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Regional Single-Family Housing Start Forecast Accuracy

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Abstract

This paper extends earlier research regarding the predictability of residential construction activity in regional housing markets. This category of forecasts are used in numerous banking, government, utility, and retail applications. To analyze forecast accuracy, quarterly frequency data are assembled from previously published econometric forecasts for Florida and its six largest metropolitan economies. The sample simulation period covers 1985:1 - 1996:2 and includes all three business cycle phases: expansion, recession, and recovery. For this time frame, single-family unit start forecasts are compared to univariate time series and random walk alternatives. Results indicate that structural model forecasts of regional housing construction are comparatively less reliable than those for nonagricultural employment. Moreover, single-family starts in Florida also perform less well against the two benchmarks than do the multi-family counterparts for the same housing markets. Modelers should possibly consider increasing coverage breadth to include other variables as a means for improving information content in residential construction forecasts.

Key Words: Regional Housing Start Forecasts

Introduction

Regional economic forecasts have traditionally featured estimates for expected additions to existing housing stocks. Despite widespread usage, the accuracy of regional econometric forecasts has not been extensively evaluated. Growing interest in this issue has been demonstrated in recent years, but relatively little research has occurred (West and Fullerton, 1996a; Fullerton and West, 1998). While numerous studies have staged so-called econometric methodology "horse races," relatively few have examined ex ante out-of-sample forecast accuracy (Weller, 1990; LeSage, 1990; Shoesmith, 1992). Only one study (Fullerton and West, 1998) has provided an extensive review of ex ante residential construction predictive accuracy.

Regional housing starts receive enormous amounts of attention because they represent highly important components of state and local economic activity (Zandi, 1999). In many markets, for example, residential building trends impact directly on regional sales tax collections and public finance (Fullerton, 1998; Fullerton and West, 1998). Real estate and non-realtor businesses alike utilize housing forecasts as indicators of expected market growth and general business conditions. Residential construction forecasts are relied upon numerous other applications, as well.

Commercial banks and other lending agencies utilize prediction trends as a means for avoiding potential over-lending during periods of supply and demand mismatches. Developers monitor housing start projections when allocating resources for speculative building activities in anticipation of actual contract negotiations with prospective buyers.

Retail materials supply, furnishings, and home appliance store chains subscribe to regional housing forecast reports in order to ensure that appropriate staff and inventory levels are maintained. Public utilities use these forecasts to plan for additional capacity additions such as water mains and electric distribution sub-stations. Consulting firms also utilize metropolitan housing activity projections in the development of growth management plans for local government entities and in the preparation supporting documentation for builders seeking financial institution loan approvals. Finally, national economic forecasts also monitor their own housing model extrapolations with regional market projections that more accurately simulate the impacts associated with domestic migration flows.

Because national housing start forecasts do not apply systematically to state and metropolitan areas, regional forecasting models of residential construction are relied upon very heavily (Crone and McCaughlin, 1999). The objective of this study is to gauge the relative reliability of single-family housing starts forecasts developed at sub-national levels, including both state and metropolitan statistical area (MSA) data. By concentrating on single-family construction activity, the analysis goes one step beyond what has previously occurred in the limited literature on both national and regional housing start predictive accuracy. Recent cross-section data results for sub-state residential construction forecasts report attractive extrapolation properties (Lenze, 2000). Time series evidence for regional single-unit forecasts, however, has not previously been assembled.

Section two provides a review of previous research efforts. Section three reviews the data and methodologies utilized below. Florida and its six largest metropolitan economies provide the regional construction market sample to be analyzed. Empirical results are discussed in the fourth section. A summary and conclusions are comprise the final section.

Previous Studies

Regional structural equation models (RSEMs) have long been used to analyze expected changes in the supply of new housing units. RSEM housing forecasts have not, however, been subjected to accuracy evaluation in manner similar to their national macroeconomic counterparts (see McNees, 1992). Predictive accuracy assessment based on ex ante forecasts is particularly rare. Lenze (2000) examines a cross-section sample of urban and rural counties in Florida. Some initial time series efforts have also been completed with respect to total housing starts and multi-family housing starts (Fullerton and West, 1998; Laaksonen, Fullerton, and West, 1998). By and large, however, this branch of the literature remains relatively unexplored.

