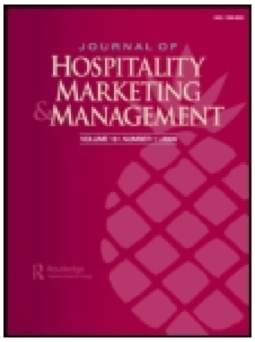

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Understanding Discount Program Risk in Hospitality: A Monte Carlo Approach

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This study exhibits the usefulness of simulation analysis in understanding discount program risk from hospitality consumer behavior. A comprehensive review of hospitality discount programs, discussion of the methodological approach, and potential extensions of the technique is provided, along with applications to hypothetical restaurant and casino discount programs. We show changes from complex consumer behavior that are difficult to directly measure or forecast with traditional methods. One simulation outlines a scenario in which the profitability of restaurant discount programs can easily be misinterpreted leading to poor management decisions, while the other simulation reveals a scenario where casino house advantages could vary substantially from those typically used in profitability calculations.

KEYWORDS *discount programs, Monte Carlo, risk analysis, consumer behavior, restaurant, gambling*

INTRODUCTION

In order to deseasonalize demand and to stimulate short-term sales, firms frequently use undifferentiated marketing tools such as price discounts and other promotions. Hospitality companies in particular, are in an

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advantageous position to collect detailed information on their customers, which allows for more differentiated promotional tactics. In general, evaluating how consumers will respond to a complex marketing program can be a challenging task. Uncertainty surrounding the behavior of individual consumers in response to different service offerings and pricing structures can complicate the evaluation of promotional programs. It can be especially unclear how profitable programs are at the individual consumer level—either the program has yet to be implemented and potential effects remain unknown, or the aggregation of revenue hides how individual consumers respond. Customers may combine discounts, stack coupons, or use other co-promotions that conceal individual profitability to operators. In part, this is a result of the increasingly complex loyalty programs that are offered by operators.

It has become a popular fact that many purchasers have become so clever in using discounts that they become entirely unprofitable consumers, and this has led some companies to reevaluate established discount designs to avoid these exploitative consumers (Ambros, 2011; Harris, 2011). Promotions in the hospitality industry are frequently ineffective, involve heavy price discounting or high-cost "freebies," and fail to accomplish the basic goals of short-term profitability and enhanced consumer loyalty (e.g., Lucas, 2004). Often operators cannot afford short-run promotional mistakes, as profits are diminished and capital is in scarce supply. Therefore, there is a fundamental need for methods of assessment of all promotions applied in the hospitality industry. We address this need by providing a methodological contribution to the hospitality literature, which enables risk-evaluation of discount programs, before their launch.

This study first includes a review of hospitality discount programs: how they are implemented, how they are measured, and how they vary between hospitality industries. Next, an overview of Monte Carlo (MC) methods is provided, with a discussion about how they can be used to understand and improve discount program design. To illustrate these concepts, two different discount programs are modeled. The first example is based on a simple restaurant program, which is modeled using features found in Microsoft Excel. The second example is a more complex casino discount program, modeled using *R*. Both examples illustrate how MC methods can be used to assess overall program returns, and to view how profitability may vary among customers. Finally, the potential extensions of this method within the hospitality sector are discussed.

LITERATURE REVIEW

Loyalty programs are implemented by companies to reward valuable customers, to generate information in order better to understand and serve the customer, to manipulate consumer behavior, and to defend against competition (O'Malley, 1998). Ultimately, these programs pursue value-added, interactive, and long-term focused relationships by identifying, maintaining, and increasing the purchase behavior of the best customers (Meyer-Waarden, 2008; Xie & Chen, 2013). Loyalty programs have two main goals: (a) to increase sales revenues by increasing purchase levels and (b) to maintain the current customer base by strengthening the bond between the customer and the brand. Companies are thought to benefit by achieving either or both of these (Uncles, Dowling, & Hammond, 2003). The literature, however, also emphasizes the difference between frequency and loyalty programs. The goal of frequency programs is to build repeat business, whereas the objective of loyalty programs is to build emotional brand attachment (Shoemaker & Lewis, 1999). The emotional bond–affective commitment impacts guest perception (Mattila, 2006; Wilkins, Merrilees, & Herington, 2009). There is some disagreement as to whether these programs are effective in increasing loyalty and return on investment, because often revenues are monitored and costs are not considered (Ni, Chan, & Shum, 2011).

