Simulating the Effect of Pay Table Standard Deviation on Pulls Per Losing Player at the Single-visit Level

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Abstract

While holding par constant, changes in the standard deviation of the pay table produced an inverse effect on pulls per losing player (PPLP), across six different virtual slot machines. This result establishes the standard deviation of a game as a crucial determinant of a slot player's experience. Three different single-trip scenarios were examined via computer simulation, with 50,000 players engaging each game. For example, virtual players began with 100 units, terminating play at bankruptcy or 200 units. As players focus on the outcome of single visits, understanding the determinants of PPLP (or time on device) will help management engineer desirable customer experiences at the trip level. In part, this can be achieved by altering the product mix to better match the expectations of the clientele. Given the remarkable bankruptcy rate of the trip simulations, proxies for value such as PPLP serve as crucial evaluation standards in the satisfaction process.

Keywords: Slot operations, slot management, casino operations, slot mix, casino management, slot machine volatility

Introduction

Previous research has found gaming value to be a key determinant of satisfaction with the slot experience (Lucas, 2003). Time on device lies at the heart of gaming value, especially when one considers the staggering bankruptcy rates at the single-visit measurement grain. That is, given the single-visit bankroll of most slot players, there is a great chance of bankruptcy (Kilby, Fox, & Lucas, 2004). Losing players are forced to consider relatively abstract notions of gaming value. For example, these gamblers are left to consider proxies for value, such as time on device. As a result, management needs to know which game factors affect time on device. Is it par, hit frequency, or the standard deviation of the game's pay table?

To date, there is a paucity of research addressing the trip-level effects of par (house advantage), hit frequency, and standard deviation of the pay table. For example, at the single-visit grain, it is not known which of these variables will produce the greatest effect on the customer experience. While popular theory favors par and hit frequency as the greatest influences on short-term outcomes, there is no empirical support for this idea (Dunn, 2004; Kilby, Fox, & Lucas, 2004). The existing research suggests that the standard deviation of the pay table may have the most profound effect on the short-term

outcome of slot players (Lucas & Dunn, 2005; Lucas, Dunn, Roehl, & Wolcott, 2004). This study expands on the start positions provided by these researchers. Specifically, the effect of pay table standard deviation on time on device is experimentally examined via computer simulation, at the single-visit or trip measurement grain.

Understanding the determinants of time on device will help casino executives better manage the experience of slot players. Given that an overwhelming percentage of these players lose, any information that aids management in the establishment of value is paramount. For those operating casinos in repeater markets, such as many riverboat and Indian gaming jurisdictions, the clientele often comprise frequent visitors and highly involved gamblers. These types of players are likely to have well established expectations with regard to time on device. A visit characterized by a rapid loss of bankroll is not likely to increase repatronage intentions. This is an especially important concern when easily accessible competitors are present, as is the case in the Las Vegas locals' market. By understanding the antecedents of time on device, operators can better match their product to the desired outcomes of their clientele.

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Literature Review

Time on Device

In Lucas (2003), slot patrons of a Las Vegas Strip property were asked to rate various aspects of their gaming experience. The scope of the survey ranged from physical aspects of the environment to more traditional service aspects, such as staff friendliness. A primary goal of the research was to better understand the satisfaction process of slot players. The results indicated that gambling value was a strong predictor of overall satisfaction with the slot experience. The gambling value construct comprised the scale items listed in Table 1.

Table 1.
Gambling value construct: Scale items

1. In this casino, I was able to play slots for a reasonable amount of time, given my investment.
2. In this casino, the number of payouts (winning plays) by the slots is reasonable.
3. You can win playing the slots at this casino.
4. The slot machines in this casino are fair.

Source: Lucas (2003).
Note. Chronbach's Alpha = 0.93

Using responses from 195 completed surveys, the model produced a significant and positive effect for the gambling value construct (df = 192, B = 0.43, p < 0.01). That is, a one-unit increase in the gambling value score produced a 0.43-unit increase in the overall satisfaction score. All survey questions were measured via a 9-point scale anchored by "Disagree Completely" and "Agree Completely."

Included in the gambling value construct is the notion that time on device is a component of gambling value. Although slot players may realize that their chances of winning are slim, they still have expectations regarding length of play, whether measured by pulls, spins, or time on device. Further, this perception of value is most important to those players that lose their gambling bankroll. It would stand to reason that winning players would be more likely to leave satisfied. To the contrary, losing players are left with more abstract notions of satisfaction, such as the aforementioned time on device perceptions.