Several factors contribute to the absence of attention on RSEMs residential construction forecast accuracy. For many regions, a relatively short history of RSEMs modeling implies severe degrees of freedom constraints with respect to available samples of previously published forecasts. Census Bureau MSA definition changes can

occasionally reduce the number of available data points for fast growing metropolitan markets as well as for urban areas that experience out-migration. Also, there are few incentives for commercial econometricians to perform critical forecast evaluation exercises. Finally, regional housing market data are frequently subject to large revisions over time, handicapping the earlier published forecasts that were created utilizing preliminary estimates for numerous variables.

Similar to other regional models, the Florida modeling system assumes that the national economy drives the regional economy, while the impact of regional economy on the national economy is generally not very large. Given that, the Florida modeling system follows the traditional top-down approach historically utilized in regional econometrics (Bolton, 1985; Hunt and Snell, 1997). A detailed summary of the Florida model structure is provided in Fullerton and West (1998). In basic terms, the 660 equations cover demographics, employment, personal income, residential building activity, and taxable sales.

Principal drivers for the state and metropolitan housing start equations include net migration, proxy variables for regional affordability indexes, mortgage rates, consumer confidence, unemployment, employment growth, population distribution by age cohort, an index of 5-year building trends relative to state household growth, average values per unit built, and national housing starts. Because of the wide range of economic conditions observed throughout Florida (West, 1995), specifications for the different equations are not always identical and have changed over time. Table 1 lists representative coefficients of determination for the seven housing start equations utilized to generate the forecasts under consideration. All of the R-square coefficients are greater than 0.80, reflecting a fairly high level of explanatory power in terms of in-sample goodness-of-fit.

Nelson (1984), argues that different economic prediction methodologies are comparable only when they are made ex ante and simultaneously. While previously published RSEMs forecasts exist ex ante for the state of Florida and its largest metropolitan statistical areas (MSAs), competing methodology benchmark forecasts do not. To overcome this obstacle, univariate extrapolative methodologies are used ex post to replicate forecasts with a similar absence of knowledge about the simulation periods in question below. Although univariate projection techniques utilize less input information than RSEMs, they frequently provide relatively accurate forecasts. This holds especially true when RSEM simulation exercises are handicapped by poor exogenous variable forecasts (Ashley, 1988).

Fullerton and West (1998) examine the historical track record for quarterly housing activity forecasts in Florida and its six largest metropolitan economies. Total regional housing starts are utilized without distinguishing between single-family and multi-family construction. The sample period in this case also covers all phases of the national business cycle. Results indicate that RSEM housing start forecast performance is acceptable with respect to univariate ARIMA models. Surprisingly, however, a simple

random walk prediction rule generally outperforms the RSEMs forecasts for total housing starts.

Data and Methodology

While Fullerton and West (1998) examine the accuracy of total housing start forecasts at the regional level, an important question remains. Should housing start forecast precision be analyzed with respect to the component parts of single-family and multi-family housing activity? This paper investigates whether similar results are generated when single-family housing start forecast accuracy alone is assessed.

Structural model ex ante housing forecasts exist in published form for the state of Florida and its six largest metropolitan statistical areas: Fort Lauderdale, Jacksonville, Miami, Orlando, Tampa, and West Palm Beach. This information has been recorded since the mid-1970s by the University of Florida econometric forecasting research program. Single-family starts data used herein are derived from quarterly forecasts published in **The Florida Outlook** between 1985:1 and 1996:2 (for example, see West and Fullerton, 1996b). A maximum out-of-sample simulation length of ten quarters ahead can be extracted from those publications.

