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Estimating the Effect of Casino Loyalty Program Offers on Slot Machine Play

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Abstract

Annual investment in casino free-play campaigns is usually great, yet little is known about its ability to generate increased gaming expenditures/behavioral loyalty. A method and model are advanced to estimate the impact of these costly and notoriously difficult-to-measure programs, providing critical business intelligence for use in the management of these ongoing campaigns. Actual slot machine performance data from two tribal casinos were examined, allowing for an empirical test of a critical link within an existing theoretical model of customer responses to loyalty programs. Using data from two 365-day samples, our model successfully explains the variation in slot wagering at both donor casinos. One resort's free-play campaign shows signs of success while the other's indicates a need to retool its $15 million annual campaign. Although the theoretical linkage of customer responses to loyalty programs (LPs) is well established in the broader context, yet its applicability to casino LPs remains questionable given the mixed support from this study and the results of extant free-play research.

Keywords

casino management; casino operations; casino marketing; customer loyalty; free-play offers; loyalty programs

Free-play (FP) awards have been established as a critical and potentially costly play incentive in most U.S. gaming markets (Fein, 2009; Gruetze, 2012; Sortel, 2010). These incentives are essentially cash awards issued to slot machine players, with one catch; they must be wagered at least one time before the player can cash out any remaining FP credits. In this golden age of FP, it has become the dominant form of player reinvestment for many U.S. gaming operators (Gruetze, 2012). Some casinos report FP awards in excess of 20% of annual revenues (Barker, 2015; Belko, 2016). The Sands Bethlehem alone is on record for issuing more than US$2 million in FP per week, over a 9-month period (Gruetze, 2012). Overall, Pennsylvania casinos redeemed US$622 million in FP for the fiscal year ended 2015, including five properties that each redeemed more than US$50 million in FP offers (Belko, 2016). In spite of the industry-wide popularity and considerable cost of these offers, little is known about their effect on customer behavior.

There are essentially two kinds of FP awards in casino loyalty programs (LPs): discretionary FP (DFP) and earned FP (EFP). DFP offers are electronic currency awarded to slot players by casino management. The dollar amount of these awards is determined by management, but it is usually a function of each customer's historical tracked play over a defined qualification period (e.g., the preceding 30-day period). These offers are most often communicated via direct mail materials sent to club members by way of the postal service.

Like DFP, EFP awards are also electronic currency. A key difference between these two types of offers is the way in which they are awarded to players. Players can elect to convert the loyalty club points they earn from playing slots into EFP credits, should they choose to use/redeem their club points in this manner. In most casinos, other point redemption options include obtaining free meals in restaurants, free show tickets, and more. EFP is only one of several point redemption options, which greatly limits the associated cost of such offers. The point liability is already established by the customer's play, so management is already committed to these costs, whether they are incurred via EFP or complimentary awards redeemed in restaurants. LP members can convert their point balances to EFP credits at their discretion, so these awards are not accompanied by direct mail materials.

For management, DFP is the primary concern as the cost of these offers is not included in the point liability that is built into the LP design. DFP costs are incremental to the guaranteed benefit structure of the LP, yet they are ongoing

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and based on member play. Because DFP awards offer management much more flexibility with regard to reinvestment levels, they are the primary LP benefit (Lucas & Kilby, 2008).

Of course, players are attracted to DFP offers, as these incentives extend play time and give players a shot at hitting a jackpot without risking additional bankroll. In return, management hopes that DFP offers will stimulate increased spend per trip and/or increased trip frequency (Belko, 2016). As a critical first step, it would be helpful to know the extent to which players access their own bankroll after losing the DFP credits. This information would address important concerns related to whether DFP offers stimulate additional play or merely cannibalize trip-level gaming budgets. In spite of the industry-wide popularity of DFP offers, this and other important questions remain.

