El Paso Housing Sector Econometric Forecast Accuracy

Thomas M. Fullerton, Jr. and Brian W. Kelley

There is comparatively little empirical evidence regarding the accuracy of regional housing sector forecasts. Much of the recent analysis conducted for this topic is developed for housing starts and indicates a relatively poor track record. This study examines residential real estate forecasts previously published for El Paso, TX using a structural econometric model. Model coverage is much broader than just starts. Similar to earlier studies, the previously published econometric predictions frequently do not fare very well against the selected random walk benchmarks utilized for the various series under consideration.

Key Words: applied econometrics, metropolitan housing sector forecasts

JEL Classifications: C53, R15, R31

Regional housing sector forecasts are widely used to shape public policy and business decisions (West 2003a). They are often reported in the media as business cycle indicators and can serve to inform public opinion about the current state of the economy. Despite their widespread usage, relatively little research has examined the accuracy of housing sector forecasts. Time constraints plus contractual obligations provide commercial economists with little incentive to perform such tests. Lack of access to complete data sets makes it difficult for academicians to undertake research in this area. This study takes advantage of such a data set to perform accuracy analyses for housing sector forecasts compiled over time for a relatively large metropolitan market in Texas.

Data utilized consist of residential real estate forecasts published by the University of Texas at El Paso Border Region Modeling Project between 1998 and 2003. The housing sector of the model includes variables such as starts, stocks, prices, and affordability for the El Paso County Metropolitan Statistical Area (MSA). El Paso is the sixth largest MSA in Texas and is located directly across the border from Ciudad Juárez, the largest city in the state of Chihuahua in Mexico. The model is used to generate econometric forecasts of El Paso and Ciudad Juárez, as well as Chihuahua City and Las Cruces. Chihuahua City is the capital and second largest city in the state of Chihuahua. Las Cruces is the second largest MSA in New Mexico. Housing equations are

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included in the model only for El Paso (Fullerton 2001). Macroeconomic data for the United States and Mexico are used as explanatory variables in many of the equations and obtained from Global Insight (Alemán; Behravesh, Hodge, and Latta).

The forecasts are *ex ante* in the sense that all of the model predictions published each year are for periods beyond those used in parameter estimation. As such, they satisfy the evaluation criteria established in several earlier studies for realistic model assessment (Christ; Granger; Howrey, Klein, and McCarthy). Along those same lines, preliminary estimates for El Paso housing data are not available during the year in progress in the manner that such data are for unemployment rates or transportation aggregates. Although the housing sector estimation results are generally good, it is well known that good in-sample fits do not guarantee reliable out-of-sample simulation performance (Leamer; McCloskey and Ziliak). Given the important role that residential real estate plays in local economic performance, assessment of housing model forecasting performance merits additional attention (Reback; Smith and Tesarek).

Although recognition that real estate forecast assessment is useful, how to carry out such an exercise is not immediately obvious (McNees 1978; West 2003a). To say that forecast errors are large or small is meaningless without a frame of reference (McNees 1992). The required accuracy of a forecast will, in large part, depend on the way in which the forecast is used. Preferably, a standard can be generated from a long history of previous results for a variety of statistical and econometric models that forecast the same types of data, or for one model type forecasting across a large number of regional markets. In the case of metropolitan housing sectors, neither of the above options for a predictive accuracy standard exists. Consequently, forecast precision is assessed relative to random walk (RW) benchmarks using root mean square error comparisons (RMSE) (Harvey, Leybourne, and Newbold; Inoue and Kilian). References to other regional housing sector studies are also made, but the collective value of such comparisons is constrained by the limited number of regional housing forecast accuracy studies currently available.

Literature Review

The literature devoted to regional econometric forecast accuracy covers a variety of topics and methods. Regional housing sector forecast accuracy studies are still relatively scarce, but growing in number and scope. One common approach to forecast accuracy analysis involves comparing the model of interest to alternative benchmarks (Stekler). Such benchmarks include vector autoregressive, autoregressive integrated moving average, and RW forecasts (Fair and Shiller; Moore; Nelson). Studies that are limited to benchmark comparisons commonly use RMSE calculations to determine relative predictive accuracy.

Without an absolute standard to compare the RMSE results of the structural equation model, the benchmark comparison is a good starting point. Ashley, Granger, and Schmalensee propose a regression technique wherein the mean square errors (MSE) of any two forecast methods can be compared and potentially shown to be statistically different. That method has been previously utilized in advertising and gross domestic product analyses (Kolb and Stekler) and may be of use in other applications such as regional housing markets.

A variety of time series methods has been utilized to develop comparison benchmarks for econometric forecasts. Historically, RW forecasts have provided stiff competition for the out-of-sample structural model simulations (Ashley 1988; Zarnowitz). No-change RWs that rely on the last available historical observation generally perform better for variables displaying erratic growth patterns. RWs with drift utilize the last observed rate of change. That method frequently provides competitive extrapolations for variables that exhibit relatively stable rates of change.

An early effort to forecast residential real estate centered on the housing component of gross national product in the United States

(Friend and Taubman). Although that model's housing forecasts are found to be more accurate than those of a RW, the *U*-coefficients for both approaches are relatively high (Stekler). High *U*-coefficients for both methods are an indication of the general difficulty associated with forecasting the housing sector that has also been encountered in subsequent studies. Several factors have been found to contribute to challenges typically faced in real estate predictive efforts.

