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Regional Real Property Valuation Forecast Accuracy

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REGIONAL REAL PROPERTY VALUATION
FORECAST ACCURACY

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VALUATION FORECAST
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ABSTRACT

The purpose of this study is to identify, evaluate, and critique four econometric and statistical alternatives to present forecasting practices for property valuation forecasts: (1) a traditional income elasticity method, (2) a regional structural econometric model, (3) a statistical ARIMA method, and (4) trend analysis. Forecast evaluation for 2001-2007 will be conducted for the property valuations of Single and Multi-Family residences and Commercial and Industrial properties in El Paso, Texas (MSA).

TABLE OF CONTENTS

PAGE

ACKNOWLEDGEMENTS v

ABSTRACT vi

TABLE OF CONTENTS vii

LIST OF TABLES viii

CHAPTER

1. Introduction 1
2. Literature Review 3
3. Data and Methodology 6
    - 3.1 Traditional Income Elasticity Method 8
    - 3.2 Structural Econometric Model 9
    - 3.3 Univariate ARIMA Model 9
    - 3.4 Trend analysis 10
    - 3.5 Forecast Assessment 10
4. EMPIRICAL RESULTS 16
    - 4.1 Traditional Income Elasticity Model Specifications 16
    - 4.2 Regional Economic Structural Model Specifications 25
    - 4.3 Univariate ARIMA Model Specifications 32
    - 4.4 Trend Model Specifications 36
    - 4.5 General Observations 41
5. CONCLUSION 45

REFERENCES 47

APPENDIX 51

CURRICULUM VITAE 56

LIST OF TABLES

TABLE **PAGE**

Table 4.1.1: Variable Mnemonics and Equation Statistics 16

Table 4.1.2: Traditional Income Elasticity Model (1) Estimation Results 18

Table 4.1.3: Traditional Income Elasticity Model (1) Simulation Results 19

Table 4.1.4: Random Walk Benchmark Simulation Results 21

Table 4.1.5: Random Walk with Drift Benchmark Simulation Results 22

Table 4.1.6: Modified Theil Inequality Coefficients: Traditional Income Elasticity Model RMSEs to Random Walk Benchmark & Random Walk with Drift....................... 23

Table 4.1.7: Error Regression Results: Random Walk Benchmark vs. Traditional Income Elasticity Model Forecast Errors 24

Table 4.1.8: Error Regression Results: Random Walk Benchmark with Drift vs. Traditional Income Elasticity Model Forecast Errors 25

Table 4.2.1: Regional Structural Economic Model (2) Estimation Results...................... 27

Table 4.2.2: Regional Structural Economic Model (2) Simulation Results 29

Table 4.2.3: Modified Theil Inequality Coefficients: Regional Economic Structural Model RMSEs to Random Walk Model & Random Walk with Drift.............................. 30

Table 4.2.4: Error Regression Results: Random Walk Benchmark vs. Regional Structural Economic Model Forecast Errors 32

Table 4.2.5: Error Regression Results: Random Walk with Drift vs. Regional Structural Economic Model Forecast Errors 32

Table 4.3.1: Final Univariate ARIMA Property Valuation Model Specifications 33

Table 4.3.2: Univariate ARIMA Model (3) Simulation Results...................................... 34

Table 4.3.3: Modified Theil Inequality Coefficients: Regional Economic Structural Model RMSEs to Random Walk Model & Random Walk with Drift.............................. 35

Table 4.3.4: Error Regression Results: Random Walk Benchmark vs. ARIMA Forecast Errors.. 37

Table 4.3.5: Error Regression Results: Random Walk Benchmark with Drift vs. ARIMA Forecast Errors 37

Table 4.4.1: Trend Analysis (4) Estimation Results 38

Table 4.4.2: Trend Model (4) Simulation Results 39

Table 4.4.3: Modified Theil Inequality Coefficients: Trend Model RMSEs to Random Walk Model & Random Walk with a Drift 40

Table 4.4.4: Error Regression Results: Random Walk Benchmark vs. Trend Forecast Errors 42

Table 4.4.5: Error Regression Results: Random Walk Benchmark with Drift vs. Trend Forecast Errors 42

Table 4.5.1: Average Values of the Modified Theil Inequality Coefficients at each Step Length 44

CHAPTER 1

INTRODUCTION

The importance of accurate revenue forecasting is ever more relevant in municipal budgeting. A survey of 328 cities in 2003 by the National League of Cities (NLC) indicates that many U.S. cities and towns have cut staff and services while increasing fees. (Fecht, http://www.citymayors.com/report/usfiscal_crisis.html, 2003) Many cities, including El Paso, struggle with increases in health care costs, and growing worker pensions. Responses have included personnel cuts, curtailed infrastructure investment, higher user fees, and rain day fund draw downs.

Revenue for most municipalities consists of taxes, franchises, service revenues, operating revenues, non-governmental revenues, and intergovernmental revenues. Approximately 64.2 percent of the taxes for the City of El Paso’s 2008 budget come from property taxes (City of El Paso FY2008 Budget). Budget difficulties caused the mayor’s office to propose 100 job cuts in 2005 (Crowder, 2004). The adopted 2008 budget includes an $8.03 million increase in revenue, $7.7 million of which results from projected increases in property tax collections. At present, property tax forecasts are based on historical trend analyses under the assumption that the assessed valuation will continue to grow. The Central Appraisal District revalues properties every three years. Preliminary new valuations are estimated by May of that year. Final property valuations are determined by July of that year, in time for the annual budget hearings regarding the next fiscal year (Property Tax Code, 2005). With more cities facing budget shortfalls, the need for accurate revenue forecasting is growing.

Relatively few cities have compared forecasting methods for property tax revenues (Sexton 1986). Time and personnel constraints often force local governments to rely on judgmental methods or simple trend revenue projections. A helpful first step in accurately analyzing property tax collections is to assess property valuations behavior over time.

Residential and commercial structures are the primary components of property valuations for most cities. Growth rates for those categories frequently vary. In Texas, changing demographic compositions can cause property tax projections based on historical growth and current average property valuations to overestimate future property tax revenues (Murdock and White, 1998). The objective of this thesis is to estimate the accuracy and/or reliability of alternative methods of forecasting the property valuations of single and multi-family housing and real commercial and industrial property in El Paso to assist with municipal revenue forecasting.

CHAPTER 2

LITERATURE REVIEW

When researching revenue forecasting the majority of the studies examine the degree to which cities and counties use forecasting techniques (Frank, 1990) and ask the question of whether these techniques prove to be helpful in budget preparation. Three issues affect the choice of revenue forecasting technique: relative accuracy of forecasting methods, conservatism in forecasting, and public management (Wong, 1995). For instance, Forrester (1991) examines a wide cross-section of U. S. municipal governments, to determine the extent to which governments use forecasting and whether it is a tool government can use in the budget process to reflect their long-term objectives. Through a survey of 431 municipal governments with populations 50,000 or greater, only 3.7% of respondents used econometric forecasting techniques when projecting property taxes (Forrester, 1991).

One analysis of non-tax general fund revenue concludes that exponential smoothing models are generally the most accurate (Cirincione, Gurrieri and Van De Sande, 1999). Past research, however, has shown that municipalities generally know little about revenue forecasting techniques, especially times series analysis (Bahl and Schroeder, 1984; Frank 1990) and that their lack of knowledge has led them to rely heavily on expert judgment to forecast revenues (Reddick, 2004). Bretschneider, Bunch and Gorr (1992) examine revenue forecasting errors in 2,572 Pennsylvania local government budgets. A substantial number of the 209 finance officers surveyed rely on trend and judgmental techniques. In spite of that, McCollough and Frank

(1992) find that empirical comparison of quantitative and judgmental forecasting generally show the former to be more accurate then the latter.

MacManus and Grothe (1989) study revenue forecasting techniques and accuracy in fifteen U.S. counties with populations over 100,000 in 1980. Results in that effort indicate that fiscal stress leads to the adoption of more sophisticated revenue forecasting techniques. This shift from the "best guess" short-term revenue forecast methods to multi-year projections are seen as a necessary way to avoid being overly myopic on the consequences of decisions (Bahl and Schroeder, 1984; Schroeder, 1982; Beckett-Camarata, 2006).

Many prior studies conducted with respect to property valuation have analyzed changing tax rates or estimating the market value of property (Janssen, 1999). Edelstein (1974) shows that property taxes are capitalized in housing values and that accessibility to the center of a city is a determinant of market value as are housing attributes. The analysis examines attributes that yield services over the capital lives of housing structures. A market value-tax model is developed by hypothesizing that the changes in supply factors are relatively inelastic in the short run as compared to changes in market demand factors for residential structures.

Several subsequent efforts have examined the predictability of municipal revenues. Approaches to forecasting municipal revenues have differed depending on the category of revenue studied (Cirincione, Guerrieri and Van De Sande, 1999). The use of econometric and statistical methods has been largely limited to the income elasticity approach in which tax revenue or tax base changes are forecast as the product of the tax's estimated income elasticity and exogenously provided projections of personal income growth (Sexton, 1986). The income elasticity approach has proven useful for income, sales, use and other taxes that are closely related to income. Property taxes are still the dominant source of revenue for municipalities and the applicability of the income elasticity method to them may be more tenuous. However, structural models of property valuation explicitly recognize the importance of both demand and supply side factors in property valuation (Sexton, 1986).

Univariate time series approach can also be useful, especially when information is limited (Granger and Newbold, 1977). Along those lines, Netzer (1961) recommends that various property use classes be analyzed separately. In some cases, regional revenue models built using different methodologies may yield revenue forecasts that contain complementary information (Fullerton, 1989).

Chang (1979) analyzes municipal revenue forecasting for Mobile, Alabama, using a small annual data sample from 1962 to 1976 for 15 revenue sources. The property tax component was estimated as a function of inflation, transactions of taxable properties, net additions to taxable property, and the frequency of reassessment for these properties. Also included is a dummy variable for the period during which Mobile's suburbs grew rapidly. The number of building permits proxies for additions to taxable property. Inequality coefficients estimated for the revenue forecasts indicate acceptable model performance relative to a random walk benchmark (Theil, 1975).

Several different aspects of the El Paso metropolitan economy have been studied using econometric and time series methods (Fullerton, 2001, 2004; Fullerton and Elias, 2004.) Those efforts also include analyses of municipal property tax abatement policies (Fullerton, 2002; Fullerton and Aragonès, 2006). As with many other municipalities, however, residential and commercial property valuation predictability in El Paso has not previously been investigated (Forrester, 1991; Frank and McCollough, 1992). This study attempts to partially fill this gap in the literature by completing such an analysis.