These questions are quickly complicated by the related game and marketing system technologies. Once DFP awards are initially wagered, the recipient has satisfied the compulsory play requirement, and any surviving DFP credits are transferred to the slot machine's credit meter. At this point, the player could cash out the surviving credits and leave the casino. If the player continued to wager, the game/tracking system could not differentiate between (a) wagers placed from the transferred DFP credits and (b) wagers made from additional funds inserted by the player. This technological limitation prevents casino marketers from knowing how much, if any, of a player's own bankroll is wagered after exhausting the DFP credits. The results of this research address this important issue, providing valuable feedback to gaming operators. The method and model advanced herein could be adapted for use by any casino to measure the effectiveness of its FP campaign. In addition, the results add to the broader research stream related to the general efficacy of LPs on customer behavior.

Literature Review

In general, LPs have been found to mildly increase performance measures of overall business volumes (Dorotic, Bijmolt, & Verhoef, 2012). This conclusion holds for continuous/ongoing LPs such as those offered by airlines (Liu & Yang, 2009). Similar to the airline industry, casino LPs are continuous and ongoing. In addition, most gaming markets are saturated with similar LPs, making program benefits less distinct. Although the model advanced in Dorotic et al. (2012) claimed broad support for the positive relationship between reward redemption and customer expenditures within LPs, they are careful to note that this relationship tends to vary across program structures, industries, market conditions, and other variables. As the extant gaming literature will show, the applicability of this proposed linkage remains equivocal within casino LPs.

FP Research

Few studies have attempted to directly measure the efficacy of FP offers, but for those that have, the results are generally unfavorable (Lucas, Dunn, & Singh, 2005; Rüdisser, Flepp, & Franck, 2015; Suh, 2012). Rüdisser et al. (2015) conducted a field experiment in a Swiss casino, whereby patrons were randomly assigned to control and treatment groups upon arriving at the casino. Control group members received no FP award and treatment group members received various amounts of FP. Although many different comparisons were made between the control and treatment groups, the authors found that the casino's win per player (actual and theoretical) was significantly less for those in the treatment group.

Rüdisser et al. (2015) also noted that the results were consistent with Tversky and Kahneman's notion of loss aversion, whereby people feel losses more intensely than they enjoy gains of the same magnitude (Tversky & Kahneman, 1991, 1992). Specifically, once the gamblers comprising the treatment group were endowed with a FP award, they became comparatively risk averse in their wagering behavior. The endowment itself provided a basis for loss, activating the tendency for loss aversion. In support of this notion, the average bet for the treatment group was significantly less than the average bet for the control group.

The loss aversion premise is especially noteworthy because the casino operators had mentioned that the primary purpose of the FP awards was to encourage the house money effect, as described in Thaler and Johnson (1990). Specifically, the casino operators had theorized that the FP endowment/windfall would produce riskier and more capricious wagering behavior, just as Thaler and Johnson had found with those who invested windfall gains. Furthermore, management held that this riskier wagering behavior would carry over to bets placed with the recipient's own bankroll, once the FP award was lost.

Suh (2012) conducted a field experiment on two randomly selected groups of players from the same tier of the donor casino's database. One group received a US$50 DFP award and the other received a US$100 DFP award. The results indicated no significant difference in the gaming activity across these two award levels.

In Lucas et al. (2005), the player-level data were comprised of trips on which a player received a DFP award (LP era) and trips on which the same player did not receive a DFP award (pre-LP era). The objective was to determine whether a change in spend per trip was associated with the DFP trips. Two offer levels were examined, one at US$50 and one at US$100. At the US$50 level, the DFP trips produced significantly less coin-in than the trips with no DFP. Although not statistically significant, the DFP trips at the US$100 level also produced a negative effect.

Contrary to the other FP studies, Suh, Dang, and Alhaery (2014) produced a positive result for DFP variables in models designed to predict daily coin-in in two U.S. riverboat casinos. The authors noted that variance inflation factors (VIFs) for one casino's model exceeded 5.0, but individual VIFs were not reported. It was unclear to what extent the DFP variables were affected by these cautionary levels of multicollinearity.

To date, no study has examined property-level redemption data from all FP offer activity, over the course of a full year. Only cross-sectional data sets and partial-year samples have been studied. In addition, all the data sets from U.S. casinos were gathered prior to 2008. Since then, gaming has expanded across the United States and markets have become more competitive, resulting in more aggressive and more expensive FP campaigns (Barker, 2015; Belko, 2016; Gruetze, 2012). Moreover, no research has quantified FP effects in terms of incremental win per dollar of FP redeemed. This is a most important metric for evaluating the efficacy of the overall campaign. Finally, no one has separately considered the effects of DFP and EFP. The current study addresses all these gaps in the literature.