Discount programs are often integrated into a larger loyalty program, but tend to strictly refer to some sort of price discrimination mechanism. There is evidence that within the retail sector, such forms of price dispersion cannot be explained solely by differences in costs (see, for example, Bornstein & Rose, 1994; Leslie, 2004; Shepard, 1991). These programs can vary from designs as simple as a restaurant punch card to multiproduct rebates that include adjustments based on second-degree (e.g., volume) and third-degree (e.g., age) price discrimination mechanisms. In order to be effective, loyalty programs and the rewards they offer need to be perceived as valuable by customers. The literature shows that the effectiveness of loyalty programs is impacted by numerous factors, including: reward timing (Dowling & Uncles, 1997; Huang & Chen, 2010; Yi & Jeon, 2003), database management (Bowen & Shoemaker, 1998; A. Palmer, McMahon-Beattie, & Beggs, 2000), program user-friendliness, ease of reward redemption and the range of rewards offered (Kivetz & Simonson, 2002; Shoemaker & Lewis, 1999), members' perceptions of the value of rewards and their attainability (Dube & Shoemaker, 1999; O'Brien & Jones, 1995; Shoemaker et al., 1999), and sense of community as a member (Rosenbaum, Ostrom, & Kuntze, 2005).

Loyalty programs provide both psychological and economical value to program members. By earning rewards, consumers feel a sense of appreciation and recognition, and this psychological experience increases the transaction utility of a purchase and the likelihood of continuing the relationship (Lemon, White, & Winer, 2002). Furthermore, it increases the overall value perception of staying in the relationship by making consumers feel important (Bitner, 1995). Additional psychological benefits offered by loyalty programs include the opportunity to indulge in guilt-free luxuries (Liu, 2007), and the enjoyment of accumulating points to qualify for a reward

(Dowling & Uncles, 1997). Economic value is provided to program members by the rewards that are offered to members for repeat purchase behavior. Reward types include monetary based and special treatment based. Monetary-based rewards, such as bonus points and discount vouchers, offer utilitarian benefits (Furinto, Pawitra, & Balqiah, 2009). Special treatment-based rewards, on the other hand, offer hedonic benefits and are intended to influence customers' attitudinal attachment such as trust and assurance (Furinto et al., 2009). Verhoef (2003) suggested that monetary-based rewards are most preferred by customers. McCall and Voorhees (2010) found that special treatment-based rewards had limited impact on relationship quality.

Tiered programs, where benefits are based on members reaching threshold levels of consumption, are effective because they provide members with a sense of identity and fit, which can enhance a customer's commitment level to the brand and the program (Bergami & Bagozzi, 2000). Furthermore, customer behavior changes as customers transition between tiers and anticipate and experience changes in member benefits. In fact, members are known to accelerate their purchase frequency and magnitudes as their arrival at the next tier approaches, creating aspirational value (Shoemaker et al., 1999). It has been shown that the thought of getting closer to earning a reward stimulated an increase in purchase behavior (Kivetz, Urminsky, & Zheng, 2006).

Tiered programs allow companies to segment customers based on behavior, thereby more effectively providing differentiated rewards (Rigby & Ledingham, 2004). Aside from segmenting customers into tiers according to their value to the company, loyalty program members are segmented based on their personal values and performance outcomes are expected to vary between and within segments (R. Palmer & Mahoney, 2005). Segmentation allows businesses to understand their customers more deeply and to develop strategies relevant to marketing and improve profitability (Foedermayr & Diamantopoulos, 2008). Effective segmentation can increase the effectiveness of loyalty programs by targeting successfully, meeting customers' wants and needs, and improving customer retention. Companies, however, must recognize the importance of tracking customers' movements among segments because they are always changing (Badgett & Stone, 2005; So & Morrison, 2004).

Restaurant Programs

Restaurant managers are generally aware that customer loyalty is important to their success. Loyal customers allow for lower marketing and transaction costs as well increased revenues and lower price sensitivity. Previous research has shown that factors such as a restaurant's aesthetics and employee attitudes may impact guest loyalty more effectively than reward programs (Skogland & Siguaw, 2004). Despite this, many restaurants attempt to implement loyalty or frequency programs to enhance customer loyalty. Dining programs are commonly frequency-focused, based on point systems that offer financial rewards (free meals or discounts for a certain number of points collected). Previous research found this method to be ineffective because it is mainly based on delayed redemption practices, whereas most restaurant customers prefer more immediate rewards (Jang & Mattila, 2005). Immediate rewards can include discounts or free items. These practices mirror more a promotion than an actual reward and do not induce loyalty but rather promotion seeking behaviors. Research has identified the difference between loyal customers and frequent customers (Mattila, 2001).

