8-2019

Hotel Sector Forecast Accuracy in El Paso: 2006-2016

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Comments:
Technical Report TX19-1
Thomas M. Fullerton, Jr. and Adam G. Walke, 2019, Hotel Sector Forecast Accuracy in El Paso: 2006-2016, Technical Report TX19-1, University of Texas at El Paso Border Region Modeling Project.
A revised version of this study is forthcoming in *Atlantic Economic Journal.*

THE UNIVERSITY OF TEXAS AT EL PASO

UTEP BORDER REGION MODELING PROJECT

TECHNICAL REPORT TX19-1

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This technical report is a publication of the Border Region Modeling Project and the Department of Economics & Finance at The University of Texas at El Paso. For additional Border Region information, please visit the www.academics.utep.edu/border section of the UTEP web site.

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Corporate and Institutional Sponsors:

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Special thanks are given to the corporate and institutional sponsors of the UTEP Border Region Econometric Modeling Project. In particular, El Paso Water Utilities, Hunt Communities, and The University of Texas at El Paso have invested substantial time, effort, and financial resources in making this research project possible.

Continued maintenance and expansion of the UTEP business modeling system requires ongoing financial support. For information on potential means for supporting this research effort, please contact Border Region Modeling Project - CBA 236, Department of Economics & Finance, 500 West University, El Paso, TX 79968-0543.

HOTEL SECTOR FORECAST ACCURACY IN EL PASO: 2006-2016*

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Abstract: This study evaluates the accuracy of previously published econometric forecasts for seven lodging sector variables that measure hotel activity in El Paso, Texas. The hotel forecasts have been generated annually using an econometric model of the El Paso metropolitan economy from 2006 forward. Predictive accuracy is evaluated relative to random walk benchmarks. Assessment is completed using both descriptive forecast error summary statistics as well as formal statistical tests. The econometric model outperforms the random walk benchmarks for a majority of the variables analyzed. However, statistical tests of forecast error differentials do not yield conclusive evidence in favor of the econometric historical track record. Tests of directional forecast accuracy also produce mixed results. Although the structural econometric model of hotel business conditions in this appears to provide useful predictive information, analysts and planners should also monitor recent history closely.

Keywords: Hotel Econometric Models, Forecast Evaluation, Statistical Tests, Directional Accuracy, El Paso
JEL Codes: Z30 – Tourism Economics; C52 – Model Evaluation, Validation, and Selection; C53 – Forecasting and Prediction Methods; R15 – Regional Econometric Models

Acknowledgements: Financial support for this research was provided by El Paso Water, City of El Paso Office of Management & Budget, National Science Foundation Grant DRL-1740695, the UTEP Center for the Study of Western Hemispheric Trade, and the Hunt Institute for Global Competitiveness at UTEP. Econometric research assistance was provided by Ernesto Duarte, Patricia Arellano, and Omar Solis. Helpful comments and suggestions were provided by Katherine Virgo, Demi Miller, Emily Morrow, and five anonymous referees.

** A revised version of this study is forthcoming in Atlantic Economic Journal.*

INTRODUCTION

Forecasts serve a variety of purposes in the hotel industry, providing vital inputs for marketing and pricing strategies, routine budgetary planning, and capital investment decisions. In particular, demand forecasts play an important role in the revenue management strategies that are frequently employed in the hospitality sector. Accurate forecasts of future demand are especially critical for hotels due to the perishable nature of room nights, which cannot be stored for later use. Many hotel chains rely extensively on demand forecasts to handle the allocation and pricing of rooms among various customer segments in order to maximize revenue per available room (Cross et al., 2011). Forecasts of the supply of hotel rooms are also useful for corporate and public-sector planners. Trends in room occupancy rates within particular metropolitan areas are frequently employed by hotel chains in judging the likely profitability of potential locations for new hotels (Law, 1998). Finally, forecasts of hotel revenues are likely of interest to municipal governments for which the latter are often important components of the tax base.