Method

The data sets were donated by management from two tribal casinos operating in the Western United States. These donors wished to remain anonymous, and will hence be referred to as Resort A and Resort B. The annual slot win for both these casinos exceeded all other sources of departmental revenue, with both resorts operating an on-site hotel, a variety of restaurants, and other nongaming amenities. Both casinos relied heavily on operating profits from slot machines. Both properties operated in markets in which all their direct competitors offered point-based LPs of a similar structure. Further description of these resorts is not possible here, as it could potentially identify the properties and violate the nondisclosure agreement required to obtain the performance data.

The data set from both resorts included 365 sequentially ordered daily observations from July 1, 2013, through June 30, 2014. Time series regression analysis was used in the formal analysis of the data. The method used here was consistent with that of previous researchers who have successfully modeled similar casino performance data (Lucas, 2014; Suh & Tanford, 2012; Suh & Tsai, 2013). Simultaneous entry of the predictor variables was used and hypothesis tests of the DFP and EFP variables were one-tailed, at $\alpha = .05$. The data were screened in SPSS, version 21, and the time series regression analysis was performed in EViews, version 8.

The data set for each property was analyzed separately, with CCOIN-IN serving as the dependent variable in both equations. CCOIN-IN represented the aggregate daily dollar value of all carded wagers placed in electronic gaming devices. These devices included coin- and/or voucher-operated reel slot machines, video poker machines, and electronic table games. Carded wagers represented tracked slot play from LP members only. CCOIN-IN was selected as a dependent variable because it represented the least biased business volume indicator for electronic gaming devices.

The key variable, DFP, represented the aggregate daily dollar value of DFP offers redeemed across all electronic gaming devices. These awards were issued by management after evaluating the historical play (i.e., gaming value) of individual LP members. For example, management would evaluate an individual's play over the previous 90-day period to determine the value of his or her award for the current period. The daily sum of all *initial* wagers related to individual DFP rewards determined the value of DFP for each day of the sample.

Based on the success of models used by previous researchers in predicting aggregate daily coin-in levels (Lucas, 2014; Suh & Tanford, 2012; Suh & Tsai, 2013), most of the remaining control variables were binary variables representing holidays, day of the week, and outliers. In the current study, Wednesday served as a base period for the day of the week variables, as this day often represents the slowest day in terms of casino wagering activity. The following U.S. holiday variables included New Year's Day (NYD), Martin Luther King Day (MLKDAY), Presidents' Day (PRESDAY), Valentine's Day (VALDAY), St. Patrick's Day (PATSDAY), Memorial Day (MEMDAY), Independence Day (INDDAY), Labor Day (LABDAY), Thanksgiving Day (THKSDAY), Christmas Day (XMAS), and New Year's Eve (NYE). Holidays such as NYE included the effects of special events organized for the casino's best players.

EFP was added to the current model to represent the aggregate daily dollar value of all earned FP credits redeemed. EFP credits were created when players converted LP points into slot credits, in lieu of using their points to acquire items such as meals or show tickets. Although EFP credits were substantially limited by the LP's point accumulation constraints, this variable would still affect CCOIN-IN levels. Finally, TREND was included to account for the possible effects of a linear trend in CCOIN-IN over the sample term. This variable was set to a value of 1 on July 1, 2013, and increased by 1 each day, until reaching a maximum value of 365 on June 30, 2014. In summary, the following equation specifies the full model, which was separately applied to each data set.

