CBRE HOTELS

The World's Leading Hotel Experts.

ASSESSING ACCURACY: *HOTEL HORIZONS®* FORECASTS

HOTELS

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EXECUTIVE SUMMARY

- The *Hotel Horizons®* econometric forecasting models use national and MSA data as the foundation to hotel market forecasts and are comprised of multi-equation demand and supply models. Assessments of near-term supply changes are made by locally based CBRE Hotels consultants working in offices across the U.S. A committee of CBRE hotel experts performs a thorough final review of each model prediction.
- The U.S. hotel industry had another strong year in 2017 with RevPAR up 2.9% over the prior year. In this report, we examine how accurately *Hotel Horizons®* modeling predicted this performance as well as the performance of years previous to 2017.
- *Hotel Horizons®* econometric forecast models rely on economic forecasts from CBRE Econometric Advisors to guide our hotel market forecasts. There were a small number of errors and economic forecasts did not meaningfully affect hotel market forecasts.
- For the nation, *Hotel Horizons®* chain scale and location RevPAR forecasts had a mean absolute error of 1.69% and 1.31% from Q1 2014-Q4 2017, respectively. In 2017, these errors were 0.02% for both the chain scales and the locations. Indicating a strong forecast performance for the year.
- MSA level RevPAR forecasts show similar levels of performance in terms of mean absolute errors. In 2017, 37 of the 60 markets examined had a mean absolute error of less than 3%. 8 of these had a mean absolute error under 2%, indicating extremely high levels of precision in forecasts of those markets.
- *Hotel Horizons®* forecast accuracy generally improved over time. The mean absolute error of the one-year ahead forecast across markets was 2.64% for 2015 and 2.43% for 2017, down from 2.67% in 2016. National forecasts improved as well, but had a spike in mean absolute error in 2016 as ADR was overpredicted.

1. INTRODUCTION, OVERVIEW OF U.S. HOTEL MARKET FUNDAMENTALS SINCE 2014

This report contains an accuracy self-assessment of the CBRE Hotels' Americas Research *Hotel Horizons*® forecasts. This assessment is developed from comparisons between forecast changes in hotel market performance and actual changes during the period 2013 through 2017. We also compare our econometric forecasts to forecasts from an intuitive scenario. Previous analysis were conducted during 2005, 2010, 2014, 2015, and 2016.[1] As part of the 2017 assessment, we examine outcomes from the industry recovery that produced record occupancies through 2017 and the impact of economic events on hotel market forecasting accuracy. Specifically, the study analyzes *Hotel Horizons*® forecasts released during the first quarter of each year from 2013 through 2017.

We analyze short-term accuracy defined as rolling one-year forecasts versus actual results for revenue per available room (RevPAR), average daily rate (ADR), occupancy (OCC), demand (*i.e.,* rooms sold), and supply (*i.e.*, rooms available). Long-term accuracy over the five-year interval also is reported. The exhibits contained herein display information about annual forecasting accuracy for all U.S. hotels, hotel chain scales, across locations, and for 59 of the 60 *Hotel Horizons*® Metropolitan Statistical Area (MSA) markets[2]. We rely on various statistical measures, such as mean absolute error and Theil's U2 statistic, to assess accuracy.[3]

The period covered in this self-assessment was a period of modest, mostly steady economic activity, highlighted by a number of meaningful dips on the road to economic recovery. Changes in general economic conditions brought about coincidental, but not necessarily synchronous, movements in hotel market performance measures. This response is reflected in the performance history for U.S. hotels shown in Exhibit 1. Between 2013 and 2017, RevPAR for all U.S. hotels increased each year, but the pace of growth slowed. Both Upper- and Lower-Price hotels experienced these fluctuations through growth deceleration over 2013-2017 with a slight increase to the pace of growth in lower-priced hotels occurring in 2017.

[1] See www.cbrehotels.com
[2] Milwaukee was not included in this assessment because it is a new market to the *Hotel Horizons*® portfolio. Therefore, Milwaukee has insufficient previous forecasts to compare against their current forecasts.
[3] These measures are defined later in this report and in Appendix A.

Exhibit 1: U.S. Hotel Performance, 2014-2017 (Y-O-Y % Change)

ALL HOTELS	2014	2015	2016	2017
Occupancy	3.4	1.5	0.1	0.8
ADR	4.7	4.5	3.0	2.2
RevPAR	8.2	6.1	3.1	2.9
UPPER PRICE HOTELS				
Occupancy	2.8	1.1	0.0	0.3
ADR	4.7	4.0	2.5	1.5
RevPAR	7.6	5.1	2.5	1.8
LOWER PRICE HOTELS				
Occupancy	3.7	1.7	0.0	0.9
ADR	4.4	4.8	2.9	2.6
RevPAR	8.3	6.6	2.9	3.5

Source: CBRE Hotels' Americas Research, STR Q1 2019.

The implications for forecasting in conditions such as these are twofold. First, entirely unexpected events, such as the 2015 economic softening, numerous natural disasters, or closely-fought election results, cannot be woven into forecasts performed prior to such events. Second, modern forecasting models perform best during prolonged cyclical up phases and down phases and perform their worst around turning points. The rapid decline in oil prices as well as the sudden rise in financial market volatility during the latter half of 2015 were largely unexpected and may have influenced hotel performance in unanticipated ways. In 2016, many of the gateway markets in the U.S. experienced declines as a result of the strong dollar curbing the spending power of international visitors. Recent uncertainty surrounding trade policy represents a largely unanticipated risk.

The remainder of this report is organized as follows. Section 2 describes how CBRE Hotels' Americas Research approaches hotel market forecasting including discussions about the data used, the statistical techniques employed, and the potential sources of forecasting errors. In Section 3, we provide details about the measures introduced to assess the accuracy of *Hotel Horizons®* forecasts. Sections 4 and 5 present the results of our assessments for all U.S. hotels, chain scales, locations, and 59 of the 60 *Hotel Horizons®* MSAs we cover, respectively. Section 6 examines the comparative accuracy across scenarios. The final section gives a summary of our forecasting effort during the period 2013-2017.

2. HOW *HOTEL HORIZONS®* FORECASTS ARE PRODUCED

CBRE Hotels' Americas Research prepares forecasts of the hotel markets in the U.S. based on generally accepted econometric procedures and sound judgment regarding fundamental relationships of the economic and behavioral market indicators to hotel financial performance. These relationships have been tracked by CBRE (formerly PKF Hospitality Research) for over 70 years. The models that underlie econometric forecasts rely on statistical linkages estimated with historical data that come from actual market transactions involving individuals and firms interacting in hotel markets.

2.1 Econometric Models

The *Hotel Horizons*® econometric forecasting models, because they represent an entire sector of the national and MSA economies, fall into the category of multi-equation, demand and supply models. These models have a general structure as defined below but vary in their form for particular market applications. The three estimated equations are:

1. *Demand* - The number of rooms occupied (*i.e.*, accommodated demand) is the dependent variable in this equation which is explained by either gross domestic (metropolitan) product, real personal income, or total employment, which serve as the primary independent variables, along with the lagged changes in any of these variables and the lagged demand from the prior year.[4]
2. *Supply Change* - (change in the number of rooms available) is the dependent variable, which is explained by real ADR and OCC, serving as the main independent variables along with the change in supply from the prior period.[5]
3. *ADR (Real)* - is the dependent variable, which is explained by occupancy, the primary independent variable, along with ADR from the previous period.[6]

These equations are estimated with ordinary least squares in a non-simultaneous fashion using data from STR and CBRE Econometric Advisors (CBRE EA) dating back to the late 1980s. The parameters (coefficients on each variable) are then used to forecast demand, supply change, and ADR by multiplying the parameters by CBRE EA forecast of the economic variables and relevant previously estimated values (lagged variables). Three additional calculations are made with these results as follows:

1. Supply change is added to the previous period number of available rooms to produce an available rooms level in future periods.
2. Number of rooms sold is divided by number of available rooms to obtain occupancy percent in each future period.
3. Expected inflation is added to real ADR to convert to nominal ADR.

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[4] Different numbers of lags are used for independent variables based upon statistical significance.
[5] *Ibid*.
[6] Different numbers of lags are used for independent variables based upon statistical significance.

Regression equation estimations using time-series data, such as the work done to produce *Hotel Horizons®* forecasts, may have an econometric problem of autocorrelation. For each of the equations estimated by CBRE, we run tests to detect the presence of autocorrelation, and if the problem is found, corrective measures are introduced.[7]

2.2 Judgmental Intervention

The econometric models predict future room supply in small increments (*e.g.,* 50 rooms per quarter). In reality, rooms typically enter and leave markets in larger blocks (*e.g.,* 300 rooms) as new hotels are placed in, and removed from, service. When, for example, it becomes apparent that a new hotel(s) will be put in service within the next 18 months the modeled supply change will be manually adjusted to account for the opening of the new hotel. The reverse also is true when it becomes apparent that a hotel(s) are taken out of service (*e.g.,* demolished or converted to an alternative use). These assessments of near-term supply changes are made by locally based CBRE Hotels consultants working in the various offices across the U.S.