At the macroeconomic level, an ongoing struggle to accurately forecast interest rates has proven to be particularly problematic for real estate studies because of the sensitivity of residential construction to financing costs (Cooper and Nelson). Similarly, Hendershott and Weicher further note that failures to predict important inflationary trends can lead to housing sector forecasts that fall wide of the mark. National tax policy changes can also result in compounded errors in real estate and other model sector forecasts (Fullerton and West; Lowry). At the regional level, local construction sector dependency on population growth patterns also introduces considerable cross-block reverberation errors in out-of-sample model simulations (Charney and Taylor). Net migration flow estimates can especially cause problems in forecasting many markets because of frequent revisions to historical data and complicated interplays between local and national labor market conditions. An even more problematic regional data obstacle is posed by the absence of vacancy rate data for many metropolitan economies. Given the central role of vacancy rates in market behavior (DiPasquale and Wheaton), this represents a serious handicap for a large number of regional econometric models.

To date, the track record for regional housing forecasts is checkered at best. Stekler and Thomas reported limited evidence that favors the performance of a regional construction model in an early study. Fullerton and West, however, conducted a housing start forecast accuracy study for Florida and its six largest metropolitan economies. That study covered the period from 1986 to 1995, and included all phases of the business cycle. Structural model predictive accuracy is compared to both univariate time series and no-change RW benchmarks. Although the structural forecasts usually outperform the time series model, in only half of the comparisons do the econometric predictions obtain greater precision than their RW counterparts. Two subsequent studies using data for Florida report similar outcomes for single- and multifamily starts (Fullerton, Laaksonen, and West; Fullerton, Luevano, and West).

For the work at hand, there is also a question as to whether certain regions are inherently more difficult to forecast. West (2003b) explores labor market forecast accuracy across different metropolitan areas in Florida. Evidence reported therein indicates that regional market characteristics strongly influence forecast accuracy. Specifically, high unemployment rates tend to be associated with higher forecast errors. Because El Paso's unemployment rate tends to be substantially greater than the national average, it does not bode well for housing sector predictive accuracy. An earlier study of the transportation sector in the 216-equation borderplex model indicates that this phenomenon may affect the degree of precision associated with the out-of-sample simulations for this regional market (Fullerton 2004).

In light of the difficulty associated with forecasting housing starts, Fullerton, Luevano, and West suggest expanding real estate coverage in structural econometric models (SEMs) to include more variables. There are a total of 11 equations in the residential real estate block of the borderplex model. They include multi- and single-family starts, average monthly mortgage payments, affordability, multi- and single-unit housing stock variables, median new and resale prices, and sales of existing units (Fullerton 2001). In the material that follows, econometric forecasts for those variables are evaluated for relative predictive accuracy using previously published data from 1998 to 2003.

Data and Methodology

Complete annual data for the 11 El Paso real estate and housing construction variables are

Table 1. Descriptive Statistics for El Paso Housing Data: 1970–2003

Variable	Mean	Standard Deviation	Maximum	Minimum	No. Obsv.
Total housing starts[a]	5.11	2.50	11.88	2.07	30
Single-family starts	4.29	2.17	10.72	1.90	30
Multifamily starts	0.82	0.74	3.47	0.08	30
Total housing stock	204.04	36.81	255.57	131.47	31
Single-family stock	150.30	24.98	190.91	104.70	31
Multifamily stock	53.74	12.25	64.67	26.77	31
Median new price[b]	67.20	24.23	103.34	21.96	33
Median resale price	58.27	19.90	92.03	21.48	33
Average payment[c]	476.70	128.18	666.63	185.80	30
Affordability index[d]	173.82	47.12	257.27	91.69	30
Existing units sold	9.43	3.45	19.18	5.30	28

Notes: The data in Table 1 are for El Paso County, TX.

Source: Historical data are available from the Border Region Modeling Project section of the University of Texas at El Paso web site, www.utep.edu.

[a] Housing starts, stocks, and sales data are reported in thousands.

[b] The price and payment data are in nominal dollars.

[c] The average monthly mortgage payment does not include insurance or taxes.

[d] The affordability index base year is 1980.

available back to 1975 for all of the series. As indicated in Table 1, median price estimates are available from 1970 forward. Housing starts and stocks are reported in thousands. The existing units-sold data are reported for both single- and multiunit dwellings in thousands. Average monthly mortgage payments are reported in current dollars and do not include property taxes or insurance. The median new and resale price series for single-family stand-alone units are reported in thousands of nominal dollars. The two median price series are based on aggregate data. As such, they may fail to capture the true nature of local real estate pricing dynamics resulting from home improvements and other hedonic factors (Gatzlaff and Ling). Descriptive statistics for the historical data through 2003 are shown in Table 1.

The forecast data analyzed in this study are taken from the Borderplex Economic Outlook reports published by the University of Texas at El Paso between 1998 and 2003 (see Fullerton and Tinajero). Data used in the analysis are obtained from the 3-year forecasts published annually between 1998 and 2003. A total of 15 observations per variable is available for comparison with actual historical values. For most series, RW benchmarks provide the comparison data (Theil). In those instances where the variables exhibit upward growth trends, RW with drift benchmarks are utilized to increase overall accuracy competitiveness (Zarnowitz).

The residential real estate and housing construction block of the borderplex econometric model consists of nine stochastic equations and two identities (Fullerton 2001). Parameter estimation is accomplished using a nonlinear ARMAX procedure (Pagan). That method is useful in regional econometric applications because it can handle autoregressive, moving average, and mixed data generation processes. The stochastic equations are re-estimated once per year after new data become available for El Paso and preliminary historical estimates are revised. That process usually occurs during the third quarter in late August and early September.

