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Toward Improving Hotel Prognostications Through the Application of Probabilistic Methodologies

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Abstract

Existing and generally accepted methodologies for developing projections of future hotel performance have been recently described as "grossly inadequate" and we note they have essentially remained unchanged for decades. Notably, current methodologies result in point estimates of future performance and do not adequately consider the inherent risk in lodging investments. Borrowing from research in other fields, and particularly from the area of finance, we suggest the use of probabilistic, that is, stochastic methodologies. In particular, we recommend hotel investors, operators, and analysts use Monte Carlo simulation. Also, this article provides information regarding why probabilistic methodologies are appropriate and general guidance regarding how to apply such approaches.

Keywords

lodging; projections; probabilistic methodologies

Introduction

This article addresses a problem that prognostications related to the hospitality industry, and particularly those related to hotel real estate having specific point estimations (such as in market studies, feasibility studies, and appraisals), are generally inaccurate to some extent and, therefore, may not have optimal usefulness for decision-making purposes. We present a new approach for such projections[1] that we believe may be both more accurate and more powerful to practitioners such as hotel investors, operators, and analysts, when used for both internal and external purposes and when used for both actual decision-making and due diligence purposes.

Lodging analysts are generally trained to develop projections that conclude with precise figures, that is, point estimates, despite that traditional methods of applying *Net Present Value* (NPV) and *Internal Rate of Return* (IRR) analyses do not cover the range of possible results (Atkinson et al., 1997; O'Neill, 2011; Rushmore et al., 2012; Rushmore & O'Neill, 2015). Also, the generally accepted approaches of deriving point estimations have been shown to be based on future projections of a number of economic, demographic, and other factors (Hua et al., 2008; Lee et al., 2016; Nilsson et al., 2002; O'Neill & Carlbäck, 2011) that essentially always deviate from projections.

Furthermore, it has been recently noted that traditional methods of analyzing hotel real estate are grossly inadequate (Woods, 2018). Risks exist because no prognosticator can make perfect forecasts. Two hotel investments with identical levels of projected IRR may carry significantly different levels of risk, but traditional analysis methods would not provide relevant guidance in this regard. Furthermore, point estimates would provide merely a single parameter of anticipated return with no indication of the level of uncertainty of the number. For example, two hotel investments may each show an expected IRR of 17%, but one may have half the likelihood of achieving that rate of return.

It appears the fundamental methodology for conducting hotel feasibility studies has remained largely unchanged for more than 50 years (e.g., Hodgson, 1968), and there have been only limited changes in the methodology for conducting hotel appraisals for more than 40 years (e.g., Rushmore, 1975). Some academic research, generally outside the hospitality field, has concluded that there may be greater value for practitioners if the conclusions of such projections consider risk and are presented in ranges, rather than only as specific figures that do not consider risk, because projections that consider risk and are presented as both ranges and specific figures allow practitioners to make more valid decisions that better simulate real-world possibilities

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(Leung, 2014; Schoemaker, 1993). For example, when the expected IRR of two hotel investments is 17%, but one is shown to have an *SD* of 3 percentage points, whereas the second has an *SD* of 6 percentage points, the second carries substantially greater risk.

In particular, in the real estate and investment fields, researchers maintain that professionals should employ a possibility distribution of projections, that is, probabilistic or stochastic projections, for correcting drawbacks of traditional projection methods of using only specific figures, that is, deterministic projections, to improve accuracy and relevance (Amédée-Manesme et al., 2013; Gimpelevich, 2011; Leung, 2014). Specifically, projections presented with specific values provide a point estimate of parameters, which disregard uncertainty and risk.

On the other hand, projections presented in ranges render intervals which more likely subsume actual values (Atherton et al., 2008; Gimpelevich, 2011). With more accurate and reliable forecasts encompassing likely variation, a firm should expect to gain increased revenues as the firm appropriately employs forecasts that consider variability in operations (Weatherford & Kimes, 2003). Furthermore, probabilistic approaches are superior to sensitivity analyses (Leung, 2014; Woods, 2018).