$$
\begin{aligned}
\text{CCOIN}-\text{IN}_{ij} &= c + B_j\left(\text{DFP}_{ij}\right) + B_j\left(\text{EFP}_{ij}\right) \\
&+ B_j\left(\text{MON}_{ij}\right) + B_j\left(\text{TUE}_{ij}\right) + B_j\left(\text{THU}_{ij}\right) \\
&+ B_j\left(\text{FRI}_{ij}\right) + B_j\left(\text{SAT}_{ij}\right) + B_j\left(\text{SUN}_{ij}\right) \\
&+ B_j\left(\text{NYD}_{ij}\right) + B_j\left(\text{MLKDAY}_{ij}\right) \\
&+ B_j\left(\text{PRESDAY}_{ij}\right) + B_j\left(\text{VALDAY}_{ij}\right) \\
&+ B_j\left(\text{PATSDAY}_{ij}\right) + B_j\left(\text{MEMDAY}_{ij}\right) \\
&+ B_j\left(\text{INDDAY}_{ij}\right) + B_j\left(\text{LABDAY}_{ij}\right) \\
&+ B_j\left(\text{THKSDAY}_{ij}\right) + B_j\left(\text{XMAS}_{ij}\right) \\
&+ B_j\left(\text{NYE}_{ij}\right) + B_j\left(\text{TREND}_{ij}\right) + e_{ij}.
\end{aligned}
$$

Table 1.
Descriptive Statistics and Correlation Matrices for Continuous Model Variables: Resorts A and B (*N* = 365).

Descriptive Statistics	*M*	Median	*SD*	Minimum	Maximum
Resort A variables					
CCOIN-IN	US$4,856,105	US$4,722,809	US$1,169,936	US$2,666,611	US$8,745,281
DFP	US$42,531	US$38,954	US$25,494	US$7,811	US$151,320
EFP	US$9,704	US$9,317	US$2,537	US$2,839	US$18,349
TREND	183	183	106	1	365
Resort B variables					
CCOIN-IN	US$568,876	US$534,284	US$224,638	US$252,426	US$1,817,497
DFP	US$3,469	US$3,314	US$1,880	US$532	US$12,453
EFP	US$2,875	US$2,644	US$1,146	US$1,242	US$9,319

Correlation Coefficients	CCOIN-IN	DFP	EFP	TREND
Resort A variables				
CCOIN-IN	—			
DFP	.55**	—		
EFP	.79**	.37**	—	
TREND	.20**	.02	.14**	—
Resort B variables				
CCOIN-IN	—			
DFP	.34**	—		
EFP	.98**	.39**	—	
TREND	.13*	.53**	.17**	—

Note. DFP = discretionary free-play; EFP = earned free-play.
*Significant at α = .05, two-tailed.
**Significant at α = .01, two-tailed.

The model predicted CCOIN-IN for the *i*th day at the *j*th resort, where *i* ranged from 1 to 365 and *j* ranged from 1 to 2. The correction variables included autoregressive (AR) and moving average (MA) terms, which were added as needed to meet the assumption of independence. These variables adjusted for serial correlation between errors and between CCOIN-IN values. Binary variables were also included on an as-needed basis to express outlier effects. These variable names were based on the month and day of the outlier date, for example, JAN 25. Such cases were identified by studentized deleted residuals in excess of 3.0 and visual inspection of scatter plots of predicted CCOIN-IN values and studentized deleted residuals. With sample sizes of 365 days, outliers were to be expected.

Given that players must wager the DFP awards once before they are able to cash out any remaining award balance, the following alternative hypothesis (H_a) was advanced for both Resort A and Resort B:

Alternative Hypothesis (H_a): $B_{DFP} > 1$.

If the results fail to reject this hypothesis, then the regression coefficient will be multiplied by the appropriate property's overall house advantage on all related wagers. This product will determine whether the incremental gains in wagering volume were sufficient to cover the direct costs of the DFP awards. If the H_a is rejected, then the results would suggest that DFP recipients are not wagering beyond the minimum requirement to claim the offers.

Results

Data Screening

Time series plots of CCOIN-IN were examined to evaluate the general condition of each response variable. Per Kennedy (1998), such plots are used to visually assess the stationarity of the response variables (CCOIN-IN). Specifically, these plots aid in identifying problematic departures from the conditions of a constant mean and constant variance, over the course of the sample term. Overall, the time series plots exhibited a reasonably constant mean and variance. Although some spikes in CCOIN-IN were present in both samples, these observations were addressed by way of holiday and outlier variables. TREND was added to both models to address the possibility of significant differences in the mean of CCOIN-IN over the sample term. The addition of these variables prevented the transformation of CCOIN-IN, which would complicate interpretation of the results.