CHAPTER 3

DATA AND METHODOLOGY

Property taxation is a primary revenue source for the City of El Paso. Determining the accuracy of potential forecasting models for those revenues may help improve budgetary processes for municipal government. In the State of Texas, a municipal property tax is a calculation based on the total assessed property minus new construction divided by one hundred and multiplied by the taxable rate. This study focuses on the total assessed property values that are a key component when calculating future tax rates. Unless a municipality conducts multi-year budgeting, property value estimations in Texas tend to be based on historical information. The chief appraiser of the Appraisal District updates estimates in May and by September 30, or within 60 days after the taxing unit receives the appraisal roll, whichever date is later (Property Tax Code, 2005).

The El Paso Central Appraisal District, created in 1981 by the Texas legislature in response to taxpayer dissatisfaction with inequalities in property assessments (Bland and Laosiriarat, 1997), assesses property valuations on an annual basis. A combination of three methods is utilized: cost, income, and market comparison data. The cost method (Property Tax Code, 2005) requires that the Chief Appraiser: (1) use cost data obtained from generally accepted sources; (2) make any appropriate adjustment for physical, functional, or economic obsolescence; (3) make available to the public, on request, cost data developed and used by the chief appraiser as applied to all properties within a property category subject to a reasonable fee for that information; (4) clearly state the reason for any variation between generally accepted cost data and locally produced cost data if there is a difference of more than 10 percent; and (5) make available to the property owner, on request, all applicable market data that demonstrate the difference between the replacement cost of the improvements to the property and the depreciated value of the improvements.

The income method requires that the Chief Appraiser (1) analyze comparable rental data available to the District or the potential earnings capacity of the property, or both, to estimate the gross income potential of the property; (2) analyze comparable operating expense data available to the District to estimate the operating expenses of the property; (3) analyze comparable data available to the chief appraiser to estimate rates of capitalization or rates of discount; and (4) base projections of future rent or income potential and expenses on reasonably clear and appropriate evidence. In developing income and expense statements and cash-flow projections, the chief appraiser shall consider: (1) historical information and trends; (2) current supply and demand factors affecting those trends; and (3) anticipated events such as competition from other similar properties under construction (Property Tax Code, 2005).

If the chief appraiser uses the market data comparison method of appraisal to determine the market value of real property, the chief appraiser shall use comparable sales data and adjust the comparable sales to the subject property. Until 2004, the El Paso Central Appraisal District conducted reappraisals once every three years. That practice caused any increase in the gross valuation to be attributed solely to new construction.

The sample of single- and multi-family housing starts and commercial property valuation range from 1981 to 2007 and includes the number of properties appraised (El Paso County Reports, 1982-2007). The number of housing starts for authorized single family and multi-family residential construction is another determinant of new construction. Those data series are available from the University of Texas at El Paso Border Region Modeling Project website at an annual frequency (www.utep.edu).

The County of El Paso personal income data series ranges from 1969 to 2006 and are expressed in millions of nominal dollars. The average percentage increase over the 37-year data range is 7.9 percent. The personal income data set is available through the Bureau of Economic Analysis (www.bea.gov). The unemployment rate is included in the data set, as are inflation adjusted wages and salaries for the County of El Paso. Also included is the annual population estimate for the county. This series is available through the Census website (www.census.gov). Other variables employed below as well as the forecasted 2007 dataset are from the Border Region Modeling Project at the University of Texas at El Paso (Fullerton and Molina, 2007). Published annually, each report contains three years worth of forecasts.

County and municipal governments usually face strict budget-balancing requirements wherein access to accurate revenue forecasts is a definite asset to the budgetary process. As discussed previously the practice of local government revenue is not very advanced. As Bahl and Schroder (1984) document, judgmental or simple trend projections are common forecasting techniques even among larger city governments. Four commonly used comparison criteria are employed: traditional income elasticity methods, regional structural econometric model, univariate autoregressive integrated moving average models (ARIMA), and trend equations. These methods have been used in previous literature (e.g. Sexton 1987) and are typical techniques used by municipalities in revenue forecasting (Forrester, 1991).

3.1 TRADITIONAL INCOME ELASTICITY METHOD

The income elasticity forecasting approach is to directly estimate the market value-income relationship (Sexton, 1987; Sexton and Sexton, 1986). It uses an equation of the form:

(1) $\ell nMV_t = a + b\ell nY + \mu_t$

where MV is the current value of the property stock, Y is personal income, μ is a random error, and t is a time index. A principal advantage of this approach is that it incorporates variations in local economic conditions without extensive data requirements.

3.2 REGIONAL STRUCTURAL ECONOMETRIC MODEL

The systems of equations approach to modeling, forecasting, and policy analysis for regional and national economies can be traced back to 1936 (Dhane and Barten 1989). Its overall design flexibility has made it an invaluable tool in corporate planning and public policy analysis. These models are especially useful in dynamic forecasting applications. The University of Texas at El Paso border forecasting system contains 208 equations. Among other variables, it forecasts residential real estate trends, population, personal income, wages and salaries, plus labor market conditions for El Paso (Fullerton 2001). Its structure provides some of the primary inputs for the property value system of equations in this study.

3.3 UNIVARIATE ARIMA MODEL

Box and Jenkins (1976) provide a broad framework for univariate and multivariate time series analysis. It requires stationary data whose means and variances do not change over time (Pindyck and Rubinfeld, 1998). Although many El Paso time series are non-stationary, they often can be transformed into stationary variables by differencing them (Fullerton and Elias, 2004). Once stationarity is achieved, a univariate autoregressive integrated moving average (ARIMA) equation of the following form can be estimated:

(2) $d(MV_t) = \theta_o + \rho_1 d(MV_{t-1}) + \rho_2 d(MV_{t-2}) + \ldots + \rho_\rho d(MV_{t-\rho}) + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \ldots + \theta_q\varepsilon_{t-q}$

where d is a difference operator.

3.4 TREND ANALYSIS

The simple trend model that is often used by municipalities will be compared to the other three types of analysis. A linear regression equation of

(3) $MV_i = a_i + c_i t + \varepsilon_i$

where t is equal to 1 in 1981 and to increase by 1 in each year thereafter.

3.5 FORECAST ASSESSMENT

To further assess model performance once parameter estimation is complete, out-of-sample or *ex ante* forecast simulations are utilized. When models are used for forecasting eventually predicted and actual values can be directly compared. Even if there is a good in-sample fit it is difficult to predict all future behavior based on the past. Although encouraging from a modeling perspective, good in-sample estimation performance does not guarantee accurate out-of-sample simulation performance (Leamer, 1983; McCloskey and Ziliak, 1996). A series of rolling forecasts are created for each modeling approach and then compared to random walk benchmarks and random walk benchmarks with drift. Random walk benchmarks have been used in a variety of studies to test the efficacy of a broad range of extrapolation models including structural equation and ARIMA models (Fair and Shiller, 1990; Fullerton and Kelley, 2006).

For each set of forecasts, the number of periods simulated is three. That number corresponds to the appraisal cycles historically used by the El Paso Central Appraisal District. The random walk is an example of a simple stochastic time series in which successive change in y_t is drawn independently from a probability distribution with zero mean. Thus, y_t is determined by,

(4) $y_t = y_{t-1} + \varepsilon_t$

with $E(\varepsilon_t) = 0$ and $E(\varepsilon_t\varepsilon_s) = 0$ for $t \neq s$.

A random walk with drift is a simple extension of the random walk benchmark that accounts for a trend (upward or downward) in the series y_t and is determined by

(5) $y_t = y_{t-1} + d + \varepsilon_t$

so that on average the process will tend to move upward (for $d > 0$).

Two descriptive statistics are used to quantify each method's predictive accuracy. The first is a root mean square error (RMSE).

(6) $$\text{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(Y_t^s - Y_t^a\right)^2}$$

where Y^s = forecasted value of Y_t
Y^a = actual value
T = number of forecast observations

RMSE provides a measure of the deviation of the simulated variable from its time path, but is unbounded (Pindyck and Rubinfeld, 1998). The second statistic is an inequality coefficient that ranges from 0 to 1 (Theil, 1975).

(7) $$U = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(Y_t^s - Y_t^a\right)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(Y_t^s\right)^2} + \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(Y_t^a\right)^2}}$$

The inequality statistic proportions are useful as means of breaking down forecast error patterns. The bias proportion U^m is an indication of systematic error, since it measures the extent to which the average values of the simulated and actual series deviate from each other. The variance U^s indicates the ability of the model to replicate the degree of variability in the variable of interest. The covariance proportion U^c is an indication of the unsystematic error or the remaining error after deviations from average values have been calculated. The ideal distribution of the second moment U-statistic proportions for any U>0 is $U^m = U^s = 0$ and $U^c = 1$ (Pindyck and Rubinfeld, 1998). The proportions estimated are shown in Equations 8, 9, and 10.

(8) Bias Proportion $U^M =$ $$\frac{\left(\overline{Y}^s - \overline{Y}^a\right)^2}{\left(\frac{1}{T}\right)\sum\left(Y_t^s - Y_t^a\right)^2}$$

(9) Variance Proportion $U^S =$ $$\frac{\left(\sigma_s - \sigma_a\right)^2}{\left(\frac{1}{T}\right)\sum(Y_t^s - Y_t^a)^2}$$

(10) Covariance Proportion $U^C =$ $$\frac{2(1-\rho)\sigma_s\sigma_a}{\left(\frac{1}{T}\right)\sum(Y_t^s - Y_t^a)^2}$$

The RMSEs for each methodology are also utilized to generate modified Theil inequality coefficients (Web, 1984). The modified Theil inequality coefficients are calculated as the ratio of the RMSEs for each property category for each model to the random walk benchmark, then to a random walk with drift. While descriptive, modified Theil inequality coefficients have been shown to provide reliable indicators for assessing the predicative accuracy of econometric forecasting models (Webb, 1984). In this study, a modified Theil inequality coefficient greater than one will imply that the random walk benchmark or random walk with drift has a smaller absolute forecast errors than the competing methodologies. Alternatively, if a modified Theil coefficient is smaller than one, it will imply that the prediction errors of a model are small than those associated with random walk benchmarks or random walk with drift.

While modified Theil coefficients provide valuable descriptive information regarding forecast precision, formal statistical tests are also necessary in assessing the predictive accuracy. One method or indirect procedure by Ashley, Granger and Schmalensee (1980), tests for the significance of improvements in mean-squared forecasting error among two competing forecasting methods. The relationship among the sample statistics for the entire out-of-sample period yields the following Equation 11:

(11) $MSE(e_1) – MSE(E_2) = [s^2(e_1)- s^2(e_2)] + [m(e_1)^2-m(e_2)^2]$

where MSE = sample mean-squared error,

s^2 = sample variance

m = sample mean

The null hypothesis tested is shown in Equation 12.