This study analyzes the accuracy of econometric hotel sector forecasts for El Paso, Texas. El Paso is a regional trade hub on the border with Mexico. Business travelers, many of whom are connected with cross-border manufacturing enterprises, represent an important segment of the hotel customer base in this region. In addition, tourist traffic may play an increasingly important role in the regional economy if local government redevelopment and tourism promotion efforts are successful. These efforts include the 2014 opening of a downtown baseball stadium and current plans to develop a new downtown arena. The econometric forecasts analyzed in this study have been employed by hotel managers, city administrators, and others for planning purposes. The accuracy of these predictions therefore has ramifications for public- and private-sector management and investment decisions. While the lodging sector has often behaved as a lagging indicator to the economy in general, that pattern is not a permanent feature of the landscape and each market will follow patterns that will present unique challenges to generating accurate predictions (Corgel and Wooworth, 2012).

The econometric forecast data included in the sample have appeared in published regional forecast reports each year since 2006 using a model developed at The University of Texas at El Paso Border Region Modeling Project (Fullerton, 2001; Fullerton et al., 2019). The timeframe covered by the analysis includes both expansionary and contractionary phases of the local business cycle. Seven hotel sector variables, related to supply, demand, prices and revenues, are included in the econometric model. The econometric forecasts are compared against random walk benchmarks using a variety of forecast evaluation techniques, including forecast error decompositions, statistical tests of forecast error differentials, and statistical tests of directional accuracy. Such tests have not been widely applied in the tourism forecast evaluation literature (Song and Li, 2008).

LITERATURE REVIEW

Several previous tourism-related studies have compared the forecasting accuracies of econometric models and alternative techniques. Brännäs et al. (2002) models guest nights at Swedish hotels as a function of price and income explanatory variables. Forecasts derived from that model are somewhat more accurate than those generated using an autoregressive integrated moving average (ARIMA) model at forecast horizons under one year. In a comparison of econometric and extrapolative techniques, Songet al. (2003) finds that a static regression model and a time-varying parameter model generally outperform the alternatives, including ARIMA, in forecasting inbound tourism to Denmark. However, a simple random walk (or 'no change') forecast is competitive with many of the econometric techniques considered in terms of accuracy.

In analyzing previous studies that compare econometric forecasts with various types of alternatives, Witt and Witt (1995) reports that the econometric models perform best in 29 percent of the cases. Random walk forecasts outperform the competing models in 23 percent of the cases. That study also analyzes different ways of measuring forecast accuracy. The econometric forecasts tend to perform better using measures of directional accuracy as opposed to metrics involving forecast error magnitudes. While much of the forecast evaluation literature focuses on competing modeling techniques, other factors can also affect the degree of forecast accuracy. These factors include the vintage of historical data used to estimate forecasts and the frequency with which forecasting models are updated (Kimes, 1999).

As suggested by Witt and Witt (1995), relative forecast accuracy rankings often depend, to some extent, on the specific evaluation methodology employed. Koupriouchina et al. (2014) shows that different forecast error measures yield contradictory evidence regarding the comparative accuracy of competing sets of daily hotel occupancy forecasts. This suggests that reliance on a single forecast accuracy metric or a few very similar metrics may yield an incomplete assessment of overall model predictive performances. Interestingly, while 17 different forecast accuracy measures are compared in that analysis, none involve statistical hypothesis testing.

Error differentials and directional accuracy tests have been used in a handful of tourism forecasting studies. Martin and Witt (1989) uses two sets of statistical tests to compare the accuracy of seven forecasting approaches. In general, "naïve" random walk forecasts of tourist flows outperform econometric model predictions. Law (1998) uses Mann-Whitney *U*-tests to compare the accuracy of neural network, random walk extrapolation, and regression-based forecasts of room occupancy rates in the Hong Kong hotel industry. The results of the tests indicate that the neural network forecasts are significantly more accurate than the two competing approaches. Witt et al. (2003) employs statistical tests of forecast bias and directional accuracy to evaluate forecasts of tourist stays in Denmark. For two- and three-year forecast horizons, the relative rankings of competing forecasts hinge on the specific evaluation methodology employed. Finally, De Mello and Nell (2005) applies a test of equal predictive accuracy to evaluate tourism forecasts. A cointegrated structural vector autoregressive model significantly outperforms the alternatives for multi-step forecasts.

Song et al. (2011) develops econometric forecasts to predict the effects of the Great Recession on hotel demand in Hong Kong. Income levels in the home countries of hotel patrons and the price of hotel rooms are found to be critical factors affecting demand. Demand in the highest room price category is predicted to decrease in the immediate aftermath of the recession.