Finally, a committee of hotel experts from CBRE performs a thorough review of each model prediction. Locally based consultants throughout CBRE also participate in these reviews. The quarterly forecasts for the current year, as well as the annual forecasts beyond the current year, are subject to review. This committee modifies predictions from the model when there is compelling evidence that factors have come into play in a market that the model could not possibly foresee. A hurricane Katrina-style event, as an extreme example, would cause the committee's forecast to differ noticeably from the model's prediction in not only the MSA in which the event occurred but also competing MSAs within the region. In most instances, however, the committee either defers to the model prediction or makes modest adjustments.

2.3 Data Sources and Issues

The forecasts utilize historical data from STR beginning in Q1 1987 and involve three performance measures – rooms available, rooms occupied, and rooms revenue. Using these measures, we compute three additional measures - ADR, occupancy percent, and RevPAR. The STR universe, more than five million rooms, is intended to represent an exhaustive sample of hotel rooms in the U.S. However, STR analysts occasionally modify the census, altering the historical record. Hence, in producing this accuracy assessment, we made certain that forecast results and histories are in synchronization.

The second important data source for *Hotel Horizons®* forecasts is CBRE EA. The vast array of economic variables provided by this firm, both at the national and MSA geographic strata.

[7] We do not test for, nor expect, distortions resulting from another issue sometimes encountered when performing econometric analyses with time series data known as spurious correlation.

provide a rich testing environment for the development of stable relationships between economic and hotel market experiences. We use the historical information from CBRE EA and STR to build regression equations. Next, we use the forecasts of economic variables from CBRE EA to forecast hotel demand, supply, and ADR; and then compute OCC and RevPAR.

An implication of using CBRE EA forecasts is that our forecasts incorporate errors from their models along with errors from our models. The impact of these errors on *Hotel Horizons®* forecasting accuracy is discussed with regard to scenario in section 6. As an illustration, Exhibit 2 presents errors from CBRE EA's 2017 annual employment forecast of the 60 *Hotel Horizons®*

Exhibit 2: CBRE EA's Percent Change in Employment, 2017

MSA	FORECAST	ACTUAL	ERROR	MSA	FORECAST	ACTUAL	ERROR
Albany	0.8	0.8	0.0	Milwaukee	1.1	0.1	-1.0
Albuquerque	0.6	0.8	0.3	Minneapolis	1.4	2.2	0.8
Anaheim	1.8	0.5	-1.3	Nashville	1.9	3.1	1.2
Atlanta	2.1	3.1	1.0	New Orleans	1.2	0.2	-1.0
Austin	2.2	2.5	0.2	New York	0.9	1.5	0.6
Baltimore	1.2	1.0	-0.3	Newark	1.2	0.0	-1.2
Boston	1.4	1.8	0.3	Norfolk-VA Beach	1.0	-0.2	-1.2
Charleston	2.6	2.0	-0.6	Oahu	1.3	0.9	-0.3
Charlotte	2.0	2.5	0.5	Oakland	1.8	1.8	-0.1
Chicago	1.1	0.7	-0.4	Omaha	1.1	1.5	0.4
Cincinnati	1.6	2.2	0.7	Orlando	3.5	3.5	0.0
Cleveland	1.5	0.6	-0.9	Philadelphia	1.4	1.8	0.4
Columbia	2.1	1.0	-1.1	Phoenix	2.9	2.2	-0.7
Columbus	1.9	2.1	0.2	Pittsburgh	0.6	1.0	0.3
Dallas	2.8	3.1	0.3	Portland	2.1	2.3	0.1
Dayton	1.6	1.0	-0.6	Raleigh-Durham	2.3	2.7	0.5
Denver	2.1	2.0	-0.1	Richmond	1.9	1.6	-0.2
Detroit	1.6	1.9	0.3	Sacramento	1.9	1.6	-0.4
Fort Lauderdale	2.5	2.9	0.4	Saint Louis	1.3	0.8	-0.5
Fort Worth	2.5	2.6	0.1	Salt Lake City	2.5	2.6	0.1
Hartford	0.9	0.9	0.1	San Antonio	1.3	2.3	1.0
Houston	0.6	1.3	0.6	San Diego	1.7	1.5	-0.2
Indianapolis	1.6	2.0	0.4	San Francisco	1.7	2.0	0.3
Jacksonville	2.9	2.5	-0.5	San Jose-Santa Cruz	2.2	1.5	-0.7
Kansas City	1.1	1.8	0.7	Savannah	1.7	2.6	0.9
Long Island	1.0	1.1	0.1	Seattle	2.8	2.6	-0.2
Los Angeles	1.4	1.2	-0.2	Tampa	2.2	2.5	0.4
Louisville	1.6	1.8	0.2	Tucson	1.9	0.1	-1.8
Memphis	1.2	1.1	-0.1	Washington DC	1.6	1.8	0.2
Miami	2.0	1.7	-0.3	West Palm Beach	2.8	2.2	-0.6

Sources: CBRE Econometric Advisors, CBRE Hotels' Americas Research

MSAs, all of which, except for Milwaukee, are included in this report. We see from Exhibit 2 that most forecast errors for CBRE EA MSAs are quite small (within one percent). We believe these minor errors generally had minimal impact on the *Hotel Horizons®* forecast error.

3. ACCURACY ASSESSMENT METHODOLOGY

Assessing the accuracy of forecasts involves an analysis of errors, and often an examination of the sources of those errors. The 2017 version of CBRE Hotels' Americas Research self-assessment of *Hotel Horizons®* forecasts involves both the investigations of absolute errors – those from taking differences between actual performances realized after forecasting and forecast performance made before realizations – and relative errors – those from taking differences between *Hotel Horizons®* forecasts and forecasts from an intuitive approach.

3.1 Absolute Measures

The errors generated from *Hotel Horizons®* forecasts, *e*, may be defined as the differences between actual hotel market results, *A*, reported each year by STR and the CBRE Hotels' Americas Research forecast numbers, *F*, such that

$$e = A - F \tag{1}$$

An appropriate way to represent these differences involves not allowing negative and positive 'misses' to cancel each other. The effect of the mathematical signs needs to be removed either by taking the absolute value of e ($|e|$) or by squaring e (e^2). Thus, the mean absolute error (MAE) can be defined as

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|e_i| \tag{2}$$

Also, the root mean square error (RMSE) can be defined as

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e^2}. \tag{3}$$

RMSE is commonly used in statistical literature due to its mathematical flexibility; however, MAE has an advantage in that it has a straightforward interpretation. The MAE is the average amount, higher or lower, the forecast was off by as measured in the same units as the forecast. For this simplicity of interpretation, MAE is the measure used most throughout this paper.

3.2 Relative Measures

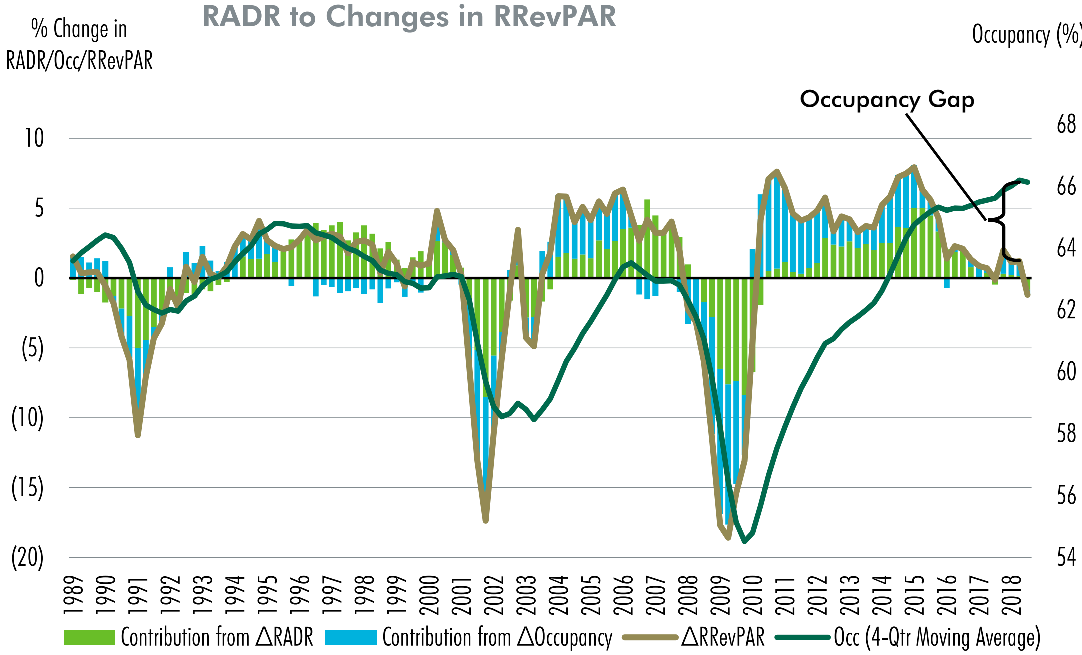
Forecasts are often evaluated in relative terms as well as absolute terms. Typically, the forecast results generated by the theoretically preferred model are evaluated against results from an alternative, more simply conceived set of assumptions about the future referred to as the intuitive model. To construct intuitive forecasts against which to compare *Hotel Horizons*®, we use rolling three-year historical averages to represent intuition-based expectations. To determine which forecast method is superior, we take the ratio of the RMSE of each forecast.