Because revised historical data estimates are utilized for the univariate forecast benchmarks, comparison criteria are fairly stringent. The original RSEMs forecasts were created using preliminary estimates of the late sample historical data. This favors the univariate extrapolative methods slightly over the structural equation models, but cannot be avoided due to data constraints. For the state, the sample ranges from the first quarter of 1967 through the fourth quarter of 1995. MSA single-family housing start data series are not available prior to the first quarter of 1974. For Orlando, there are eleven fewer observations due to the MSA boundary definition change associated with the addition of Lake County in 1993. All phases of a complete business cycle (expansion, contraction, and recovery) are included in the period under consideration. Rapid expansion occurred in the mid 1980s, a recession took place in the early 1990s, and a recovery emerged by the mid 1990s.

The six metropolitan statistical areas included in this analysis provide an interesting cross section characterized by a wide variety of economic activities (West, 1995). Summary statistics for residential construction in the sample markets and the United States are shown in Table 2. For Florida and its six largest MSAs, the coefficients of variation, measured as the ratios of the standard deviations to their respective means, range from 30.2 percent to 39.7 percent. The corresponding figure for national stand-alone dwelling units is only 19.7 percent. As a consequence of residential construction variability, Florida RSEM prediction and confidence intervals tend to be fairly wide.

Univariate ARIMA and random walk models are used to assess the residential construction forecast accuracy of the regional econometric models. All seven single-family housing start data series are first-differenced to create stationary working series.

After satisfying the stationarity requirement, autocorrelation functions are utilized to indicate potential autoregressive and moving average parameters. The random walk extrapolation rule is simpler, using only the latest available historical observation as the multi-period forecast.

Simulations using these approaches are then segregated by quarters-ahead forecast. This process gives rise to 37 one-to-three-step forecasts, 36 four-step forecasts, 35 five-step forecasts, 34 four-step forecasts and so-forth to match the number of available historical RSEM forecast values. For the Orlando housing market, fewer forecasts are obtained because the its MSA definition changed after the first quarter of 1993. Altered commuting patterns and demographic expansion resulted in the addition of Lake County to the Orlando MSA, which previously included only Orange, Osceola, and Seminole counties. This causes eight fewer observations to be obtained for each step-length for Orlando relative to the other MSAs and the state of Florida.

Forecast data from all three simulation techniques, segregated by step-length, are then compared to actual multi-family housing start data from the simulation period. Prediction errors are utilized to calculate root mean squared error (RMSE) values separately for all ten forecast periods. Modified Theil inequality coefficients are calculated as the ratios of the structural model RMSEs to those associated with the univariate ARIMA and random walk housing start equations. The modified Theil inequality coefficients obtained this way provide reliable indicators with respect to the predictive accuracy of econometric forecasting models (Webb, 1984; West, 1996). When a modified Theil inequality coefficient is greater than one, it implies that the univariate ARIMA model, or that the random walk model, generates smaller absolute forecast errors than the structural model. Conversely, if the modified Theil inequality coefficient is smaller than one, it implies that the RSEM prediction errors are smaller than those of the univariate ARIMA equation or than those of the random walk model.

Empirical Results

Table 3 lists the final univariate ARIMA model specifications for the state and MSAs. In contrast to the relatively stable multi-family housing start ARIMA specifications reported by Laaksonen, Fullerton, and West (1998), multiple specification changes were required for the single-family time series. The minimum number of changes is 4 for the state, Miami, and Orlando. Similar to the multi-family case, Jacksonville proved to be the most difficult single-family series to model. Eleven univariate ARIMA model specification changes were required for that MSA.

Previously published econometric model single-family housing start forecast RMSEs are compared to univariate ARIMA forecast RMSEs to obtain relative measures of forecast accuracy across all ten step-lengths. Modified Theil inequality coefficients for this procedure appear in Table 4. Structural model extrapolations compare favorably to the univariate ARIMA benchmarks in only 32 of the 70 calculations. This is in sharp contrast to both Fullerton and West (1998) and to Laaksonen, Fullerton, and West (1998)

wherein the structural model forecasts outperform the ARIMA out-of-sample simulations. Similar to those studies, no distinct temporal patterns are uncovered with respect to the relative forecast accuracy of these competing methods. Short step-length accuracy does not imply relative accuracy at outer step-lengths and vice versa.

