	32.55	88.1	52.80	10.041
1980	31.93	87.4	56.77	11.506
1981	32.24	103.4	65.15	14.029
1982	34.52	116.6	62.70	10.686
1983	35.13	125.3	84.70	8.630
1984	31.92	138.2	92.70	9.580
1985	39.48	143.0	86.50	7.480
1986	34.69	112.2	85.75	5.980
1987	30.71	96.9	81.23	5.820
1988	32.54	92.7	85.25	6.690
1989	27.54	98.6	85.28	8.120
1990	36.12	89.1	70.18	7.510
1991	35.68	89.8	70.30	5.420

Quarterly Data, 1976Q1-1991Q4

PERIOD	SAUTAX	DISPIPC	GASOLINE	UNEMRATE	AVGTEMMI
1976Q1	2623625	5374	59.63	7.73	25.50
1976Q2	3257423	5462	60.46	7.50	54.80
1976Q3	4265514	5540	62.65	7.73	64.17
1976Q4	2990757	5665	62.88	7.76	30.13
1977Q1	2900058	5781	64.01	7.47	22.20
1977Q2	3437203	5936	65.80	7.10	56.67
1977Q3	4736933	6094	66.29	6.90	64.80
1977Q4	3289880	6256	66.25	6.63	35.77
1978Q1	3193383	6401	64.05	6.27	18.73
1978Q2	3940377	6583	65.34	5.97	53.27
1978Q3	5177235	6748	68.72	5.93	65.43
1978Q4	3632835	6954	70.24	5.83	35.70
1979Q1	3402507	7049	73.37	5.83	19.10
1979Q2	4169422	7176	84.90	5.67	52.17
1979Q3	5528581	7381	98.57	5.77	64.17
1979Q4	3791065	7563	104.47	5.93	37.23
1980Q1	3469772	7785	119.67	6.23	21.93
1980Q2	4136579	7848	126.63	7.33	53.47
1980Q3	5502107	8074	126.50	7.53	65.60
1980Q4	3869993	8299	125.27	7.50	33.37
1981Q1	3582774	8588	136.57	7.40	24.73
1981Q2	4428879	8757	140.10	7.37	54.07
1981Q3	5893448	9088	137.80	7.40	64.23
1981Q4	4183835	9188	136.83	8.30	35.97
1982Q1	3856305	9533	132.53	8.80	19.50
1982Q2	4529763	9661	125.70	9.40	52.63
1982Q3	6111348	9793	132.07	9.97	63.83
1982Q4	3996157	9937	127.93	10.67	39.80
1983Q1	3951080	10033	118.87	10.37	28.07
1983Q2	5101357	10192	125.03	10.17	51.40
1983Q3	6953093	10423	128.23	9.33	68.10
1983Q4	5048680	10706	124.23	8.47	34.33
1984Q1	4826129	11064	121.17	7.87	22.90
1984Q2	5968190	11209	123.07	7.50	53.90

1984Q3	7764153	11379	120.37	7.47	64.80
1984Q4	5592278	11465	120.30	7.20	38.57
1985Q1	5325222	11584	114.60	7.33	23.03
1985Q2	6957844	11919	122.57	7.30	54.87
1985Q3	9016941	11882	122.90	7.17	64.50
1985Q4	6483921	12099	120.63	7.00	34.23
1986Q1	6226121	12318	109.83	7.00	24.37
1986Q2	7621132	12525	92.20	7.13	55.47
1986Q3	10349770	12560	86.43	6.97	64.57
1986Q4	7244747	12626	82.50	6.83	36.30
1987Q1	6600765	12928	89.30	6.60	28.43
1987Q2	7755735	12880	94.43	6.23	57.70
1987Q3	10778424	13196	98.53	5.97	66.57
1987Q4	7808976	13552	97.10	5.90	37.37
1988Q1	7350873	14154	91.67	5.70	22.13
1988Q2	8994803	14332	94.67	5.47	55.80
1988Q3	11870547	14570	97.60	5.47	67.20
1988Q4	8487779	14850	94.50	5.33	35.27
1989Q1	7742075	15133	92.80	5.20	23.33
1989Q2	9557917	15214	109.93	5.23	52.50
1989Q3	12797516	15322	105.93	5.27	65.00
1989Q4	9553560	15558	100.20	5.33	31.90
1990Q1	8502283	15917	103.40	5.27	28.70
1990Q2	10136516	16092	106.43	5.30	53.67
1990Q3	12960986	16242	118.93	5.57	64.67
1990Q4	9069234	16443	136.97	5.97	37.83
1991Q1	7762826	16443	115.73	6.47	26.00
1991Q2	9760408	16604	114.00	6.77	58.30
1991Q3	13212342	16706	113.67	6.80	65.13
1991Q4	9118655	16885	112.63	6.97	36.23