Probabilistic approaches are superior to best-worst case analyses (Woods, 2018), as well. Financial forecasts inherently must account for variability of outcomes. In such instances, using point estimates of input variables becomes unrealistic. For instance, even a simple case of projecting annual hotel room revenue would require an approximation of room occupancy and average daily rate (ADR). A deterministic analysis would essentially involve deriving "point" estimates of those two inputs to calculate the projected revenue. However, those point estimates would not incorporate any possibility of variability. That is, "what if" the occupancy is higher or lower than the point estimates approximated?

In other words, probabilistic approaches permit the application of ranges in both input and output. For example, two prospective hotel investments may have an estimated stabilized occupancy of 74%, though the estimated *SD* of one may be 4 percentage points, whereas the second has an *SD* of 8 percentage points (input). As a result of these differences in standard deviation of input, the output, for example, estimated range of future market value,[2] would differ for these two investments even though each carries the same expected stabilized occupancy.

One simple approach to incorporating such variability is to use "what if" scenarios to estimate room revenue. "What if" scenarios allow forecasters to create different scenarios by varying the value of each input (Raychaudhuri, 2008). So, for instance, one could derive a "base" scenario, and then create a "worst" case and a "best" case scenario by varying the inputs. However, such an approach has multiple disadvantages. First, it may not be clear *what* should be the correct level of each input in the best and worst case scenarios. More importantly, each of those inputs, even in this simple example, may not behave in the same manner, that is, the two different inputs may not be at their best/worst case levels at the same time. Therefore, to appropriately incorporate such risk in the variance of input variables, we need an approach that allows us to statistically estimate the best and worst case levels. Furthermore, this approach must also permit us to incorporate various combinations of the best and worst case level inputs in the models.

In accordance with the benefits from projections presented in ranges, researchers in nonhospitality literature propose several modeling methods. For example, Gimpelevich (2011) provided practitioners in the real estate investment field with a new practical method using the simulation-based excess return model (SERM), arguing that the new modeling with a probability range, compared with traditional *Discounted Cash Flow* (DCF) analysis enables practitioners to consider various outcomes such as market value, loan-to-value (LTV) ratio, NPV, and IRR. Similarly, Mohamed and McCowan (2001) suggested a method of investment in projects employing Interval Mathematics along with possibility theory to deal with inherent uncertainty. Leung (2014) recommended employing projections including random walk and real options analyses. Since the new methods capture numerous risk factors which affect projected parameters within reasonable probability, results from the new methods are more accurate than traditional investment analysis techniques.

In other words, once lodging investors and operators have the opportunity to check the accuracy of traditional prospective financial analyses, they almost always conclude that the projections were not accurate; the question is how inaccurate were the projections.

How Inaccurate Are Lodging Prognostications?

Previous research showed that the conclusions of deterministic appraisals that prospectively estimated future market value of hotels differed from actual hotel sale transaction prices by an average of 5.0%, whereas the conclusions of a hotel automated valuation model (AVM) differed from actual hotel sale prices by an average of 9.8% (O'Neill, 2004).

In the context of hotel room revenue management, Baker and Collier (2003) compared forecasted hotel room prices between a new forecasting model, price setting method (PSM), and an industry standard method, bid price method (BPM). According to results of the study, the PSM reflecting the latest demand forecast error to estimate parameters with probability ranges statistically outperformed BPM which optimized the price, as a point estimate at the beginning of time periods. Specifically, room price obtained from PSM generated a 34% increase in average room revenue.

How Should Practitioners Apply Lodging Prognostications Within Ranges?

Given that existing, deterministic prognostication methods presented with specific figures in the lodging industry have limitations, new methods can and should be devised for developing more accurate projections. A few studies recommend practitioners in the lodging industry employ *Monte Carlo* simulations as used in nonhospitality fields (e.g., science, finance, and real estate research), which enable practitioners to rigorously determine uncertainty and risk by using probability distributions (Hoesli et al., 2006; Leung, 2014).