Re-estimation of the econometric model is carried out in year t with data for most El Paso variables available through year $t - 1$. For several key series, historical data estimates are only available through year $t - 2$. The latter include 10 personal income, nine labor market, and five demographic variables. Simulation data are used to fill in the historical gaps for year $t - 1$ before forecasting years t, t

+ 1, and t + 2 every October. For the RW predictions, actual data for year $t - 1$ are used in all of the calculations discussed below. Appendix 1 lists the El Paso housing block equations from the 2005 version of the model. Variable definitions and units of measurement are reported in Appendix 2. Similar to many regional real estate models, a mix of market-specific and national data is used in the various equation specifications (Fullerton and West; Rosenthal).

Two methodologies are used to analyze the accuracy of the residential real estate econometric predictions. The first is descriptive, and involves calculations of the RMSE and the second-moment proportions of the Theil U-coefficient for each set of econometric model forecasts and their corresponding RW benchmarks. The second approach uses a linear regression procedure based on the method outlined in Ashley, Granger, and Schmalensee. It is applied to the output from all 11 housing equations to determine if the MSEs of the structural equation forecasts are statistically different from the RW MSEs.

The RMSE measures the square root of the variance of forecasting errors for a given forecast method. Further insight into the nature of the forecast errors can be gleamed by examining the Theil inequality components, U^M, U^S, and U^C, representing bias, variance, and covariance proportions, respectively (Theil). The bias proportion measures the extent to which the average values of the simulated and actual series deviate from each other. It provides an indication of systematic error. Optimally, the bias proportion will approach zero. The variance proportion indicates the ability of the model to replicate the degree of variability in the variable of interest. Again, as simulation performance improves, the variance proportion approaches zero. The covariance proportion measures unsystematic error. As simulation accuracy improves, the covariance proportion approaches one. The optimal distribution of the inequality proportions over the three sources for any $U > 0$ is $U^M = U^S = 0$ and $U^C = 1$ (Pindyck and Rubinfeld; Theil).

The U-coefficient inequality proportions are calculated as shown below:

$$(1)\quad U^M = \frac{\bar{P} - \bar{A}}{(1/n)\sum\left(Y_t^P - Y_t^A\right)^2},$$

$$(2)\quad U^S = \frac{s_P - s_A}{(1/n)\sum\left(Y_t^P - Y_t^A\right)^2},$$

$$(3)\quad U^C = \frac{2(1 - r)s_P s_A}{(1/n)\sum\left(Y_t^P - Y_t^A\right)^2}.$$

In Equations 1 through 3, $\bar{P}$, $\bar{A}$, and s_P, s_A are the means and standard deviations of the $Y^P{}_t$, $Y^A{}_t$ series, respectively, whereas r measures the correlation between the predicted and actual series. The sum of the proportional coefficients should be equal to one. As the distribution for the proportional coefficients indicates, forecast error attributable to bias and a failure to replicate the proper variance should be minimized. Any prediction error that is present would ideally be ascribed to the unsystematic component of the data being analyzed, and this type of error is embodied in the U^C proportional coefficient (Theil).

Because the RMSEs and the Theil U-coefficient proportions are descriptive measures, an alternative comparison to which statistical significance can be attributed is helpful. Ashley, Granger, and Schmalensee use a methodology that considers the following null hypothesis:

$$(4)\quad MSE(e_1) = MSE(e_2),$$

where MSE refers to the mean-squared error of two competing forecast errors e_1, e_2. By defining

$$(5)\quad \Delta_t = e_{1t} - e_{2t} \quad \text{and} \quad \sum_t = e_{1t} + e_{2t},$$

Equation (4) can be rewritten as

$$(6)\quad \begin{aligned} MSE(e_1) &= MSE(e_2) \\ &= \left[m(e_1)^2 - m(e_2)^2\right] + [\mathbf{cov}(\Delta, \Sigma)] \end{aligned}$$

where m denotes sample mean and **cov** denotes sample covariance for the out-of-sample forecast period. For the purposes of this analysis, let e_1 be associated with the forecast errors of a given benchmark RW process and e_2 be associated with the forecast errors of a corresponding econometric equation from Appendix 1. Forecasts from the econometric model will be judged as superior if the joint null hypothesis that $\mu(\Delta) = 0$ and $\mathbf{cov}(\Delta,\Sigma) = 0$ can be rejected in favor of the alternative hypotheses described below.

Two regression equations can be drawn from Equation (6) 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 given by:

$$(7) \quad \Delta_t = \beta_1 = \beta_2[\Sigma_t - m(\Sigma_t)] + u_t,$$

where u_t is a randomly distributed error term. The test for $\mu(\Delta) = 0$ is embodied in the interpretation of β_1, whereas the test for $\mathbf{cov}(\Delta,\Sigma) = 0$ is embodied in the interpretation of β_2. A positive value for β_2 will always indicate that the MSE in the RW forecast errors is larger than the MSE in the structural equation model forecast errors. Therefore, a significantly positive β_2 will indicate structural equation model superiority. The interpretation of β_1 will depend on the signs of the error means. When both error means are positive, econometric forecast superiority results when the joint null hypothesis that $\beta_1 = \beta_2 = 0$ is rejected in favor of the alternative hypothesis that both are nonnegative and at least one is positive. If either β_1 or β_2 is significantly negative, the econometric forecast cannot be considered more accurate than its RW benchmark. If one of the estimates is insignificantly negative and the other is positive, a one-tailed t-test can be performed to test for significance. Last, if both estimates are positive, an F-test can be used to test if they are jointly different from zero. However, because the F-test does not take sign into account, a four-pronged test results, and 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).

