Municipal Non-Residential Real Property Valuation Forecast Accuracy

K. Nicole Arnold Cote and Wm. Doyle Smith and Thomas M., Jr. Fullerton

University of Texas at El Paso

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Thomas M. Fullerton, Jr.
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ABSTRACT

The objective of this study is to estimate the accuracy and/or reliability of alternative methods of forecasting property valuations of non-residential real commercial and industrial property in El Paso to improve municipal revenue forecasting. This study seeks to identify and evaluate four econometric and statistical alternatives to present forecasting practices for non-residential property valuation forecasts: (1) a traditional income elasticity method, (2) a regional structural econometric model, (3) a statistical ARIMA method, and (4) trend analysis. In order to evaluate the four models, ex ante forecast simulations are created for each modeling approach and then compared to random walk and random walk with drift models for both commercial and industrial property values. Results indicate that the random walk with drift model outperformed all four models for both commercial and industrial property values. In addition, results also indicate that the random walk model outperformed all four models for industrial property values.

Keywords: Non-residential property valuation forecasts, regional economics, applied econometrics

INTRODUCTION

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). 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. Because property taxation represents the primary revenue source for the City of El Paso, the accuracy of revenue forecasting is ever relevant in municipal budgeting. Many cities, including El Paso, struggle with increases in health care costs, and growing worker pensions. Responses have included personnel cuts, curtailed infrastructure investment, and higher user fees. At present, property tax forecasts are based on historical trend analyses under the assumption that the assessed valuation will continue to grow. Relatively few cities have compared forecasting methods for property tax revenues (Sexton, 1987). Time and personnel constraints often force local governments to rely on judgmental methods or simple trend revenue projections.

The objective of this study is to estimate the accuracy and reliability of alternative methods of forecasting property values for non-residential commercial and industrial property in El Paso. This study seeks to identify and evaluate four econometric and statistical alternatives to present forecasting practices for non-residential property valuation forecasts: (1) a traditional income elasticity method, (2) a regional structural econometric model, (3) a statistical ARIMA method, and (4) trend analysis. *Ex ante* forecast simulations are utilized to calculate root-mean-squared-error values for each methodology in order to generate modified Theil inequality coefficients for each of the four models relative to the random walk and random walk with drift models.

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, & Van De Sande, 1999). Past research, however, has shown that municipalities generally know little about revenue forecasting techniques, especially times series analysis (Bahl & 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, Frank and McCollough (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 & 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, & 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 & 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 & Elias, 2004.) Those efforts also include analyses of municipal property tax abatement policies (Fullerton, 2002; Fullerton & 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 & McCollough, 1992). This study attempts to partially fill this gap in the literature by completing an analysis of non-residential property valuation predictability.

Many aspects of regional economic predictability have been examined in recent years for the Borderplex area encompassed by El Paso and Ciudad Juarez. Fullerton and Barraza de Anda (2008) document some of the difficulties associated with modeling demographic trends as a consequence of cross border data asymmetries. Those difficulties, plus frequently large historical data revisions, pose obstacles for accurate housing sector forecasts in El Paso (Fullerton & Kelley, 2008). International manufacturing aggregates for Ciudad Juarez also have a mixed record when it comes to econometric forecast accuracy (Fullerton & Novela, 2010). Perhaps surprisingly, the regional forecasting track records for the municipal water grids on both sides of the border have been found to be relatively accurate (Fullerton & Molina, 2010). Given all of the above, it is difficult to anticipate what the results will be for non-residential property valuations in El Paso. It is, therefore, an important piece of the regional economic puzzle that merits empirical attention.

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. The County of El Paso personal income data series ranges from 1969 to 2006 on an annual basis and are expressed in millions of nominal dollars. 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 & Molina, 2007). Published annually, each report contains three years worth forecasts.

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).

TRADITIONAL INCOME ELASTICITY METHOD

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

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

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.

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 & 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.

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 & Rubinfeld, 1998). Although many El Paso time series are non-stationary, they often can be transformed into stationary variables by differencing them (Fullerton & Elias, 2004). Once stationarity is achieved, a univariate autoregressive integrated moving average (ARIMA) equation of the following form can be estimated:

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

where d is a difference operator.

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

$$MV_i = a_i + c_i t + \varepsilon_i \tag{3}$$

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

FORECAST ASSESSMENT

To further assess model performance, once parameter estimations are made for each of the four models, out-of sample or ex ante forecast simulations are utilized. A series of rolling forecasts are created for each modeling approach and then compared to random walk benchmarks and random walk with drift benchmarks. 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.