The above-described ratio is called Theil's U2 statistic, after Henri Theil, the econometrician that first suggested the measure. Theil's U2 provides a measure of relative accuracy and is centered on 1.0. If the U2 statistic is less than 1.0, the *Hotel Horizons*® method results in a smaller RMSE than the intuitive forecast and is thus the more accurate forecast. If U2 is 1, the two forecasts are the same, and if U2 is greater than 1, the intuitive forecast performs better than the *Hotel Horizons*® forecast (see Appendix A for details). The measure is asymmetric, *i.e.* more accurate *Hotel Horizons*® forecasts will always between 0 and 1 while less accurate forecasts are unbounded. This means that averaging U2 statistics is not meaningful. Instead, we report the proportion of U2 statistics that are either over or under 1.

4. ACCURACY OF U.S. AND CHAIN SCALE, AND LOCATION FORECASTS

Long-to-medium term forecasting accuracy experienced some difficulty over the period 2013-2017. Exhibit 3 provides historical performance context for these forecasts and illustrates a phenomenon that CBRE Hotels' Americas Research has been examining closely and have dubbed the "rate paradox." The rate paradox represents a change in the historical relationship between occupancy and rate. Even as occupancy continued to grow well past historical long-run averages after 2015, rate stagnated or moved more slowly than history would suggest. This created an "occupancy gap," a conspicuous gap between the level occupancy and rate growth that. Several hypotheses for why the relationship shifted here ranging from the rise of online travel agencies, new revenue management software, loyalty redemption policies, to dramatic increases in sharing economy room supply. Whatever the cause, the paradox caused rate predictions to be overly optimistic in forecasts of 2015 and 2016. Corrections were made to the models and judgmental intervention afterward to correct this disturbance.

Exhibit 3: Contributions from Changes to Occupancy and RADR to Changes in RRevPAR



Sources: CBRE Hotels' Americas Research, STR Q1 2019.

The change in rate behavior also flowed through to the other predictions as well. The conventional story for late cycle hotel performance is that rate gains typically contribute more to RevPAR in the later cycle as occupancy decreases to the long-run average capacity. When the gains from rate did not materialize, neither did the decrease to occupancy. Although more accurate than the ADR forecast, occupancy and demand were under-forecast as a result of the assumptions around rate.

To quantify long-term accuracy, implied compound average growth rates (CAGR) were calculated for 2017 market forecasts of RevPAR via the discrete compounding formula:

$$CAGR_{RevPAR} = \left(\frac{2017\ RevPAR}{Starting\ RevPAR}\right)^{1/Years} - 1 \qquad (4)$$

where 'Years' is the number of years between the starting date and 2017. This CAGR is calculated for both the forecast and the actual values, and the difference indicates the error. MAE for the individual markets is calculated to give some indication of the average error for individual market forecasts. An aggregate measure is also calculated to give an indication of the accuracy of the forecast as a whole as well as the direction of the error. Results are tabulated in percentage terms in Exhibit 4. MAE attains a high in 2015 and the Market Average aggregate error, previously quite small, increases in 2014 and 2015. The forecasts overpredicted rate growth and thus overpredicted RevPAR CAGR by 1.33% as the occupancy gap grew and the rate paradox set in.

Exhibit 4: Long Term Forecast of 2017 Performance

	5 Year CAGR (as of 2012.4)			4 Year CAGR (as of 2013.4)			3 Year CAGR (as of 2014.4)			2 Year CAGR (as of 2015.4)		
FORECASTS:	Forecast(%)	Actual(%)	Diff.(%)	Forecast(%)	Actual(%)	Diff.(%)	Forecast(%)	Actual(%)	Diff.(%)	Forecast(%)	Actual(%)	Diff.(%)
Market Average	5.60	5.45	0.14	5.47	5.36	0.11	4.73	4.14	0.59	4.14	2.80	1.33
Mean Absolute Error			1.92			2.20			1.98			2.31
Albany							4.53	-1.27	5.80	-0.62	-3.30	2.67
Albuquerque	4.33	4.94	-0.61	4.93	5.38	-0.45	4.28	5.17	-0.88	4.82	4.99	-0.17
Anaheim	6.03	6.74	-0.72	6.96	6.45	0.51	6.14	5.56	0.58	7.40	3.83	3.57
Atlanta	6.48	7.51	-1.02	4.93	7.92	-2.99	6.25	6.29	-0.04	6.14	4.84	1.30
Austin	4.48	5.30	-0.83	5.01	4.13	0.88	1.48	2.94	-1.46	1.87	0.33	1.54
Baltimore	6.92	2.25	4.67	5.41	2.45	2.95	6.39	0.70	5.69	3.39	0.79	2.60
Boston	5.83	5.02	0.81	5.85	4.86	0.99	5.93	2.91	3.02	6.36	0.55	5.81
Charleston				5.70	6.45	-0.75	6.00	4.97	1.02	3.83	4.72	-0.89
Charlotte	5.72	5.99	-0.26	5.34	7.26	-1.92	4.88	5.08	-0.19	3.14	3.09	0.05
Chicago	6.80	3.24	3.56	5.51	2.96	2.55	5.76	1.60	4.16	4.72	-0.83	5.55
Cincinnati	4.30	6.63	-2.33	6.46	6.45	0.01	4.46	5.34	-0.88	3.56	3.98	-0.42
Cleveland	5.57	2.92	2.65	6.12	1.89	4.23	4.72	1.22	3.50	2.81	-1.49	4.31
Columbia							4.06	4.93	-0.88	3.88	4.93	-1.05
Columbus	5.53	5.11	0.43	4.12	5.13	-1.01	3.80	4.77	-0.97	5.82	2.93	2.89
Dallas	6.65	6.92	-0.28	6.66	6.05	0.62	5.17	5.05	0.11	4.82	2.66	2.16
Dayton							3.81	6.64	-2.83	3.66	5.84	-2.19
Denver	6.79	7.47	-0.67	6.68	7.24	-0.56	7.03	4.43	2.60	4.15	2.71	1.44
Detroit	5.32	6.74	-1.42	4.21	6.59	-2.37	4.32	5.43	-1.10	3.61	4.94	-1.33
Fort Lauderdale	5.94	5.87	0.07	5.82	5.47	0.34	5.49	3.69	1.80	4.84	1.53	3.31
Fort Worth	5.55	5.95	-0.40	4.60	6.25	-1.65	3.71	5.03	-1.32	3.09	3.70	-0.61
Hartford	6.80	4.25	2.55	5.29	4.44	0.85	4.55	4.42	0.13	4.08	3.01	1.07
Houston	6.60	3.22	3.38	5.44	0.70	4.74	0.43	-2.27	2.70	-4.64	-1.70	-2.94
Indianapolis	4.73	5.99	-1.27	4.93	7.05	-2.11	5.17	6.18	-1.01	3.96	5.19	-1.23
Jacksonville	6.01	9.23	-3.23	5.79	9.51	-3.71	5.57	8.60	-3.03	7.86	7.83	0.03
Kansas City	4.89	7.28	-2.39	5.75	7.95	-2.21	4.52	6.31	-1.80	3.60	5.38	-1.77
Long Island	5.58	3.87	1.70	5.44	2.82	2.62	4.43	3.60	0.82	2.54	2.21	0.32
Los Angeles	5.77	7.47	-1.70	6.41	7.61	-1.20	5.80	6.70	-0.90	5.85	5.70	0.15
Louisville							4.93	3.33	1.60	3.33	0.74	2.60
Memphis	4.58	5.64	-1.07	5.20	6.47	-1.27	5.94	4.52	1.42	4.76	4.72	0.03
Miami	5.42	3.10	2.32	7.04	1.80	5.24	4.66	0.06	4.60	3.23	-2.43	5.65
Minneapolis	5.40	4.25	1.15	6.01	3.57	2.44	5.89	2.30	3.59	3.12	0.63	2.49
Nashville	4.64	10.90	-6.25	5.99	10.57	-4.57	8.97	8.05	0.92	6.41	6.64	-0.23
New Orleans	4.03	2.50	1.53	4.02	1.54	2.48	2.90	0.58	2.32	1.61	-0.84	2.45
New York	5.14	0.17	4.97	3.57	-0.71	4.28	2.11	-1.57	3.68	-1.04	-1.10	0.06
Newark	6.86	3.38	3.47	6.06	3.50	2.56	4.57	2.98	1.59	4.44	2.29	2.15
Norfolk-VA Beach							3.69	6.91	-3.22	3.52	6.61	-3.10
Oahu	7.45	4.44	3.01	6.05	2.76	3.30	4.81	2.55	2.25	3.94	2.08	1.86
Oakland	7.50	9.67	-2.17	6.61	9.30	-2.69	8.63	7.79	0.84	10.71	4.07	6.64
Omaha							1.87	0.95	0.92	1.19	0.88	0.31
Orlando	6.43	7.59	-1.16	6.32	7.72	-1.39	5.22	6.86	-1.64	8.62	6.56	2.06
Philadelphia	3.72	2.27	1.45	3.73	3.06	0.66	4.87	2.53	2.34	5.62	1.13	4.49
Phoenix	5.07	7.05	-1.99	5.53	7.38	-1.85	3.75	6.79	-3.04	3.37	4.03	-0.65
Pittsburgh	5.24	-1.62	6.86	4.79	-2.02	6.81	2.41	-4.57	6.98	0.64	-6.18	6.81
Portland	5.55	8.47	-2.92	6.74	7.97	-1.22	6.75	6.81	-0.06	7.54	3.36	4.19
Raleigh-Durham	5.51	5.72	-0.21	5.40	5.96	-0.56	3.19	4.16	-0.97	2.51	2.70	-0.18
Richmond	4.34	6.19	-1.84	4.43	8.08	-3.65	3.61	7.03	-3.42	6.05	5.45	0.60
Sacramento	5.91	10.03	-4.13	5.29	10.56	-5.26	4.82	10.92	-6.09	7.60	9.97	-2.38
Saint Louis	4.34	5.52	-1.18	5.19	5.19	0.00	3.94	3.62	0.32	4.87	2.72	2.14
Salt Lake City	4.76	5.95	-1.19	3.94	7.02	-3.08	5.56	7.60	-2.03	7.28	5.52	1.76
San Antonio	6.11	3.36	2.75	5.33	3.24	2.09	4.53	2.57	1.96	3.01	2.26	0.74
San Diego	6.69	5.87	0.82	5.29	6.28	-0.99	4.90	5.36	-0.46	7.64	3.72	3.91
San Francisco	6.17	6.61	-0.44	7.91	5.18	2.74	7.89	2.76	5.14	6.90	0.59	6.31
San Jose-Santa Cruz							10.22	8.17	2.06	10.07	4.04	6.04
Savannah							6.58	5.41	1.17	6.90	2.32	4.58
Seattle	6.50	7.47	-0.97	4.50	7.38	-2.88	6.31	5.68	0.63	3.15	4.11	-0.96
Tampa	6.06	7.93	-1.87	5.85	9.20	-3.35	7.02	8.42	-1.41	7.43	5.91	1.51
Tucson	7.01	5.93	1.09	4.27	7.33	-3.06	7.00	9.53	-2.53	6.78	11.36	-4.58
Washington DC	4.66	3.50	1.16	3.45	4.81	-1.36	5.28	4.71	0.57	3.82	4.41	-0.59
West Palm Beach	7.07	6.08	0.99	5.29	5.27	0.01	5.63	3.80	1.83	5.34	2.36	2.97