The modified Theil U-statistics are presented without formal hypothesis tests conducted on them. As shown by Mizrach (1992), Theil inequality coefficients provide useful descriptive measures of relative extrapolation precision but cannot be used in significance tests when forecast errors are serially correlated. While formal inferential tests are not feasible with the current data set, West (1996) has shown out-of-sample accuracy rankings based on root mean square error measures such as U-coefficients to perform reliably. The descriptive approach is also used with respect to the random walk results discussed below.

Previous regional econometric research (Ashley, 1988) indicates that the possibility that a random walk methodology can produce superior housing start forecasts relative to RSEM forecasts should not be discounted. In the random walk approach, the last available historical observation is used as the forecast for all of the various step-lengths. The Theil inequality coefficients for the RSEM and random walk comparisons are reported in Table 5. In only 29 instances out of a possible 70 do the inequality coefficient exhibit values less than one. This implies that the random walk method compares surprisingly well to the RSEM approach, especially when the cyclical nature of residential construction is taken into account. Multiple empirical factors may have contributed to this result. Information constraints such as the absence of regional housing market vacancy rates probably also hamper the collective simulation performance of the structural models that cannot be overcome by employing demographic proxies for overbuilding (DiPasquale and Wheaton, 1994; Topel and Rosen, 1988).

Additional difficulties for the structural model out-of-sample track records probably also arise from two types of periodic exogenous input forecast inaccuracies. Single-family construction volumes react strongly to interest rate changes, but financial market yield projections have long been noted for their collective unreliability (Cooper and Nelson, 1972). Demographic growth factors also exert important influences on regional housing stock additions (Berson, 1997; Lenze, 2000). Regional net migration is usually modeled as dependent on local versus national labor market conditions. Both components are subject to large scale measurement errors and revisions related to sample survey fluctuations. Consequently, interest rate and unemployment forecast errors can easily escalate into fairly substantial housing start prediction errors. The latter create additional problems since they can lead to outer period simulation inaccuracies in demographic flows, further hampering residential construction extrapolations. Structural model interaction effects can thus contribute to a reverberative error spiral that results in a compounding process with negative implications for housing start projections (Charney and Taylor, 1984).

The strong performance of the random walk forecasts is at variance with earlier results concerning structural model out-of-sample simulations for regional employment. Data quality issues may play roles in this turn of events since housing start estimates are based upon survey drawn start-to-permit ratios while employment series are taken directly from unemployment insurance count data. However, because the results in Table 5 parallel the results for both multi-family starts (Laaksonen, Fullerton, and West, 1998) and for total starts (Fullerton and West, 1998), care should probably be exercised when utilizing structural econometric models to analyze future regional housing market conditions. Because of the wide variety of market characteristics associated with the metropolitan economies comprising the sample, it is likely that other regional forecasting efforts may encounter similar accuracy problems. At a minimum, these results underscore the fact that high R-square measures do not guarantee out-of-sample simulation precision or reliability.

Given the above, it may be preferable to imbed univariate or other atheoretic time series specifications for the housing start sectors of structural models. Such an approach has been tested for the nonresidential construction put-in-place equations in a recent model of the El Paso borderplex economy (Fullerton, 1998). To also insure that RSEM systems of equations provide useful information, incorporation of additional residential real estate variables that may be easier to forecast should be considered. Examples of the latter include single- and multi-family stock estimates, prices for new and existing dwelling units, affordability indexes, monthly average mortgage payments, and sales of existing units (Fullerton, 2000; Zandi, 1999).

Conclusion

Regional housing start forecasts are used in numerous commercial and public policy resource allocation decisions. Examples include real estate lending, retail chain inventory and staffing management, public utility infrastructure investment and facility location, state and local government revenue analysis, and private consulting support documentation efforts on behalf of public sector growth management planning efforts. In spite of the importance of regional residential construction trends in terms of local economic performance, widespread usage of these forecasts has not resulted in careful assessment of the forecast records for these variables over time. Such an effort is carried out in the material at hand.