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 & Shiller, 1990; Fullerton & Kelley, 2006). The random walk is an example of a simple stochastic time series in which successive change in y_t is drawn independently from probability distribution with zero mean. Thus, y_t is determined by,

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

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

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

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

With the out-of-sample or *ex-ante* forecast simulations, resulting prediction errors are then used to calculate root-mean-squared-error (RMSE) values. The RMSEs for each methodology are then utilized to generate modified Theil inequality coefficients (Web, 1984). The modified Theil inequality coefficients are calculated as the ratios of each of the four model's RMSEs relative to the RMSEs of the random walk and random walk with drift models. While descriptive, modified Theil inequality coefficients have been shown to provide reliable indicators for assessing the predicative accuracy of econometric forecasting models (Webb, 1984).

The Theil coefficients are decomposed into bias (U^m), variance (U^s) and covariance (U^c) components. 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 values for the second moment error proportions are $U^m = U^s = 0$ and $U^c=1$. Theil inequality coefficients will vary between 0 and 1. If U=0, the predictive performance is considered a perfect fit. If U=1, the predictive performance of the model is as "bad" as it can possibly be (Pindyck & Rubinfeld, 1998).

A modified Theil inequality coefficient or U-coefficient greater than one indicates that the random walk benchmark or the random walk with drift has smaller absolute forecast errors than the competing methodologies. Alternatively, if a modified Theil coefficient is less than one, it will imply that the prediction errors of a model are smaller than those associated with random walk benchmarks or random walk with drift. Simply put, if the modified Theil inequality coefficient is greater than one, it indicates that the random walk model or the random walk with drift model outperforms that particular model. Conversely, if the U-coefficient is less than one, it indicates that the forecasts for that particular model are more accurate than those associated with the random walk or random walk with drift.

In addition, error differential regression results for both the random walk benchmark and the random walk with drift benchmark are compared to the commercial and industrial property values for each of the four forecasting models.

EMPIRICAL RESULTS

Traditional Income Elasticity Model Specifications

Each model is estimated for two major categories of real property: commercial and industrial. All models are estimated using 1981-2007 annual data for El Paso, Texas (MSA). Table 1.1 summarizes the variable definitions used for each model.

Table 1.1
Variable Mnemonics and Equation Statistics

Series	**Description**
Endogenous Variables	
COM	Real Property: Commercial
INDUST	Real Property: Industrial
Exogenous Variables	
ELPPOP	El Paso Population
ELYP	El Paso Personal Income
EPOCOMSP	El Paso Other Commercial Space Permit Values
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 has an estimated equation for each property category and the estimated coefficients satisfy the 5-percent significant criterion. Table 1.2 gives the model specifications resulting from the traditional income elasticity method. The t-statistics appear in parentheses below each corresponding coefficient. Equations 1-2 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 2.

Table 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.

Table 1.2
Traditional Income Elasticity Model (1) - Estimation Results

Equation 1 Industrial Property, valuation in dollars

INDUST = f(ELYP)

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

log(INDUST) = -5.36 + 1.09 * log (ELYP)
(-2.26) (10.57)

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 2 Commercial Property, valuation in dollars

COM = f(ELYP)

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

log(COM) = 4.8324 + 0.7349 * log(ELYP)
(7.38) (25.68)

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				

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 1.3 reflect very low RMSEs; however, the Theil inequality coefficients are less than optimal. While the Theil inequality coefficient or U-statistic in Table 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 1.3
Traditional Income Elasticity Model (1) Forecast Results

	1-step	2-step	3-step	4-step	5-step	6-step	7-step
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

Table 1.4
Random Walk Benchmark Forecast Results

	1-step	2-step	3-step	4-step	5-step	6-step	7-step
Commercial							
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
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
Industrial							
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
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

Forecast results for the random walk and random walk with drift benchmarks are found in Tables 1.4 and 1.5. The results demonstrate less than an ideal distribution of the three Theil inequality proportions across all seven forecasted period lengths. RMSEs for the random walk benchmark are higher than RMSEs for the traditional income elasticity model 4 out of 7 steps for commercial property values and 5 out of 7 steps for industrial property values. This differs from the results of the random walk with drift model where the RMSEs were dramatically lower than the RMSEs traditional income elasticity model for all 14 steps for both commercial and industrial property values. The distribution of the three Theil inequality proportions continues to be less than ideal at all step-lengths.