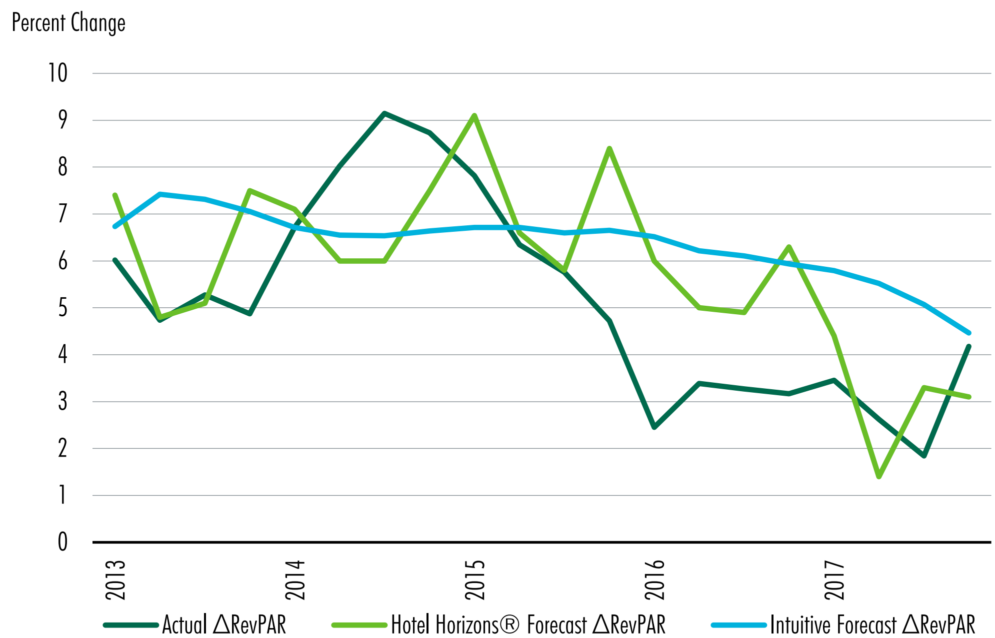
Sources: CBRE Hotels' Americas Reseach, STR Q1 2019.

4.1 Description of the Intuitive Forecast and Short-Term Predictions

Theil's U2 statistic uses a simplified forecast as a basis of comparison, in our case the three-year rolling average of the growth rate. This is an attempt to capture the behavior of a market participant that would make an educated guess on the future based strictly on what has occurred in the recent past. To perform this analysis, we use one year's worth of quarterly forecasts gathered from the March editions of *Hotel Horizons*®. This allows us to compare forecasts from as late as March 2017 to actual data through 2017. Moreover, they allow us to examine how forecasts changed over time and in response to new information.

Exhibit 5 presents short-term RevPAR forecasts, illustrating the effects of the rate paradox on forecast accuracy. RevPAR is overpredicted starting in Q4 2015.

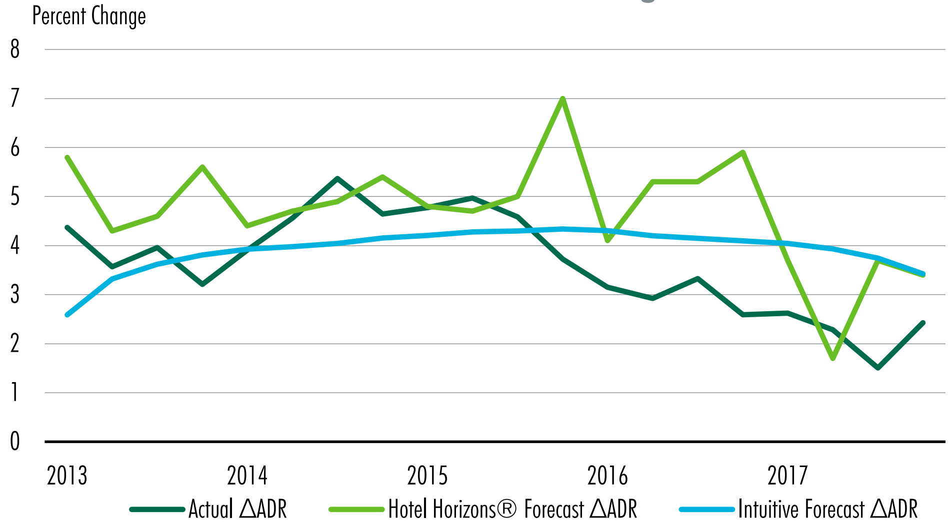
Exhibit 5: One-Year-Ahead Hotel Horizons® Forecast, Actual and Intuitive Forecast RevPAR Change



Sources: CBRE Hotels' Americas Research, STR Q1 2019.

We can decompose the RevPAR growth forecast into its constituents, ADR and occupancy growth. Exhibit 6 presents the short-term ADR change forecasts from *Hotel Horizons*® and the intuitive forecast compared to the actual rate of change. As noted previously, *Hotel Horizons*® over-predicted ADR in 2015 and 2016. These predictions became more accurate in 2017. The intuitive forecast tries to follow the actual data, but since it can only incorporate information from the past realized values of ADR, it is slow to react.

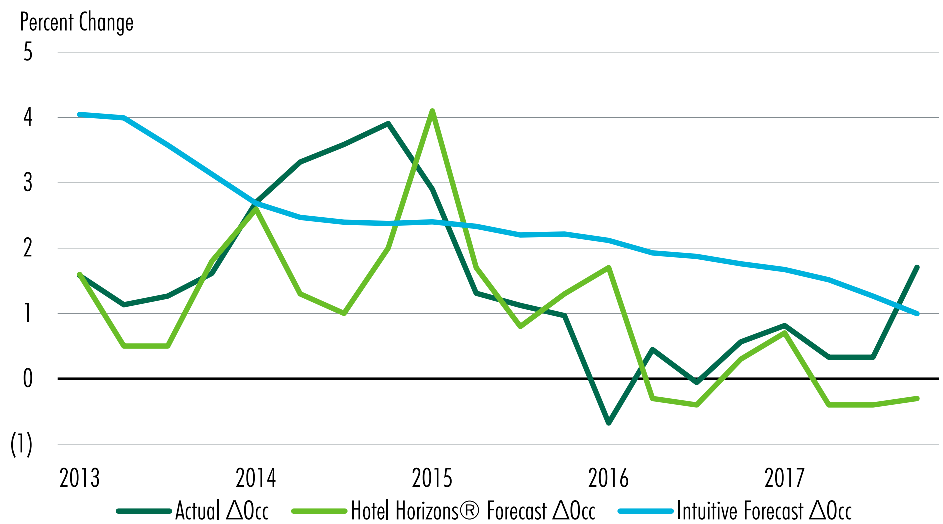
Exhibit 6: One-Year-Ahead *Hotel Horizons*® Forecast, Actual and Intuitive Forecast ADR Change



Sources: CBRE Hotels' Americas Research, STR Q1 2019.