Specifically, hotel analysts should be cautious when determining input variables which are employed for projecting lodging properties' values. In practical fields, the selection of input variables is likely to rely on practitioners' intuitions rather than rigorous criteria, which may generate unreliable estimation. Furthermore, even if practitioners rigorously select input variables, a slight change in input variables which are affected by market conditions and vary depending on time may affect the residuals of outcomes and potentially result in misinterpretation of true values (Gimpelevich, 2011). In this regard, traditional appraisal models with specific figures are likely to fail to capture actual values because single point measures fail to comprehend the importance and uncertainty of each input variable (Hoesli et al., 2006; Loizou & French, 2012).

On the contrary, Monte Carlo simulation, which has been frequently adopted in finance, and increasingly is being adopted in the real estate field, allows practitioners to identify each input variables' uncertainty and appraise outcomes within ranges of possibility, contingent on a variation of input variables (Hoesli et al., 2006; Leung, 2014). Monte Carlo simulation may be used to generate stochastic (probabilistic) samples of an underlying phenomenon of interest (Rode et al., 2001). Monte Carlo simulation allows analysts to estimate the underlying distribution of each of the input variables. The distribution assumption can then be used to generate the parameters for each of the inputs. Each input parameter (e.g., one parameter for occupancy and another for ADR) then leads to a set of output parameters (e.g., room revenue). This outcome parameter then represents an output in the simulation as a scenario outcome. The Monte Carlo simulation generates thousands of such outcome scenarios. The collection of these outcome scenarios are then statistically analyzed to estimate outcome scenario parameters, including the underlying distribution of these parameters. All of these outcomes allow the decision-maker to evaluate the risk and uncertainty in the estimates.

Monte Carlo simulation has been adopted to forecast values such as stock prices and future cash flows, analyzing uncertainty and risk of input variables for more robust investment forecasting (Dixit & Pindyck, 1994; French & Gabrielli, 2004; Pellat, 1972). Considering that Monte Carlo simulation estimates actual values within the ranges of possibility along with a random selection process, the approach enables practitioners to address and incorporate uncertainty generated from each input variables' variation, thereby generating more robust outputs (Kelliher & Mahoney, 2000).

Woods (2018) provided some general guidance for applying Monte Carlo simulation. Practitioners should identify and include all possible input and output variables in a mathematical model. Input variables may include firm-specific factors (e.g., occupancy, ADR, labor costs, and capital expenditures) and macro-economic variables (e.g., interest rates, market growth rates, and expected future competition). Then, as a core process for addressing uncertainty and risk of input variables, analysts need to identify input variables which have uncertainty and risk, allowing practitioners to obtain probability distributions of uncertain variables. Then, Monte Carlo simulation is applied to simulate the model with a myriad of combinations of uncertain input variables. Accordingly, practitioners can obtain an extensive range of outcomes from randomly selected combinations of prespecified input variables with probability distributions, along with analyzing the mean of the final conclusion, for example, market value (Woods, 2018).

Through the power of today's personal computing software, Monte Carlo simulation can be performed in Microsoft Excel (Leung, 2014). Though not required, Excel add-ins such as "@ Risk" (produced by Palisade) can aid such analyses. Practitioners typically need to determine which inputs have risk and variability, estimate or make assumptions regarding the standard deviations of these variables, and then make a determination regarding a specified number of probabilistic iterations in the Monte Carlo simulation, for example, 5,000 or 10,000 iterations (Leung, 2014). Such estimates and assumptions typically can be made through at least one or more of four approaches: historical observations, experiments with observations, theoretical distributions, and the practitioner's judgment (Woods, 2018). For example, evaluation of historical amounts and fluctuations of benchmarks, revenues, and expenses of the subject hotel (or comparable hotels in the case of analyzing a proposed property) would allow prognosticators to estimate not only amounts, that is, means, but also dispersion, for example, standard deviation, and type of distribution, for example, triangular distribution.