(12) H_0: $MSE(e_1) = MSE(e_2)$,

where MSE is the mean-squared error of two competing forecast errors, e_1, e_2.

For this purpose, $MSE(e_1)$ represents the mean-squared error for a random walk benchmark and $MSE(e_2)$ represents the mean-squared error for each model.

By defining for observation *t*,

(13) $\Delta_t = e_{1t} - e_{2t}$ and $\sum_2 = e_{1t} + e_{2t}$

Then, Equation 11 can then be re-written as follows:

(14) $MSE(e_1) – MSE(E_2) = [s^2(cov(\Delta,\sum)] + [m(e_1)^2-m(e_2)^2]$

where *cov* = sample covariance for the simulation period

m = sample mean

If the joint null hypothesis

(15) $cov(\Delta,\sum) = 0$ and $\mu(\Delta) = 0$

can be rejected in favor of the alternative hypotheses described below, then it can be determined that one forecast model outperforms the random walk benchmark. The alternative is that both quantities are non-negative and at least one is strictly positive.

Two regression equations can be extracted from (14) to test if the MSEs are significantly different. The structure of the regression equation used to test the null hypothesis depends on the signs of the error means. When the error means are of the same sign, the regression equation used to test the joint null hypothesis is the following

(16) $\Delta_t = \beta_1 + \beta_2[\sum_t - m(\sum_t)] + u_t$

Where μ_t is an error term and the null hypothesis is $\beta_1 = \beta_2 = 0$, against the alternative $\beta_1 \geq 0$ and $\beta_2 \geq 0$ and at least one $\beta_i > 0$. If either the estimate for β_1, or β_2 is significantly negative, then the null hypothesis cannot be rejected. If an estimate of either β_1 or β_2 is negative but not significant, then a t-test can be performed on the remaining positive estimate. If both estimates are non-negative, then the join F-test is appropriate, where significance levels are equal to half of those from an F distribution. However, since the F-test does not take sign into account on 4-pronged test results, the true significance that both estimates are positive will not be more than half the probability obtained from the F distribution (Ashley, Granger, and Schmalensee, 1980).

When both error means are negative, Equation 16 is still used to test the null hypothesis (12). In this case if β_1 is found to be significantly negative, and β_2 is either insignificant or significantly positive, the model forecasts are most accurate. Conversely, a significantly positive $\beta 1$ will indicate the random walk benchmark outperforms the model.

If the error means of the forecasts are of opposite signs, a different regression equation must be employed to test the null hypothesis (12). In this situation, the dependent variable becomes the sum of the forecast errors:

(17) $\sum_t = \beta_1 + \beta_2[\sum_t - m(\Delta_t)] + u_t$

Again, if $\beta_1 = \beta_2 = 0$, the test fails to rejection Equation 12. As before, interpretation of the β_2 coefficient is the same, but interpretation of the β_1 depends on which of the error means is positive and which is negative. One possibility is that the random walk benchmark has a negative error mean and the model has a positive error mean. In this case, if β_1 is significantly negative, with β_2 insignificant or significantly positive, this will indicate that the model outperforms the Random Walk Benchmark or superior. However, if β_1 is significantly positive, or β_2 is significantly negative, the random walk forecasts are more accurate (Fullerton and Kelley, 2006).

The final occurrence is when the random walk has a positive error mean and the model has a negative error mean. Under these circumstances, a significantly positive β_1 with a significantly positive or insignificant β_2 points to model superiority. Alternatively, if either of the equation parameters is significantly negative, the random walk predictions are favored (Ashley, Granger, and Schmalensee 1980; Kolb and Stekler 1993).

CHAPTER 4

EMPIRICAL RESULTS

4.1 TRADITIONAL INCOME ELASTICITY MODEL SPECIFICATIONS

Each model is estimated for four major categories of real property: residential single family housing, multi-family housing, commercial and industrial. All models are estimated using 1981-2007 data for El Paso, Texas (MSA). Table 4.1.1 summarizes the variable definitions used for each model.

Table 4.1.1: Variable Mnemonics and Equation Statistics

Series	Description
Endogenous Variables	
RSF	Real Property: Residential Single Family Housing
RMF	Real Property: Residential Multi-Family Housing
COM	Real Property: Commercial
INDUST	Real Property: Industrial
Exogenous Variables	
ELPPOP	El Paso Population
ELYP	El Paso Personal Income
EPSFHP	El Paso Single Family Housing Permits
EPSFHS	El Paso Single Family Housing Starts
EPMFHS	El Paso Multi-Family Housing Starts
EPMFHSTK	El Paso Multi-Family Housing Stock
EPOCOMSP	El Paso Other Commercial Space Permit Values
MXREX	Mexico, Exchange Rate Period Average, Peso/$
INDSPER	Industrial Permits
t	Time, years
Equation Statistics	
SUM SQ	Error Sum of Squares
STD ERR	Standard Error of Regression
R SQ	R-Squared Coefficient of Determination
R BAR SQ	Adjusted R- Square Coefficient of Determination
F	F Statistic for Joint Slope Coefficient Equality to Zero Hypothesis
DW	Durbin Watson Serial Correlation Statistic

The traditional income elasticity model (1) has an estimated equation for each property category and the estimated coefficients satisfy the 5-percent significant criterion. Table 4.1.2 gives the model specifications resulting from the traditional income elasticity method. The t-statistics appear in parentheses below each corresponding coefficient. Equations 1-4 have relatively high R-squared and low sum-squared residuals. Based on Durbin Watson (DW) and the range of the statistic as described in Pindyck and Rubinfeld (1998) allows one to reject the null hypothesis of no serial correlation or positive serial correlation present in equations 1, 2, and 4. In Equation 2, the DW of 1.295 falls within the limits of indeterminate results.

Table 4.1.3 summarizes the out-of-sample or *ex-ante* forecast accuracy using the traditional income elasticity model. Descriptive statistical testing, root-mean-square errors (RMSE) and Theil inequality coefficients are used to determine forecast accuracy. The forecast date was segregated by step-length and compared with actual valuations estimates for every three year from 2001 to 2007. The resulting prediction errors are then used to calculate the root mean squared error (RMSE) values for all 7 forecast step-lengths. The Theil coefficients are decomposed into bias (U^m), variance (U^s) and covariance (U^c) components. As previously stated the ideal values for the second moment error proportions are $U^m = U^s = 0$ and $U^c=1$. Overall the results in Table 4.1.3 reflect very low RMSEs; however, the Theil inequality coefficients are less than optimal. Theil inequality coefficients will vary between 0 and 1. If U=0, $Y_t^s = Y_t^a$ for all a and t perfect fit is obtained. If U=1, the predictive performance of the model is as "bad" as it can possibly be (Pindyck and Rubinfeld, 1998). While the Theil inequality coefficient or U-statistic in Table 4.1.3 is near zero for all property categories, the decomposed proportions for bias proportions (U^m) are high at all step-lengths for each property type. Consequently, the covariance proportion never reaches more than 7.9 percent.

Table 4.1.2: Traditional Income Elasticity Model (1) Estimation Results

Equation 1

Residential Single Family Housing, valuation in dollars

RSF = f(ELYP)

Ordinary Least Squares, Annual data for 26 periods from 1981 to 2006

$$\log(RSF) = \underset{(3.14)}{2.1967} + \underset{(31.98)}{0.8981} * \log(ELYP)$$

Sum Sq	0.099	Std Err	0.0645	LHS Mean	22.74
R Sq	0.977	R Bar Sq	0.9761	F (1,24)	25.36
DW	0.920				

Equation 2

Residential Multi-Family Housing, valuation in dollars

RMF = f(ELYP)

Ordinary Least Squares, Annual Data for 24 periods from 1982 to 2005

$$\log(RMF) = 5.576 + 0.6498 * \log(ELYP)$$

Sum Sq	0.2102	Std Err	0.2102	LHS Mean	20.44
R Sq	0.6770	R Bar Sq	0.6636	F (1,24)	9.6480
DW	0.5118				

Equation 3

Industrial Property, valuation in dollars

INDUST = f(ELYP)

Ordinary Least Squares, Annual Data for 24 periods 1982 to 2005

$$\log(INDUST) = \underset{(-2.26)}{-5.36} + \underset{(10.57)}{1.09} * \log(ELYP)$$

Sum Sq	0.6315	Std Err	0.1777	LHS Mean	19.7197
R Sq	0.8484	R Bar Sq	0.8408	F (1, 20)	3.5429
DW	1.2950				

Equation 4

Commercial Property, valuation in dollars

COM = f(ELYP)

Ordinary Least Squares, Annual Data for 24 periods 1982 to 2005

$$\log(COM) = \underset{(7.38)}{4.8324} + \underset{(25.68)}{0.7349} * \log(ELYP)$$

Sum Sq	0.1033	Std Err	0.0656	LHS Mean	21.6442
R Sq	0.9649	R Bar Sq	0.9635	F (1,24)	79.15
DW	0.9615				

Table 4.1.3: Traditional Income Elasticity Model (1) Simulation Results

		1-step	2-step	3-step	4-step	5-step	6-step	7-step
Residential Single Family Housing	RMSE	602,515,539	448,941,945	541,365,265	1,874,759,186	4,256,225,621	5,053,755,895	6,127,249,170
	Theil-U	0.0265	0.0188	0.0213	0.0668	0.1345	0.1502	0.1695
	U^m	0.9867	0.4271	0.2088	0.5970	0.6795	0.8717	1.0000
	U^s	0.0012	0.5647	0.7891	0.3902	0.3141	0.1283	0.0000
	U^c	0.0121	0.0082	0.0022	0.0128	0.0064	0.0000	0.0000
Residential Multi-Family Housing	RMSE	163,681,801	165,948,957	163,739,146	119,806,804	107,759,740	139,917,315	188,495,456
	Theil -U	0.0774	0.0771	0.0747	0.0517	0.0457	0.0544	0.0704
	U^m	0.9530	0.9973	0.9728	0.6850	0.4179	0.6902	1.0000
	U^s	0.0148	0.0014	0.0128	0.2352	0.5821	0.3098	0.0000
	U^c	0.0322	0.0012	0.0143	0.0799	0.0000	0.0000	0.0000
Commercial	RMSE	368,989,400	435,457,286	417,909,266	598,233,453	616,216,640	928,501,660	943,814,737
	Theil -U	0.0525	0.0588	0.0538	0.0713	0.0708	0.0984	0.0966
	U^m	0.9092	0.9669	0.9950	0.8225	0.7968	0.9793	1.0000
	U^s	0.0907	0.0310	0.0004	0.1558	0.2032	0.0207	0.0000
	U^c	0.0001	0.0021	0.0046	0.0217	0.0000	0.0000	0.0000
Industrial	RMSE	178,678,026	183,436,498	208,128,658	166,866,070	146,529,498	80,169,845	114,421,296
	Theil -U	0.1490	0.1502	0.1684	0.1261	0.1095	0.0533	0.0720
	U^m	0.9457	0.9629	0.9487	0.9250	0.8529	0.2082	1.0000
	U^s	0.0135	0.0156	0.0249	0.0243	0.1471	0.7918	0.0000
	U^c	0.0408	0.0214	0.0264	0.0506	0.0000	0.0000	0.0000