The Role of Hit Frequency

Earlier attempts to understand which components of a slot machine influenced pulls per losing player (PPLP) are described in Kilby, Fox, and Lucas (2004). Many expected

Hit frequency is defined as the number of outcomes that produce a pay-out of at least one coin, divided by the number of all possible outcomes.

hit frequency to be a driving force behind PPLP, along with par. This popular notion prompted an experiment designed to test the relationship between hit frequency and PPLP.

Hit frequency is defined as the number of outcomes that produce a pay-out of at least one coin, divided by the number of all possible outcomes. In terms of hit frequency, the top award and the minimum payout are equal. That is, they both represent an outcome characterized by a pay-out of at least one coin.

Hit Frequency Experiment

To isolate the effect of hit frequency, par was held constant, across ten different reel slot machines. However, the hit frequency ranged from 6.7% to 29.6%, across the same ten machines. All the slot machines were two-coin multipliers. Next, the pay tables were entered into the computer and the games were simulated according to varying stop criteria. The stop criteria were as follows:

1. Each player started with $100 and quit when $200 ahead or bankrupt;
2. Each player started with $100 and quit when $300 ahead or bankrupt; and,
3. Each player started with $200 and quit when $400 ahead or bankrupt.

These stop criteria were employed to simulate the operating conditions of actual players. For example, most players do not have an infinite amount of money or time to play, so their experience is subject to constraints. A change in the constraints or the pay tables could produce different results.

The simulation was conducted under each of the three sets of stop conditions. A total of 50,000 virtual players engaged each of the ten slot machines and played according to the prescribed stop criteria. While a similar pattern was present in the results of all three simulations, the PPLP did not appear to be linearly related to hit frequency. That is, increases in hit frequency did not produce increases in PPLP, as popular theory would have it. In fact, the PPLP for the game featuring a 10.6% hit frequency was greater than that produced by the game with a 29.6% hit frequency. Despite this counterintuitive result, no evidence of an inverse relationship between PPLP and hit frequency was present. The two variables appeared to be unrelated in Kilby, Fox, and Lucas (2004).

The problem with using hit frequency as a proxy for PPLP is that it does not consider the magnitude of the pay-out (i.e., hit). The pattern in the results was most likely caused by differences in the standard deviation of the pay tables. Unfortunately, the original experiment could not be modified to this end, as the original pay tables were not available.

House Advantage (Par)

Casino executives have positioned their slot floors with regard to price (i.e., par) for many years, but how does par affect time on device or pulls per losing player? In the long term, a player will produce more wagers on a game with a 5% par than she will on a game with a 6% par, all else held constant. This is true because the 5% game keeps less of her bankroll each time that it is cycled through the machine. For example, on a 5% game, if she makes 100, one-dollar wagers, on average, she will have $95 of her bankroll remaining for additional wagering. Consider the same scenario for the 6% game. She would expect to have $94 remaining after 100, one-dollar wagers. In the long run, as par increases, the number of pulls per player decreases, all else held constant. At this point, some might conclude that lower pars would provide more time on device, or PPLP. However, there is more to consider when it comes to the effect of par.

Kilby, Fox, and Lucas (2004) offer the following example of how the effect of par can be misunderstood. Table 2 is a hypothetical reel strip for a three-reel slot machine.

Table 2.
Reel strip for a three-reel slot machine

Symbols	Reel 1	Reel 2	Reel 3
Blanks	200	200	200
Cherries	1	1	1
Total	201	201	201

Note. Cells represent the number of symbols on each reel.

Given this game's configuration, there are 8,120,601 possible outcomes. This is the product of the total number of symbols on each reel (i.e., 201 x 201 x 201). However, assume that only one combination will result in a payout (i.e., 3 cherries). That payout could be 90% of the amount wagered over those 8,120,601 trials, or it could be 95%. That is, the par of this game could be equal to 10%, 5%, or any other percentage. In any case, almost everyone that plays this game will wager their bankroll only one time. This does not look like a game that will produce a desirable experience with regard to time on device. In fact, a player would need an enormous bankroll and an abundance of time to simply determine whether the game's par was 5% or 10%. Although this is an extreme example, it makes the point that par alone may not be the best proxy for time on device.