Table 1.5
Random Walk with Drift Benchmark Forecast Results

	1-step	2-step	3-step	4-step	5-step	6-step	7-step
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

Modified Theil Inequality Coefficients: Traditional Income Elasticity Model to Random Walk and Random Walk with Drift

Modified Theil inequality coefficients are 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 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.

Using U< 1.0 as a general guideline, for commercial property values, results indicate that the traditional income elasticity forecasts was only slightly more favorable than the random walk benchmarks, with 4 out of 7 inequality coefficients being less than 1.0. For industrial property values, the random walk benchmarks outperformed the traditional income model 5 out of 7 times, with inequality coefficients greater than 1.0. However, the random walk with drift completely out performs the traditional income elasticity model with inequality coefficients being greater than 1.00 for 14 of the 14 steps for both commercial and industrial property values.

Differential Error Regression Results: Random Walk and Random Walk with Drift Benchmarks vs. Traditional Income Elasticity Model Forecast Errors

In addition, differential error regression results for both the random walk benchmark and the random walk with drift benchmark were compared to the traditional income elasticity model. Error differential regression results for the random walk benchmark compared to the traditional income elasticity model are found in Table 1.7. The forecast error means are found in parentheses below each variable name. Unlike the modified Theil inequality coefficients, the differential error regression results provide mixed results, with the differential error regression results showing the random walk as statistically significant for commercial property values, but with inconclusive results regarding industrial property for the random walk benchmark.

Table 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
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	4.8330	25.3960	5.6375	1.18755	1.2051	0.6359	1.6414	
Average - Random Walk w/Drift	2.8054	6.3042	6.5827	8.4848	2.0305	2.1660	586.75	

The differential error regression results for random walk with drift also differ from the modified Theil inequality coefficients that indicated the random walk with drift model as the superior model for both commercial and industrial property values. As shown in Table 1.8, the differential error regression results show the random walk with drift model to be the more accurate technique for commercial property values, but indicating inconclusive results regarding industrial property for random walk with drift.

Table 1.7
Differential 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
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)	

Table 1.8
Differential 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
Commercial	-386,000,000	-0.051	0.253	Random Walk with Drift
(Both error means neg.)	(-7.797202)	(-0.502965)	(0.621842)	
Industrial	-95,865,765	0.362	1.315	Inconclusive
(RWE neg.; Tradt'l Income Elasticity Pos.)	(-3.54699)	(1.146556)	(0.268423)	

Regional Structural Econometric Model Specifications

The empirical summaries for the regional structural econometric model for all property value equation parameter estimates are reported in Table 2.1. The sample period used for the estimates is 1981 to 2007. On average r-squared is 95.1 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). Table 2.2 shows forecast 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, where if U = 0 there is a perfect fit.

Table 2.1
Regional Structural Econometric Model (2) Estimation Results

Equation 1	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 2	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

The regional structural econometric model (RSEM) is also benchmarked against random walk and random walk with drift benchmarks using the modified Theil inequality coefficients and error differential results. The modified Theil inequality coefficients are calculated as the ratios of the RSEM's root-mean-square-errors to those associated with the random walk and random walk with drift. Again, a modified inequality coefficient of less than one indicates that the RSEM forecasts are more accurate than those of the random walk or random walk with drift. Conversely, a U-coefficient greater than one implies that the random walk or random walk with drift model generates smaller absolute forecast errors and is a more accurate forecast method.

Table 2.2
Regional Structural Econometric Model (2) Forecast Results

	1-step	2-step	3-step	4-step	5-step	6-step	7-step
Commercial							
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
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
Industrial							
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
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

Modified Theil Inequality Coefficients: Regional Structural Econometric Model to Random Walk and Random Walk with Drift

Modified Theil inequality coefficients results between the regional structural econometric model (RSEM) and random walk and random walk with drift benchmarks are in Table 2.3. Using U< 1.0 as a general guideline, it is apparent that the RSEM compares favorably to the random walk benchmarks overall. In 9 of the 14 inequality coefficients estimated, results of 0.99 or less are observed. For commercial property values, the RSEM outperformed the random walk benchmarks 6 out of 7 steps. For industrial property values, the random walk benchmarks outperformed the RSEM 4 out of 7 steps. The random walk with drift consistently out performs the RSEM with 12 of the 14 modified inequality coefficients greater than one, with 7 out of 7 for commercial property values and 5 out of 7 times for industrial property values.