Furthermore, the amount of effort to redeem rewards needs to be reasonable in order to keep customers' interest (Hobbs & Rowley, 2008). For example, if restaurant customers have to frequent a restaurant too many times before they can redeem a free meal, they may lose interest and/or in fact lose track of the actual evidence (such as punch cards) of previous visits. The fact that most restaurant customers want variety in their food choices and usually do not frequent the same restaurants constantly, also contributes to the difficulty of creating effective restaurant programs. It also needs to be considered that restaurants' average guest checks are generally a lot lower than, for example, hotel revenues per stay. Therefore, a higher frequency of restaurant visits is crucial to funding a loyalty program. In addition, if the reward requirement is not immediate, customers may prefer products as rewards that they do not normally purchase (*luxury rewards*), such as an expensive bottle of champagne or cognac, which is in contrast to *necessary rewards* such as gas or grocery coupons. Nonmonetary rewards that may be used by restaurants can include preferred reservations or seating and personalized recognition.

Jang and Mattila (2005) found that fast-food and casual-dining customers preferred immediate and monetary rewards over point systems, luxury, and nonmonetary rewards. These results were consistent with previous research (Prelec & Loewenstein, 1997). In addition, it can be assumed for restaurants with higher service expectations that frequency programs would not serve the needs of their target market. For this type of customer, programs need to go beyond the frequency approach and become more sophisticated—for example, a customer database tracking customer behaviors is needed to allow for customization and to create rewards that persuade antecedents of attitudinal attachment, such as service quality and customer satisfaction (Zeithaml, Berry, & Parasuraman, 1996).

Restaurants typically employ frequency programs, which are shown not to foster loyalty (Shoemaker et al., 1999). Furthermore, most restaurants have an unstructured recognition of loyalty and believe that customer loyalty is achieved through personalized service and consistent food quality. Although service and food quality are important and restaurants may be successful at impacting short-term customer behavior through frequency programs, their loyalty program efforts have not effectively evolved. Consequently, restaurants have a need to structure their efforts to build emotional attachments that create long-term orientation and drive loyalty. Furthermore, recent research suggests that restaurant loyalty programs could increase loyalty and reduce their financial burden by providing nonmonetary rewards to retain long-term oriented customers, and decrease defection by providing immediate monetary rewards to customers with a low long-term orientation (Park, Chung, & Woo, 2013). However, in general, a gap in theory and practice exists, calling for a more sophisticated approach to restaurant loyalty programs.

Casino Programs

Loyalty in the casino industry is a complicated system dependent on location, physical attributes, games offered, amenities, hospitality attributes, and staff attributes. Given competitive pressures for a small pool of high limit players, casinos often offer discount on loss programs (Eadington & Kent-Lemon, 1992; Salmon, Lucas, Kilby, & Dalbor, 2004). The programs structures vary somewhat, but typically involve reductions in the amount of borrowed casino markers (short-term loans) that players must repay, should the players have a net actual loss after a specific trip.[1] Lucas, Kilby, and Santos (2002) have provided a review of discount program structures and some potential issues. Although the discount programs were originally designed as a mechanism to encourage players to repay outstanding markers, discount programs have since evolved into a play incentive (Lucas & Kilby, 2008). They have since been adopted widely throughout the casino industry (Salmon et al., 2004), with a pronounced presence in baccarat. Baccarat is the most popular game among high-roller casino patrons, accounting for the majority of casino revenue in gambling enclaves, such as Macao SAR (Loi & Kim, 2010).

Lucas and Kilby (2008) discussed four cost principles that affect discount program profitability in the casino industry: game probability and discount magnitude, number of hands played, volatility of the wagering size, and the bet's payoff odds. Game probability defines the upper limit for any discount to be profitably offered; an increase in the minimum number of hands played will reduce the operators' risk, since it guarantees a minimum theoretical win that can defray some of the fixed costs associated with high-roller gamblers (e.g., airfare and accommodations). Volatility of the wagering size and the payoff odds add similar forms risk, since negative variance increases the amount of discounts that are paid out, whereas positive variance creates no extra revenue.