When both error means are negative, Equation (7) is still used to test Equation (4) but the interpretation of β_1 changes. In this case, if β_1 is found to be significantly negative and β_2 is either insignificant or significantly positive, the structural equation model is deemed superior. Conversely, a significantly positive β_1 will indicate RW superiority.

If the error means of the forecasts are of opposite signs, a different regression equation must be used to test Equation (4). For such a case, the dependent variable becomes the sum of the forecast errors:

$$(8) \quad \Sigma_t = \beta_1 + \beta_2[\Delta_t - m(\Delta_t)] + u_t.$$

Once again, if $\beta_1 = \beta_2 = 0$, the test fails to reject Equation (4). 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. For the sample data available to complete this study, the only category of opposite signs involves negative RW error means and positive structural equation error means. As such, if β_1 is significantly negative with β_2 either insignificant or significantly positive, the structural equation model is deemed superior. Further, if β_1 is insignificant while β_2 is significantly positive, the structural predictions are also regarded as most accurate. Last, if β_1 is significantly positive or β_2 is significantly negative, it will indicate RW forecast superiority.

Outlier analysis is also applied to the forecast errors. When forecast errors lie outside of two standard deviations, they may bias the results. Consequently, any prediction errors that exceed that threshold will be removed from the sample. Given the small number of sample observations, removal of the outliers can potentially lead to degree of freedom difficulties for the error differential regressions. For that reason, results are reported below both with and without the outliers in the sample.

Empirical Results

Estimates for the RMSEs and second-moment proportions of the U-statistic are reported in

Table 2. For 7 of the 11 variables, the previously published econometric forecasts obtain RMSEs that are lower than those of the RWs with which they are compared. Those outcomes vary somewhat from earlier regional housing studies that report evidence that tends not to favor structural model predictions. However, some problems are noted with respect to replicating the El Paso housing cycles in the SEM. For 7 of the 11 variables in Table 2, the structural model *U*-var variance proportion statistics are larger than those of the RW benchmarks. Furthermore, the magnitude of the RMSE differentials is relatively small in some of the cases.

Although comparing second-moment proportions of the SEM with those of the RW can be useful, they also provide information about weaknesses in an individual model's out-of-sample simulation performance. Bias represents the main cause for error in over half the equations. The ability to replicate variance represents the smallest proportion in 7 of the 11 equations. Unsystematic error contributes about as much as bias does to the errors for many of the variables. Model improvements should be possible when the error results from bias or variance, but unsystematic error is usually difficult to correct.

Outliers are present in 4 of the 11 equations. In the case of multifamily housing stock, two observations are removed. For total housing stock, median new price, and median resale price only one observation per series is excluded. As shown in Table 2, removal of the outlier observations does not change the accuracy rankings associated with any of the RMSE estimates for the SEM and RW forecasts. The overall patterns observed for the *U*-statistic second-moment proportions also remain intact for each of the four variables in question.

RMSE estimates by step length are reported in Table 3. Limited numbers of observations mean that some caution should be exercised when examining these results. There are six 1-year-ahead forecasts, five 2-year-ahead forecasts, and four 3-year-ahead forecasts available for each set of predictions. For obvious reasons, outliers are not removed from the calculations shown in this table. Similar to other regional housing forecast accuracy studies (Fullerton, Luevano, and West; Fullerton and West), the 1-year-ahead RMSEs tend to be smallest but there are no definitive temporal patterns across step lengths in Table 3. Also reminiscent of earlier empirical work in this area, the rankings for two methodologies are less definitive than what might be indicated in Table 1. For 1-year-ahead forecasts, the SEM RMSEs are lower for 6 of the 11 variables. For the two-step predictions, the SEM forecast data are more accurate in only 5 of the 11 cases examined. For the 3-year-ahead forecasts, seven SEM RMSEs are smaller than their RW counterparts.

Information provided by the RMSE estimates and proportional inequality statistic comparisons are descriptive only. To further examine relative forecast precision, a MSE differential regression technique is used. The purpose of this step is to establish whether the Borderplex model forecast MSEs and the RW MSEs are statistically different from each other. As noted above, the equation is arranged so that the signs of the regression parameters can determine which method is most accurate.

Table 4 summarizes the regression output for the 11 housing variables. For structural forecasts that are compared with RW and RW with drift predictions, only the most competitive of the latter forecasts are reported. Results using the MSE regression approach are consistent with the RMSE results reported in Table 2. In four cases, affordability, single-family starts, median new price, and median resale price, the regression results point to statistically superior structural model precision. In three instances, single-family stocks, multifamily stocks, and multifamily starts, the outcomes indicate statistically superior RW accuracy. For the remaining four variables, total housing stock, total housing starts, existing units sold, and average monthly mortgage payment, the results are inconclusive.