The ex ante predictions are for future time periods through 2015 and are not evaluated due to the unavailability of historical data corresponding to the forecast period. One distinguishing feature of this analysis is that it evaluates the accuracy of *ex-ante* hotel sector forecasts, i.e. those produced before actual data on the forecasted variables became available.

Hotel forecasts, it should be noted, receive comparatively less attention than tourism demand (Wu et al. 2017). In spite of that general pattern, within the hotel forecasting branch of research, niche markets and regional destinations are receiving more attention. The study at hand falls within that category and takes advantage of an annual-frequency data sample that provides fairly broad informational coverage for the sector as a whole. Broader coverage is an important distinguishing characteristic for this study because most lodging sector forecasts tend to focus on specific variables such a room nights sold, in part because structural system forecasts are less common. However, as noted in one recent study, the hotel sector economic impacts cover multiple lines of business (OE, 2016). Accuracy assessment with annual-frequency data is relatively rare in the academic literature. That is because such analyses are infeasible until several years after the first ex-ante forecasts are published in order to have enough historical data for statistically valid accuracy assessments. Such a data set is available for El Paso, one of the largest urban economies in Texas. A preliminary accuracy assessment of the hotel sector forecasts published each year for El Paso was inconclusive (Fullerton and Walke, 2013). This study differs from the prior effort in several respects.

The first difference is that study is able to employ 10 more annual frequency forecast observations than the preceding effort. That represents a 33-percent increase in the sample size. A second difference is that Fullerton and Walke (2013) uses only one set of random walk benchmark comparative forecasts while this inquiry includes both random walk and random walk with drift benchmarks. As with the previous study, the current exercise deploys both descriptive and formal inferential accuracy statistics. This study goes one step further, however, by also completing formal directional accuracy assessments of the published hotel sector predictions. The data and forecast evaluation methodologies utilized to evaluate the forecasts are described next

METHODOLOGY

Econometric hotel sector forecasts with overlapping, three-year time horizons have been published for El Paso each year since 2006 (see Fullerton et al., 2019). These forecasts are compared against historical data, which end in 2016. This results in a sample of 30 econometric forecast observations and paired historical observations for seven hotel sector variables. Similar to the model employed by Corgel and Woodworth (2012), lodging sector econometric predictions for El Paso are heavily influenced by national income fluctuations.

Regional predictor variables also in the model include population and a peso-per-dollar real exchange rate index. The latter is included in the model specification due to the importance of cross-border economic activity for Borderplex commerce and industry (Fullerton et al., 2017). Two sets of benchmark forecasts are also generated. The first is a random walk that is constant across each three-year forecast horizon. The second is a random walk with drift, calculated as $\hat{y}_{t+p} = y_t + pd$, where p is the number of years ahead, ranging from one to three, and d is a drift factor equal to the most recent historical year-over-year change in the variable (Pindyck and Rubinfeld, 1998).

Historical summary statistics for the seven variables analyzed are shown in Table 1. The table summarizes the full historical data sample that begins in 1988, prior to the first forecasts, and ends in 2016. The data are obtained from Texas hotel reports published by Source Strategies, Inc. Over this time period the number of hotels in El Paso increased from 60 to 81 and the number of room nights available increased by more than 42 percent.

Room rates in El Paso have, on average, increased at about the same rate as the national consumer price index, with nominal rates approximately doubling between 1988 and 2016, from $40.57 to $79.66. Closely correlated with room rates are revenues per room. Customers can occasionally bargain for lower rates than those advertised and management will sometimes offer discounts. The room occupancy rate has remained above 60 percent since 1993 and averaged 63.1 percent over the full historical period. In general, these trends suggest that expansion within El Paso's hotel sector has paralleled regional economic growth.

Table 1
Summary Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Number of Hotels	71	7	60	81
Room Nights Available, 1000s	2,775.2	322.0	2,343.3	3,337.9
Room Nights Sold, 1000s	1,760.6	298.9	1,199.6	2,249.8
Occupancy Rate (%)	63.1%	4.7%	51.2%	71.0%
Room Price	$58.65	$11.69	$40.57	$79.66
Revenue per Room	$37.41	$9.50	$20.77	$53.69
Total Revenues ($ Thousands)	$106,532	$38,258	$48,666	$179,227

Source: Author calculations using data from the The University of Texas at El Paso Border Region Modeling Project (see Fullerton et al., 2019).