Monte Carlo Methods in Hospitality

MC simulation involves combining probability distributions from different variables, then using random number generation to simulate potential uncertain outcomes. As a simple example, instead of a predictive approach to forecast 100 restaurant customers arriving for lunch, a MC approach could involve simulating a normal distribution of restaurant customers, with an average of 100 per day, and a standard deviation of 10. The random-number-based simulation could then be used to answer questions such as, "How often will more than 115 customers arrive for lunch?" The MC approach recognizes that there are several different factors that contribute to any result, each with its own level of uncertainty. Once a sufficient number of simulated trials are produced, the numerous outcomes can be combined to understand the distribution of overall risk and reward.

Since the seminal contribution of Hertz (1964), MC methods have been established as a useful tool for managers to evaluate scenarios under uncertainty. In particular, this risk analysis method has been frequently used by industry managers and investors to evaluate financial investment decisions (see, for example, Glasserman, 2004). They have also been proposed as a useful method for evaluating the profitability of new products (Kotler & Schult, 1970). Although there are no studies that have examined how MC models can be applied to hospitality discount program modeling and decision making, there are a handful of studies that have extended typical MC applications to the field of hospitality. Cacic and Olander (1999) used MC modeling as a financial investment tool for hotel appraisals; Sheel (1995) used MC analysis to explore hotel operation and revenue management scenarios; Field, McKnew, and Kiessler (1997) extended the technique to the food service industry, showing how the method could be used to evaluate restaurant operation design choices; and Atkinson, Kelliher, and LeBruto (1997) provided a detailed description of how MC analysis, using a spreadsheet add-on program called Crystal Ball, can be used by hospitality financial managers during the capital budgeting process.

Risk analysis methods, and specifically MC simulations, have also been used widely in gaming literature and in practice to simulate gaming outcomes and accordingly build game payout probabilities (Barr & Durbach, 2008; Lucas & Singh, 2008; Lucas, Singh, & Gewali, 2007). The popularity of this method is not surprising given that MC methods allow users to estimate gaming outcomes under varying forms of uncertainty in advance of the introduction of any particular game, rule change, or player strategy—avoiding potentially costly errors. Gaming is also a good candidate for MC simulation since it is one of the few applications where probability distributions are known, rather than estimated. Past studies, such as those by Walden (1966), Thorp and Walden (1973), and MacDonald (2002), have examined how game rules affect profitability using MC analysis.

APPLYING MONTE CARLO SIMULATION TO HOSPITALITY DISCOUNT PROGRAMS

As described in the review of literature, discount program design has become increasingly complex and could clearly benefit from a better risk analysis. Using two representative examples, this section illustrates how MC simulation of consumer behavior in response to discount programs can reveal important outcomes in advance of program inauguration.[2] The first simulation is a typical restaurant discount program that is modeled using Microsoft Excel. The second simulation is of a typical casino discount program, which is modeled using the open-source computing package, R.

Restaurant Discount Program Simulation

Restaurant discount programs tend to be relatively straightforward in their design (in part, to ensure that customers can appreciate their benefits), but even small combinations of program features can make estimates of profitability difficult to compute directly. Our simulation of a hypothetical quick service restaurant program involves both a discount on the gross sale of goods (10% off of all purchases) and a free meal component that is a function of frequenting the restaurant a requisite number of times (a free meal for every 10 purchases). Since this is a hypothetical and illustrative example, our prior experience is used to build the model assumptions. We assume that there is a 50% increase in patronage among customers enrolled in the program, and evaluate the change in income accordingly. The model assumptions allow for distributions around the customer purchase size (in dollars), the cost of goods sold, the probability of patronizing the restaurant (program members are assumed to patronize at a higher percentage), the probability of joining the loyalty program (if not already a member), and the probability of using a free meal credit if it is available. These assumptions are provided in Table 1.