It is notable that the mean of the output of such analyses, for example, market value, generally will be different than the output of traditional DCF analyses because of the *Flaw of Averages* (Leung, 2014). The Flaw of Averages occurs when using deterministic models instead of stochastic ones because of the mistaken assumption that evaluating a property around average conditions yields a correct result. In fact, for example, the variability of different inputs has different levels of impact on outcomes (Woods, 2018).

It is also notable that for lodging projections, Monte Carlo simulation is more appropriate than bootstrapping. Bootstrapping is typically used to generate additional samples from an original sample, that is, to resample, but generally does not make assumptions regarding parameters such as the sample mean and standard deviation as would be the case with Monte Carlo simulation (Efron & Tibshirani, 1994). That is, with bootstrapping, new samples are generated from the original sample of observations. However, Monte Carlo simulation involves data generation procedures to develop a sample from an underlying distribution, that is, mean and standard deviation. While both methods may generate additional samples, the approaches are different.[3] Since Monte Carlo simulation allows data generation mechanisms to be defined for each of the inputs in a model, it is a preferred method of business forecasting.

How Have These Techniques Been Applied in Other Aspects of Hospitality?

The techniques described in this article already have been applied or proposed in other aspects of the hospitality industry, such as revenue management (Gu, 2003; Yüksel, 2007; Zakhary et al., 2011).

Zakhary et al. (2011) proposed a new approach to project hotel arrivals and occupancy rate, using the Monte Carlo simulation method. Grounded on historical data, they simulated all possible outcomes of hotel reservation processes and then yielded forecasts of parameters with probability distributions. Furthermore, they compared the results from Monte Carlo simulation with existing approaches with point estimates. According to the comparison, the accuracy of the Monte Carlo simulation approach was superior to traditional forecasting models.

Similarly, prognostications presented in probability ranges can be applied to capital budgeting in the hotel industry. Atkinson et al. (1997) suggested a software program, Crystal Ball, to address the uncertainty and risks of input variables. Before making a decision for capital budgeting, practitioners have difficulty in estimating future cash flows because traditional methods rely on a point estimation, ignoring the fluctuation caused by uncertainty and risk. By using simulation software, a point estimation can be replaced by probability distributions of outcome values incorporating uncertainty and risk of input variables. Results from the estimation can be adopted by practitioners for more accurate capital budgeting decisions, and these estimations can be performed using Excel in addition to Crystal Ball.

Recently, Sharma and Alfnes (2019) incorporated risk and uncertainty into forecasting cash flows in a restaurant setting. Their stochastic Monte Carlo simulation estimated cost–benefit forecasts and found that several of the variables in the analysis were not normally distributed. For instance, on the cost side, the food cost difference was found to have a triangular distribution, and price change percentage appeared to have a uniform distribution. Cash flow for the focal menu items appeared to have triangular, beta central, and Wiebull distributions. In their study, none of these distributions had a linear mean or variance function. Therefore, using the usual range estimates approximated by a normal distribution would have provided inaccurate forecasts for decision-making purposes. Their study incorporated the nonlinear distribution of the key variables of interest. Doing so allowed the researchers to assess the likelihood of the cash flows being positive or negative. Resulting analyses suggested two key takeaways. First, simulating data using simple data generation mechanisms (such as those in Monte Carlo simulation) can provide key insights into the *true* nature of the probability distribution of these variables. Second, if the underlying variables are indeed nonlinearly distributed, then the system will be deterministic within a certain range of values, but then could behave chaotically, and diverge in an unstable manner. In other words, their study demonstrated that even in simplistic models of DCF analysis using secondary data, the variables of interest could be characterized by nonlinear distributions. In such situations, any explanation of the phenomenon that utilizes parametric analysis should incorporate the true distribution of these variables. Otherwise, the results only will be valid within a certain range, and unpredictable thereafter.