Table 1 includes descriptive statistics and bivariate correlations for the continuous model variables from both data

Table 2.
Results of Time Series Regression Analyses-Dependent Variable: Aggregate Daily Carded Coin-In (CCOIN-IN).

	Resort A		Resort B	
Variable [VIF_A; VIF_B]	*B*	*SE B*	*B*	*SE B*
Constant	334,396.85		376,931.08	
DFP [1.35; 1.17]	11.75**	0.92	24.27**	4.05
EFP [1.90; NA]	319.86**	9.50	NA	NA
MON [1.95; 1.74]	540,080.67**	76,160.72	−57,505.76*	22,570.10
TUE [1.91; 1.75]	572,301.32**	67,407.12	−65,512.04**	18,065.35
THU [1.94; 1.73]	506,006.43**	68,405.33	54,201.24**	18,046.69
FRI [1.75; 1.76]	1,086,256.31**	73,633.39	224,591.89**	22,678.87
SAT [1.84; 1.87]	1,629,923.91**	73,405.86	353,849.51**	25,046.25
SUN [1.78; 1.79]	1,047,237.87**	72,171.46	136,220.57**	24,869.64
NYD [NA; 1.02)	NA	NA	635,756.16**	91,072.36
VALDAY [NA; 1.03]	NA	NA	508,469.48**	84,517.79
INDDAY [1.03; NA]	920,352.41**	335,445.71	NA	NA
LABDAY [NA; 1.02]	NA	NA	496,199.68**	83,632.22
THKSDAY [1.03; NA]	716,277.59**	273,167.65	NA	NA
NYE [1.02; 1.05]	1,076,109.83**	320,702.02	978,426.06**	92,824.35
TREND [1.07; NA]	874.32**	324.16	NA	NA
JAN 25 [1.06; NA]	1,621,845.57**	345,194.54	NA	NA
JAN 26 [1.02; NA]	−939,602.84**	337,959.03	NA	NA
FEB 01 [NA; 1.02]	NA	NA	423,364.54**	83,257.61
MAR 01 [NA; 1.02]	NA	NA	747,308.37**	83,543.53
MAR 19 [1.03; NA]	−1,321,405.41**	326,912.69	NA	NA
MAY 31 [NA; 1.02]	NA	NA	509,290.16**	83,831.94
JUN 28 [NA; 1.04]	NA	NA	−342,566.34**	85,571.69
SEP 07 [1.05; NA]	−1,456,997.09**	330,513.01	NA	NA
SEP 14 [1.06; NA]	−1,313,965.79**	331,472.42	NA	NA
SEP 21 [1.05; NA]	−1,815,547.95**	333,747.64	NA	NA
SEP 28 [1.05; NA]	−1,875,227.44**	328,414.44	NA	NA
AR (1)	0.3450**	0.0522	0.5151**	0.0458
MA (4)	0.1348*	0.0547	NA	NA
AR (7)	NA	NA	0.1990**	0.0462
MA (7)	0.1077*	0.0542	NA	NA
R^2	92.01%		83.40%	
Model *F* Statistic	178.48**		100.49**	

Note. "NA" represents not applicable, that is, some variables did not appear in the final model for both resorts. Only the predictor variables that produced statistically significant effects are shown here. Other than DFP and EFP, all hypothesis tests were two-tailed. VIF_A represents the variance inflation factor for the listed variable in the Resort A model, whereas VIF_B represents the same in the Resort B model. DFP = discretionary free-play; EFP = earned free-play; MON = Monday; TUE = Tuesday; THU = Thursday; FRI = Friday; SAT = Saturday; SUN = Sunday; NYD = New Year's Day; VALDAY = Valentine's Day; INDDAY = Independence Day; LABDAY = Labor Day; THKSDAY = Thanksgiving Day; NYE = New Year's Eve; JAN = January; FEB = February; MAR = March; MAY = May; JUN = June; SEP = September; AR = autoregressive; MA = moving average. Model coefficients and standard errors are expressed in terms of US$.
*statistical significance at $\alpha = .05$.
**statistical significance at $\alpha = .01$.

sets. The difference in the mean for CCOIN-IN across the two resorts highlights the considerable difference in business volume for these two properties. Resort A is located much closer to a major metropolitan area, hence the much greater CCOIN-IN levels. This difference carries over to DFP levels, with the average daily redemption levels much greater at Resort A.