In order to project the profitability of this program, the behavior of 10,000 hypothetical customers that represent a hypothetical restaurant's customer base was simulated and compared to simulated outcomes in the absence of a discount program. We illustrate the results of these simulations in Figure 1. Both the revenue curve and the cost curve show increases over the course of the study, with substantial day-to-day variation. The gross income curve is provided as a 28-day moving average to more clearly illustrate the average impact. Under the discount program assumptions, we observe gross income rising until a peak near the 45-day mark, and then descending into a lower long-run equilibrium. When we compare these results to the 28-day moving average when there is no discount program (all nonmembers), we observe that short-run income is appears higher (again, peaking near the 45-day mark), but the long-run equilibrium indicates that income will be lower with the discount program in place. The average value

TABLE 1 Frequency and loyalty program comparison

	Traditional frequency programs	Real loyalty programs
Objectives	Build traffic, sales, and profits	Build sales, profits, and the brand
Strategy	Offer incentives for repeat transactions	Build personal brand relationships
Focus	A segment's behavior and profitability	An individual's emotional and rational needs and their value
Tactics	Segmented rewards	Customer recognition
	Transaction status	Individual value, tenure
	Free/discounted product	Preferred access, service
	Collateral product discounts	"Insider" information
	Rewards such as miles or points	Value-added upgrades and add-ons
	Value-added upgrades/add-ons	Emotional "trophy" rewards
	Rewards "menu"	Tailored offers/messages
Measurement	Transactions	Individual lifetime value
	Sales growth	Attitudinal change
	Cost structure	Emotional responses

Note. Adapted from Shoemaker and Lewis (1999).

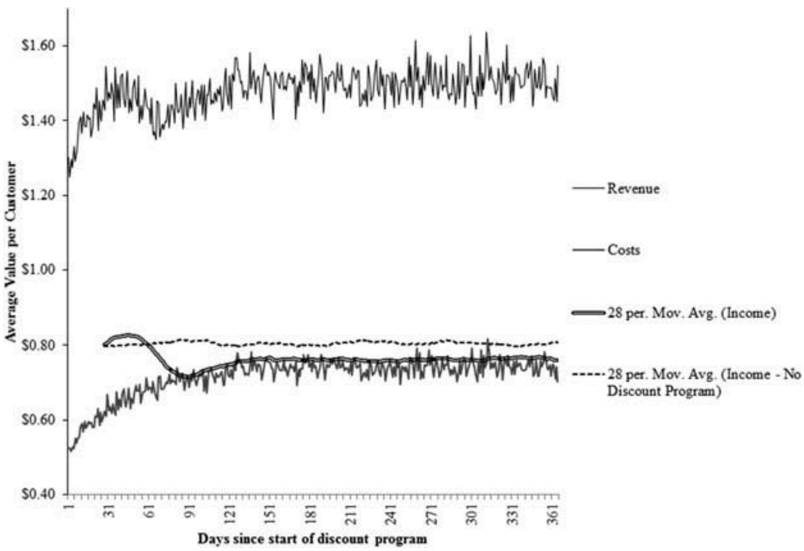

FIGURE 1 Discount program gross profitability per customer.
Note. The revenue curve and the cost curve increase over the course of the study, with substantial day-to-day variation. The gross income curve is provided as a 28-day moving average. Under the discount program assumptions, we observe gross income rising until a peak near the 45-day mark, and then descending into a lower long-run equilibrium. Compared to the 28-day moving average when there is no discount program, we observe short-run income is higher, but the long-run income is lower, with the discount program in place.

per customer is estimated to be roughly $0.80 per day without the discount program in place, whereas the long-run income per available customer is $0.74 with the discount program.

TABLE 2 Restaurant model assumptions

	%				%	
	Daily average probability of patronizing (nonmember)	Daily average probability of patronizing (member)	Probability of joining loyalty program if not already joined	Purchase size	Cost of goods sold (share of retail)	Probability of using free meal if available
M	10	15	20	$12.00	40	90
10th percentile	1	1	5	$6.50	28	99
90th percentile	30	30	25	$18.00	55	85
SD	11	11	8	$4.49	11	5

[a]Standard deviation is computed based on the mean, 10th percentile, and 90th percentile values.

Given that the program assumes a lofty 50% increase in patronage among enrolled customers, the MC simulation shows that the overall program design of this nature may warrant reconsideration, especially if managing the program creates overhead costs in addition to the projected loss of $0.06 per available customer. Demonstrating the importance of using simulation to show the full scope of program returns is the evidence that the long-run equilibrium of the discount program will not be reached until roughly 100 days into its operation—one can imagine a scenario where management that only examined bottom-line figures a month or two into the program's roll-out would label the program a success, as it had achieved a short-run increase in income. Then, when income fell again later, management may attribute the decline to an external factor, rather than the long-run impacts of the discount program. Additionally, the simulation revealed sufficient day-to-day noise that not considering long-run averages could lead to further misunderstanding of program returns.