Simulation results for the naïve methodology or random walk benchmarks and random walk with drift are found in Tables 4.1.4 and 4.1.5. Under the random walk benchmark, the last available historical observations issued as the forecast for all target periods (Fullerton and West, 1998). This simpler procedure also obtains outcomes that are less than an ideal distribution of the three Theil inequality proportions across all seven simulation period lengths. RMSEs for the random walk benchmarks are also higher with the exception of industrial property and in the sixth and seventh step-lengths for residential and commercial properties. This differs from the results of the random walk with drift methodology, a procedure that resulted in dramatically lower RMSEs for commercial and industrial property and only four step-lengths with increases in the single family and multifamily housing property categories. The distribution of the three Theil inequality proportions continues to be less than ideal at all step-lengths. However, the U-statistic for the random walk and the random walk with drift are relatively similar to the traditional income elasticity model with the exception of industrial property. The traditional income elasticity model has higher U-statistics for industrial property when compared to the random walk benchmark and random walk with drift.

Modified Theil inequality coefficients are then calculated as the ratios of the traditional income elasticity model RMSEs to the RMSEs of a random walk benchmark and random walk with drift. Results associated with the random walk are found in Table 4.1.6. A modified inequality coefficient or U-coefficient less than one indicates that the traditional income elasticity model forecasts for that step-length are more accurate than those associated with the random walk. Conversely, if the U-coefficient is greater than one than the random walk method out performs the traditional income elasticity. With this general guideline, the result is that the traditional income elasticity forecasts only slightly compare favorable to the random walk

Table 4.1.4: Random Walk Benchmark Simulation Results

		1-step	2-step	3-step	4-step	5-step	6-step	7-step
	RMSE	908,740,891	1,362,387,837	2,095,372,867	3,693,293,274	5,426,326,097	5,432,783,429	4,017,800,503
Residential Single	Theil -U	0.0428	0.0606	0.0879	0.1406	0.1776	0.1630	0.1050
Family	U^m	0.8706	0.6641	0.7381	0.7642	0.7163	0.8633	1.0000
Housing	U^s	0.1294	0.3359	0.2619	0.2358	0.2837	0.1367	0.0000
	U^c	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	RMSE	81,482,375	30,348,987	54,474,042	165,484,395	323,837,783	323,837,783	180,775,209
Residential Multi-	Theil -U	0.0435	0.0153	0.0275	0.0792	0.1144	0.1362	0.0673
Family	U^m	0.9876	0.0162	0.7599	0.6117	0.6061	0.9221	1.0000
Housing	U^s	0.0124	0.9838	0.2401	0.3883	0.3939	0.0779	0.0000
	U^c	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	RMSE	576,102,578	493,348,092	407,865,491	675,463,112	612,659,151	952,860,925	362,711,686
	Theil -U	0.0843	0.0669	0.0523	0.0807	0.0699	0.1012	0.0350
Commercial	U^m	0.8989	0.8758	0.8784	0.6787	0.6213	0.9638	1.0000
	U^s	0.1011	0.1242	0.1216	0.3213	0.3787	0.0362	0.0000
	U^c	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	RMSE	19,797,104	18,511,637	20,304,700	112,035,722	104,338,623	269,604,145	168,098,291
	Theil -U	0.0190	0.0179	0.0195	0.1039	0.0913	0.2099	0.1094
Industrial	U^m	0.6120	0.0451	0.2236	0.5450	0.3197	0.9028	1.0000
	U^s	0.3880	0.9549	0.7764	0.4550	0.6803	0.0972	0.0000
	U^c	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4.1.5: Random Walk with Drift Benchmark Simulation Results

		1-step	2-step	3-step	4-step	5-step	6-step	7-step
Residential Single Family Housing	RMSE	147,671,043	659,816,515	1,083,221,890	602,170,365	2,649,638,178	371,333,655	6,724,217
	Theil -U	0.0066	0.0285	0.0437	0.0205	0.0798	0.0097	0.0002
	U^m	0.6505	0.3918	0.6155	0.1401	0.5646	0.6516	1.0000
	U^s	0.3154	0.5684	0.3836	0.5758	0.4340	0.3484	0.0000
	U^c	0.0341	0.0397	0.0009	0.2841	0.0014	0.0000	0.0000
Residential Multi-Family Housing	RMSE	110,958,137	65,896,328	34,702,792	63,826,914	270,051,239	61,839,029	306,404,643
	Theil -U	0.0542	0.0340	0.0173	0.0289	0.1186	0.0226	0.0966
	U^m	0.6615	0.5034	0.6517	0.0135	0.6154	0.5023	1.0000
	U^s	0.1893	0.0384	0.2895	0.6347	0.3544	0.4977	0.0000
	U^c	0.1493	0.4582	0.0588	0.3518	0.0302	0.0000	0.0000
Commercial	RMSE	163,211,334	95,534,644	43,734,784	217,707,550	454,056,375	372,838,314	1,911,550
	Theil -U	0.0217	0.0121	0.0053	0.0246	0.0508	0.0350	0.0002
	U^m	0.5218	0.6176	0.0439	0.1017	0.4974	0.5015	1.0000
	U^s	0.4529	0.3757	0.3082	0.6405	0.5026	0.4985	0.0000
	U^c	0.0253	0.0067	0.6479	0.2579	0.0000	0.0000	0.0000
Industrial	RMSE	53,338,662	22,786,164	57,654,775	50,595,858	119,089,140	43,532,656	168,326
	Theil -U	0.0497	0.0216	0.0585	0.0431	0.1065	0.0276	0.0001
	U^m	0.8027	0.4256	0.6657	0.0371	0.4993	0.4980	1.0000
	U^s	0.0005	0.2043	0.0052	0.4816	0.5007	0.5020	0.0000
	U^c	0.1968	0.3701	0.3291	0.4813	0.0000	0.0000	0.0000

Table 4.1.6: Modified Theil Inequality Coefficients: Traditional Income Elasticity Model RMSEs to Random Walk Benchmark & Random Walk with Drift

	1-step	2-step	3-step	4-step	5-step	6-Step	7-Step	Average
Residential Single Family Housing								
Random Walk	0.6630	0.3295	0.2584	0.5076	0.7844	0.9302	1.5250	0.7140
Random Walk w/Drift	4.0801	0.6804	0.8205	3.1133	1.6063	13.6097	911.22	133.5902
Residential Multi-Family Housing								
Random Walk	0.7344	0.6804	0.8777	0.4854	0.7027	0.4321	1.0427	0.7079
Random Walk w/Drift	0.3289	0.3134	1.3778	1.2586	0.6769	2.2626	419.9581	60.8823
Commercial								
Random Walk	0.6405	0.8827	1.0246	0.8857	1.0058	0.9744	2.6021	1.1451
Random Walk w/Drift	2.2608	4.5581	9.5555	13.6787	2.8305	2.4904	493.74	75.5882
Industrial								
Random Walk	9.0255	9.9093	10.2503	1.4894	1.4044	0.2974	0.6807	4.7224
Random Walk w/Drift	3.3499	8.0503	3.6099	3.2980	1.2304	1.8416	679.7593	100.1628
Average - Random Walk	2.7658	2.9505	3.1027	0.8420	0.9743	0.6585	1.4626	
Average - Random Walk w/Drift	2.5049	3.4006	3.8409	5.3372	1.5860	5.0511	626.1704	

benchmarks. In 18 of the 28 inequality coefficients estimated, results of 0.99 or less are observed. On average the traditional income elasticity forecast results are quite favorable for residential single family housing and multi-family housing property values, where the random walk forecasts for commercial and industrial property valuations compared more favorably to the actual valuation. While there is a temporal pattern it is only apparent in the sixth and seventh step lengths were the random walk with drift has smaller absolute errors than the traditional income elasticity model.

However, in comparison to the random walk with drift the traditional income elasticity model is far from ideal. The random walk with drift inequality coefficients estimate greater than 1.00 for 23 of the 28 and on average consistently out performs the traditional income elasticity model by a considerable margin in the sixth and seventh step. The traditional income elasticity model is unable to predict the dramatic increase in the data occurring within the final step-lengths.

Error differential regression results for the random walk benchmark compared to the traditional income elasticity model are found in Table 4.1.7. The forecast error means are found in parentheses below each variable name. Like the descriptive forecast assessment techniques the

Table 4.1.7: Error Regression Results: Random Walk Benchmark vs. Traditional Income Elasticity Model Forecast Errors

Variable	β_1 (t-statistic)	β2 (t-statistic)	Joint F-test (probability)	Most Accurate
Residential Single Family Housing	772,000,000	0.01	0.05	Traditional Income Elasticity
(Both Error Means Neg.)	(-2.844866)	(0.227201)	(0.823145)	
Residential Multi-Family Housing	-13,097,735	0.78	11.28	Traditional Income Elasticity
(RW neg.; Tradt'l Income Elasticity Pos.)	(-0.457947)	(3.359171)	(0.003989)	
Commercial	3,600,377	0.09	1.36	Random Walk
(Both error means neg.)	(0.077749)	(1.167477)	(0.260122)	
Industrial	-64,971,737	1.26	10.31	Inconclusive
(RWE neg.; Tradt'l Income Elasticity Pos.)	(-2.174923)	(3.210359)	(0.005458)	

error regression results provide mixed results among the various property types. Similar to the RMSE ratios the traditional income elasticity methodology is statistically significant for two variables residential single family housing and residential multi-family housing. Commercial and industrial variables reflect the results of the RMSEs ratios with a random walk benchmark statistically significant for commercial property and inconclusive results regarding industrial property. In Table 4.1.8 the inconclusive determinations differ from the RMSE ratios that overwhelmingly indicated the random walk with drift as the superior methodology. Instead when the random walk with drift error differential was calculated inconclusive results were found for three of the variables. Only commercial property indicate that random walk with drift was the most accurate technique.