Formal Data Analysis

Table 2 includes the results of the time series regression analysis of data from both Resort A and Resort B. Only the variables that produced statistically significant results are shown in Table 2. All other variables were omitted from the final models to reduce multicollinearity.

The Resort A model explained 92.01% of the variation in CCOIN-IN over the 365-day sample period, with an F statistic of 178.48 (df = 22 and 342, $p < .00005$). The results failed to reject the H_a, as DFP produced a positive and statistically significant effect (B = 11.75, $p < .00005$). After accounting for the effects of the other predictor variables, a US$1 increase in DFP resulted in a US$11.75 increase in CCOIN-IN. EFP also produced a positive and statistically significant effect (B = 319.86, $p < .00005$).

The Resort B model posted an R^2 of 83.40%, with an F statistic of 100.49 (df = 17 and 347, $p < .00005$). Like Resort A, the results failed to reject the H_a, with DFP recording a positive and statistically significant effect (B = 24.27, $p <$ .00005). For Resort B, a US$1 increase in DFP resulted in a US$24.27 increase in CCOIN-IN. EFP was omitted from the final model due to elevated multicollinearity resulting from its inclusion.

Once the DFP coefficients were estimated for Resorts A and B, a two independent-samples t-test (unequal variances) was conducted to determine whether the difference between the two coefficients was statistically significant. This two-tailed test was conducted at α = .05. The result indicated that the observed difference of US$12.52 (i.e., US$24.27−US$11.75) was statistically significant ($t = -3.01$, df = 688, p = .0026).

Diagnostics

To address the issue of serial correlation, correlograms were examined with respect to the autocorrelation functions (ACF) and partial ACF (PACF). Although both models produced significant correlations between lagged values of CCOIN-IN and between lagged values of the model errors, the appropriate AR and MA terms were added to remedy these conditions.

The variance in the error terms was examined via scatter plots of the studentized deleted residuals and predicted values of CCOIN-IN. These graphs revealed no evidence of problematic heteroskedasticity. Linearity was evaluated by examining scatter plots of predictor variable values against those of CCOIN-IN values. These plots revealed no evidence of nonlinear relationships. The distribution of the error terms was assessed via histograms, with neither model producing a problematic departure from the normal distribution.

Discussion

The results from both properties failed to reject the H_a, suggesting that DFP redeemers were wagering beyond the compulsory redemption requirement. The extent of this additional wagering did vary by property, as indicated by a statistically significant difference between the regression coefficients for the DFP variables from Resorts A and B. This difference was important, as the magnitude of these coefficients is critical to the process of estimating the incremental win associated with DFP redemption.

The magnitude of Resort A's coefficient suggested that the incremental win (i.e., revenue) associated with DFP redemption was insufficient to cover the offer costs. The dependent variable, CCOIN-IN, represented the daily dollar value of tracked wagers placed by LP members—it was not revenue. To compute the incremental revenue associated with DFP redemption, the DFP coefficient would need to be multiplied by Resort A's average house advantage on slot machine wagers. In this case, the DFP coefficient (US$11.75) would be multiplied by 7.5% to produce an incremental win of US$0.88. This outcome suggests that for every US$1 of DFP redeemed in Resort A, management could expect to see an increase of US$0.88 in carded win. Therefore, Resort A's DFP program was essentially exchanging US$1 for US$0.88. In addition to this unappealing result, there were many other operating and LP program costs to cover, aside from the direct offer costs. This finding suggested that management should take a critical look at the DFP program. It certainly did not mean that DFP was not a viable option for the LP, it simply suggested that revisions to the offer process should be seriously considered.

The same calculation for Resort B yielded an incremental win estimate of US$1.64 (US$24.27 × 6.75%). Although much more favorable than Resort A's result, again, there were other operating and LP costs to cover. Still, this outcome was more encouraging with respect to the efficacy of Resort B's existing DFP program.