Exhibit 7 presents the short-term occupancy change forecasts from *Hotel Horizons*® and the intuitive forecast compared to the actual rate of change. Here the *Hotel Horizons*® forecast follows the actual values more closely and nimbly adapts to changing conditions. Although there were slight missteps in 2014 and 2016, the *Hotel Horizons*® forecast is better at adapting to new conditions than the intuitive forecast.

Exhibit 7: One-Year-Ahead Hotel Horizons® Forecast, Actual and Intuitive Forecast Occupancy Change



Sources: CBRE Hotels' Americas Research, STR Q1 2019.

4.3 Chain Scales

The hotel inventory in the U.S. can be subdivided in many ways. Two common delineations are by market segment for chain-affiliated hotels and by property locations. Each quarter, *Hotel Horizons®* forecasts are prepared for these two categorizations. Exhibits 8 and 9 present forecast accuracy in two panels – one for chain scales and the other by locations. The hotel populations differ between these two subdivisions in that the chain scale delineation does not include independent hotels while the location subdivision includes independents. The U.S. hotel industry is comprised of approximately 70% chain-affiliated hotels and 30% independents. Hence, the chain scale subset is somewhat smaller and tends to include larger, higher quality properties than the location subset.

Exhibit 8: Absolute *Hotel Horizons* RevPAR Forecasting Accuracy, 2013-2017

PANEL A: BY CHAIN SCALE						
Mean Absolute Error of Chain Scale RevPAR (%)						
	2013	2014	2015	2016	2017	Average
Economy	1.94	2.12	0.39	2.38	0.37	1.44
Midscale	0.20	2.04	0.92	2.46	0.40	1.21
Upper Midscale	1.37	4.09	0.93	3.72	0.11	2.04
Upscale	0.03	3.30	3.56	2.56	0.55	2.00
Upper Upscale	0.06	1.63	3.40	2.48	0.19	1.56
Luxury	0.09	2.69	2.90	2.98	0.83	1.90
All	0.89	1.62	1.21	2.37	0.02	1.22
Individual Chain Scale Average	0.62	2.64	2.02	2.76	0.41	1.69
PANEL B: BY LOCATION						
Mean Absolute Error of Location RevPAR (%)						
	2013	2014	2015	2016	2017	Average
Airport	1.77	3.04	0.41	3.01	0.29	1.71
Interstate	1.79	2.26	1.69	2.36	1.58	1.94
Resort	0.84	0.12	1.28	1.28	0.18	0.74
Small Metro/Town	0.04	3.18	0.68	0.93	0.30	1.03
Suburban	1.24	2.28	0.27	0.33	0.05	0.83
Urban	1.80	0.59	2.78	2.46	0.59	1.64
All Locations	0.89	1.62	1.21	2.37	0.02	1.22
Individual Locations Average	1.25	1.91	1.19	1.73	0.50	1.31
Sources: CBRE Hotels' Americas Research Q1 2019						

Exhibit 9: Relative *Hotel Horizons* RevPAR Forecasting Accuracy, 2013-2017

PANEL A: BY CHAIN SCALE						
Theil's U2 Analysis of Chain Scale RevPAR						
	2013	2014	2015	2016	2017	%<1
Economy	6.25	0.64	2.24	0.42	0.05	60.0
Midscale	0.73	0.64	18.41	0.15	0.81	80.0
Upper Midscale	0.51	2.15	9.15	0.59	0.25	60.0
Upscale	0.04	1.12	2.17	0.26	0.12	60.0
Upper Upscale	0.06	2.47	1.93	0.35	0.06	60.0
Luxury	0.05	0.84	1.25	0.17	1.69	60.0
All Chain scales	0.25	2.03	0.63	0.01	0.54	80.0
%<1	85.7	42.9	14.3	100.0	85.7	
PANEL B: BY LOCATION						
Theil's U2 Analysis of Location RevPAR						
	2013	2014	2015	2016	2017	%<1
Airport	4.28	0.84	0.48	0.63	0.07	80.0
Interstate	0.71	0.92	1.14	0.60	3.52	60.0
Resort	1.96	0.68	3.55	0.40	0.09	60.0
Small Metro/Town	0.02	1.39	1.46	0.37	0.20	60.0
Suburban	0.76	1.01	0.68	0.10	0.01	80.0
Urban	0.88	2.68	1.07	0.60	0.20	60.0
All Locations	0.25	2.03	0.63	0.01	0.54	80.0
%<1	71.4	42.9	42.9	100.0	85.7	

Sources: CBRE Hotels' Americas Research Q1 2019

The forecast accuracy assessed in Exhibits 8 and 9 is for annual RevPAR growth rates at the end of each year from 2013-2017 which were published in March of that year. Exhibit 8 details MAE, a standard measure of absolute forecast accuracy (*i.e.*, direct comparison of forecast results to actual results). Exhibit 9 details Theil's U2 statistic, a comparison of *Hotel Horizons*® forecasts to a simpler, more basic forecast presented in the text above and formally defined in Appendix A.

For chain scales, the average MAE for the analysis period is fair at 1.69%. This measure varies as expected by year from 2013 through 2017. The larger MAE in the early years and especially in 2016 reflect the confusion created by the rate paradox and macroeconomic volatility that emerged in the second half of 2016. Forecast MAE noticeably improved in 2017 when insight on the new rate relationship was incorporated. From the RMSE analysis of 2013-2017, the order of accuracy is: midscale, economy, upper upscale, luxury, upscale, and upper midscale.

From the U2 analysis (*i.e.*, comparing model forecasts to the non-econometric forecasts), midscale hotels were forecast relatively better than other chain scales. From 2013-2017, aggregate *Hotel Horizons*® forecasts were superior to the non-econometric forecast except in

2015. In contrast to the MAE analysis, 2015 was the most difficult year for *Hotel Horizons®* forecasts in terms of the U2 statistic. Upper Midscale and Midscale chain scales had large U2 statistics, indicating that the MAE of the *Hotel Horizons®* forecast was ten to twenty times as large as the intuitive forecast; however, the MAEs for these chain scales were 0.92 and 0.93, quite accurate and well below the average. An examination of Exhibit 5 can provide some insight on how this is possible. The years 2014 and 2015 correspond with intersections of the actual RevPAR and intuitive forecast, meaning that some intuitive forecasts during these years were extremely close to the true values. Since the error of the intuitive forecast is in the denominator of the U2 formula, values of the U2 statistic become large as the forecast error for the intuitive forecast approach zero. The combination of econometric modeling and expert judgment underlying *Hotel Horizons®* gives a more accurate prediction than the intuitive forecast for most chain scales and locations outside of the previously mentioned problem years.

4.4 Locations

For locations, the average MAE for the period is an excellent 1.22%, outperforming our chain scale findings. From the MAE analysis of 2013-2017, the order of accuracy is: resort, suburban, small metro/town, urban, airport and interstate. The performance mirrors the behavior of the chain scale forecasts. MAE was generally higher in earlier years, particularly 2015 and 2016. By 2017, accuracy was attained at a high level for all locations.

Hotel Horizons® location forecasts were superior to the intuitive forecast from 2014 through 2017 based on the U2 analysis with the exceptions of resort and small metro/ town in 2015 and interstate hotels more generally. Over the five-year period airport and suburban locations performed better than other locations in relative accuracy (*i.e.*, compared to the intuitive approach). As in the case of the chain scale forecasts, 2015 proved to be the most challenging for modeling hotel performance on a relative basis, and the *Hotel Horizons®* forecasts are more accurate than the intuitive forecasts for most locations.

4.5 Chain Scale Accuracy Over Time

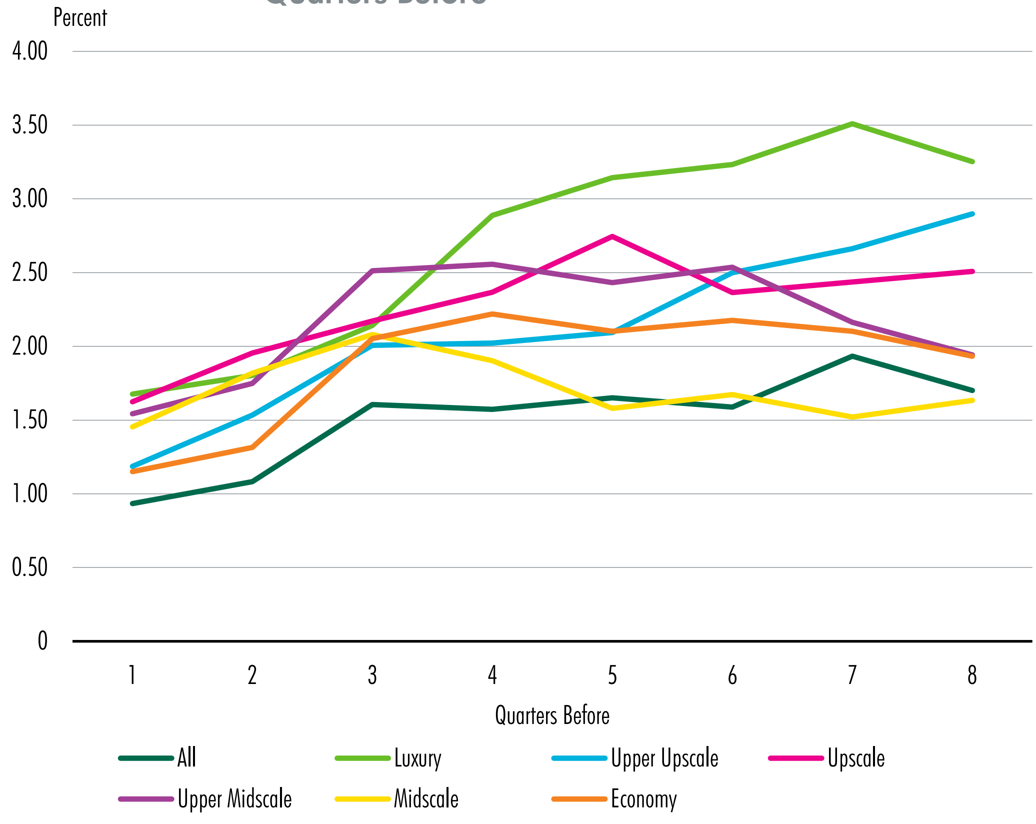
It seems a sensible proposition that near-term forecasts should have a higher level of accuracy than forecasts made for distant time horizons. We provide insight into how the average accuracy of our chain scale forecast changes as we move farther from the date of the forecast by calculating the MAE of forecasts made in each quarter compared to the realizations of the variables in future quarters. Exhibit 10 presents the results of this analysis in tabulated form and Exhibit 11 presents the results as a chart.