Table 2.3
Modified Theil Inequality Coefficients: Regional Structural Econometric 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
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	1.1118	1.6260	6.2693	.5250	0.6762	0.6654	1.4243	
Average - Random Walk w/Drift	1.1577	2.4358	2.5147	4.6561	1.2852	2.9289	763.2611	

Differential Error Regression Results: Random Walk and Random Walk with Drift Benchmarks vs. Regional Structural Econometric Model Forecast Errors

Differential error regression results for the random walk benchmark compared to the regional structural econometric model (RSEM) are found in Tables 2.4 and 2.5. The differential error regression results reflect that the RSEM is the most accurate and superior model for both commercial and industrial property values when compared to the random walk and the random walk with drift benchmarks. The differential error regression results are at odds with the modified Theil inequality coefficients that indicated that the random walk model was favored over the RSEM for industrial property values and the random walk with drift benchmark was statistically more accurate for both commercial and industrial property values, outperforming the RSEM 12 of the 14 steps.

Table 2.4
Differential Error Regression Results: Random Walk Benchmark vs. Regional Structural Economic Model Forecast Errors

Variable	β_1 (t-statistic)	$\beta 2$ (t-statistic)	Joint F-test (probablity)	Most Accurate
Commercial	244,000,000	0.238	8.404	RSEM
(Both error means neg.)	(5.803551)	(2.898948)	(0.010464)	
Industrial	5,446,736	0.242	9.659	RSEM
(Both error means neg.)	(0.426817)	(3.107858)	(0.006768)	

Table 2.5
Differential Error Regression Results: Random Walk with Drift vs. Regional Structural Economic Model Forecast Errors

Variable	β_1 (t-statistic)	$\beta 2$ (t-statistic)	Joint F-test (probablity)	Most Accurate
Commercial	-146,000,000	0.108	0.833	RSEM
(Both error means neg.)	(-2.932288)	(0.912946)	(0.374823)	
Industrial	-25,447,292	0.119	0.571	RSEM
(Both error means neg.)	(-1.30864)	(0.755742)	(0.460786)	

UNIVARIATE ARIMA MODEL SPECIFICATIONS

Functional form for univariate ARIMA models depends critically upon the stationarity characteristics associated with the series. Both property valuation series require first-order differencing to obtain stationarity. In both cases, the same univariate ARIMA model framework was utilized for each property category for all 14 sample sub-periods.

Table 3.2 describes the ARIMA forecast results for each property category at each step length from 2001 through 2007. Each specified property simulates results in a low U-statistic 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. Commercial property have low U-statistics, but relatively low covariance proportions as well, making the results less than optimal.

Table 3.2
Univariate ARIMA Model (3) Forecast Results

	1-step	2-step	3-step	4-step	5-step	6-step	7-step
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	0.2033	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	51,819,967	47,388,724	144,231,592	243,349,589	2,866,008
Theil –U	0.0750	0.0338	0.0526	0.0411	0.1103	0.1845	0.1367
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	.6288	0.0779	0.0000
U^c	0.0546	0.2441	0.2127	0.3879	0.1172	0.0916	0.0000

Table 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
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	4.6643	1.2895	1.6162	0.4039	1.0069	0.7922	1.8276	
Average - RW w/Drift	1.6354	2.4024	3.6210	3.4390	1.4940	3.6661	1035.7104	

Modified Theil Inequality Coefficients: Univariate ARIMA Model to Random Walk and Random Walk with Drift

Modified Theil inequality coefficient results using the standard Box-Jenkins equations versus random walk and random walk with drift benchmarks are shown in Table 3.3. Overall, random walk and random walk with drift outperformed the ARIMA in three of the four possible events. The ARIMA model performs favorably compared to the random walk benchmark for commercial but not for industrial properties. As shown in Table 3.3, the ARIMA forecasts for commercial property values are favorable to the random walk benchmarks at all steps except the seventh step. For industrial property values, however, the random walk benchmark outperforms the ARIMA model 5 out of 7 steps, with modified Theil inequalities greater than 1.0. However, the random walk with drift model consistently outperforms the ARIMA model for both commercial and industrial property, 7 out of 7 steps for commercial and 5 out of 7 steps.

Differential Error Regression Results: Random Walk and Random Walk with Drift Benchmarks vs. ARIMA Model Forecast Errors

The differential error regression results for the ARIMA model compared to the random walk and random walk with drift benchmarks can be found in Tables 3.4 and 3.5. As was the case with the modified Theil inequality coefficients, the ARIMA model proved superior to the random walk model for commercial property values and, similar to the inequality coefficients, the random walk with drift proved statistically more accurate that the ARIMA model. However, the error differential results for random walk for industrial property values and random walk with drift for commercial proved to be inconclusive.