Four approaches are utilized to evaluate the econometric and benchmark forecasts. First, Theil U-statistics are calculated as shown in Equation (1), where F represents forecasted values of a given variable, A represents actual historical values, and T is the total number of forecast periods. The numerator of Equation (1) is the root mean squared error (RMSE). U-statistics are similar to RMSE in that smaller values of the statistic indicate smaller mean squared forecast errors but, unlike RMSE, U-statistics are unit free and range between zero and one.

$$U = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(F_t - A_t)^2} \Big/ \left(\sqrt{\frac{1}{T}\sum_{t=1}^{T}(F_t)^2} + \sqrt{\frac{1}{T}\sum_{t=1}^{T}(A_t)^2}\right) \qquad (1)$$

Second, in addition to computing summary measures of the size of forecast errors, it may also be of interest to analyze the composition of those errors. Toward this end, the mean squared error (MSE) can be decomposed into three parts, known as the proportions of inequality. The first is U-bias, which measures systematic divergence between the mean values of the forecasted and actual time series (Equation 2). The second is U-var, the variance proportion, which measures difference between the variability of the forecasted and actual series (Equation 3). The third is U-cov, the covariance proportion, which measures unsystematic or random error (Equation 4). The three components sum to one. If forecast error exists then, ideally, the error should be random in nature, rather than systematic, i.e. U-bias = U-var = 0 and U-cov = 1 (Pindyck and Rubinfeld, 1998)

$$U - bias = (\bar{F} - \bar{A})^2 / \left(\frac{1}{T}\right) \sum_{t=1}^{T} (F_t - A_t)^2 \tag{2}$$

$$U - var = (\sigma_F - \sigma_A)^2 / \left(\frac{1}{T}\right) \sum_{t=1}^{T} (F_t - A_t)^2 \tag{3}$$

$$U - cov = 2(1 - \rho)\sigma_F \sigma_A / \left(\frac{1}{T}\right) \sum_{t=1}^{T} (F_t - A_t)^2 \tag{4}$$

The third evaluation procedure consists of statistical tests of forecast error differentials. For the sake of clarity, the econometric forecast errors, denoted e2, are assumed to be smaller, on average, than the random walk forecast errors, denoted e1, in the subsequent exposition. The purpose of these tests is to determine whether this difference in accuracy is statistically significant. The null hypothesis is that the econometric forecasts do not represent a significant improvement over the random walk. Ashley et al. (1980) note that the null hypothesis for an error differential regression test can be expressed as shown in Equation (5), by defining two new variables that represent the difference of forecast errors for the two models, $\Delta_t = e_{1t} - e_{2t}$, and the sum of the forecast errors, $\theta_t = e_{1t} + e_{2t}$.

$$\mathrm{H}_0: MSE(e_1) - MSE(e_2) = [\mu(e_1)^2 - \mu(e_2)^2] + \mathrm{cov}(\Delta, \theta) = 0 \tag{5}$$

A regression-based procedure which uses values for Δ_t and θ_t as data inputs can be employed to test this null hypothesis. The specification of the regression equation depends on the signs of the econometric and random walk forecast error means. If the error means have the same sign, the null hypothesis can be tested using Equation (6) and, if the error means have opposite signs, Equation (7) is employed instead.

$$\Delta_t = \beta_1 + \beta_2[\theta_t - \mu(\theta_t)] + \varepsilon_t \tag{6}$$

$$\Sigma_t = \beta_1 + \beta_2[\Delta_t - \mu(\Delta_t)] + \varepsilon_t \tag{7}$$

The signs of the regression coefficients, β_1 and β_2, provide information regarding comparative forecasting performance. The coefficient β_1 indicates which set of forecast errors is larger, on average. If β_1 has the same sign as the mean of e_{1t}, then the random walk forecast errors, e1t, are larger, on average, than the econometric forecast errors, e_{2t}. As pointed out by Kolb and Stekler (1993), the test for $\beta_2 = 0$ is equivalent to a test of the hypothesis that $cov(\Delta, \theta) = 0$. If β_2 is positive, the variance of e_{1t} is larger than the variance of e_{2t}.