Table 4.1.8: Error Regression Results: Random Walk Benchmark with Drift vs. Traditional Income Elasticity Model Forecast Errors

Variable	β_1 (t-statistic)	β2 (t-statistic)	Joint F-test (probability)	Most Accurate
Residential Single Family Housing (Both Error Means Neg.)	-1,270,000,000 (-3.583641)	-0.472 (-3.788605)	14.354 (0.001611)	Inconclusive
Residential Multi-Family Housing (RW neg.; Tradt'l Income Elasticity Pos.)	-63,129,799 (-2.45492)	0.514 (2.324967)	5.405 (0.003989)	Inconclusive
Commercial (Both error means neg.)	-386,000,000 (-7.797202)	-0.051 (-0.502965)	0.253 (0.621842)	Random Walk with Drift
Industrial (RWE neg.; Tradt'l Income Elasticity Pos.)	-95,865,765 (-3.54699)	0.362 (1.146556)	1.315 (0.268423)	Inconclusive

4.2 REGIONAL ECONOMIC STRUCTURAL MODEL SPECIFICATIONS

The empirical summaries for the regional econometric structural model for all property value equation parameter estimates are reported in Table 4.2.1. The sample period used for the estimates is 1981 to 2007. The residential single family housing equation reflects a coefficient of determination for the dependent variable of 97.3 percent. This measure indicates that the model explains more than 97 percent of the variation in residential single family housing valuation over the sample period. On average r-squared is 93.8 percent for each equation. However, it is important to remember that searching for a high r-squared runs a real danger of finding an equation that fits the data, but captures accidental features of the particular data rather than the underlying relationship that is sought (Kennedy, 2003).

Five of the estimated coefficients in Table 4.2.1 equation 1 fail to satisfy the 5-percent significance criterion. They include all variables except the aggregate personal income. This may be an indicator that single family housing starts and housing stock do not influence the property valuation as indicated by the Central Appraisal District. Single family housing starts are the number of privately owned new housing units on which construction has been started over some period. Single family housing stock is the number of existing homes in an area. Normally, the single family housing stock will increase at a similar rate as population growth. However, in this equation the other three coefficients include the constant term, the population and the peso per dollar rate.

In an effort to explain two major increases in single family housing valuations that occurred in 1985 and 1995 a review was done of the major changes in the economy. The large turning points coincide with the Mexico peso devaluation; therefore, the Mexican exchange rate period average was used and resulted in an equation that predicted expected increases. When this data set is incorporated the overall diagnostics for Equation 1 improve. Though it is only statistically significant at 34 percent without the changes in the exchange rate the forecast results in spurious data. However, the use of this data set does requires in-depth investigation to determine the cause of this relationship between single family housing valuations in El Paso County and currency devaluations in Mexico. Even with the Mexico exchange rate there are a

Table 4.2.1: Regional Structural Economic Model (2) Estimation Results

Equation 1

Residential Single Family Housing, valuation in dollars

(RSF) = f(ELYP, ELPPOP, EPSFHP, EPSFHS, MXREX)

Ordinary Least Squares, Annual data for 26 periods from 1981 to 2006

(RSF) = 114,680,379 + 1.061 * (ELYP) - 2,580.82 * (ELPPOP)
(0.199) (6.61) (-0.2429)
- 660,718.62 * (EPSFHP) + 267,561.18 * (EPSFHS) - 115,042,539.90 * (MXREX)
(-0.929) (0.553) (-0.977)

Sum Sq	7.70E+18	Std Err	6.20E+08	LHS Mean	8.18E+09
R Sq	0.9731	R Bar Sq	0.9664	F (1,20)	0.032
DW	0.9248				

Equation 2

Residential Multi-Family Housing, valuation in dollars

(RMF) = f(ELYP, ELPPOP, EPMFHS, EPMFHSTK)

Ordinary Least Squares, Annual Data for 24 periods from 1982 to 2005

(RMF) = -424,055,311.30 + 0.06386 * (ELYP) - 3,418.31 * (ELPPOP)
(-1.304) (5.077) (-3.714)
+ 44,378.99 * (EPMFHSTK) + 54,056.74 * (EPMFS)
(8.23) (2.564)

Sum Sq	6.54E+16	Std Err	5.58E+07	LHS Mean	7.96E+08
R Sq	0.9467	R Bar Sq	0.9365	F(1,21)	1.700
DW	2.1503				

Equation 3

Industrial Property, valuation in dollars

(INDUSTRIAL) = f(ELYP, ELPPOP, INDSPER)

Ordinary Least Squares, Annual Data for 24 periods 1982 to 2005

(INDUSTRIAL) = - 984,667,083.90 + 0.0075 *(ELYP) + 1,990.96 * (ELPPOP)
(0.133) (0.652) (-0.022)
+ 1.945 * (INDSPER)
(1.75)

Sum Sq	3.77E+16	Std Err	4.58E+07	LHS Mean	3.98E+08
R Sq	0.9179	R Bar Sq	0.9042	F (1,18)	6.310
DW	2.2713				

Equation 4

Commercial Property, valuation in dollars

(COM) = f(ELYP, ELPPOP, OCOMSP)

Ordinary Least Squares, Annual Data for 24 periods 1982 to 2005

(COM) = 2,853,655,471 + 0.288284 * (ELYP) - 5004.393 * (ELPPOP) +1.307*(EPOCOMSP)
(4.51) (11.09) (-3.702) (1.56)

Sum Sq	3.34E+17	Std Err	1.23E+08	LHS Mean	2.66E+09
R Sq	0.9849	R Bar Sq	0.9829	F (1,22)	20.330
DW	1.3097				

large number of slope coefficients that are statistically insignificant indicating a serious flaw in the overall model.

Based on the Durbin Watson serial correlation is present in each equation with the exception of equation 4. Equation 2 simulation results in four variables meeting the 5 percent confidence criterion. However, with the Durbin Watson above 2, negative serial correlation is present.

Table 4.2.2 shows simulation results for each variable. Of the three proportions, the bias proportion, U^m, is relatively large this means that the average predicted change deviates substantially from the average realized change (Theil, 1966). However, each U-statistic is relatively low, under 16.4 percent, where if U = 0 there is a perfect fit. This is especially the case for multi-family housing property valuations the average RMSE is at 4.5 percent the lowest of the alternative models.

The regional econometric structural model is also benchmarked against a random walk procedure and the random walk with drift using the modified Theil inequality coefficients and error differential results. The Modified Theil inequality coefficients are calculated as the ratios of the structural model RMSEs to those associated with the random walk and random walk with drift. Both measures are calculated using the traditional formulations for each individual extrapolation step-length. Again, a modified inequality coefficient of less than one indicates that the structural model forecasts for that step-length are more accurate than those of the random walk counterpart. Conversely, a U-coefficient greater than one implies that the random walk generates smaller absolute forecast errors for the step-length in question meaning it is a more accurate forecast method. In cases where the RMSEs for both methods are equal a value of one implies that neither technique outperforms the other.

Table 4.2.2: Regional Structural Economic Model (2) Simulation Results

		1-step	2-step	3-step	4-step	5-step	6-step	7-step
	RMSE	360,779,587	631,179,251	1,145,969,492	2,921,390,171	5,078,903,175	5,485,208,544	4,257,391,493
	Theil -U	0.0165	0.0270	0.0460	0.1082	0.1648	0.1649	0.1119
Residential	U^m	0.5645	0.1488	0.4450	0.7308	0.7249	0.8697	1.0000
Single Family	U^s	0.4088	0.3635	0.4937	0.2604	0.2669	0.1303	0.0000
Housing	U^c	0.0267	0.4876	0.0614	0.0089	0.0082	0.0000	0.0000
	RMSE	36,493,988	20,650,767	47,812,041	80,334,305	152,677,620	211,369,332	211,342,587
Residential	Theil -U	0.0189	0.0103	0.0232	0.0365	0.0636	0.0850	0.0796
Multi-Family	U^m	0.6191	0.9085	0.4457	0.0454	0.3303	0.9233	1.0000
Housing	U^s	0.0274	0.0796	0.2356	0.5248	0.6459	0.0767	0.0000
	U^c	0.3534	0.0120	0.3187	0.4298	0.0237	0.0000	0.0000
	RMSE	271,786,969	252,826,354	160,246,683	356,738,728	437,982,903	624,733,161	591,105,681
	Theil -U	0.0381	0.0333	0.0199	0.0408	0.0486	0.0642	0.0584
Commercial	U^m	0.8845	0.9701	0.8544	0.3036	0.3114	0.9997	1.0000
	U^s	0.1155	0.0238	0.0959	0.4721	0.6886	0.0003	0.0000
	U^c	0.0000	0.0060	0.0497	0.2243	0.0000	0.0000	0.0000
	RMSE	34,679,595	50,713,370	78,708,442	58,455,663	66,513,674	182,061,764	204,902,170
	Theil -U	0.0332	0.0468	0.0711	0.0494	0.0553	0.1325	0.1367
Industrial	U^m	0.3495	0.7473	0.9076	0.1458	0.0000	0.8373	1.0000
	U^s	0.0233	0.0380	0.0148	0.7354	1.0000	0.1627	0.0000
	U^c	0.6272	0.2146	0.0775	0.1187	0.0000	0.0000	0.0000

Table 4.2.3: Modified Theil Inequality Coefficients: Regional Economic Structural Model RMSEs to Random Walk Model & Random Walk with Drift

	1-step	2-step	3-step	4-step	5-step	6-Step	7-Step	Average
Residential Single Family Housing								
Random Walk	0.3970	0.4633	0.5469	0.7910	0.9360	1.0096	1.0596	0.7434
Random Walk w/Drift	2.4431	0.9566	1.7368	4.8514	1.9168	14.7716	633.14	94.2599
Residential Multi-Family Housing								
Random Walk	0.7344	0.6804	0.8777	0.4854	0.5839	0.6527	1.1691	0.7405
Random Walk w/Drift	0.3289	0.3134	1.3778	1.2586	0.5654	3.4181	1.0242	1.1837
Commercial								
Random Walk	0.4718	0.5125	0.3929	0.5281	0.7149	0.6556	1.6297	0.7008
Random Walk w/Drift	1.6652	2.6464	3.6641	8.1569	2.0118	1.6756	309.23	47.0069
Industrial								
Random Walk	1.7518	2.7395	3.8764	0.5218	0.6375	0.6753	1.2189	1.6316
Random Walk w/Drift	0.6502	2.2256	1.3652	1.1553	0.5585	4.1822	1,217.2922	175.3470
Average - Random Walk	0.8387	1.0989	1.4235	0.5816	0.7180	0.7483	1.2693	
Average - Random Walk w/Drift	1.2719	1.5355	2.0359	3.8556	1.2631	6.0119	540.1720	

Modified Theil Inequality Coefficients results between the structural model and random walk benchmarks and the random walk with drift are in Table 4.2.3. Using U< 1.0 as a general guideline, it is apparent that the structural model compares favorably to the random walk benchmarks. In 20 of the 28 inequality coefficients estimated, results of 0.99 or less are observed. The seven modified Theil inequalities with a result greater than 1.0 were primarily the industrial property absolute forecast errors for the first, second, third and seventh step-lengths. With a unitary outcome in the sixth step of the residential single family housing property, this indicates that neither the random walk benchmark nor the regional econometric structural model is superior. The random walk with drift continues to result in smaller absolute forecast errors with 20 of the 28 modified inequality coefficients greater than one.