Par Manipulation in Practice

Lucas and Brandmier (2005) offer a less extreme example of how changes in par affect gaming behavior. In their study, par was manipulated in $5.00 reel slots. This manipulation was unknown to the gamblers. In the winter of 2002 the games had a 5% par, which was increased to 7.5% in the winter of 2003. The objective was to measure the effect of the 50% increase in par on the slot win. Thus, it was a year-over-year design that compared revenue performance across the same period of time (i.e., the same dates). Further, the game locations and themes remained constant across the two periods. The standard deviation of the pay tables did change minimally as a result of the par change, which was unavoidable. A standard deviation variable was also included in their model to account for its possible effect on performance.

Although the standard deviation variable did produce a significant and negative effect on performance, the par change did not. In fact, the average dollar-amount of theoretical win (t-win) per unit increased from $529, in 2002, to $582, in 2003. This change was not statistically significant, but remains surprising. Although the par of reel slots is unknown to players, any increase in t-win on the heels of a 50% increase in the house advantage is counterintuitive. This result supports the notion that the limited bankroll of players diminishes their ability to discern even great differences in par over the course of a single visit. Thus, the effect of par on the player experience may be misunderstood, as differences between long-term effects and short-term effects confuse the issue. Given the bankroll constraints of most players, standard deviation may take on an exaggerated importance when attempting to manage the customer experience on today's slot floor.

Pay Table Standard Deviation

While no published research has examined the effect of standard deviation on PPLP, there are some results that describe the effect of standard deviation on the dollar-amount wagered. Lucas and Dunn (2005) examined the effect of various location and game characteristics on the performance of 167, $0.25, reel, slot machines, over a 91-day period in late 2002. The data were gathered from a Las Vegas Strip hotel casino. The pay table's standard deviation was one of ten independent variables employed to explain differences in unit-level coin-in. That is, the model was designed to explain why one slot machine received more or less wagers than the other games in the data set. The standard

deviation variable produced a significant and negative effect on coin-in (df = 155, B = -0.16, p < 0.05). As this was a double-log model, a one-percent increase in the standard deviation variable produced a 16-percent decrease in the coin-in variable.

This inverse relationship was expected, as greater amounts of variance reduce the number of times the player can wager his bankroll before losing it all. Alternatively stated, the number of bankroll iterations decreases, as the standard deviation increases. Lucas, Dunn, Roehl, and Wolcott (2004) produced a similar result, in a double-log model designed to predict the performance of $1.00, reel, slot machines, also from a Las Vegas Strip property. In their study, a one-percent increase in the standard deviation variable produced a 27-percent decrease in the coin-in variable. This result, along with that of Lucas and Dunn (2005), is related to the current study in that the standard deviation of the pay table is established as an inverse effect on wagering activity.

Satisfaction Process of Losing Players

Why manage time on device? Lucas (2003) demonstrated the importance of the gaming value construct in the overall satisfaction process of slot players. Further, losing players, at the single trip or visit level, must rely on something other than winning to evaluate their gaming experience. The simulation described in Kilby, Fox, and Lucas (2004, pp.137-8) produced a bankruptcy rate that ranged from 86.2% to 96.6% of all players, under quite reasonable behavioral assumptions. At any point within this range, a considerable percentage of virtual players lost their entire session bankroll. Figure 1 incorporates the hypothesized effect of a pay table's standard deviation within the theoretical framework of a slot player satisfaction model.

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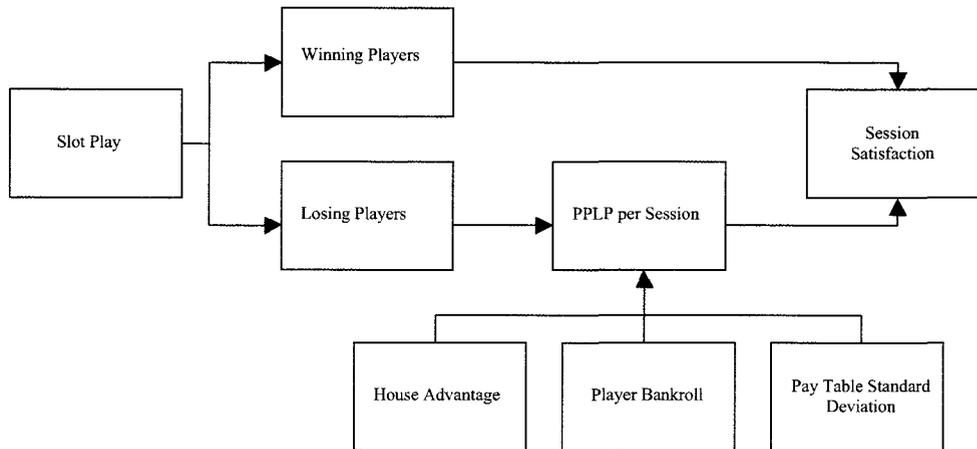