The t- and F-statistics associated with the estimated regression equations can be used to determine whether the econometric forecasts represent significant improvements over the random walk benchmarks. If the signs of both parameter estimates indicate econometric forecast superiority, then an F-test of the joint null hypothesis $\beta_1 = \beta_2 = 0$ can be used. The significance level associated with this F-statistic is never more than half the probability obtained from F-distribution tables (Ashley et al., 1980). When the signs of the parameter estimates imply opposite conclusions regarding relative forecast accuracy, then one-tailed t-tests are used. If the signs of both coefficients indicate that the random walk forecasts are more accurate than the econometric forecasts, it is more appropriate to test whether the random walk forecasts are significantly better than their econometric counterparts. This is achieved by first redefining e_1 as the econometric forecast and e_2 as the random walk forecast and then repeating the procedure outlined above.

The fourth and final forecast evaluation approach differs from those mentioned because it examines directional accuracy instead of error magnitudes. Actual and forecasted directional changes can be analyzed using Table 2 where the sum of n_{11} and n_{22} is equal to the sum of correct directional forecasts and the sum of n_{12} and n_{21} equals the sum of incorrect directional forecasts. The sum of all forecasts is N. For the purpose of this analysis, increases and decreases in the variables of interest are defined with respect to the values of those variables observed in the year immediately prior to the beginning of each forecast period.

Table 2.
Directional Forecast Accuracy Assessment Forecast

		Increase	Decrease	Total
	Increase	n_{11}	n_{12}	n_{10}
Actual	Decrease	n_{21}	n_{22}	n_{20}
	Total	n_{01}	n_{02}	N

Note: The authors designed this table based upon Henriksson and Merton (1981).

Tests of directional accuracy sometimes examine the null hypothesis that forecasts lack informational content for predicting the direction of change. The null of no informational content indicates that a correct forecast is no more likely than an incorrect forecast. A two-tailed test of this null hypothesis implies an alternative hypothesis that either forecasts tend to correctly predict directional changes or, conversely, that there is a tendency to systematically predict the wrong direction of change. Following Henriksson and Merton (1981), a one-tailed test is instead used in order to assess whether or not forecasts systematically predict the correct direction of change. Therefore, the modified null hypothesis considered for this analysis is that the forecasts are either systematically incorrect or, at least, no more likely to be correct than incorrect.
The analysis employs a test of directional accuracy developed by Pesaran and Timmermann (1992). It should be noted that, unlike the error differential regression test described above, the Pesaran-Timmermann test does not require data for two competing sets of forecasts.

$$\mathrm{PT} = \left(\hat{P} - \hat{P}_0\right) / \sqrt{\mathrm{var}\left(\hat{P}\right) - \mathrm{var}\left(\hat{P}_0\right)} \quad (8)$$

The Pesaran-Timmermann test statistic, denoted PT, is shown in Equation (8). The first variable, $\hat{P}$, is the proportion of times that the directional change is correctly forecasted, i.e. $(n_{11} + n_{22})/N$. The second variable, $\hat{P}_0$, is the proportion of correct predictions that would be expected if the forecasted directional changes were distributed independently of the actual observed directional changes. The latter variable is calculated as $(n_{10}/N)(n_{01}/N) + (1 - n_{10}/N)(1 - n_{01}/N)$. To determine whether the difference between these two variables is statistically distinguishable from zero, the variance of each must be estimated using formulas provided by Pesaran and Timmermann (1992). The test statistic can be compared with the critical value for a one-sided normal test (Granger and Pesaran, 2000).

Finally, a chi-squared (X^2) test can also be used to evaluate the independence of forecasted and observed events (Schnader and Stekler, 1990). The chi-squared test is used in this study to corroborate the results of the Pesaran-Timmermann test. The two tests are assymptotically equivalent in the case of a 2 × 2 contingency table like Table 2 (Pesaran and Timmermann, 1992). In some cases, either forecasted or actual hotel sector variables follow steady upward or downward trends such that there is very limited variation in the direction of change. In those instances, as in other regional forecast accuracy assessment studies, both tests of directional accuracy are omitted (Fullerton et al., 2016).