Removal of the outliers for the four variables mentioned above is also carried out

Table 2. RMSE and Theil Inequality Statistics for El Paso Housing Forecasts

Series	RMSE[a]	*U*-bias[b]	*U*-var[c]	*U*-cov[d]
Total housing starts				
Structural model	0.69	0.02	0.03	0.95
Random walk	0.79	0.48	0.05	0.47
Single-family housing starts				
Structural model	0.73	0.32	0.01	0.67
Random walk	0.98	0.59	0.00	0.40
Multifamily housing starts				
Structural model	0.40	0.65	0.12	0.23
Random walk	0.31	0.47	0.16	0.37
Total housing stock				
Structural model	0.71	0.25	0.41	0.34
RW with drift	0.84	0.09	0.16	0.75
Structural model[e]	0.64	0.20	0.38	0.43
RW with drift[e]	0.67	0.03	0.07	0.90
Single-family housing stock				
Structural model	1.27	0.67	0.04	0.29
RW with drift	0.99	0.23	0.01	0.76
Multifamily housing stock				
Structural model	0.88	0.59	0.22	0.19
Random walk	0.21	0.18	0.18	0.64
Structural model[e]	0.74	0.64	0.20	0.17
Random walk[e]	0.19	0.36	0.17	0.47
Median new home price				
Structural model	4.00	0.55	0.00	0.45
Random walk	4.55	0.26	0.00	0.74
Structural model[e]	3.02	0.64	0.01	0.36
Random walk[e]	4.13	0.55	0.03	0.42
Median resale home price				
Structural model	2.02	0.01	0.58	0.41
RW with drift	3.96	0.13	0.14	0.73
Structural model[e]	2.01	0.03	0.52	0.45
RW with drift[e]	3.70	0.29	0.01	0.69
Affordability index				
Structural model	14.11	0.60	0.01	0.39
Random walk	17.78	0.68	0.05	0.27
Average monthly mortgage payment				
Structural model	23.96	0.39	0.02	0.59
Random walk	26.54	0.24	0.01	0.75
Existing housing unit sales				
Structural model	3.10	0.59	0.00	0.41
Random walk	3.08	0.60	0.00	0.40

Notes: The data in Table 2 are calculated using structural econometric and random walk forecasts for all of the variables listed in column 1.

[a] Column 2 reports the root mean square of the forecast errors (RMSE) for each method.

[b] Column 3 reports the bias proportion (*U*-bias) of the second moment of the Theil inequality coefficient calculated for each set of forecasts.

[c] Column 4 reports the variance proportion (*U*-var) of the second moment of the Theil inequality coefficient calculated for each set of forecasts.

[d] Column 5 reports the covariance proportion (*U*-cov) of the second moment of the Theil inequality coefficient calculated for each set of forecasts.

[e] Forecast errors lying beyond two standard deviations in any of the forecasts are removed from the samples where noted.

Table 3. Root Mean Square Error Statistics by Years-Ahead Forecasts

Series	One-Step RMSE[a]	Two-Step RMSE[b]	Three-Step RMSE[c]
Total housing starts			
Structural model	0.433	0.850	0.784
Random walk	0.695	0.785	0.904
Single-family housing starts			
Structural model	0.593	0.890	0.694
Random walk	0.889	0.904	1.177
Multifamily housing			
Structural model	0.422	0.304	0.471
Random walk	0.296	0.273	0.357
Total housing stocks			
Structural model	0.630	0.653	0.868
RW with drift	0.624	1.010	0.901
Single-family housing stock			
Structural model	0.722	1.139	1.897
RW with drift	0.612	1.076	1.278
Multifamily housing stock			
Structural model	0.368	0.861	1.322
Random walk	0.187	0.222	0.213
Median new price			
Structural model	4.898	3.660	2.667
Random walk	3.849	2.632	6.832
Median resale price			
Structural model	1.654	2.345	2.088
RW with drift	2.601	4.467	4.871
Affordability index			
Structural model	9.489	16.946	15.898
Random walk	12.261	20.050	21.388
Average monthly payment			
Structural model	12.317	23.325	35.287
Random walk	23.000	29.060	28.152
Existing units sold			
Structural model	2.308	3.641	3.398
Random walk	2.508	3.215	3.642

Notes: Table 3 reports the root mean square errors for the forecast errors associated with each of the variables listed in Column 1. The data are calculated using structural econometric and random walk prediction errors segregated by the number of periods being forecast.

[a] Column 2 reports the 1-year-ahead root mean square of the forecast errors (RMSE) for each method.

[b] Column 3 reports the 2-year-ahead root mean square of the forecast errors (RMSE) for each method.

[c] Column 2 reports the 3-year-ahead root mean square of the forecast errors (RMSE) for each method.

for the regression results summarized in Table 4. Similar to what occurs with the RMSE rankings, there is no material change in the results of the MSE differential tests subsequent to the exclusion of the outlier observations. One interesting development does arise in the results for the median new price variable. When the outliers are present the MSE differential is 12% and the test outcome favors the SEM forecasts in a statistically significant manner. Because differentials of less than 40% are not expected to yield reliable results, structural equation superiority is not clear cut (Ashley 2003). Removal of the outliers, however, increases the MSE differential to 46%, providing stronger evidence in favor of SEM accuracy for median prices of new single-family structures.