Although general differences in resort-level results were not unexpected, it is worth noting that Resort B's investment level in DFP appeared lower than that of Resort A. For example, using data from Table 2, Resort B redeemed 9.0% of its theoretical win in DFP (i.e., US$3,469 / [US$568,876 × 6.75%]), whereas Resort A redeemed 11.7% of its theoretical win in DFP (i.e., US$42,531 / [US$4,856,105 × 7.50%]). Of course, DFP redemptions are not the same as DFP issues, but it is not wholly unreasonable to infer a correlation between these two variables. If so, it would support the general idea of "less is more," when it comes to DFP offers. More specifically, Resort B's superior result could have been due in part to a more restrictive and/or discriminating offer protocol.

Selection Effects and Model Confounds

No variable representing daily customer counts was included in the current model. It is possible that this omission could credit or inflate the DFP coefficients, which would reduce our confidence in the estimated linkage between DFP and CCOIN-IN. In lieu of a customer count variable, the existing control variables were employed to account for the daily variation in wagering levels. The following paragraphs detail the reasons for this approach.

The current controls were included to represent the same general phenomenon as customer counts, that is, swells in daily wagering volume. For example, on Fridays, Saturdays, and Sundays wagering volumes swell, just as they do on holidays and special event days. Furthermore, models using only the current control variables have been very successful in explaining the variation in daily casino wagering volumes, with R^2 values ranging from 83% to 92% (Lucas, 2013; Lucas, Dunn, & Kharitonova, 2006; Lucas & Tanford, 2010; Suh & Tanford, 2012; Suh & Tsai, 2013). Therefore, the potential for omitted variable bias was presumed to be minimal, especially after acknowledging the presence of random variation in the criterion variables. In addition, the primary aim of the current study was to estimate DFP effects, and DFP redeemers would be a subset of customer counts. That is, a customer count variable would have introduced collinearity with the key variable, making it a less attractive proxy for general business volume.

Most importantly, customer count variables and proxies for customer counts have generally failed to produce positive effects in models designed to explain daily variation in wagering levels (Lucas, 2004; Lucas et al., 2006; Suh & Tsai, 2013). For example, Suh and Tsai (2013) used a variable representing daily poker room headcount to predict both daily slot and table game wagering volumes. It failed in both instances. The same result was produced by Lucas et al. (2006) when they used a daily bingo headcount variable to predict daily coin-in from two different hotel casinos. Finally, analysis of player databases has revealed that the bulk of casino wagering comes from a select minority of players (Maremont & Berzon, 2013), diminishing the use of general headcount data as an indicator of daily wagering volumes.

For Resort A, any inflation in the DFP coefficient resulting from the omission of a customer count variable only strengthens the case that these offers are not associated with positive cash flows. For Resort B, the potential inflation effect remains; however, its impact is not likely material.

Reward Redemption and Customer Expenditures

The theoretical link between Reward Redemption and Customer Expenditures from the Dorotic et al. (2012) model remains questionable for gaming operators. In terms of DFP results, the findings from Suh (2012), Rüdisser et al. (2015), Lucas et al. (2005), and Resort A failed to support a positive relationship between redeemed rewards and additional gambling. Only the results from Suh et al. (2014) and Resort B supported this link in the theoretical model.

This general lack of support could be due to the technological issue that obscures the origin of slot machine credits. Because operators cannot distinguish surviving DFP credits from credits initiated by the player's own bankroll, they may unknowingly overissue DFP awards to customers. Alternatively, unchecked award matching could be occurring. In this case, marketers from competing resorts could continue to match one another's increases in DFP awards, without knowing whether the existing offers are producing an acceptable return. Ultimately, it could be a measurement issue that is behind these unfavorable results. The method and model advanced in this article could help gaming operators avoid overinvestment in DFP campaigns by providing critical estimates of returns on the existing offer structure. In addition, this approach can be replicated using audited secondary data collected by any operator with an online player tracking system.