EMPIRICAL RESULTS

Table 3 reports *U*-statistics and proportions of inequality for the econometric (EC), random walk (RW), and random walk with drift (RWD) forecasts. The econometric forecasts are more accurate for four of the seven industry performance measures that are the dependent dependent variables. In particular, econometric forecasts outperform the benchmark forecasts in the sales, room price, and revenue categories. A similar pattern is documented in Fullerton and Walke (2013). Standard random walk forecasts are more accurate than econometric forecasts for the supply of hotels and hotel room nights as well as for the room occupancy rate. The comparative performance of the econometric and random walk forecasts aligns with that documented in some previous tourism-related studies (Witt and Witt, 1995; Song et al., 2003) in a study of tourism demand. The random walk with drift is not more accurate than the alternatives for any of the variables analyzed.

The composition of the forecast errors is quantified by the MSE proportions of inequality shown in the last three columns of Table 3. The proportions of forecast error due to bias are reported in Column 4. Optimally, the value of *U-bias* for any variable analyzed will be equal to zero. For most of the econometric forecasts, designated by the EC acronym, bias is fairly minimal as a source of predictive inaccuracy. For one variable, the number of hotels, the bias proportion is greater than 0.5. Although not reported herein, the estimation results for the number of hotels in El Paso exhibits very good empirical properties. The usual response to biased out-of-sample simulation errors is to modify the specification of that equation. Because the overall magnitude of the forecast errors is small, that step may not be necessary, but will be considered.

Column 5 of Table 3 summarizes the variance proportion of the MSA decomposition. Ideally, the value of *U-var* will be null for any time series being forecasted. For the econometric forecasts, *U-var* is below 0.16 for all of the hotel variables. Those results indicate that the EC predictions do a good job of replicating the variability in each of the El Paso lodging sector time series included in the model.

Column 6 of Table 3 reports the covariance proportions of each set of forecasts. For perfect forecasts, the magnitude of *U-cov* will be equal to one for any time series that is being simulated. Relatively large covariance proportions suggest that the random components of forecast errors predominate over systematic deviations between the means and variances of the actual and predicted series. Encouragingly, the econometric forecast error covariance proportions are above 0.7 in all cases but one. The exception to this pattern is the EC projections for the number of hotels. As noted above, the forecast errors for the number of hotels tend to be biased, but also tend to be small. The EC evidence in Columns 5 and 6, jointly, imply that the non-biased portions of the prediction inaccuracies for the number of hotels are random in nature. If forecasts are to be flawed, that is a relatively benign manner in which to be imperfect.

Table 3.
U-Statistics and MSE Proportions of Inequality

Variable	Forecast	U-Stat.	U-Bias	U-Var	U-Cov
	EC	0.0256	0.5228	0.0216	0.4556
Number of Hotels	**RW**	**0.0213**	0.0001	0.0735	0.9264
	RWD	0.0425	0.1283	0.3885	0.4832
	EC	0.0326	0.0842	0.0864	0.8294
Room Nights Available	**RW**	**0.0186**	0.3601	0.0661	0.5738
	RWD	0.0272	0.1004	0.3131	0.5865
	EC	**0.0209**	0.0012	0.0115	0.9873
Room Nights Sold	RW	0.0246	0.2156	0.0005	0.7839
	RWD	0.0475	0.0069	0.2214	0.7717
	EC	0.0238	-0.1142	0.1536	0.7322
Occupancy Rate	**RW**	**0.0198**	0.0000	0.0074	0.9926
	RWD	0.0540	0.0074	0.5303	0.4623
	EC	**0.0198**	0.2023	0.0018	0.7959
Room Price	RW	0.0296	0.4341	0.0151	0.5508
	RWD	0.0483	0.0049	0.1758	0.8194
	EC	**0.0353**	0.2234	0.0445	0.7320
Revenue per Room	RW	0.0356	0.1908	0.1066	0.7026
	RWD	0.0948	0.0133	0.3991	0.5876
	EC	**0.0248**	0.1014	0.0172	0.8814
Total Revenues	RW	0.0471	0.4666	0.0066	0.5268
	RWD	0.0750	0.0007	0.1261	0.8732

Note: Bold text in Columns 2 and 3 indicates the most accurate set of forecasts for each variable.
Columns 4, 5, and 6 report the MSE proportions of inequality, *U-bias*, *U-var*, and *U-cov*.
EC is the acronym for the econometric model forecasts.
RW is the acronym for the random walk forecasts.
RWD is the acronym for the random walk with drift forecasts.
Source: Information in the table comes from author calculations based on data from the University of Texas Border Region Modeling Project (see Fullerton et al., 2019).
RW is the acronym for the random walk forecasts.
RWD is the acronym for the random walk with drift forecasts.
Source: Information in the table comes from author calculations based on data from the University of Texas Border Region Modeling Project (see Fullerton et al., 2019).