The findings in this paper largely confirm evidence reported in earlier efforts regarding

Table 4. Mean Square Error Differential Regression Results

Variable	β_1 (t-statistic)[a]	β_2 (t-statistic)[b]	F (p-statistic)[c]	Most Accurate[d]	MSE Differential[e]
Cases in Which Both Error Means are Positive					
Multifamily starts	−0.114*	−0.032	0.453	RW	42%
	(−5.199)	(−0.673)	(0.265)		
Cases in Which Both Error Means are Negative					
Total housing starts	−0.470	−0.011	1.494	IND	22%
Total housing stock	(−1.452)	(−0.068)	(0.133)		
Outliers retained	0.114	0.107	2.35	IND	15%
	(0.449)	(0.784)	(0.066)		
Outliers removed[f]	0.159	0.004	1.728	IND	16%
	(0.587)	(0.025)	(0.111)		
Affordability index	−3.793*	0.065	0.318	SEM	37%
	(−1.879)	(0.564)	(0.291)		
Single-family starts	−0.455*	0.177*	4.690	SEM	44%
	(−1.75)	(5.108)	(0.015)		
Single-family stock	0.571*	0.119	0.646	RWD	39%
	(2.753)	(0.804)	(0.218)		
Existing units sold	−0.012	−0.035	2.343	IND	1%
	(−0.155)	(−0.941)	(0.069)		
Cases in Which Random-Walk Error Mean is Negative and Structural Equation Error Mean is Positive					
Multifamily stock					
Outliers retained	0.641*	−0.665*	38.599	RW	76%
	(4.907)	(−10.940)	(0.000)		
Outliers removed[f]	0.570*	−0.680*	21.046	RW	93%
	(3.701)	(−8.366)	(0.001)		
Median new price					
Outliers retained	0.655	1.070*	3.927	SEM	12%
	(0.439)	(1.982)	(0.035)		
Outliers removed[f]	−0.528	0.579*	2.485	SEM	46%
	(−0.527)	(1.577)	(0.071)		
Median resale price					
Outliers retained	−1.864	0.861*	6.529	SEM	48%
	(−0.671)	(3.537)	(0.007)		
Outliers removed[f]	−1.705	1.052*	4.844	SEM	70%
	(−0.512)	(3.406)	(0.017)		
Mortgage payment	1.873	0.338	0.704	IND	
	(0.199)	(0.839)	(0.209)		18%

Notes: Table 4 reports the mean square error differential regression results for the forecast errors associated with each of the variables listed in Column 1. The null hypothesis tested is equality of the MSEs of the random walk and econometric forecasts for each variable. Since the desired signs of the coefficients are predetermined, a one-tailed t-test is appropriate.

[a] Column 2 contains the constant term and associated t-statistic for each equation.

[b] Column 3 contains the slope coefficient and associated t-statistic for each equation.

[c] Column 4 contains the computed F-statistics and associated significance levels for a joint test that both regression parameters are equal to zero. Given the discussion above regarding the expected signs of β_1, β_2, the significance levels for the F-statistics reported in column 4 are halved to reflect the true probability of rejecting the joint null hypothesis that the parameter estimates are not equal to zero.

[d] Column 5 contains the interpretation of the regression output in terms of model superiority. Indeterminate (IND) designations imply that the regression results were inconclusive with regard to model superiority. Structural equation model (SEM) designations imply that the regression results point toward a statistically significant reduction in MSE for the SEM. Random walk (RW) and Random walk with drift (RWD) designations imply that the regression output favored those comparative benchmarks in statistically significant manners.

[e] Column 6 contains the percentage reduction in MSE from the competing models.

[f] Forecast error outliers beyond two standard deviations were detected and removed.

* t-statistics are significant at the 93% level in one-tailed tests.

the relatively low accuracy of regional econometric housing sector forecasts (Fullerton, Laaksonen, and West; Fullerton, Luevano, and West). Results obtained herein suggest that regional structural equation models utilizing annual data may be reliably used for forecasting only some housing sector variables. In other cases, equal or superior levels of precision can be achieved from standard RW extrapolation rules. Because the data included in this study cover a fairly broad range of housing sector variables, its results raise a cautionary flag with regard to users of metropolitan residential real estate forecasts.

Although the latter point should be taken seriously, additional work remains before any firm conclusions can be reached. El Paso is a market in which the unemployment rate is typically several percentage points higher than the national average. Metropolitan economies in this category frequently exhibit higher prediction errors than other markets (West 2003b). Data quality, or lack thereof, may also hamper the effectiveness of the housing block in the Borderplex model. Vacancy rates are currently not available for either structure category. Also, the two median price series are based on aggregate data and may be less representative of the El Paso real estate market than alternative assessed value or limited hedonic series approaches that are currently not feasible to implement (Gatzlaff and Ling).

Another limitation in this study is the relatively small sample size of the out-of-sample forecast errors. Ashley, Granger, and Schmalensee report statistical significance for a sample that contains only 20 observations. Subsequent research indicates that MSE reductions of 40% to 70% are required for statistical significance at the 5% level to be attributed at these sample size levels (Ashley 2003). This is borne out in the results in Table 4 where, with the exception the median new price variable, MSE differences of less than 37% point to inconclusive evidence with regard to model superiority. As more observations become available, larger sample sizes may yield different assessments regarding the accuracy of the structural model simulations. It would also be helpful to examine whether the results obtained in this study are unique to the El Paso housing market or if they are representative of what occurs for a wider geographic range of residential real estate forecasting efforts.

Conclusion

This study examines the historical accuracy of 11 housing variables that are forecast every year for the El Paso metropolitan economy. Data used in the analysis are obtained from 3-year forecasts published between 1998 and 2003. The accuracy of each of the 11 sets of previously published predictions is assessed relative to RW benchmarks. In cases where positive growth trends are present, a RW with drift procedure is utilized.

The structural equation model forecasts and RW benchmarks are compared using RMSE statistics and the Theil *U*-coefficient second-moment proportions. Because these are only descriptive measures, an error differential regression technique is also used to help establish relative forecast precision. The latter technique determines if differences between the MSEs of the two sets of prediction data are statistically significant.