EXHIBIT 10: MEAN ABSOLUTE ERROR OF CHAIN SCALE REVPAR (%) BY QUARTERS BEFORE

Quarters Before	All	Luxury	Upper Upscale	Upscale	Upper Midscale	Midscale	Economy
1	0.93	1.68	1.19	1.62	1.54	1.45	1.15
2	1.08	1.80	1.53	1.96	1.75	1.82	1.31
3	1.60	2.14	2.01	2.17	2.51	2.08	2.05
4	1.57	2.89	2.02	2.37	2.56	1.90	2.22
5	1.65	3.14	2.09	2.74	2.43	1.58	2.10
6	1.59	3.23	2.50	2.36	2.54	1.67	2.18
7	1.93	3.51	2.66	2.44	2.16	1.52	2.10
8	1.70	3.25	2.90	2.51	1.94	1.63	1.93

Sources: CBRE Hotels' Americas Research Q1 2019.

Exhibit 11: MAE of Chain Scale RevPAR Forecasts by Quarters Before

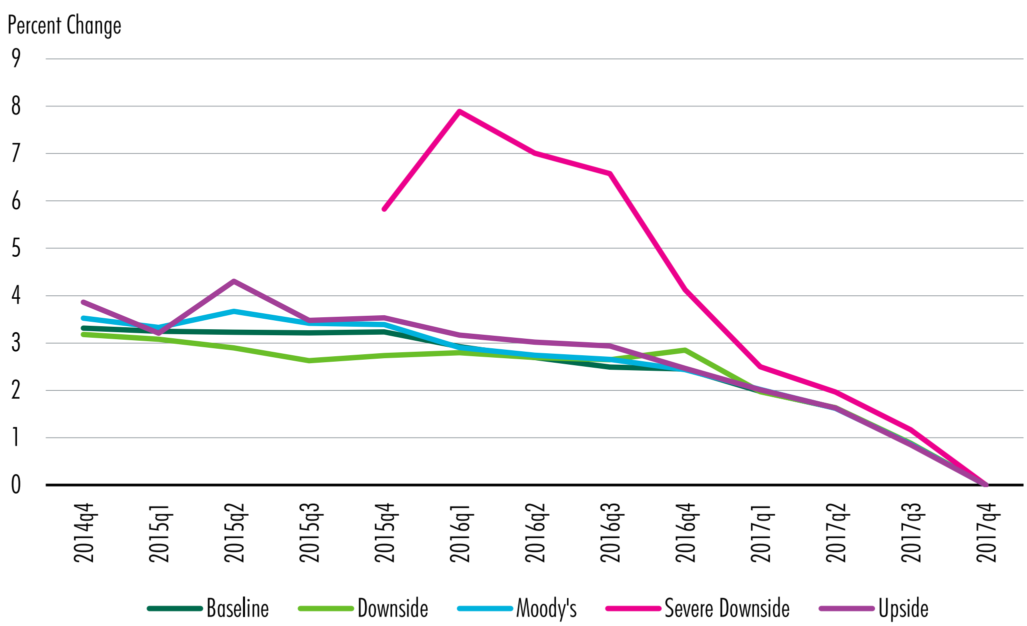


Sources: CBRE Hotels' Americas Research, STR Q1 2019.

The different chain scales have a remarkably consistent pattern. Errors for 1-quarter forecasts, *i.e.* forecasts of the next quarter, have the smallest error. As the number of quarters out the forecast extends increases, so too does the error until five quarters or more out, where errors sometimes increase (as in the upper upscale case) or decrease (as in the upper midscale case), but generally stay essentially the same. This provides some evidence that the use of short-term forecasts is sufficient to compare probable longer-term accuracy. Forecasts within the first year are generally the most accurate. In addition, errors for quarterly forecasts are generally higher than for annual forecasts, since exceptionally low and high quarters will often cancel each other out in aggregation. Luxury hotels are an especially difficult chain scale to forecast because of the variety of properties it includes. Many luxury properties are not familiar brands but unique destinations that intrinsically present more uncertainty.

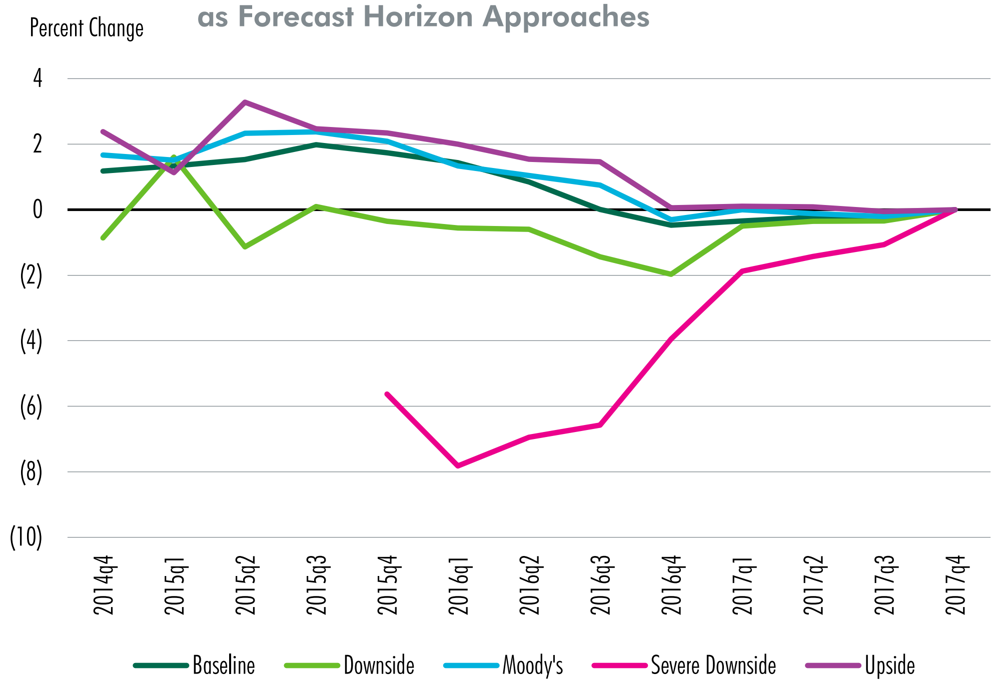
An alternative way to look at scenario forecasts over time is to plot how the forecast for the year of 2017 converges to the actual values as new information is added to our forecasts. Exhibit 12 illustrates this convergence across all markets by scenario in terms of MAE while Exhibit 13 illustrates the average error of the forecasts without taking the absolute value. Exhibit 13 therefore gives a measure of the direction of the bias of errors rather than the absolute scale of the errors.

Exhibit 12: Market Mean Absolute Error for 2017 RevPAR Change as Forecast Horizon Approaches



Sources: CBRE Hotels' Americas Research, STR Q1 2019.

Exhibit 13: Market Average Error for 2017 RevPAR Change as Forecast Horizon Approaches



Sources: CBRE Hotels' Americas Research, STR Q1 2019.

In terms of MAE, the downside scenario has the lowest error through 2015, thereafter the baseline scenario is the most accurate. The severe downside, representing an extreme situation, has the largest error. Turning to the direction of bias in Exhibit 13, the severe downside and downside scenario have a predictably downward bias. The upside scenario and Moody's scenarios have a generally positive bias; however, during 2017 the baseline scenario exhibited a negative bias, and the upside prediction was the most accurate.