Casino Discount Program Simulation

Casino discount program analysis has tended to focus on the combined effect of the percentage of losses refunded and the number hands played to adjust the game's normal house advantage. In this simulation of casino discount program returns we extend this analysis by adding simulation of patron behavior, in terms of when they end a playing session. Typically, patron behavior outside of the enforced rules of the game is not modeled for its on program returns, but as we show in this example using MC methods, such behavior can have a significant impact on the computed house advantage.

To illustrate the broad issue examined with this simulation, consider a patron that wins $100,000 over a session at a single casino. If that patron continues to play that session, and then loses back the $100,000, they will not receive a discount, since their net overall loss will be zero. However, if instead of continuing to play at the same property, the patron moves their play to another casino and there loses the $100,000; then, the patron would receive a discount on the loss, since their loss would be recorded as part of a new trip—a patron with a 10% discount on loss would, after winning $100,000 at one casino and then losing $100,000 at another casino, would have a net return of $10,000 due to the discount on loss.

The lack of congruency in recorded trips provides an incentive for patrons to set win limits by leaving one casino and resetting their win/loss record to zero. In locations with many casinos offering discount programs, such as in Las Vegas or Atlantic City, there may be few barriers for a patron to switch gaming locations several times in a single trip. Typical industry calculations of discount program house advantages do not account for this sort of patron behavior, focusing instead on the actual rules of the game and the long-run effect of any discount program. This therefore biases theoretical win calculations.

In this hypothetical example, we simulate virtual consumers to generate pay tables and resulting house advantages for a baccarat game using the statistical program, R. Baccarat is a pure chance card game that is often played at high stakes, and therefore is more likely to see discounts on loss than other, lower stakes, games. We assume that some patrons may be prone to set win limits by ending play after reaching a target win level—this is not uncommon behavior and setting win limits has even been proposed as a responsible gambling tool by some researchers (Walker, Litvin, Sobel, & St. Pierre, 2014). Accordingly, we set the following parameters for our simulation: starting bankroll (bankroll) = 100 units; target win amount (target win) = 200 units; varied number of units wagered per hand (wager), varied maximum number of hands that can be played (max hands), and the discount given by the casino on net losses at the end of the session (discount).

Simulations then follow the typical rules of baccarat, where a patron bets on the "player," "banker," or "tie" and receives the appropriate payout based on the results of the hand. Since a banker wager yields the lowest house advantage, we further assume that the simulated gamblers always choose this bet, winning 45.86% of hands (+0.95 units), losing 44.62% of hands (−1.00 unit), and tying 9.52% of hands (± 0.00 units). As shown in Figure 2, the patron continues to place wagers until they lose their entire bankroll, reach their target win level, or reach the maximum number of hands—we use a maximum number of hands threshold to account for potential time limitations of play. If a wager was made where the patron's remaining bankroll is less than the set wager size, then only the remaining bankroll size is wagered. A larger number of simulations was used (n = 1,000,000) compared to the restaurant example because of the need for precision in detecting different long-run outcomes. We use the R programming language for these simulations, since it can more efficiently compute a large number of simulations.

Postdiscount player simulations were aggregated and then divided by the total amount wagered over the course of the simulation to measure the house advantage (inclusive of the given discount program and player behavior). Figure 3 illustrates the differences in computed house advantage for target win to wager ratios of 10, 25, 50, and +∞, when the maximum number of hands played is set to 300.[3] As is shown, although all target win to wager ratio curves have the same house advantage at a discount rate of 0%, the slope of the change in house advantage becomes steeper for smaller target win to wager ratios. The house advantage can be substantially different than what is expected. A target win to wager ratio equal to 50 is effectively identical to the +∞ ratio, but a ratio of 10 shows remarkable differences in the computed house advantage—this would be akin to a $10,000 average bet with a target win of $100,000.