From Table 2, Resort A redeemed US$15,523,815 in DFP over the 1-year sample period (i.e., US$42,531 × 365). A rigorous and objectively derived estimate of the return on this investment represents a critical piece of business intelligence for management. Moreover, DFP is an annual investment, increasing the importance of estimating its effectiveness as a marketing tool. Better measurement could lead to important changes in the DFP campaign as well as increased operating profits.

DFP and Attitudinal Loyalty

Some may contend that the results associated with the DFP variables are moot, due to assumed contributions to the more enduring attitudinal loyalty. In theory, this attitudinal loyalty will ultimately translate into behavioral loyalty. To the contrary, researchers have found that LPs tend to produce behavioral effects as opposed to attitudinal loyalty (Dowling & Uncles, 1997; Whyte, 2004). In addition, Sharp and Sharp (1997) noted that LPs featuring economic incentives were likely to encourage behavioral loyalty more than attitudinal loyalty. The results of the current study should be evaluated with regard for these positions, until researchers are able to establish a compelling link between DFP redemption and attitudinal loyalty.

EFP Awards

Table 1 shows strong correlations between EFP and CCOIN-IN, and EFP posted an impressive regression coefficient in the Resort B model. These results may be due to the fact that players do not need to make a special trip to the casino to redeem these credits. EFP awards can be redeemed at any time, at the player's discretion. Furthermore, the dollar value of EFP awards is usually much less than DFP awards, as the EFP is capped by the LP's restrictive point-earning protocol. It is possible, if not likely, that player's visit the casino, lose their bankrolls, and then activate their EFP credits to prolong their gaming session. Such behavior would definitely create a strong correlation between EFP and CCOIN-IN.

The DFP awards are issued in greater dollar values and are date restricted. They are also delivered in direct mail pieces. These differences may cause some players to think of DFP awards as *bankroll* for a separate trip rather than a play/trip *incentive*. Others may choose to think of DFP as a trip-level bankroll subsidy, producing a cannibalization effect as noted in Lucas et al. (2005). Alternatively, it could be that overinvestment in DFP awards or indiscriminate award-granting processes have diminished their capacity to produce greater returns. Finally, the greater monetary value of the DFP awards could serve as a more meaningful endowment, leading to loss aversion as described in Rüdisser et al. (2015). In any case, future researchers may want to look into the differences in the relative and actual cost and effectiveness of these two kinds of FP awards.

Future Research

Although the method and model advanced here are helpful in understanding the effectiveness of existing DFP campaigns, further replication of the research would be valuable. Differences in results are to be expected, as variations in market, gaming regulations, and DFP campaign parameters are bound to exist. Still, knowledge of whether significant and positive returns are generally associated with DFP redemptions would be helpful in addressing critical operating issues as well as theoretical linkages such as the one examined in this study. In spite of their clear importance, very little is known about the effectiveness of contemporary DFP programs.

As previously noted, differences in the effectiveness of EFP and DFP awards are something worthy of further investigation. This could be yet another example of less is more, when it comes to casino marketing. For example, the previously noted measurement issue could lead to overinvestment in DFP which could lead to declines in the incremental spend per trip. In support, Suh (2012) found no difference in the gaming activity of those who received greater DFP awards. Additional work is needed to better understand the effects associated with changes in offer value and offer frequency.

At a more general level, little is known about differences in the efficacy of LPs across user levels (Dorotic et al., 2012). The returns on DFP may vary greatly by user level. As casinos create database tiers based on daily and/or trip gaming values, this would be an area of meaningful research for which the data have already been collected. The method and model from this study could be replicated across the various tiers to determine whether critical differences in the results are present. This would be akin to the notion of examining customer behavior across light, medium, and heavy user groups. Such work could also lead to important changes in casino LP design. For example, the results could identify overinvestment in specific tiers, leading to important revisions in the offer granting process. Revisions such as these could save millions of dollars annually.

Following the completion of this study, Resort A did revamp the offer protocol for its DFP campaign. The extent to which the results of this work influenced management's decision is not known. Regardless, Resort A has expressed interest in replicating this analysis once a sufficient number of new observations become available. If permitted to describe the program adjustments, a same-store replication of this study could provide valuable insight regarding DFP campaign management.

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