5. ACCURACY OF MSA FORECASTS

The *Hotel Horizons*® universe covers 60 of the largest Metropolitan Statistical Areas (MSA) in the U.S. in terms of the size of the hotel market. These area-specific forecasts are generated each quarter and for each market for the aggregate categories of upper-price and lower-price hotels.[8] We evaluate the accuracy of 59 of our MSA forecasts by short-term (i.e., one year forward) during the 2013-2017 evaluation period. In Exhibit 14 we present evidence of the absolute accuracy of *Hotel Horizons*® forecasts of MSA RevPARs for one-year periods beginning in 2013 and ending in 2017. Specifically, the evaluation covers forecasts made in March of each year for that calendar year. In Exhibit 15 we present evidence of the accuracy of *Hotel Horizons*® forecasts relative to a non-econometric, intuitive approach to forecasting.

[8] A list of these MSA markets can be found at www.pip.cbrehotels.com. Upper-price hotels include the chain scale divisions luxury, upper- upscale and upscale; lower-price hotels include economy, mid-price, and upper mid-price chain scales.

Exhibit 14: Absolute Hotel Horizons RevPAR Forecasting Accuracy, 2013-2017

Mean Absolute Error of Market RevPAR

	2013	2014	2015	2016	2017	Average
Albany			3.42	4.00	2.78	3.40
Albuquerque	1.11	0.01	1.70	3.34	3.91	2.01
Anaheim	3.68	3.09	3.30	2.75	0.38	2.64
Atlanta	2.59	6.68	1.62	0.65	1.41	2.59
Austin	5.35	0.43	5.25	1.04	0.52	2.52
Baltimore	4.57	2.71	6.41	1.99	1.81	3.50
Boston	0.70	2.92	0.48	6.56	1.08	2.35
Charleston		4.51	0.07	1.94	1.85	2.09
Charlotte	4.64	7.47	0.89	0.28	1.40	2.94
Chicago	2.31	0.99	1.23	3.75	5.46	2.75
Cincinnati	3.08	4.50	4.56	1.08	0.67	2.78
Cleveland	3.77	2.37	1.86	2.91	7.44	3.67
Columbia			0.90	4.80	2.11	2.60
Columbus	0.37	1.63	5.87	0.44	1.65	1.99
Dallas	4.20	1.67	2.95	0.48	2.61	2.38
Dayton			3.86	6.19	1.32	3.79
Denver	1.02	9.95	0.37	1.63	0.36	2.66
Detroit	2.40	4.69	0.36	0.21	2.74	2.08
Fort Lauderdale	2.19	3.93	1.78	4.49	3.16	3.11
Fort Worth	1.22	3.56	1.47	0.33	0.27	1.37
Hartford	4.45	1.14	2.78	2.88	1.71	2.59
Houston	3.05	2.27	5.21	3.94	10.99	5.09
Indianapolis	0.26	3.79	1.39	2.44	0.29	1.63
Jacksonville	3.19	5.64	1.89	0.28	1.22	2.45
Kansas City	2.03	6.45	2.90	0.58	2.76	2.94
Long Island	4.68	0.91	1.53	1.40	2.92	2.29
Los Angeles	1.01	3.23	1.96	3.42	2.60	2.45
Louisville			3.24	2.43	4.82	3.50
Memphis	2.21	6.67	1.97	0.90	1.23	2.59
Miami	3.35	0.92	0.26	8.01	3.18	3.15
Minneapolis	3.13	0.57	0.68	0.27	6.17	2.16
Nashville	6.06	9.82	0.12	0.10	1.29	3.48
New Orleans	1.12	0.46	1.80	2.75	1.82	1.59
New York	2.49	2.02	5.45	2.29	1.35	2.72
Newark	3.29	1.38	0.20	2.14	0.41	1.48
Norfolk-VA Beach			1.19	2.48	3.60	2.42
Oahu	2.83	3.07	0.35	1.58	0.27	1.62
Oakland	1.97	4.25	4.95	5.50	0.29	3.39
Omaha			0.64	1.09	0.13	0.62
Orlando	1.82	2.28	2.98	3.88	7.94	3.78
Philadelphia	4.68	2.98	3.46	0.72	0.78	2.52
Phoenix	1.96	5.18	8.08	1.39	0.67	3.46
Pittsburgh	4.36	0.62	4.27	8.19	4.05	4.30
Portland	2.54	3.53	5.15	2.71	1.16	3.02
Raleigh-Durham	0.45	4.33	3.69	2.24	0.27	2.20
Richmond	7.48	5.97	4.33	0.91	1.50	4.04
Sacramento	2.64	2.22	6.07	0.26	4.36	3.11
Saint Louis	2.45	4.08	0.30	1.97	1.15	1.99
Salt Lake City	4.55	1.62	4.80	4.93	5.41	4.26
San Antonio	6.20	0.05	2.13	1.58	0.91	2.17
San Diego	1.68	3.71	3.01	4.40	2.62	3.08
San Francisco	4.52	1.37	3.13	4.26	1.19	2.90
San Jose-Santa Cruz			6.34	4.78	1.14	4.09
Savannah			4.71	4.55	1.32	3.53
Seattle	1.09	5.77	0.13	3.96	3.07	2.80
Tampa	1.01	5.33	3.58	2.37	1.21	2.70
Tucson	5.75	4.43	0.33	3.73	9.35	4.72
Washington DC	6.47	5.74	0.82	2.68	1.07	3.36
West Palm Beach	4.51	4.78	1.67	4.88	4.06	3.98
Market Average	3.05	3.48	2.64	2.67	2.43	2.84

Sources: CBRE Hotels' Americas Research Q1 2019

Exhibit 15: Relative Hotel Horizons RevPAR Forecasting Accuracy, 2013-2017

Theil's U2 Analysis of Market RevPAR

	2013	2014	2015	2016	2017	%<1
Albany			1.00	0.43	0.45	66.7
Albuquerque	0.47	0.00	0.60	1.18	1.36	60.0
Anaheim	8.04	13.51	12.46	0.61	0.09	40.0
Atlanta	9.79	0.86	2.63	0.18	0.25	60.0
Austin	2.28	0.17	4.78	0.13	0.09	60.0
Baltimore	2.00	0.54	1.89	2.03	0.43	40.0
Boston	0.17	0.82	1.01	0.74	0.26	80.0
Charleston		1.10	0.03	0.72	0.67	75.0
Charlotte	0.48	1.17	23.69	0.18	0.14	60.0
Chicago	0.46	1.88	2.04	0.62	0.88	60.0
Cincinnati	1.10	1.11	2.90	0.28	0.15	40.0
Cleveland	3.78	0.52	1.97	1.28	0.66	40.0
Columbia			0.50	4.68	0.47	66.7
Columbus	0.12	1.05	3.44	0.17	0.36	60.0
Dallas	1.14	18.77	1.45	0.12	0.30	40.0
Dayton			1.05	1.94	0.25	33.3
Denver	1.99	1.12	0.17	0.20	0.06	60.0
Detroit	1.23	3.51	0.20	0.05	3.00	40.0
Fort Lauderdale	2.94	1.00	8.87	0.52	0.84	40.0
Fort Worth	0.83	0.60	0.55	0.15	0.05	100.0
Hartford	1.76	1.28	0.57	0.78	9.32	40.0
Houston	0.43	0.79	0.33	0.20	0.88	100.0
Indianapolis	0.04	2.93	26.23	7.84	0.06	40.0
Jacksonville	0.97	1.00	1.88	0.18	0.34	80.0
Kansas City	4.26	0.74	3.13	0.12	1.45	40.0
Long Island	2.22	0.12	1.98	1.34	0.90	40.0
Los Angeles	0.30	9.02	2.59	1.46	0.28	40.0
Louisville			31.43	0.57	0.49	66.7
Memphis	0.98	0.88	0.53	0.46	0.64	100.0
Miami	1.42	0.33	0.11	0.63	1.70	60.0
Minneapolis	5.60	1.29	2.63	0.16	0.64	40.0
Nashville	1.72	1.51	0.05	0.02	0.18	60.0
New Orleans	0.23	0.12	0.36	0.45	0.66	100.0
New York	0.61	0.63	0.86	0.77	2.98	80.0
Newark	0.58	0.65	0.23	1.29	0.24	80.0
Norfolk-VA Beach			0.37	0.86	1.12	66.7
Oahu	2.44	0.30	0.05	0.41	0.14	80.0
Oakland	2.17	47.59	2.31	0.76	0.03	40.0
Omaha			0.13	0.40	0.10	100.0
Orlando	1.61	0.75	60.57	0.76	2.74	40.0
Philadelphia	0.73	52.73	1.48	0.35	0.10	60.0
Phoenix	0.85	1.23	1.15	0.27	0.15	60.0
Pittsburgh	0.67	0.32	0.93	0.74	5.24	80.0
Portland	1.17	2.32	1.62	0.45	0.12	40.0
Raleigh-Durham	35.06	0.71	5.75	0.85	0.03	60.0
Richmond	1.11	0.89	0.84	1.85	0.28	60.0
Sacramento	0.94	0.86	1.20	4.72	4.80	40.0
Saint Louis	1.86	1.20	0.13	0.40	0.37	60.0
Salt Lake City	1.16	1097.81	0.64	1.20	2.07	20.0
San Antonio	7.72	0.07	1.32	0.56	14.86	40.0
San Diego	1.02	1.29	1.61	1.19	0.74	20.0
San Francisco	5.53	0.63	0.58	0.59	0.12	80.0
San Jose-Santa Cruz			2.97	0.47	0.12	66.7
Savannah			1.46	0.62	0.19	66.7
Seattle	2.42	1.39	0.17	0.57	1.14	40.0
Tampa	0.24	1.93	0.71	0.77	0.24	80.0
Tucson	8.87	32.40	0.07	0.55	1.13	40.0
Washington DC	2.38	1.07	0.19	1.43	0.94	40.0
West Palm Beach	217.65	18.07	0.65	0.51	7.31	40.0
%<1	38.0	47.1	45.8	76.3	74.6	

Sources: CBRE Hotels' Americas Research Q1 2019

The column averages of MAE shown at the bottom of Exhibit 14 indicate that the one-year *Hotel Horizons*® market RevPAR forecasts improved from about 3% to 2.4% between 2013 to 2017. These results are good in the light of the above-mentioned forecasting difficulties. The rate paradox affected markets unevenly and irregularly. In addition, we would expect that smaller units of observation, in this case markets, would have higher MAE than larger national aggregates as the positive and negative differences in the markets cancel each other out when aggregated. Some large errors have ready explanations. For example, Hurricane Harvey's devastation in Houston was unknown at the beginning of 2017.