Empirical results reported above indicate that structural model forecast accuracy for regional single-family construction activity does not fare well relative to accuracy benchmarks provided by either univariate ARIMA equations or random walk predictions. This is in contrast to earlier research results for total housing starts and multi-family housing starts. Because the sample herein encompasses a wide variety of regional housing markets, the implication is fairly clear. Future large scale econometric modeling efforts should consider imbedding alternative time series specifications for this portion of the real estate block of equations typically contained in such systems.

In the case of multi-family residential construction activity, the RSEM forecasts surpassed the accuracy levels associated with either of the benchmark methodologies. That makes the results reported in this paper all the more surprising. Single-family housing activity has traditionally proved easier to model in Florida than has multi-family starts. That stand-alone residential starts fail to match the relative accuracy performance of their multi-family counterparts is unexpected. Given the wide variety of market coverage in the sample, it would not be surprising if these results are representative for state and local modeling efforts in general. Confirmation using housing supply forecast data for other regional markets would be helpful.

Similar to earlier prediction accuracy research, distinct patterns across forecast period lengths are not established for this category of regional econometric analysis. As can be seen in Tables 4 and 5, the inequality coefficients follow widely variant paths for all of the construction markets examined. Rules-of-thumb regarding relative housing stock forecast variability across time do not appear possible on the basis of these results.

Univariate ARIMA model and random walk prediction rule forecasts can almost be generated ex post with the same complete lack of knowledge about the forecasting period as that associated with ex ante structural model forecasts. From this aspect, these different methodologies are comparable. The requirement regarding usage of identical data sets is not satisfied, however, in this study. The data used to generate univariate ARIMA and random walk model forecasts rely upon revised data for all observations in the base period. In case of RSEMs, the latest base period observations were preliminary estimates, not final revised data. This unavoidable data issue favors the univariate extrapolative techniques. For cases in which expected housing supply trends under variant business cycle phases are required, the traditional approach may still prove superior.

Additional research regarding single-family forecast accuracy elsewhere is warranted since numerous issues remain unanswered. Questions raised by this paper include whether structural model residential forecast difficulties are unique to Florida. Do multi-family start forecasts always outperform their single-family counterparts for other regions? Also, is it more difficult to model and forecast small MSA single-family construction starts or do they perform better relative to standard univariate benchmarks? On the basis of these initial results, it appears that regional housing start forecasting is a difficult task no matter what level of aggregation is utilized. Given that, expansion of residential real estate equation blocks to include additional data beyond unit starts is recommended.

References

Ashley, Richard. 1988. "On the Relative Worth of Recent Economic Forecasts." **International Journal of Forecasting** 4: 363-376.

Berson, David W. 1997. "The Importance of Demographics in Economic Analysis." **Business Economics** 32: 12-16.

Bolton, Roger. 1985. "Regional Econometric Models." **Journal of Regional Science** 25: 495-520.

Charney, Alberta H. and Carol A. Taylor. 1984. "Decomposition of Ex-ante State Model Forecasting Errors." **Journal of Regional Science** 24: 229-247.

Cooper, J. Phillip, and Charles R. Nelson. 1972. "The Ex-ante Prediction Performance of the St. Louis and FRB-MIT-Penn Econometric Models and some Results on Composite Predictors." **Journal of Money, Credit, and Banking** 4: 1-32.

Crone, Theodore M., and Michael P. McLaughlin. 1999. "The Philadelphia Story: A New Forecasting Model for the Region." Federal Reserve Bank of Philadelphia **Business Review** (September/October): 13-23.

DiPasquale, Denise, and William C. Wheaton. 1994. **Urban Economics and Real Estate Markets**. Englewood Cliffs, NJ: Prentice Hall.

Fullerton, Thomas M., Jr. 1998. "Specification of a Border Region Econometric Forecasting Model." **South Dakota International Business Conference Proceedings** 5: 35-41.