Results of the accuracy assessment procedures are mixed. For 7 of the 11 variables, the structural forecasts have lower RMSEs than their respective RW benchmarks. That result, however, is partially overturned once the forecast errors are segregated by step length. The Theil coefficient second-moment proportions indicate that bias and failure to replicate variability are sometimes more problematic for the econometric forecasts than for their RW counterparts. In most cases, however, the proportional component related to forecast variance is close to zero, implying that the structural equation model is fairly effective in replicating the variance of the housing data in the sample.

The error differential regression estimates point to superior econometric forecast performance for 4 of the 11 variables tested. In four cases, inconclusive results with respect to relative accuracy are obtained. RWs are shown to be more precise in the remaining three sets of forecasts. Taken together, these results indicate that the structural model is statistically more reliable than RWs for less than 50% of the residential real estate variables modeled for El Paso during the period under consideration.

Regional housing forecast assessment has not previously received very much attention. Because this study only examines results for one market, it is not known if the results obtained here also apply to other metropolitan economies. Eventually, analysis of larger samples will become feasible for El Paso and other regional housing markets. Use of quality-adjusted or repeat-sales housing price indices may prove helpful for markets in which those data are available. Although those steps are likely to be productive, the track record to date for regional econometric housing forecasts is not overly encouraging. Consumers of these forecasts should, therefore, exercise caution when using them.

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Appendix 1

Borderplex Model El Paso Housing Sector Equations Block

El Paso Residential Construction and Real Estate Identities

(A1) $ELHTS + ELHSFS + ELHMFS$

(A2) $ELHTSTK = ELHSSTK + ELHMSTK$

El Paso Residential Construction and Real Estate Stochastic Equations

(A3) $ELHAFRD = f(JHAFFORD1NS, (ELYP/ELPPOP)/ELHPYMT)$

Nonlinear Least Squares, Annual Data for 31 Periods, 1973–2003

$$
\begin{aligned}
ELHAFRD = {} & 63.7585 * JHAFFORD1NS \\
& (13.6141) \\
& + 4626.81 * (ELYP/ELPPOP)/ELHPYMT \\
& (33.5226) \\
& - 7.49366 \\
& (2.21990)
\end{aligned}
$$

Sum Sq	293.624	Std Err	3.2383	LHS Mean	173.820
R Sq	0.9956	R Bar Sq	0.9953	F 2, 28	3,161.62
DW(1)	1.7849	DW(2)	1.9337		

(A4) $ELHPYMT = f((RMMTG30CON/100) * ELHPX.1, ELHAFRD.1)$

Nonlinear Least Squares, Annual data for 31 periods, 1974–2004

$$
\begin{aligned}
ELHPYMT = {} & 74.7790 * (RMMTG30CON/100) \\
& (32.4966) \\
& * ELHPX.1 \\
& + 1.14438 * ELHAFRD[-1] \\
& (14.1916) \\
& - 137.545 \\
& (6.06619)
\end{aligned}
$$

Sum Sq	10565.6	Std Err	19.4253	LHS Mean	488.979
R Sq	0.9743	R Bar Sq	0.9725	F 2, 28	531.698
DW(1)	2.0930	DW(2)	2.1180		

(A5) $ELHPX = f(ELHPX.1, PHU1EAVGNS, ELHSALE.1/ELPPOP.1, ELHPN.1)$

Nonlinear Least Squares, Annual Data for 27 Periods, 1978–2004

$$\begin{aligned} ELHPX = \; & 0.81629 * ELHPX[-1] \\ & (9.7035) \\ & - 0.02364 * PHU1EAVGNS \\ & (0.66782) \\ & + 483.757 * ELHSALE.1/ELPPOP.1 \\ & (4.39158) \\ & + 0.15145 * ELHPN[-1] - 2.16536 \\ & (1.81819) \qquad\qquad (0.56417) \end{aligned}$$

Sum Sq	88.0012	Std Err	2.0976	LHS Mean	68.3357
R Sq	0.9814	R Bar Sq	0.9758	F 6, 20	175.687
DW(1)	2.0938	DW(2)	2.2434	H	−0.4102

$$AR\_0 = -0.54743 * AR\_1 - 0.36751 * AR\_2$$

(2.49300) (1.66844)

(A6) $ELHPN = f(ELHPN.1, PHU1NMEDNS, ELPHH.1/ELHSSTK.1)$

Nonlinear Least Squares, Annual Data for 32 Periods, 1973–2004

$$\begin{aligned} ELHPN = \; & 0.59326 * ELHPN[-1] \\ & (5.21847) \\ & + 0.14439 * PHU1NMEDNS \\ & (3.63144) \\ & + 26.2919 * ELPHH.1/ELHSSTK.1 \\ & (1.62362) \\ & - 13.7706 \\ & (0.95640) \end{aligned}$$

Sum Sq	152.561	Std Err	2.3342	LHS Mean	72.6286
R Sq	0.9897	R Bar Sq	0.9886	F 3, 28	893.923
DW(1)	2.0543	DW(2)	2.0348	H	−0.2424

(A7) $ELHSFS = f(ELHSFS.1, MA4(ELPNM.1), RMMTG30CON * ELHPN.1/JPGDP.1)$

Nonlinear Least Squares, Annual Data for 31 Periods, 1974–2004

$$\begin{aligned} ELHSFS = {} & 0.62294 ELHSFS[-1] \\ & (5.58330) \\ & + 0.26020 * MA4(ELPNM.1) \\ & (3.41323) \\ & - 0.25468 * RMMTG30CON \\ & (3.16530) \\ & * ELHPN.1/JPGDP.1 \\ & + 3.64751 \\ & (3.93649) \end{aligned}$$