Although many of the discount program levels still appear profitable from these figures (albeit less so that originally thought), if complimentaries

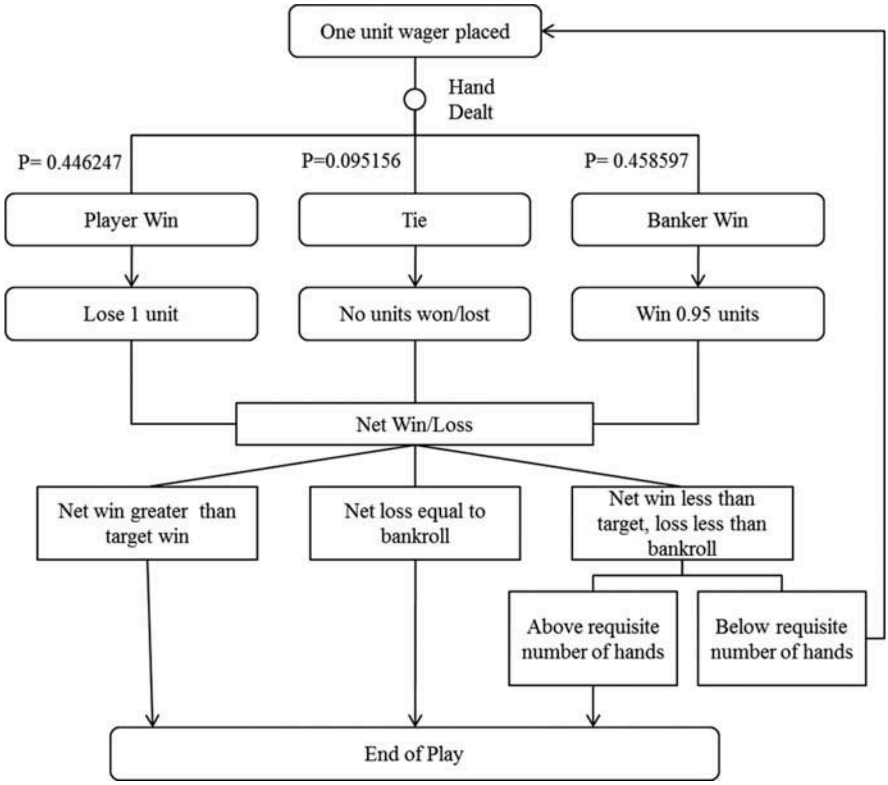

FIGURE 2 Diagram of baccarat player behavior during simulation.

Note. Since a "banker" wager yields the lowest house advantage, we assume the simulated gamblers always choose this bet, winning 45.86% of hands (+0.95 units), losing 44.62% of hands (−1.00 unit), and tying 9.52% of hands (±0.00 units). The patron continues to place wagers until they lose their entire bankroll, reach their target win level, or reach the maximum number of hands.

(comps) and other miscellaneous play incentives are also being provided to the player based on a theoretical win that is computed from typical industry house advantages, then the overall marketing design may not be providing a suitable return to the firm. In the absence of such a MC-based approach, it would not be possible to understand the interactions of game design, discount program design, and consumer behavior, and their subsequent effects on firm profitability.

DISCUSSION

This study described how MC simulation analysis could be used more widely in the hospitality field to understand operational and marketing issues. The primary contribution of this study was methodological, demonstrating

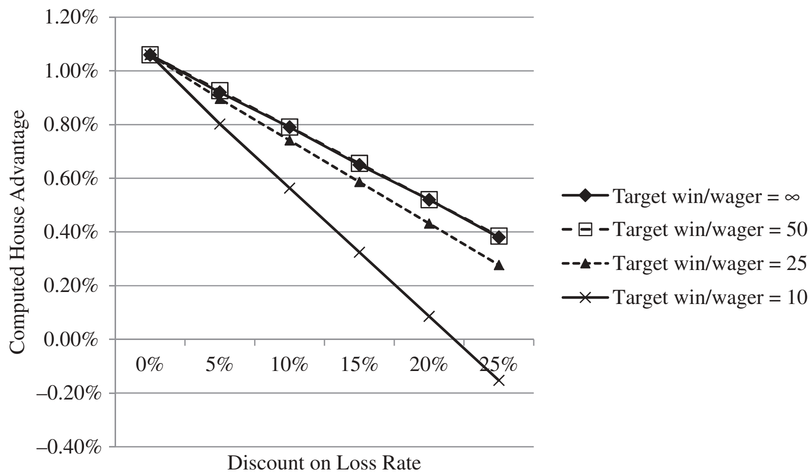

FIGURE 3 Multiple computed house advantages with maximum hands played of 300.