While providing valuable comparison information, the inequality coefficients have a drawback associated with them. Namely, it is generally difficult to tell when a difference in the relative accuracies of two competing prediction methodologies is statistically significant. Statistical testing and inference is problematic due to the fact that forecast errors generally are serially correlated. The latter condition is further complicated due to contemporaneous correlation of forecast residuals generated by alternative techniques (Fullerton and West, 1998).

Error differential regression results for the random walk benchmark compared to the regional structural econometric model (RSEM) are found in Table 4.2.4. The forecast errors means are found in the first column below the variable names. The statistical results reflect that the RSEM as the superior model for three variables as the modified Theil inequality coefficients initially indicated. In one case, residential single family housing, where RSEM forecasts outperformed the random walk benchmark only resulted in inconclusive error regression results. In Table 4.2.5 the error differential of the random walk with drift reflects the regional econometric structural model for each variable except the residential single family housing as being superior. This is at odds with the inequality coefficients, but not U-statistic tabulations for the multi-family housing property.

Table 4.2.4: Error Regression Results: Random Walk Benchmark vs. Regional Structural Economic Model Forecast Errors

Variable	β_1 (t-statistic)	β2 (t-statistic)	Joint F-test (probablity)	Most Accurate
Residential Single Family Housing (Both Error Means Neg.)	471,000,000 (3.835099)	-0.008 (-0.313913)	0.099 (0.757643)	Inconclusive
Residential Multi-Family Housing (Both Error Means Neg.)	44,360,656 (3.647546)	0.229 (3.700996)	13.697 (0.001938)	RSEM
Commercial (Both error means neg.)	244,000,000 (5.803551)	0.238 (2.898948)	8.404 (0.010464)	RSEM
Industrial (Both error means neg.)	5,446,736 (0.426817)	0.242 (3.107858)	9.659 (0.006768)	RSEM

Table 4.2.5: Error Regression Results: Random Walk with Drift vs. Regional Structural Economic Model Forecast Errors

Variable	β_1 (t-statistic)	β2 (t-statistic)	Joint F-test (probablity)	Most Accurate
Residential Single Family Housing (Both Error Means Neg.)	-1,570,000,000 (-5.160091)	-0.455 (-4.573319)	20.915 (0.000312)	Random Walk with Drift
Residential Multi-Family Housing (Both Error Means Neg.)	11,326,136 (0.523451)	0.218 (1.724002)	2.972 (0.103971)	RSEM
Commercial (Both error means neg.)	-146,000,000 (-2.932288)	0.108 (0.912946)	0.833 (0.374823)	RSEM
Industrial (Both error means neg.)	-25,447,292 (-1.30864)	0.119 (0.755742)	0.571 (0.460786)	RSEM

4.3 UNIVARIATE ARIMA MODEL SPECIFICATIONS

Functional form for univariate ARIMA or autoregressive integrated moving average models depends critically upon the stationarity characteristics associated with the series. All four property valuation series require first-order differencing to obtain stationarity. The univariate

ARIMA equation specifications are listed in Table 4.3.1. In all cases the same univariate ARIMA model framework was utilized for each property category for all 28 sample sub-periods.

Table 4.3.1: Final Univariate ARIMA Property Valuation Model Specifications

Property Type	Final Equations Specification	Number of Specification Changes
Residential Single Family Housing	AR(1), MA(1)	Zero
Residential Multi-Family Housing	MA (8)	Zero
Commercial	MA (3)	Zero
Industrial	MA (1)	Zero

Table 4.3.2 describes the ARIMA simulation results for each property category at each step length from 2001 through 2007. Each specified property simulates results in a low U-statistic below 18.4 percent and relatively low covariance proportions. The highest U-statistic occurs in the seventh step-length of RSF at 0.20 making it the worst forecast length in the group. Residential multi-family housing and commercial property have low U-statistics, but relatively low covariance proportions as well, making the results less than optimal.

Modified Theil inequality coefficient results using the standard Box-Jenkins equations versus random walk benchmarks and random walk with drift are shown in Table 4.3.3. Using U< 1.0 as general guideline as used with the previous two models, it is apparent that the univariate ARIMA compared favorably to the random walk benchmarks. In 20 of 28 inequality coefficients estimated, results of 0.99 or less are observed. It is important to note that industrial property inequality coefficients appear to have a temporal pattern in the first, second and third step lengths. It is also industrial property where the random walk benchmark outperforms the ARIMA model. As noted by Fullerton and West (1998) that the outcome for one-step ahead is not necessarily a predictor of outcomes at higher step lengths or averages across multiple step

Table 4.3.2: Univariate ARIMA Model (3) Simulation Results

		1-step	2-step	3-step	4-step	5-step	6-Step	7-Step
Residential	RMSE	131,299,383	611,191,586	1,478,736,608	2,848,506,054	3,766,458,722	3,912,855,604.67	##############
Single Family	Theil -U	0.0060	0.0262	0.0606	0.1054	0.1170	0.1123	0.1277
Housing	U^m	0.5160	0.2240	0.6951	0.7448	0.6180	0.8173	1.0000
	U^s	0.0211	0.7513	0.3049	0.2543	0.3741	0.1827	0.0000
	U^c	0.4630	0.0247	0.0000	0.0008	0.0078	0.0000	0.0000
Residential	RMSE	119,082,440	27,227,768	51,576,095	109,201,159	198,132,647	248,700,785	253,237,084
Multi-Family	Theil -U	0.0648	0.0137	0.0260	0.0513	0.0843	0.1009	0.0969
Housing	U^m	0.9964	0.0493	0.7466	0.6834	0.4915	0.8117	1.0000
	U^s	0.0009	0.9072	0.2245	0.3120	0.4076	0.0858	0.0000
	U^c	0.0027	0.0434	0.0289	0.0046	0.1009	0.1024	0.0000
Commercial	RMSE	280,794,807	307,179,111	277,415,781	259,840,883	386,820,801	649,536,369	707,889,792
	Theil -U	0.0394	0.0407	0.0350	0.0295	0.0407	0.0669	0.0707
	U^m	0.7919	0.9271	0.9529	0.2417	0.3852	0.9806	1.0000
	U^s	0.2031	0.0721	0.0220	0.4816	0.5996	0.0194	0.0000
	U^c	0.0050	0.0008	0.0251	0.2767	0.0152	0.0000	0.0000
Industrial	RMSE	82,690,062	36,213,886	51,819,961	47,388,724	144,231,592	243,349,589	2.86E+08
	Theil -U	0.0750	0.0338	0.0526	0.0411	0.1103	0.1845	0.2019
	U^m	0.8795	0.6747	0.7794	0.0332	0.2541	0.8305	1.0000
	U^s	0.0659	0.0811	0.0079	0.5789	0.6288	0.0779	0.0000
	U^c	0.0546	0.2441	0.2127	0.3879	0.1172	0.0916	0.0000

Table 4.3.3: Modified Theil Inequality Coefficients: Regional Economic Structural Model RMSEs to Random Walk Model & Random Walk with Drift

	1-step	2-step	3-step	4-step	5-step	6-Step	7-Step	Average
Residential Single Family Housing								
Random Walk	0.1445	0.4486	0.7057	0.7713	0.6941	0.7202	1.1917	0.6680
Random Walk w/Drift	0.8891	0.9263	2.2411	4.7304	1.4215	10.5373	712.03	104.6822
Residential Multi-Family Housing								
Random Walk	0.7344	0.8972	0.9468	0.6599	0.7577	0.7680	1.4008	0.8807
Random Walk w/Drift	1.0732	0.4132	1.4862	1.7109	0.7337	4.0217	1.2272	1.5237
Commercial								
Random Walk	0.4874	0.6226	0.6802	0.3847	0.6314	0.6817	1.9517	0.7771
Random Walk w/Drift	1.7204	3.2154	6.3431	5.9413	1.7768	1.7421	370.32	55.8659
Industrial								
Random Walk	4.1769	1.9563	2.5521	0.4230	1.3823	0.9026	1.7034	1.8709
Random Walk w/Drift	1.5503	1.5893	0.8988	0.9366	1.2111	5.5900	1701.1008	244.6967
Average - Random Walk	1.3858	0.9812	1.2212	0.5597	0.8664	0.7681	1.5619	
Average - Random Walk w/Drift	1.3083	1.5360	2.7423	3.3298	1.2858	5.4728	696.1700	

lengths. For commercial property the ARIMA forecasts are favorable to the random walk benchmarks at all step lengths except the seventh step-length. The residential single family housing and residential multi-family housing property types are both outperformed in the seventh step-length by the random walk benchmarks.

The ARIMA model performs favorably compared to the random walk; however, the random walk with drift consistently outperforms the ARIMA for all property types especially in the sixth and seventh step length. Specifically, the residential single family (RSF) and multi-family housing (RMF) and commercial properties as shown in Table 4.3.3 are on average better explained with the ARIMA model. The more accurate property valuation forecasts may be due to the lack of restrictions on the ARIMA models compared to the econometric structural model.

The error regression results for the ARIMA model can be found in Tables 4.34 and 4.3.5. The results indicate almost the exact opposite to the modified Theil coefficients. The random walk proved to be superior model for ever variable with the exception of industrial property when compared to the ARIMA and the modified Theil coefficients indicated otherwise. Industrial property has been difficult to forecast for all model specifications with the exception of the random walk with drift. This may be due to capital investment in the industrial properties or the reclassification of properties.

As shown in Table 4.3.5 the findings confirm much of what is indicated by the inequality coefficients. Statistically significant differences in the predictive accuracies that favor the ARIMA model occur for three of the variables residential single family housing, residential multi-family housing, and commercial property valuations. Table 4.3.5 depicts the results of error differential with random walk with drift and the ARIMA model. The results illustrate a similar outcome as the descriptive forecast assessments with statistically significant differentials for the random walk with drift in two series – residential single family housing and industrial property categories.