Figure 1. A theoretical model of slot player outcome satisfaction: The role of pay table standard deviation

In Figure 1, the term "session" describes a length of time beginning with the first wager and ending with a terminal event, including bankruptcy, a specified increase or decrease in wagering units, or time constraints. Specifically, the current study defined a session as the amount of pulls or spins incurred prior to bankruptcy or a specified increase in the number of wagering units (see methodology section). Although par will influence the average pulls per player, in the aggregate or long-term, the previously reviewed example provided by Kilby, Fox, and Lucas (2004) highlights its limitations with regard to impacting individual playing sessions (i.e., short-term interactions).

For those casino executives operating properties in markets characterized by a substantial repeater clientele, understanding the relationship between time on device

(i.e., PPLP) and trip satisfaction may take on exaggerated importance. That is, frequent or more involved gamblers may be more likely to discern differences in their gambling experiences, at the trip grain. Specifically, knowledge of the relationship between standard deviation and PPLP may help operators position their slot product according to the volatility (i.e., standard deviation) of the pay table. This knowledge would help executives better match their slot product to the desired experience of their clientele. For example, for those operating in repeater markets it may be desirable to offer an abundance of lower standard deviation games, as these venues cater to frequent visitors.

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Research Proposition

Based on the findings of the previously reviewed literature regarding the effect of standard deviation on unit-level performance, it is expected that PPLP and the standard deviation of the pay table will be inversely related (Lucas & Brandmier, 2004; Lucas & Dunn, 2005; Lucas et al., 2004). Specifically, increases in the standard deviation are expected to produce decreases in the PPLP. However, to isolate the effect of the standard deviation on PPLP, par had to be held constant. To test this notion, virtual pay tables were created for the current study and play was simulated via computer programming.

Methodology

In this section, the algorithm employed to simulate slot machine play is described. However, first, it should be noted that only play on pay tables from reel games was simulated. Reel slots are not games of skill. While the pay tables used in the simulation were not from actual games, they were based on programs produced by a major slot machine manufacturer. Only minor adjustments were needed to maintain a constant house advantage of 10% in the simulation. The par needed to be held constant to measure the effect of changes in standard deviation on PPLP. PPLP was selected to represent gaming value, as it transcended the difficulty of accounting for different rates of play across individual gamblers. Table 3 lists the pay tables (i.e., discrete outcomes), pars, and standard deviations of the simulated games. The discrete outcomes represented the difference between a single-unit wager and each possible payout, from the perspective of the player. The standard deviation of each pay table was computed using the given values for par, discrete outcomes, and the probability of each outcome.

Table 3.
Simulated Pay Tables

Pay Table #1		Pay Table #2		Pay Table #3	
Discrete Outcome	Prob. of Outcome	Discrete Outcome	Prob. of Outcome	Discrete Outcome	Prob. of Outcome
-1	0.8148263151	-1	0.8615411610	-1	0.864739337
1	0.0850000000	1	0.0750000000	1	0.071797000
4	0.0550000000	4	0.0350000000	4	0.035000000
9	0.0449408000	9	0.0150000000	9	0.015000000
19	0.0002000000	19	0.0075000000	19	0.007500000
39	0.0000300000	39	0.0057500000	39	0.005750000
59	0.0000010000	59	0.0000203500	59	0.000084000
99	0.0000008468	99	0.0000846630	99	0.000044663
199	0.0000008000	299	0.0000800000	299	0.000040000
299	0.0000001000	399	0.0000100000	399	0.000017000
399	0.0000001183	499	.00000118260	499	0.000015000
499	0.0000000200	699	0.0000020000	1,199	0.000013000
Par	10%	Par	10%	Par	10%
Sigma	2.37 coins	Sigma	5.27 coins	Sigma	6.60 coins