Table 3.4
Differential Error Regression Results: Random Walk Benchmark vs. ARIMA Forecast Errors

Variable	β_1 (t-statistic)	$\beta 2$ (t-statistic)	Joint F-test (probablity)	Most Accurate
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 3.5
Differential Error Regression Results: Random Walk Benchmark with Drift vs. ARIMA Forecast Errors

Variable	β_1 (t-statistic)	$\beta 2$ (t-statistic)	Joint F-test (probablity)	Most Accurate
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

TREND MODEL SPECIFICATIONS

Table 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. The forecast results in Table 4.2 of the trend analysis also struggled with U-statistics. With relatively low U-statistics and high bias proportions the trend analysis as with other models is unable to explain the large prediction error that occurs in step-length five through seven.

Table 4.1
Trend Analysis (4) Estimation Results

Equation 1	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 2	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 4.2
Trend Model (4) Forecast Results

	1-step	2-step	3-step	4-step	5-step	6-step	7-step
Commercial							
RMSE	473,871,397	546,953,320	546,792,885	792,579,327	101,164,871	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	208,887,468
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	.8304	0.1994	0.0000
U^c	0.1278	0.0686	0.0426	0.1112	0.0000	0.000	0.0000

Modified Theil Inequality Coefficients: Trend Model RMSEs to Random Walk and Random Walk with Drift

Modified Theil Inequality Coefficients results between the trend model and random walk benchmarks and the random walk with drift are in Table 4.3. Using U< 1.0 as a general guideline, it is apparent that the random walk and the random walk with drift benchmarks out performs the trend model for commercial and industrial property values.

The random walk model outperformed the trend model 6 out of 7 steps for commercial property values and 5 out of 7 steps for industrial property values, with modified Theil inequalities being greater than 1.0. For the random walk with drift model, the trend model outperforms that model 13 of the 14 modified inequality coefficients greater than one, with 7 out of 7 steps for commercial property values and 6 out of 7 steps for industrial property values.

Table 4.3
Modified Theil Inequality Coefficients: Trend Model RMSEs to Random Walk Model & R Walk with a Drift

	1-step	2-step	3-step	4-step	5-step	6-step	7-step	Average
Commercial								
Random Walk	0.8225	1.1087	1.3406	1.1734	1.6668	1.1995	3.0531	1.5319
Random Walk w/Drift	2.9034	5.7252	12.5025	18.1224	4.6905	3.0655	579.32	101.368
Industrial								
Random Walk	4.1708	4.6368	5.0090	0.6560	1.2745	0.6130	1.2387	2.8238
Random Walk w/Drift	1.5408	0.1681	1.7640	1.4527	1.1166	3.7966	1,237.0	207.57
Average - Random Walk	2.4967	2.8728	3.1748	0.3867	1.4707	0.9063	2.1459	
Average - RW w/Drift	2.2221	2.9467	7.1333	9.7876	2.9035	3.4311	908.16	

Differential Error Regression Results: Trend Model Forecasts Errors Compared to Random Walk and Random Walk with Drift Benchmarks

The differential error regression results for random walk and random walk with drift vs. trend forecast errors, as shown in Tables 4.4 and 4.5, differ somewhat from the results found from the modified Theil inequality coefficients. Where random walk and random walk with drift benchmarks were found to be superior to the trend model for both commercial and industrial property values for the modified Theil inequality coefficients, the error regressions results show the trend model is statistically significant for commercial relative to the random walk benchmark but the random walk with drift model is shown to be statistically most accurate for industrial property values. However, differential error regression results for industrial property values for both random walk and random walk with drift were found to be inconclusive.

Table 4.4
Differential Error Regression Results: Random Walk Benchmark vs. Trend Forecast Errors

Variable	β_1 (t-statistic)	β2 (t-statistic)	Joint F-test (probability)	Most Accurate
Commercial	-154,000,000	0.0071	0.0087	Trend
(Both Error Means Neg.)	(-3.2258)	(0.0932)	(0.9269)	
Industrial	-14,989,673	0.0071	13.2269	Inconclusive
(RW neg; Trend pos)	(-0.9831)	(0.0932)	(0.0022)	

Table 4.5
Differential 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
Commercial	-544,000,000	-0.1401	2.1254	Random Walk with Drift
(Both error means neg.)	(-10.5138)	(-1.4579)	(0.1642)	
Industrial	-37,762,072	0.2564	2.3879	Inconclusive
(RW neg; Trend pos)	(-2.0923)	(1.5453)	(0.1418)	

Modified Theil Inequality Coefficients

Results from the modified Theil inequality coefficients indicate that the random walk with drift model outperformed all four models (the traditional income elasticity model, the regional structural econometric model, the ARIMA model, and the trend model) for both commercial and industrial property values. The modified Theil inequality coefficients results also indicate that the random walk model outperformed all four models for industrial property values. In addition, the random walk benchmark is found to be superior to the trend model for commercial property values. Overall, the random walk and random walk with drift models outperformed the other four models 13 out of 16 possible events.