Table 4.3.4: Error Regression Results: Random Walk Benchmark vs. ARIMA Forecast Errors

Variable	**β_1 (t-statistic)**	**β2 (t-statistic)**	**Joint F-test (probablity)**	**Most Accurate**
Residential Single Family Housing (Both Error Means Neg.)	859,000,000 (5.9558)	0.086 (2.4872)	6.186 (0.0243)	ARIMA
Residential Multi-Family Housing (Both Error Means Neg.)	15,432,251 (1.3796)	0.120 (2.3219)	5.391 (0.0338)	ARIMA
Commercial (Both error means neg.)	230,000,000 (4.7997)	0.308 (3.0872)	9.531 (0.0071)	ARIMA
Industrial (Both error means neg.)	-5,362,541 (-0.3477)	0.081 (0.9684)	0.938 (0.3473)	Inconclusive

Table 4.3.5: Error Regression Results: Random Walk Benchmark with Drift vs. ARIMA Forecast Errors

Variable	β_1 (t-statistic)	β2 (t-statistic)	Joint F-test (probablity)	Most Accurate
Residential Single Family Housing (Both Error Means Neg.)	-1,190,000,000 (-3.9929)	-0.366 (-3.2923)	10.839 (0.0046)	Random Walk with Drift
Residential Multi-Family Housing (Both Error Means Neg.)	33,312,183 (0.9978)	0.581 (5.9429)	35.318 (0.0000)	ARIMA
Commercial (Both error means neg.)	-160,000,000 (-2.8386)	0.189 (1.2773)	1.631 (0.2197)	Inconclusive
Industrial (Both error means neg.)	-36,256,569 (-1.4408)	-0.101 (-0.5517)	0.304 (0.5888)	Random Walk with Drift

4.4 TREND MODEL SPECIFICATIONS

Table 4.4.1 gives the equation estimation results of the trend analysis. The commonly used trend model performed well, with statistically significant coefficients for all property types, and coefficients of determination averaging 84.7 percent. The simulation results in Table 4.4.2 of the trend analysis also struggled with U-statistics. With relatively low U-statistics and high bias

Table 4.4.1: Trend Analysis (4) Estimation Results

Equation 1 — Residential Single Family Housing, valuation in dollars

RSF = f(t)

Ordinary Least Squares, Annual data for 27 periods 1981 to 2007

RSF = -9.55E+11 + 4.83E+08 * (t)
(-11.93) (12.03)

Sum Sq	6.60E+12	Std Err	1.62E+09	LHS Mean	8.66E+09		
R Sq	0.85282	R Bar Sq	0.846933	F (1,25)	142.26		
DW	0.344						

Equation 2 — Residential Multi-Family Housing, valuation in dollars

RMF = f(t)

Ordinary Least Squares, Annual Data for 27 periods 1981 to 2007

RMF = -5.44E+10 + 27,689,111 * (t)

Sum Sq	3.62E+17	Std Err	0.2102	LHS Mean	8.20E+08
R Sq	0.7761	R Bar Sq	0.7672	F (1,25)	84.12
DW	0.6272				

Equation 3 — Industrial Property, valuation in dollars

INDUST = f(t)

Ordinary Least Squares, Annual Data for 23 periods 1985 to 2007

INDUST = -4.67E+10 + 23,618,144 * (t)
(-11.26) (11.36)

Sum Sq	9.18E+16	Std Err	6.61E+07	LHS Mean	4.18E+08
R Sq	0.8600	R Bar Sq	0.8534	F (1, 21)	126.79
DW	1.3018				

Equation 4 — Commercial Property, valuation in dollars

COM = f(t)

Ordinary Least Squares, Annual Data for 27 periods 1981 to 2007

COM = -.250E+11 - 1.27E+08 * (t)
(-14.98) (15.15)

Sum Sq	2.86E+18	Std Err	3.38E+08	LHS Mean	2.76E+09
R Sq	0.9017	R Bar Sq	0.8978	F (1,25)	224.44
DW	0.2918				

Table 4.4.2: Trend Model (4) Simulation Results

		1-step	2-step	3-step	4-step	5-step	6-step	7-step
Residential	RMSE	186,677,289	736,582,517	1,410,302,732	3,065,883,318	5,503,837,924	6,313,408,714	7,209,943,581
Single	Theil -U	0.0085	0.0320	0.0576	0.1143	0.1817	0.1953	0.2055
Family	U^m	0.9401	0.5089	0.6941	0.7578	0.7791	0.9174	1.0000
Housing	U^s	0.0390	0.4571	0.3056	0.2390	0.2207	0.0826	0.0000
	U^c	0.0208	0.0340	0.0002	0.0032	0.0002	0.0000	0.0000
Residential	RMSE	253,645,816	51,912,465	46,965,112	92,520,490	203,275,271	253,645,816	294,582,113
Multi-family	Theil -U	0.0244	0.0255	0.0226	0.0423	0.0867	0.1036	0.1146
Housing	U^m	0.6900	0.9338	0.9013	0.1244	0.4961	0.9044	1.0000
	U^s	0.0602	0.0309	0.0175	0.8075	0.5036	0.0956	0.0000
	U^c	0.2498	0.0352	0.0812	0.0681	0.0003	0.0000	0.0000
Commercial	RMSE	473,871,397	546,953,320	546,792,885	792,579,327	1,021,164,871	1,142,941,317	1,107,403,602
	Theil -U	0.0685	0.0750	0.0715	0.0966	0.1160	0.1240	0.1153
	U^m	0.9430	0.9663	0.9844	0.8474	0.8605	0.9877	1.0000
	U^s	0.0566	0.0335	0.0139	0.1443	0.1379	0.0123	0.0000
	U^c	0.0004	0.0002	0.0017	0.0083	0.0015	0.0000	0.0000
Industrial	RMSE	82,569,420	85,834,617	101,705,776	73,498,647	132,976,729	165,274,681	208,221,468
	Theil -U	0.0750	0.0764	0.0899	0.0612	0.1004	0.1187	0.1392
	U^m	0.8609	0.9307	0.9572	0.2831	0.1696	0.8006	1.0000
	U^s	0.0113	0.0007	0.0003	0.6056	0.8304	0.1994	0.0000
	U^c	0.1278	0.0686	0.0426	0.1112	0.0000	0.0000	0.0000

Table 4.4.3: Modified Theil Inequality Coefficients: Trend Model RMSEs to Random Walk Model & Random Walk with a Drift

	1-step	2-step	3-step	4-step	5-step	6-Step	7-Step	Average
Residential Single Family Housing								
Random Walk	0.2054	0.5407	0.6731	0.8301	1.0143	1.1621	1.7945	0.8886
Random Walk w/Drift	1.2641	1.1163	2.1374	5.0914	2.0772	17.0020	1072.24	157.2748
Residential Multi-Family Housing								
Random Walk	0.7344	1.7105	0.8622	0.5591	0.7773	0.7832	1.6295	1.0080
Random Walk w/Drift	0.4388	0.7878	1.3534	0.0882	0.7527	4.1017	1.4275	1.2786
Commercial								
Random Walk	0.8225	1.1087	1.3406	1.1734	1.6668	1.1995	3.0531	1.4807
Random Walk w/Drift	2.9034	5.7252	12.5025	18.1224	4.6905	3.0655	579.32	89.476
Industrial								
Random Walk	4.1708	4.6368	5.0090	0.6560	1.2745	0.6130	1.2387	2.5141
Random Walk w/Drift	1.5480	0.1681	1.7640	1.4527	1.1166	3.7966	1,237.0	178.12
Average - Random Walk	1.4833	1.9992	1.9712	0.8047	1.1832	0.9395	1.93	
Average - Random Walk w/Drift	1.5386	1.9493	4.4393	6.1887	2.1593	6.9914	722.50	

proportions the trend analysis as with other models is unable to explain the large prediction error that occurs in step-length five through seven.

In Table 4.4.3 the results indicate that the random walk benchmarks and random walk with drift perform well in comparison to the trend analysis in all property categories. The modified Theil inequality shows the random walk with drift out performing trend analysis for all variables in 23 of 28 calculations. However, the results of the modified Theil inequality coefficients reflect a split between the random walk benchmark and the trend model with only 14 instances out of the possible 28 exhibiting values less than 0.99. Also, on average the residential multi-family housing inequality coefficient is 1.00 implying that neither methodology, trend nor random walk, is superior.

Found in Table 4.4.4, the error regression results when the random walk is compared to trend forecast errors is not like the inequality coefficients, instead the trend model is statistical significant in two variables (residential multi-family and commercial) and inconclusive in the other two (residential single family and industrial). The modified Theil inequality coefficients are only favorable to the random walk benchmark and random walk with drift. However, the random walk does not outperform the trend model as clearly as does the random walk with a drift.

In Table 4.4.5 this differs from the regression results of the random walk with drift that appears to be split between the naïve model and the trend model. This result is not surprising since both the random walk with drift and the trend model account for any upward increase. It would be any downward turning points that trend model would fail to predict.

Table 4.4.4: Error Regression Results: Random Walk Benchmark vs. Trend Forecast Errors

Variable	β_1 (t-statistic)	β2 (t-statistic)	Joint F-test (probability)	Most Accurate
Residential Single Family Housing (Both Error Means Neg.)	73,507,247 (0.3278)	-0.0920 (-2.014107)	4.0566 (0.0611)	Inconclusive
Residential Multi-Family Housing (Both Error Means Neg.)	20,739,860 (1.5443)	0.1022 (1.6625)	2.7639 (0.1159)	Trend
Commercial (Both Error Means Neg.)	-154,000,000 (-3.2258)	0.0071 (0.0932)	0.0087 (0.9269)	Trend
Industrial (RW neg; Trend pos)	-14,989,673 (-0.9831)	0.0071 (0.0932)	13.2269 (0.0022)	Inconclusive

Table 4.4.5: Error Regression Results: Random Walk Benchmark with Drift vs. Trend Forecast Errors

Variable	**β_1 (t-statistic)**	**β2 (t-statistic)**	**Joint F-test (probability)**	**Most Accurate**
Residential Single Family Housing (Both Error Means Neg.)	-1,970,000,000 (-5.5796)	-0.5531 (-5.2915)	27.9998 (0.0000)	Random Walk with Drift
Residential Multi-Family Housing (Both Error Means Neg.)	-17,852,807 (-0.8454)	0.0159 (0.1410)	0.0199 (0.8896)	Trend
Commercial (Both error means neg.)	-544,000,000 (-10.5138)	-0.1401 (-1.4579)	2.1254 (0.1642)	Random Walk with Drift
Industrial (RW neg; Trend pos)	-37,762,072 (-2.0923)	0.2564 (1.5453)	2.3879 (0.1418)	Inconclusive

4.5 GENERAL OBSERVATIONS

Table 4.5.1 reports the average values of the modified Theil inequality coefficients for all seven step-lengths. The results indicate that the random walk with drift is on average more accurate then all models including the Regional Structural Economic Model. The results find each model to be favorable when compared to the random walk benchmark. Each model had difficulty predicting the large increase in the second, sixth and seventh step-length for each valuation type. This may be due reappraisal in 2004 where large percentage increases in valuation occurred. This large increase inflates the absolute forecast errors for the second step length affecting the forecast accuracy of all models. The increase to valuations continued in 2007 and 2008 tax years.