Fullerton, Thomas M., Jr. 2000. "Specification of a Borderplex Econometric Forecasting Model." **International Regional Science Review** (forthcoming).

Fullerton, Thomas M., Jr. and Carol T. West. 1998. "Regional Econometric Housing Start Forecast Accuracy in Florida." **Review of Regional Studies** 28: 15-42.

Hunt, Lester C., and Martin C. Snell. 1997. "Comparative Properties of Local Econometric Models in the U.K." **Regional Studies** 31: 891-902.

Laaksonen, Mika, Thomas M. Fullerton, Jr. and Carol T. West. 1998. "Regional Multi-Family Housing Start Forecast Performance." **Proceedings of the American Statistical Association** (Business and Economic Statistics Section): 62-67.

Lenze, David L. 2000. "Forecast Accuracy and Efficiency: An Evaluation of Ex Ante Substate Long-Term Forecasts." **International Regional Science Review** 23: 201-226.

LeSage, James P. 1990. “Forecasting Metropolitan Employment using an Export-base Error-correction Model.” **Journal of Regional Science** 30: 307-323.

Stephen K. McNees. 1992. “How Large are Economic Forecast Errors?” **New England Economic Review** (July/August): 25-33.

Mizrach, Bruce. 1992. “The Distribution of the Theil U-statistic in Bivariate Normal Populations.” **Economics Letters** 38: 163-167.

Nelson, Charles R. 1984. “A Benchmark for the Accuracy of Econometric Forecasts of GNP.” **Business Economics** 19: 52-58.

Shoesmith, Gary L. 1992. “Co-integration, Error Correction and Improved Medium-term Regional VAR Forecasting.” **Journal of Forecasting** 11: 91-109.

Topel, Robert H., and Sherwin H. Rosen. 1988. “Housing Investment in the United States.” **Journal of Political Economy** 96: 718-740.

Webb, Roy H. 1984. “Vector Autoregressions as a Tool for Forecast Evaluation.” Federal Reserve Bank of Richmond **Economic Review** (January/February) 70: 3-11.

Weller, Barry R. 1990. “Predicting Small Region Sectoral Responses to Changes in Aggregate Economic Activity: A Time Series Approach.” **Journal of Forecasting** 9: 273-281.

West, Carol T. 1995. “Regional Heterogeneity of the Florida Economy.” Chapter 1 in **The Economy of Florida**. Gainesville, FL: University of Florida Bureau of Economic and Business Research.

West, Carol T. 1996. “System-based Weights vs. Series-specific Weights in the Combination of Forecasts.” **Journal of Forecasting** 15: 369-383.

West, Carol T. and Thomas M. Fullerton, Jr. 1996a. “Assessing the Historical Accuracy of Regional Economic Forecasts.” **Journal of Forecasting** 15: 19-36.

West, Carol T. and Thomas M. Fullerton, Jr. 1996b. “Forecast Summary: Florida Economy.” **The Florida Outlook** 20: 11-26.

Zandi, Mark M. 1999. “Housing is the Key.” **Regional Financial Review** 10 (July): 4-14.

Table 1
RSEM Single-Family Housing Start Equation In-Sample Explanatory Power

Market	R^2 or Coefficient of Determination
Florida	0.852
Ft. Lauderdale	0.802
Jacksonville	0.838
Miami	0.802
Orlando	0.856
Tampa	0.881
W. Palm Beach	0.898

Note: Material in Table 1 summarizes the in-sample fits for the single-family housing start equations for Florida and the six largest metropolitan economies in the University of Florida quarterly econometric forecasting model system.