Sum Sq	30.5134	Std Err	1.0631	LHS Mean	4.2051
R Sq	0.7799	*R* Bar Sq	0.7555	*F* 3, 27	31.8963
DW(1)	1.5782	DW(2)	1.6617	H	1.4154

(A8) $$\begin{aligned} ELHMFS = {} & f[ELHMFS.1, MA4(ELPNM.1), \\ & ELPHH.1/ELHTSTK.1, MA3(ELHPN.1/JPC.1)] \end{aligned}$$

Nonlinear Least Squares, Annual Data for 31 Periods, 1974–2004

$$\begin{aligned} ELHMFS = {} & 0.34312 * ELHMFS[-1] \\ & (3.42551) \\ & + 0.11520 * MA4(ELPNM.1) \\ & (4.49688) \\ & + 14.2439 * ELPHH.1/ELHTSTK.1 \\ & (6.03248) \\ & + 5.54453 * MA3(ELHPN.1/JPC.1) \\ & (4.91207) \\ & - 16.8775 \\ & (7.65190) \end{aligned}$$

Sum Sq	3.7970	Std Err	0.3876	LHS Mean	0.7745
R Sq	0.7646	*R* Bar Sq	0.7176	*F* 5, 25	16.2437
DW(1)	1.8218	DW(2)	2.0017	H	0.2340

$$\begin{aligned} MA\_0 = {} & -0.86320 * MA\_1 \\ & (5.15957) \end{aligned}$$

(A9) $ELHSALE = f(ELHSALE.1, ELHAFRD, ELHSFS.1)$

Nonlinear Least Squares, Annual Data for 29 Periods, 1976–2004

$$
\begin{aligned}
ELHSALE = {} & 0.84484 * ELHSALE[-1] \\
& (10.8937) \\
& + 0.02625 * ELHAFRD \\
& (4.48501) \\
& + 0.28351 * ELHSFS[-1] \\
& (3.08115) \\
& - 3.84915 \\
& (4.12452)
\end{aligned}
$$

Sum Sq	20.9708	Std Err	0.9159	LHS Mean	9.9779
R Sq	0.9529	R Bar Sq	0.9472	F 3, 25	168.464
DW(1)	1.9535	DW(2)	1.8862	H	0.0234

(A10) $ELHSSTK = f(ELHSSTK.1, ELHSFS.1)$

Nonlinear Least Squares, Annual Data for 30 Periods, 1975–2004

$$
\begin{aligned}
ELHSSTK = {} & 1.03432 * ELHSSTK[-1] \\
& (50.6346) \\
& + 0.48373 * ELHSFS[-1] \\
& (6.23732) \\
& - 4.57451 \\
& (1.33279)
\end{aligned}
$$

Sum Sq	6.6576	Std Err	0.5060	LHS Mean	155.956
R Sq	0.9996	R Bar Sq	0.9995	F 3, 26	19,876.9
DW(1)	1.7104	DW(2)	1.3510	H	0.7854

$$
\begin{aligned}
AR\_0 = {} & 0.78961 * AR + 1 \\
& (6.61708)
\end{aligned}
$$

(A11) $ELHMSTK = f(ELHMSTK.1, ELHMFS.1)$

Nonlinear Least Squares, Annual Data for 31 Periods, 1974–2004

$$\begin{aligned} ELHMSTK = {} & 0.95136 * ELHMSTK[-1] \\ & (86.7937) \\ & + 0.98732 * ELHMFS[-1] \\ & (5.85308) \\ & + 2.97363 \\ & (4.39865) \end{aligned}$$

Sum Sq	10.9644	Std Err	0.6258	LHS Mean	55.7349
R Sq	0.9967	*R* Bar Sq	0.9965	*F* 2, 28	4,285.03
DW(1)	1.3786	DW(2)	1.9824	H	1.6912

Appendix 2

Borderplex Model El Paso Housing Sector Mnemonics—Endogenous Variables

ELHAFRD	El Paso County housing affordability index, National Association of Realtors
ELPHH	El Paso County total households, 1,000s
ELHMFS	El Paso County multifamily housing starts, 1,000s
ELHMSTK	El Paso County multifamily housing stock, 1,000s
ELHPN	El Paso County median new single-family housing price, nominal $
ELHPX	El Paso County median previously built single-family housing price, nominal $
ELHPYMT	El Paso average monthly mortgage payment w/o taxes or insurance, nominal $
ELHSALE	El Paso County sales of existing single-family houses, 1,000s
ELHSFS	El Paso County single-family housing starts, 1,000s
ELHSSTK	El Paso County single-family housing stock, 1,000s
ELHTS	El Paso County total housing starts, 1,000s
ELHTSTK	El Paso County total housing stock, 1,000s
ELPNM	El Paso County net migration, 1,000s
ELPPOP	El Paso County midyear population, 1,000s
ELYP	El Paso County total personal income, million $

Borderplex Model El Paso Housing Sector Mnemonics—Exogenous Variables

JHAFFORD1NS	U.S. housing affordability index, National Association of Realtors
JPGDP	U.S. gross domestic product chained price index, 2,000 = 100
PHU1EAVGNS	U.S. average sales price of existing single-family houses, thousand $
PHU1NMEDNS	U.S. median sales price of new single-family houses, thousand $
RMMTG30CON	U.S. 30-year conventional mortgage rate, percentage