Note. Target win to wager ratio curves have the same house advantage at a discount rate of 0%, but the slope of the change in house advantage becomes steeper for smaller target win to wager ratios. The house advantage can be substantially different than what is expected from a typically computed $+\infty$ ratio.

how this risk analysis technique, which has often been using in financial risk analysis, can be adapted to better understand discount programs. By modeling consumer behavior in typical restaurant and casino discount programs, we demonstrated how MC simulation enables analysis of programs that may be too difficult to understand through direct measurement or forecasting approaches. A modest theoretical contribution to gambling risk analysis was also made, as we demonstrated how non-game-related consumer behavior could impact profitability when a discount on loss program is in place.

Practically, simulation using MC analysis may lead to better ex-ante understanding of individual customer profitability and a better understanding of the distribution of possible outcomes. This method can provide relatively low-cost business intelligence for management decision making. The findings from this study's restaurant simulation revealed how a discount program may lead to a short-run increase in profitability, but that there may be a threshold at which long-run changes to profitability are negative. This result illuminates what restaurant managers may have intuitively known. Discounts and promotions in restaurants often only increase revenues in the short-run but rarely create customer loyalty and long-term profits. Restaurant managers can use this method to identify the point at which to stop implementing promotions before negative profitability occurs. This article provides a tool that indicates when to discount and to what level of monetary value. This is particularly important for restaurants that traditionally attract the wrong customers with discounts and show negative profitability because of discounts (Raab, Mayer, Shoemaker, & Ng, 2008). Finally, this result agrees with Park et al. (2013) and McCall et al. (2010), in that financial burdens can be reduced by increasing customer–program fit and separating short-term and long-term customer orientations.

The casino simulation revealed a potentially significant source of casino marketers' and operators' overestimation of theoretical win. The study clearly demonstrated that current gaming industry tools for measuring discount program returns are flawed, which can lead to lower levels of profitability (or operational losses) if an approach does not account for consumers' decision to end play at nonrandom intervals. Casino managers can use similar methods to those in this study to compute adjusted theoretical win tables, based on the probability that they expect a player to end a playing session early. More widely, casino managers should think about how MC models can be used to better understand sources of risk from consumer behavior. While the gaming industry has used MC simulation for many years to estimate the house advantage of different games, the same method can be used to analyze other forms of risk and variance that exists within their properties. For an industry where capital investments regularly exceed 1 billion USD, a better understanding of all types of firm risk would be quite useful.

These are only two straightforward examples of the potential application of MC methods in discount program evaluation. Other simulations of different programs may reveal different idiosyncrasies that are not directly evident to management from the program parameters. For example, MC could be used to better understand how business and leisure travelers may respond to a new hotel loyalty program, how day of week discounts could change restaurant consumer spending patterns, or how casino match play programs would compare to free play programs. With the ability to run complex models on common spreadsheet programs like Excel, and powerful software like R freely available for download, risk analysis using MC methods has become an accessible and inexpensive tool available to managers.

Limitations and Future Research

Of course, while MC modeling is a flexible and low-cost technique to evaluate the effect of different discount programs on consumer behavior and overall profitability, its main limitation, and one that is relevant to the examples of this study, is that the results usefulness are directly tied to the accuracy of its parameter assumptions. Omission of meaningful variables, or poor estimation of the variables' probability distributions, will distort the scenarios such that nonoptimal decisions may be made by management. Managers should still use caution and common sense when examining the results from the simulations, as having new quantitative figures to use in decision making could lead to accessibility bias in management decision-making.

Managers need to be aware of the statistical noise that may be present in simulation results and use other heuristics to exclude infeasible outcomes. The MC approach should be iterative, with several stages of simulation, evaluation, and calibration. Finally, managers should be aware that these methods often result in normal distributions, which are often useful for the most likely outcomes and those within two to three standard deviations, but extreme outliers may not be adequately captured. This can lead to biased decision-making if unlikely, but extremely impactful, events are unaccounted.

Future research could empirically examine how MC approaches to decision-making perform versus other decision-making tools and heuristics. Additionally, this method could be applied to other industries, such as lodging or travel, to reveal idiosyncratic patterns of behavior that may be unknown risks in those industries. Lastly, the projections from this study could be compared against empirical data, to see how well the predicted outcomes conform to reality. For example, gaming databases could be queried to examine whether some baccarat players are adapting their play behavior to exploit the identified discount program vulnerability.

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NOTES

1. An alternative mechanism is for the casino to provide the player with casino checks as a percentage of the amount lost.
2. For a technical resource in designing these models, see Robert and Casella (2010) and Vose (1996).
3. As a point of reference, a $100 per hand wager with a $2,500 target win rate would have a target win to wager ratio of 25.

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