Table 4.5.1: Average Values of the Modified Theil Inequality Coefficients at each Step Length

	1-step	2-step	3-step	4-step	5-step	6-step	7-step	Average
Traditional Income Elasticity								
versus Random Walk	2.7658	4.1474	3.6348	0.9017	0.9743	0.6585	1.4626	0.6585
versus Random Walk with a Drift	2.7915	3.9518	4.6761	5.4918	1.5860	5.0511	626.1704	5.0511
Regional Structural Economic								
versus Random Walk	0.8387	1.0989	1.4235	0.5816	0.7180	0.7483	1.2693	0.932
versus Random Walk with a Drift	1.2719	1.5355	2.0359	3.8556	1.2631	6.0119	540.1720	1.992
ARIMA								
versus Random Walk	1.3858	0.9812	1.2212	0.5597	0.8664	0.7681	1.5619	0.7681
versus Random Walk with a Drift	1.3083	1.5360	2.7423	3.3298	1.2858	5.4728	696.1700	5.4728
Trend								
versus Random Walk	1.4833	1.9992	1.9712	0.8047	1.1832	0.9395	1.9290	0.9395
versus Random Walk with a Drift	1.5386	2.8491	4.4393	6.5290	2.1593	6.9914	722.4992	6.9914

CHAPTER 5

CONCLUSION

Only a limited number of regional forecast studies exist in the area of property valuations. This study attempts to partially fill the gaps in property valuation forecasts by comparing four different models and their out-of-sample simulation accuracy. Municipal property tax collections continue to account for the majority general fund revenue in medium to small municipalities. While this predominately occurs in states that do not have a state income tax, the importance of property tax revenue should not be underestimated. Property tax collections for the City of El Paso, Texas represent 59.4 percent of general fund revenue generated. During times of economic downturns or budgetary shortfalls accurate forecasting is imperative in maintaining the financial health of a municipality.

Annual data for the 1981 to 2007 sample period are utilized. The data are modeled using four methodologies: traditional income elasticity, regional structural econometric model, univariate autoregressive integrated moving average (ARIMA), and trend. Each model was then benchmarked against a random walk and a random walk with drift. Parameter estimation results for each methodology exhibited relatively good statistical traits. Equation estimations occurred for four of the primary real property valuation categories: residential single family housing, residential multi-family housing, and commercial and industrial property values.

Out-of-sample predictive accuracy relative to a random walk benchmark is evaluated using seven step-lengths. Most methodologies exhibit less than ideal forecast characteristics, with relatively low U-statistics, no step-length exceeding 18.4 percent, but high bias proportions,

U^m. On average the models with the lowest U-statistics are the random walk with drift for four variables (residential single family housing, commercial and industrial property values) and the regional structural econometric model (residential multi-family housing property values). The root mean-squared errors have the identical results as the U-statistic.

The results from the error regression statistical diagnostics also reach a similar conclusion. The random walk with a drift methodology is statistically significant when compared to all four models at two property value categories including residential single family housing and commercial property. The remaining two categories of property valuations belong to the regional structural econometric model, namely the residential multi-family and industrial property valuations.

Further research employing different sample data sets and additional techniques may prove to be valuable. Overall these results suggest that additional research is necessary, especially given the importance of property valuation on municipal budgeting. Given the absence of other studies in this area, additional verification of these results would be helpful. Since the City of El Paso, Texas is a border community it may prove valuable to look at other regions that are not adjacent to a foreign country. However, due to the importance of this category as an indication of a healthy economy, more attention is warranted. This point is further highlighted by the fact that accuracy assessments are mixed and none of the results address the significant valuation increases in the fifth through seventh step-lengths.

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APPENDIX

Historical Time Series Data

Year	Real Residential Single Family Housing	Real Residential: Multi-Family Housing	Real: Commercial	Real: Industrial
1981	3,783,243,652	290,935,984	1,304,230,754	N.A.
1982	3,763,903,153	259,017,179	1,643,799,203	N.A.
1983	3,888,884,026	440,934,129	1,574,206,420	N.A.
1984	4,033,999,526	540,053,563	1,598,586,840	N.A.
1985	5,353,611,449	779,291,900	1,888,148,709	133,080,318
1986	5,518,486,585	817,541,513	1,951,752,845	182,680,455
1987	5,680,480,822	720,303,543	1,992,295,463	N.A.
1988	5,849,035,347	783,429,459	1,975,040,928	187,578,771
1989	6,146,349,322	807,499,309	2,170,669,878	331,010,178
1990	6,422,884,374	742,112,675	2,147,796,771	256,653,618
1991	6,566,347,677	663,730,013	2,054,483,220	302,728,748
1992	7,022,941,076	789,659,520	2,415,986,743	359,464,985
1993	7,283,883,537	786,103,294	2,437,102,974	283,048,613
1994	7,531,955,640	800,412,370	2,431,921,542	397,508,737
1995	8,570,390,275	876,574,825	2,525,119,412	459,473,196
1996	9,114,013,437	880,136,240	2,691,012,581	491,444,429
1997	9,372,149,728	884,526,089	2,796,414,085	490,240,146
1998	9,593,692,246	780,359,874	2,947,225,219	408,010,591
1999	9,868,747,473	909,208,915	3,031,599,717	527,684,368
2000	10,194,981,271	896,890,929	3,141,596,020	500,824,524
2001	10,664,344,004	989,360,308	3,453,309,734	515,937,352
2002	11,002,504,245	967,219,944	3,709,743,006	525,076,838
2003	11,461,881,146	977,024,416	3,900,362,193	495,575,422
2004	12,859,311,889	1,035,412,595	4,134,898,390	538,956,989
2005	14,086,819,500	1,031,686,203	4,240,751,482	511,891,605
2006	17,125,637,106	1,252,266,427	4,994,838,850	684,010,639
2007	21,143,437,609	1,433,041,636	5,357,550,536	852,108,930

Historical Time Series Data (Cont. 2)

Year	El Paso Population (In thousands)	El Paso Personal Income (Millions of Nominal Dollars)	Single-Family Starts (In thousands)	Multi-Family Starts (In thousands)
1969	364.022	1019.467		
1970	360.462	1074.011		
1971	369.189	1182.225		
1972	378.364	1285.882		
1973	398.203	1467.087	6.000	1.590
1974	411.532	1658.651	5.000	0.943
1975	427.292	1751.759	6.661	0.433
1976	440.333	1969.412	8.177	0.515
1977	450.007	2172.875	10.719	1.160
1978	460.611	2443.893	9.644	0.899
1979	472.343	2808.730	5.982	1.454
1980	483.711	3143.095	5.281	0.828
1981	497.523	3840.501	2.557	1.116
1982	511.892	4140.336	3.941	1.965
1983	521.038	4452.836	5.641	3.474
1984	529.668	4891.037	4.062	1.301
1985	538.809	5282.050	3.766	1.342
1986	549.592	5504.124	4.637	1.820
1987	559.479	5736.801	3.658	0.250
1988	568.804	6152.933	2.485	0.076
1989	580.982	6737.109	2.555	0.083
1990	595.350	7313.079	2.086	0.197
1991	608.206	7538.061	1.876	0.177
1992	619.138	8313.360	2.560	0.608
1993	634.044	8716.901	2.697	0.362
1994	646.181	9214.252	2.680	1.294
1995	654.250	9678.111	2.557	0.439
1996	656.482	10023.067	2.581	0.993
1997	665.066	10775.273	2.500	0.317
1998	671.250	11399.734	3.309	0.149
1999	675.397	11741.136	3.631	0.331
2000	681.572	12649.916	3.104	0.391
2001	687.915	13510.529	3.464	0.069
2002	694.078	14200.502	3.612	0.165
2003	702.281	14672.082	4.888	0.274

Historical Time Series Data (Cont.3)

Year	El Paso Population (In thousands)	El Paso Personal Income (Millions of Nominal Dollars)	Single-Family Starts (In thousands)	Multi-Family Starts (In thousands)
2004	712.481	15727.416	3.370	0.275
2005	721.183	16771.479	4.467	0.664
2006	736.310	17980	4.045	0.313
2007	747.640	19135	3.825	0.347

Year	Multi-Family Housing Stock (In thousands)	Other Commercial Space Permit Values (In thousands)	Mexico, Exchange Rate Period Average (Peso/$)	Industrial Permits (In millions of $)
1972	26.774		0.0125	
1973	30.041		0.0125	
1974	32.725		0.0125	
1975	34.481		0.0125	
1976	36.162	26.084	0.0154	3.328
1977	38.366	25.890	0.0226	6.325
1978	41.369	34.996	0.0226	9.505
1979	44.546	38.498	0.0226	9.113
1980	45.624	88.342	0.0230	16.779
1981	46.538	79.630	0.0245	16.282
1982	47.461	68.396	0.0564	1.675
1983	49.661	55.864	0.1201	15.515
1984	54.092	108.373	0.1678	4.336
1985	57.538	92.787	0.2569	10.564
1986	59.633	96.100	0.6118	19.057
1987	61.432	103.713	1.378	12.082
1988	62.038	90.265	2.273	11.605
1989	62.148	111.612	2.461	9.270
1990	62.282	99.526	2.813	1.734
1991	62.169	85.264	3.018	5.929
1992	62.114	116.097	3.095	7.730
1993	62.282	128.678	3.116	13.780
1994	62.591	166.573	3.375	22.307
1995	63.150	162.010	6.419	31.139
1996	63.665	162.593	7.599	27.130

Historical Time Series Data (Cont.5)

Year	Multi-Family Housing Stock (In thousands)	Other Commercial Space Permit Values (In thousands)	Mexico, Exchange Rate Period Average (Peso/$)	Industrial Permits (In millions of $)
1997	64.068	176.523	7.918	37.878
1998	64.355	158.018	9.136	12.646
1999	64.371	191.797	9.560	13.392
2000	64.371	195.371	9.456	11.861
2001	64.434	206.246	9.342	1.923
2002	64.561	224.125	9.656	0.000
2003	64.666	169.274	10.79	1.918
2004	64.888	179.300	11.29	5.959
2005	65.360	186.341	10.90	1.901
2006	65.983	353.898	10.90	2.224
2007	66.293	333.808	10.93	6.598

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