Column 6 of Table 3 reports the covariance proportions of each set of forecasts. For perfect forecasts, the magnitude of *U-cov* will be equal to one for any time series that is being simulated. Relatively large covariance proportions suggest that the random components of forecast errors predominate over systematic deviations between the means and variances of the actual and predicted series. Encouragingly, the econometric forecast error covariance proportions are above 0.7 in all cases but one. The exception to this pattern is the EC projections for the number of hotels. As noted above, the forecast errors for the number of hotels tend to be biased, but also tend to be small. The EC evidence in Columns 5 and 6, jointly, imply that the non-biased portions of the prediction inaccuracies for the number of hotels are random in nature. If forecasts are to be flawed, that is a relatively benign manner in which to be imperfect.

Error differential regression test results are displayed in Table 4. Because this test can only be conducted for pairs of forecasts, the econometric model out-of-sample simulations are only matched against the random walk forecasts. That is because the random walk with drift forecasts are never found to be most accurate in Table 3. Also, the identity of the forecast errors denoted e_1 and e_2 in Equation (5), and therefore the interpretation of the regression coefficients, differs depending on which of the two sets of forecasts is less accurate (i.e., which set of forecast errors is largest). Given that, the second column Table 4 identifies which set of forecasts is less accurate forecast within each pair. For cases in which the random walk forecast is less accurate and has the largest errors, the pairing is listed as RW and the null hypothesis examined is that the econometric model is not significantly more accurate than the random walk. For cases in which the econometric forecasts are less accurate than either of the random walk benchmarks, EC is used in Column 2 of of the random walk benchmarks, EC is used in Column 2 of Table 4 and the identities of e_1 and e_2 are modified accordingly.

Table 4.
Error Differential Regression Test Results

Variable	Least Accurate Forecast	Benchmark Error Mean	β_1 t-stat	β_2 t-stat.	F-stat.	Results
EC vs. RW						
Number of Hotels	EC	2.9667	7.5515	-1.4195	29.5201	Reject
Room Nights Available	EC	60.1297	-0.2818	4.4671	10.0171	Reject
Room Nights Sold	RW	-47.2524	-1.3739	0.3238	0.9963	FTR
Occupancy Rate	EC	-1.0587	-1.4646	0.6152	1.2618	FTR
Room Price	RW	-2.7749	-3.7374	1.6857	8.4048	Reject
Revenue per Room	RW	-1.4729	0.1633	0.1571	0.0257	FTR
Total Revenues	RW	-9.4797	-5.5844	2.6149	19.0115	Reject

Notes: In the Results column, reject means that the null hypothesis is rejected using a 5% significance criterion and FTR indicates failure to reject the null hypothesis.
The null hypotheses are:
If EC is in Column 2, H_0: the econometric model is no more accurate than the random walk;
If RW is in Column 2, H_0: the random walk is no more accurate than the econometric model;
Source: Information in the table comes from author calculations based on data from the University of Texas Border Region Modeling Project (see Fullerton et al., 2019).

The error differential regression test results in Table 4 indicate that the random walk forecasts of the number of hotels and the number of available room nights are significantly more accurate than the econometric forecasts of those variables. For room nights sold, occupancy rate, and revenue per room, neither set of predictions is found to be significantly more accurate than the other. Finally, the econometric forecasts are found to be more accurate than the random walk projections for the room price and for total revenues. As with the *U*-statistics, the error differential regression test results indicate that the random walks are competitive with the econometric forecasts.

In order to assess the historical track record of the econometric forecasts in predicting the direction of change, Pesaran-Timmermann and chi-squared tests are conducted. Because the number of hotels is forecast to increase in every year during the sample period, resulting in only positive directional change predictions, that variable is not included in the directional accuracy analysis. Directional accuracy test results for the six variables analyzed are shown in Table 5. Using the Pesaran-Timmermann test, the null hypothesis is rejected for the occupancy rate, room rate, and revenue per room variables. This suggests that the econometric forecasts provide useful information regarding the direction of change in the latter series. The results of the chi-squared test are similar, except that the econometric occupancy rate forecasts are not found to contribute useful information on directional changes when judged by this criterion.