Challenges

Although probabilistic simulation within ranges provides more robust and reliable prognostications, decisions may vary dependent on managers' perspectives, risk averseness, and capabilities. Furthermore, outcomes from the simulation approach with probability distributions may not be sufficient to allow managers to proceed to decision-making. Although expected outcomes achieved by simulations of all possible combinations of input variables will statistically provide more accurate outcomes than point estimations, the results from simulations are not always 100% accurate (Gimpelevich, 2011). That is, the answer as to whether the results within ranges are acceptable or not hinges on practitioners' judgment.

Similarly, input variables to be included in the model for generating probability distributions with uncertainty and risk may be subjective. In other words, depending on the selection of input variables (and the variability of those input variables) in a model, expected outcomes within ranges generated from the simulation approach may differ (Li, 2000). Input variables may be arbitrarily included in a model, resulting in different outcomes; thus, valid inclusion of input variables with logical rationale, based on previous research and practice, are crucial to minimize the variation between expected and actual values and thus the reliability of the projections (Schwartz & Cohen, 2004).

Future Research and Application to Academia

We recommend future research continue to explore the use of stochastic, that is, probabilistic methodologies in hotel prognostications. It could be beneficial to both academics and practitioners, for example, for researchers to develop a detailed case study of projecting future benchmarks, revenues, and expenses of an actual hotel using Monte Carlo simulation.

New hospitality prognosticators are currently trained to both work with historical figures that are specific and to develop point estimations of future benchmarks, revenues, and expenses (e.g., Rushmore et al., 2012). We recommend that academics instruct such budding hotel prognosticators regarding the use of probabilistic methodologies, including Monte Carlo simulation.

Conclusion

The use of probabilistic modeling in the hospitality real estate industry represents a leap forward relative to current approaches such as DCF analyses. Furthermore, such stochastic approaches as Monte Carlo simulation are superior to sensitivity analysis and best-worst case analysis.

The leap forward of Monte Carlo simulation could be compared to the leap of calculating compound annual growth rate (CAGR) instead of average annual growth rate (AAGR) from historical economic and demographic market data, or using DCF analysis versus direct capitalization. The output of such stochastic modeling could be used by practitioners as additional checkpoints in a similar fashion as LTV or debt service coverage (DSC) ratios.

Among the benefits of the output of Monte Carlo simulation are that such modeling may yield the range of possible returns, the percent probability that a hotel real estate investment will surpass a given hurdle rate, and ranking of the most important sources of risk and their magnitude. Furthermore, these models may consider real options, that is, rights without obligations, such as potential future renovations or expansions. It is important to note that in its inclusion of real-world possibilities, the mean of Monte Carlo simulation output typically differs from conclusions obtained through traditional DCF analysis. As a result, such simulation is likely to be a superior decision-making tool for such practitioners as potential hotel investors seeking to determine a reasonable bid price, or potential underwriters seeking to determine a reasonable mortgage amount.

Finally, the state-of-the-art methodology for projecting local lodging market performance appears to be to apply autoregressive approaches to multivariate analyses (e.g., Bloom, 2013). Such approaches could be significantly enhanced through the application of probabilistic methodologies.

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Notes

1. We note that the use of the words "projections" and "forecasts" may be inappropriate in certain documents regulated by the Securities and Exchange Commission. In such cases, projections and forecasts may, for example, be referred to as "prospective financial analyses," but these concepts apply in each case.
2. We note that probabilistic methodologies may be applied regardless of whether the desired outcome is market value or investment value.
3. We note that as it generates additional samples from an existing sample (and it may generate larger samples), bootstrapping has a benefit of permitting statisticians to test for robustness and violations to statistical assumptions. However, that benefit serves a different purpose than the purpose of business forecasting described in this article.

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