PERIOD	AVGPREMI	IOFCPOUS	IOCONEX	NINETB
1976Q1	9.03	105.1	81.2	4.95
1976Q2	9.00	107.1	79.5	5.17
1976Q3	5.41	105.7	85.5	5.17
1976Q4	4.72	105.3	85.9	4.70
1977Q1	6.24	105.2	84.2	4.62
1977Q2	6.86	104.4	83.6	4.83
1977Q3	12.63	103.8	81.5	5.47
1977Q4	8.04	98.4	75.9	6.14
1978Q1	4.34	94.8	74.1	6.41
1978Q2	8.30	94.7	70.7	6.48
1978Q3	11.69	89.5	69.6	7.32
1978Q4	6.81	88.5	62.8	8.68
1979Q1	6.74	88.4	58.1	9.36
1979Q2	9.55	89.6	53.2	9.37
1979Q3	7.34	86.7	49.0	9.63
1979Q4	8.92	86.3	51.0	11.80
1980Q1	4.26	87.4	51.1	13.46
1980Q2	9.31	87.8	47.6	10.05
1980Q3	12.32	85.4	60.1	9.24
1980Q4	6.04	89.0	68.3	13.71
1981Q1	4.13	94.5	63.3	14.37
1981Q2	11.07	103.1	70.5	14.83
1981Q3	9.79	110.1	68.3	15.09
1981Q4	7.25	105.3	58.0	12.02
1982Q1	6.19	109.9	58.2	12.90
1982Q2	8.00	114.0	61.1	12.36
1982Q3	10.56	119.8	61.8	9.71
1982Q4	9.77	122.2	69.8	7.94
1983Q1	4.95	119.4	72.4	8.08
1983Q2	10.64	123.0	89.8	8.42
1983Q3	10.02	128.7	88.4	9.19
1983Q4	9.52	130.2	88.3	8.79
1984Q1	4.69	131.6	96.0	9.13
1984Q2	8.74	132.8	90.6	9.84
1984Q3	9.89	141.7	94.0	10.34
1984Q4	8.60	147.2	90.3	8.97
1985Q1	8.21	156.5	88.0	8.18

1985Q2	8.09	149.1	87.4	7.52
1985Q3	12.59	139.2	86.0	7.10
1985Q4	10.59	128.2	84.5	7.15
1986Q1	5.20	119.5	86.7	6.89
1986Q2	8.43	114.2	88.8	6.13
1986Q3	15.46	108.3	85.2	5.53
1986Q4	5.60	107.0	82.3	5.34
1987Q1	2.94	99.9	81.9	5.53
1987Q2	6.80	97.0	82.0	5.73
1987Q3	12.21	98.7	84.4	6.03
1987Q4	8.76	92.3	76.6	6.00
1988Q1	5.06	90.0	82.7	5.76
1988Q2	4.54	90.5	85.1	6.23
1988Q3	11.54	97.6	86.9	6.99
1988Q4	11.40	93.0	86.3	7.70
1989Q1	4.58	96.0	88.8	8.53
1989Q2	9.29	100.5	81.8	8.44
1989Q3	7.33	100.5	84.8	7.85
1989Q4	6.34	97.3	85.7	7.64
1990Q1	6.02	93.2	82.0	7.76
1990Q2	10.00	92.6	79.9	7.77
1990Q3	9.73	87.5	66.3	7.49
1990Q4	10.37	83.0	52.5	7.02
1991Q1	5.36	84.7	67.2	6.05
1991Q2	9.78	92.9	74.0	5.59
1991Q3	9.60	93.3	75.4	5.41
1991Q4	10.94	88.2	64.6	4.58

Notes:
SAUTAX = Sum of Hotel/Motel Sales and Use Tax Collections in Michigan
DISPIPC = Personal Disposable Income Per Capita in the U.S.
GASOLINE = Motor Gasoline Prices in the U.S.
UNEMRATE = The Unemployment Rate of Civilian Workers in the U.S.
AVGTEMMI = Average Temperature in Michigan
AVGPREMI = Average Precipitation in Michigan
IOFCPOUS = Index of Foreign Currency Price of the U.S. Dollar
IOCONEX = The Index of Consumer Expectations in the U.S.
NINETB = Three Month U.S. Treasury Bills.