Table 2
Single-Family Housing Start Summary Statistics (in thousands)

Market	Mean	Standard Deviation	Coeff. of Variation	Observations
Florida	19.370	6.082	0.314	116
Ft. Lauderdale	1.487	0.573	0.385	88
Jacksonville	1.397	0.421	0.302	88
Miami	1.479	0.484	0.327	88
Orlando	2.545	0.968	0.380	77
Tampa	3.077	0.990	0.322	88
W. Palm Beach	1.996	0.793	0.397	88
United States	1,037.541	204.400	0.197	116

Note: Material in Table 2 summarizes quarterly housing start data drawn from a 1967-1995 sample period for Florida and the United States. Sample data for the various metropolitan markets date from 1974. The coefficient of variation for each area is calculated as the ratio of each region's standard deviation to its respective mean.

Table 3
Single-Family Housing Start Final ARIMA Model Specifications

Market	Final Model Specification		Number of Specification Changes
Florida (state)	AR(4)	MA(6, 8)	4
Ft. Lauderdale		MA(8)	6
Jacksonville	AR(4)	MA(4)	11
Miami		MA(1, 4, 6)	4
Orlando	AR(1)		4
Tampa	AR(4)	MA(4)	7
West Palm Beach	AR(1, 6)	MA(6)	9

Note: Material in Table 4 summarizes the univariate time series modeling results for each region's housing start data. The time series equations are utilized to generate comparative benchmark extrapolations for the previously published structural model forecasts.

Table 4
ARIMA Theil Inequality RMSE Ratios

MSA	Step1	Step 2	Step 3	Step 4	Step 5	Step 6	Step 7	Step 8	Step 9	Step 10	Average
Florida	0.73	0.75	0.75	0.81	0.80	0.78	0.75	0.68	0.66	0.66	0.74
FTL	0.75	1.02	1.09	0.97	1.02	1.03	0.97	0.94	0.91	0.88	0.96
JAX	0.98	1.14	1.27	1.15	1.26	1.06	0.92	0.92	0.71	0.68	1.01
MIA	1.67	1.53	2.34	2.08	1.96	1.69	1.49	1.16	0.97	0.89	1.58
ORL	0.82	1.03	0.90	1.31	1.41	1.35	1.17	0.95	0.88	0.91	1.07
TPA	0.77	0.87	1.05	1.31	1.41	1.42	1.39	1.39	1.31	1.30	1.22
WPB	0.91	0.78	1.10	1.24	1.37	1.30	1.26	1.29	1.32	1.32	1.19
AVG	0.95	1.02	1.22	1.27	1.32	1.23	1.32	1.05	0.97	0.95	1.11

Note: The modified Theil inequality coefficients are also known as Theil U-statistics. They are calculated as the ratios of forecast root mean square errors between competing methodologies. $U < 1.0$ implies structural model predictive superiority, while $U > 1.0$ implies univariate ARIMA predictive superiority.

Table 5
Random Walk Theil Inequality RMSE Ratios

MSA	Step1	Step 2	Step 3	Step 4	Step 5	Step 6	Step 7	Step 8	Step 9	Step 10	Average
Florida	0.83	0.99	1.07	1.13	1.17	1.09	1.03	0.93	0.85	0.84	0.99
FTL	0.79	1.01	1.00	0.93	0.97	0.99	0.92	0.88	0.86	0.83	0.92
JAX	1.16	1.29	1.43	1.37	1.36	1.13	0.98	0.91	0.75	0.70	1.11
MIA	1.55	1.34	1.89	1.68	1.51	1.27	1.10	0.93	0.79	0.75	1.28
ORL	0.91	1.12	0.98	1.16	1.16	1.15	1.07	0.85	0.77	0.81	1.00
TPA	0.89	0.95	1.44	1.44	1.54	1.56	1.53	1.50	1.39	1.36	1.36
WPB	0.95	0.82	1.12	1.23	1.28	1.17	1.13	1.12	1.12	1.14	1.11
AVG	1.01	1.07	1.28	1.28	1.28	1.19	1.11	1.01	0.93	0.92	1.11

Note: The modified Theil inequality coefficients are also known as Theil U-statistics. They are calculated as the ratios of forecast root mean square errors between competing methodologies. $U < 1.0$ implies structural model predictive superiority, while $U > 1.0$ implies random walk predictive superiority.