When comparing the average values of the modified Theil inequality coefficients for both random walk and random walk with drift, as shown in Table 5.1, the results show that random walk outperformed all four forecasting models 20 out of 28 calculations, while the random walk with drift outperformed the other models in 28 out of 28 steps.

Table 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	4.8330	25.3960	5.6375	1.1876	1.2051	0.6359	1.6414	5.7901
versus Random Walk with a Drift	2.8054	6.3042	6.5827	8.4848	2.0305	2.1660	586.7500	87.8748
Regional Structural Economic								
versus Random Walk	1.1118	1.6260	6.2693	0.5250	0.6762	0.6654	1.4243	1.758
versus Random Walk with a Drift	1.1577	2.4358	2.5147	4.6561	1.2852	2.9289	763.2611	111.177
ARIMA								
versus Random Walk	4.6643	1.2895	1.6162	0.4039	1.0069	0.7922	1.8276	1.6572
versus Random Walk with a Drift	1.6354	2.4024	3.6210	3.4390	1.4940	3.6661	1035.7100	150.2810
Trend								
versus Random Walk	2.4967	2.8728	3.1748	0.3867	1.4707	0.9063	2.1459	1.0873
versus Random Walk with a Drift	2.2221	2.9467	7.1333	9.7876	2.9035	3.4311	908.1600	133.7978

Recommendations for Future Research

These results suggest that further research employing different sample data sets and additional techniques may prove to be valuable, 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. Because El Paso is a border community it may prove valuable to look at other regions that are not adjacent to foreign countries. There is no reason, however, to assume that property valuations for other border municipalities behave the same as in El Paso, so further analysis for border area cities is also recommended. Due to the importance of this category as an indication of a healthy economy, more attention and empirical research is warranted.

CONCLUSIONS

This study sought to evaluate the accuracy and reliability of alternative methods of four econometric and statistical alternatives used to forecast property values for non-residential commercial and industrial property in El Paso. Although the error differential regression results provide mixed results relative to the modified Theil inequality coefficients, the results from the error regression do support the findings from the modified Theil inequality coefficients in five out of the sixteen possible events. Specifically, the differential error regression results support the modified Theil inequality coefficients results by indicating that the regional structural econometric model and the ARIMA models are statistically more accurate than the random walk model for commercial property values.

Like the modified Theil inequality coefficients, the differential error regression results also show the random walk with drift model outperforming both the traditional income elasticity model and the trend model for commercial property values, while outperforming the ARIMA model for industrial property values. However, for the traditional income elasticity model, the differential error regression results prove to be inconclusive for both commercial and industrial property values relative to both random walk and random walk with drift models. Relative to the ARIMA model, the differential error regression results prove to be inconclusive for industrial property values relative to random walk and for commercial property values relative to the random walk with drift model. In addition, the differential error regression results were inconclusive for the trend model relative to industrial property values for both random walk and random walk with drift models.

Given the importance of property valuation on municipal budgeting, further research employing different sample data sets and additional techniques may prove to be both worthwhile and valuable.

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About the Authors:

Katherine Nicole Arnold Cote, MS Economics, is Senior Budget and Management Analyst, Office of Management and Budget, City of El Paso, Texas.

Wm. Doyle Smith, Ph.D. Economics, is Associate Professor of Economics and Finance, Department of Economics & Finance, The University of Texas at El Paso. Dr. Smith is a former Minnie Stevens Piper Professor for the State of Texas and is the author and co-author of numerous refereed journal and proceedings articles in various areas of Economics.

Thomas M. Fullerton, Jr., Ph.D. Economics, is the JPMorgan Chase Professor of Economics & Finance, Department of Economics & Finance, The University of Texas at El Paso. Dr. Fullerton is also Director of the Border Region Modeling Project and is the author and co-author of numerous refereed journal and proceedings articles in various areas of Economics.