Turning to the relative accuracy measure, *Hotel Horizons*® generally outperformed the intuitive forecast except in 2014 and 2015. When the intuitive forecast is very accurate the denominator in U2 approaches zero. This can lead to large U2 statistics even when the MAE of the forecast is good. Salt Lake City, for example, had the highest U2 statistic in this study in 2014, but a modest MAE of 1.62. This is because the intuitive forecast made a near-perfect prediction in this case. It is because of this property of the U2 statistic that we report the percentage of markets that had U2 less than 1 rather than the average U2, and why absolute and relative measures of accuracy are considered together.

While most of the individual MSA U2-statistics resemble the 59 city averages, a few areas proved more problematic than others did from a forecasting perspective. These are:

- Nashville – Had a large Mean Absolute Error caused by a sudden shift in 2014, yet the small U2 statistic shows that our forecast produced a reasonably good result.
- Austin – In 2015 Austin had an unusually accurate intuitive forecast which caused the U2 average statistic to be high. In other years, the *Hotel Horizons*® model compares very favorably to the intuitive model.
- Cleveland - The *Hotel Horizons*® model for all hotels struggled somewhat in this market as indicated by the U2 statistics. This weakness is likely the result of a high forecast for RevPAR which was not met in 2014 and 2015.

A general observation is that some smaller cities are difficult to forecast because demand shock or new hotels often has a relatively larger impact on market performance. Similar to the accuracy of aggregations, larger cities have ups and downs that cancel each other out, while smaller locales are inherently more variable.

6. SCENARIO COMPARISONS OF ECONOMIC AND REVPAR FORECASTS

Hotel Horizons® has, since 2015, allowed for several alternate economic scenarios to be used in its forecast. If the user believes that the CBRE EA baseline economic forecast is too pessimistic, for example, the user can override the economic data with the Upside scenario. Alternatively, different scenarios can be chosen to set reasonable bounds on possible future performance. The position of CBRE Hotels' Americas Research is that the Baseline scenario is the most likely and thus should be the most accurate scenario.

Exhibit 16 details the RMSE of each scenario for the years 2015-2017 (the Severe Downside scenario was added for 2016 forecasts). Overly optimistic ADR forecasts previously described led the Downside scenario to produce the most accurate forecasts in the years 2015 and 2016; however, the Baseline scenario produced the second-best forecast. The Baseline scenario also produced the best forecast in 2017, after knowledge about the ADR paradox was incorporated.

EXHIBIT 16: AVERAGE QUARTERLY ACCURACY OF REVPAR FORECASTS BY SCENARIO

	MAE of RevPAR Forecasts (%)		
	2015	2016	2017
Baseline	1.21	2.37	**0.02**
Upside	1.20	4.81	1.31
Downside	**0.86**	**0.46**	1.98
Severe Downside		7.48	5.11
Moodys	1.01	3.77	1.77

* Most accurate forecast in **bold.**

Sources: CBRE Hotels' Americas Research Q1 2019

If the difficulty in predicting ADR in 2015 and 2016 was due entirely to unpredicted economic conditions, it would follow that comparing economic forecast MAE across scenarios should produce results similar to the accuracy of the forecasts. Exhibit 17 describes the accuracy and direction of error of the economic assumptions made by each of the scenarios. Scenarios that have the minimum MAE for the year have their predictions in bold.

Although the Baseline scenario is not the most accurate economic prediction in any of the years, it is second-best in each year. The Downside predictions are generally close to the Baseline and are the most accurate in 2015 and 2017. The Scenarios framework thus provides the Baseline as a dependable and generally good default option, while allowing for users with strong prior beliefs about the direction of the economy to explore potentially more accurate sets of economic assumptions. Additionally, the Severe Downside scenario was not very close to the realized economic conditions, but provides risk assessment or "worst case" information.

EXHIBIT 17: Forecast vs Actuals YoY % Change in EMP, CPI and, Income between 5 Scenarios									
BASELINE	**2015**			**2016**			**2017**		
	Forecast Δ	Actual Δ	Difference	Forecast Δ	Actual Δ	Difference	Forecast Δ	Actual Δ	Difference
EMP	1.9	1.9	0.0	1.8	1.8	0.0	1.2	1.6	-0.4
CPI	1.4	0.9	0.5	1.4	1.3	0.1	2.4	2.1	0.2
Income	3.6	2.8	0.8	4.0	2.6	1.4	2.9	4.4	-1.5
DOWNSIDE	**2015**			**2016**			**2017**		
	Forecast Δ	Actual Δ	Difference	Forecast Δ	Actual Δ	Difference	Forecast Δ	Actual Δ	Difference
EMP	**1.4**	**1.9**	**-0.4**	1.2	1.8	-0.6	**1.5**	**1.6**	**-0.1**
CPI	**1.1**	**0.9**	**0.1**	1.4	1.3	0.1	**2.4**	**2.1**	**0.2**
Income	**3.5**	**2.8**	**0.7**	3.8	2.6	1.2	**3.0**	**4.4**	**-1.4**
MOODYS	**2015**			**2016**			**2017**		
	Forecast Δ	Actual Δ	Difference	Forecast Δ	Actual Δ	Difference	Forecast Δ	Actual Δ	Difference
EMP	1.9	1.9	0.1	**1.8**	**1.8**	**0.0**	1.2	1.6	-0.4
CPI	1.5	0.9	0.6	**1.4**	**1.3**	**0.1**	2.3	2.1	0.1
Income	3.3	2.8	0.5	**3.8**	**2.6**	**1.2**	3.2	4.4	-1.2
UPSIDE	**2015**			**2016**			**2017**		
	Forecast Δ	Actual Δ	Difference	Forecast Δ	Actual Δ	Difference	Forecast Δ	Actual Δ	Difference
EMP	2.1	1.9	0.3	2.0	1.8	0.2	1.2	1.6	-0.3
CPI	2.0	0.9	1.1	2.1	1.3	0.8	1.4	2.1	-0.7
Income	3.7	2.8	0.9	4.3	2.6	1.7	3.3	4.4	-1.1
SEVERE DOWNSIDE	**2015**			**2016**			**2017**		
	Forecast Δ	Actual Δ	Difference	Forecast Δ	Actual Δ	Difference	Forecast Δ	Actual Δ	Difference
EMP	NA	1.9	NA	-2.2	1.8	-4.0	3.2	1.6	1.6
CPI	NA	0.9	NA	1.3	1.3	0.0	1.3	2.1	-0.9
Income	NA	2.8	NA	-1.8	2.6	-4.4	5.9	4.4	1.5

* Most accurate Forecast in bold

Sources: CBRE Hotels' Americas Research, STR Q1 2019

7. FORECAST ACCURACY SUMMARY

The method used to prepare *Hotel Horizons*® forecasts produces accurate hotel performance forecasts across large geographic areas, market segments, and locations. The accuracy of the forecasts is quite good for the U.S. hotel market and the sub-categories at the national level that the hotel industry uses to identify different hotel types – chain scales and locations. Locations were forecast with slightly more accuracy than the chain scale divisions. Forecasts are most accurate in the first year after they are made, but hold steady afterward.

Forecasting accuracy is shown to be uneven over the 59 included MSAs in this report, with quite large differences between forecast and actual results in certain cases, and differences well within a tolerable range of error in most cases. In general, MSA forecast accuracy has been improving over time. The Baseline scenario was found to be a good default choice, but eh alternate scenarios show promise for exploring potentially more accurate alternatives.

APPENDIX A

Econometrician Henri Theil during the 1960s and 1970s developed two statistics for measuring the accuracy of forecasts – U1 and U2. Theil's coefficients are derived using changes rather than levels in order to avoid the inflated view of accuracy. U1 has some associated statistical problems, so we focus our attention on U2, which can be thought of as a ratio of the RMSE of one forecast method to another. For U2, values less than 1 show that the forecasting technique used is better than the naïve forecast (or "intuitive forecast" in our paper) and values greater than 1 demonstrate that the technique is worse than the naïve forecast. When U2 equals 1, there is no difference between the methods.

Equation for Theil's U2 statistic:

$$U2 = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - A_i)^2}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}{A_i}^2}}$$

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