Table 5.
Directional Accuracy Statistics

Variable	PT Statistic	Conclusion	2 Statistic	F-stat.
Room Nights Available	-0.9285	Fail to Reject	0.8333	Fail to Reject
Room Nights Sold	0.9848	Fail to Reject	0.9375	Fail to Reject
Occupancy Rate	1.9754	Reject	3.7723	Fail to Reject
Room Rate	3.4202	Reject	11.3077	Reject
Revenue per Room	2.7248	Reject	7.1770	Reject
Total Revenues	1.2457	Fail to Reject	1.5000	Fail to Reject

Notes: The null hypothesis is that actual and predicted directional changes are distributed independently of one another. The null is evaluated using a 5% significance criterion.
Due to steady upward trends in forecasts of the number of hotels, that variable was omitted from the analysis. Source: Information in the table comes from author calculations based on data from The University of Texas Border Region Modeling Project (see Fullerton et al., 2019).

As noted by Koupriouchina et al. (2014), different measures of forecast accuracy often lead to different conclusions regarding the relative merits of competing hotel sector forecasts. For example, the econometric forecasts of total hotel revenues appear to perform relatively well when accuracy is measured by the size of forecast errors but not when directional accuracy track records are considered. Furthermore, as pointed out by Song and Li (2008), statistical tests of forecast accuracy provide critical evidence on the reliability of competing models. While the econometric forecasts are more accurate than the random walk alternatives for a majority of the variables considered, as gauged by standard *U*-statistics, the margin of improvement is only statistically significant for two of those variables. Overall, these results indicate that the econometric forecasts for the lodging sector in El Paso are useful and accurate, but analysts should keep a close eye on recent history.

In terms of monitoring recent hotel segment history, that recommendation from the prior paragraph parallels much of what has been observed with respect to random walk relative predictive accuracy in various regional forecasting contexts. Because hotel sales volumes are largely by-products of travel patterns, it is no surprise that some of the variables are difficult to forecast using a structural econometric approach. That is because transportation flows, historically, have proven to be relatively difficult to predict using the system of simultaneous equations used to model the hotel sector in El Paso for this study (Fullerton, 2004; Fullerton et al., 2018). Even though baseball great Satchel Paige did not recommend it, looking back seems to be necessary from a planning perspective in the lodging sector of El Paso.

CONCLUSION

This study examines the accuracy of *ex-ante* hotel sector forecasts assembled using a regional econometric model and published yearly since 2006. To provide reasonable benchmarks for accuracy comparisons, random walk and random walk with drift forecasts are generated. The various sets of forecasts are then evaluated using forecast error summary metrics, forecast error decompositions, statistical tests of comparative predictive accuracy, and tests of directional accuracy. These assessment techniques quantify different dimensions of overall forecast accuracy and, therefore, provide complementary information for evaluation assessments.

Results are mixed. For four out of seven hotel sector variables, those predictions are more accurate than random walk alternatives. However, within the latter subset of variables, only two of the econometric forecasts are significantly better than random walk benchmarks. Furthermore, in two cases, standard random walk forecasts significantly outperform the econometric model. This suggests substantial year-to-year continuity in El Paso hotel market conditions over the sample period considered. It also implies that managers and planners should carefully monitor recent hotel sector developments when developing planning scenarios. Finally, the econometric forecasts also have a mixed track record in predicting directional changes in the variables analyzed. Only in the cases of room rates and revenues per room is there strong evidence that the forecasts provide useful information regarding directions of change.

Forecasts of hotel occupancy, sales, revenues, and related variables are used by planners in a variety of contexts and the accuracy of those forecasts affects the soundness of decisions regarding pricing, budgeting, investment, and public planning. Rigorous evaluation approaches using multiple techniques, including statistical tests, is likely to help improve the outcomes future forecasting and planning efforts. In particular, published evaluations of *ex-ante* forecasts are useful for assessing previously implemented methodologies. This analysis represents a step in that direction. Further assessment of ex-ante hotel market forecast accuracy with the aid of statistical testing procedures would likey shed further light on predictive reliability and possibilities for improvement.

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