Pay Table #4		Pay Table #5		Pay Table #6	
Discrete Outcome	Prob. of Outcome	Discrete Outcome	Prob. of Outcome	Discrete Outcome	Prob. of Outcome
-1	0.8687134000	-1	0.943544649	-1	0.940507874
1	0.0717970000	1	0.045000000	1	0.050000000
4	0.0320000000	7	0.001000000	4	0.001000000
9	0.0140206000	17	0.000110000	9	0.000110000
19	0.0075000000	37	0.000200000	19	0.000200000
39	0.0057500000	57	0.000030000	39	0.000030000
59	0.0000600000	75	0.010000000	59	0.000064000
99	0.0000500000	77	0.000001000	99	0.007966300
399	0.0000400000	97	0.000080000	199	0.000080000
499	0.0000310000	197	0.000020525	299	0.000010000
699	0.0000190000	997	0.000011826	399	0.000011826
1,199	0.0000190000	3,997	0.000002000	499	0.000020000
Par	10%	Par	10%	Par	10%
Sigma	8.09 coins	Sigma	10.14 coins	Sigma	12.21 coins

Note. In Pay Table #5, actual value was 74.89, in lieu of 75. All discrete outcomes are from the player's perspective, with regard to sign (i.e., +/-).

By way of simulation, 10,000 virtual players engaged each of the six pay tables found in Table 3. This engagement was repeated five times on each of the six games, producing a total of 50,000 outcomes for each virtual game. The parameters of the three simulation scenarios were quite simple with regard to the stop criteria. The following rules were employed:

1. Each player started with 100 units and quit when 200 units ahead or bankrupt;
2. Each player started with 100 units and quit when 300 units ahead or bankrupt; and
3. Each player started with 200 units and quit when 400 units ahead or bankrupt.

Simulation Algorithm

The simulation was coded in the R programming language, version 2.2.1 (R Development Core Team, 2005). Players began with an initial bankroll of A units, and bet 1 unit per virtual spin. The game could be described as $\{(e_1, p_1), (e_2, p_2), \ldots, (e_k, p_k)\}$, where e_j represented the j-th event and p_j represented the probability with which the event e_j occurred $(p_1 + p_2 + \ldots + p_k = 1, p_j \geq 0)$. The net change in wagering units associated with event e_j was denoted by a_j, with $a_1 = -1$, and a2, a3...a12 > 0. When a_j was equal to -1, it represented a one-unit wager by the player that resulted in no payout. That is, a_j represented the wager (one unit) less a specific payout from the listed pay table. There were twelve discrete outcomes in each pay table, hence the a1 through a12 nomenclature. Next, the steps of the algorithm process are described.

Step 1 (Initialization):

Input probabilities p[j] and payoffs a[j] into arrays, enter T = target amount, P = total # of players = 10,000, and set count = 0, BANKROLL = A.

Explanation:

The target amount represented the amount of units needed for a player to end the simulation as a winner (i.e., 200, 300, or 400). Of course this amount varied across the three simulation scenarios. The spin count, or number of pulls, started at zero and increased by one unit, until bankroll (A) was equal to zero or reached or exceeded the specified target amount (T).

Step 2 (Compute cumulative probabilities c[j]):

c[1] = p[1]
c[2] = p[1] + p[2]
.....
c[k-1] = p[1] + p[2] + ... + p[k-1]
c[k] = p[1] + p[2] + ... + p[k] = 1

Explanation:

This step allowed for the assignment of probabilities to each possible outcome, as prescribed by the pay tables shown in Table 3.

Step 3 (Play the game):

For Player = 1 to P:
While (BANKROLL > 0 and BANKROLL < T)

{ u = rand(0, 1)
If c[j] < u < c[j+1], then event e_j occurs with payoff = a[j]
BANKROLL = BANKROLL + a[j]
count = count + 1}

Explanation:

Step 3 activated a random number generator to produce an outcome (u) that was associated with the cumulative probability array that was established in Step 2. That is, the random number generator was used to select an outcome, which was then multiplied by that outcome's corresponding payout. This amount was either added to or subtracted from the bankroll, until the stop criteria were reached. Additionally, each spin was counted, before reaching the stop criteria.

Step 4 (Output):

If BANKROLL = 0, output "The player loses"
If BANKROLL $\geq$ T, output "The player wins"
Compute # of pulls per losing player.

Explanation:

At this point, the number of losing players and the PPLP had been computed for each game. Once these results were produced, graphs were created to plot the PPLP by the standard deviation of each pay table. The results of all three simulation scenarios were graphed in this format, which was comparable to the results depicted in Kilby, Fox, and Lucas (2004).

Results

As shown in Figure 2, there appeared to be an inverse relationship between the pulls per losing player and the standard deviation of the pay table. Although the relationship was appropriately ordered, it did not appear decidedly linear. The decrease from the 2.37 level to the 5.27 level and the decrease from the 8.09 level to the 10.14 level were steeper than the mild decrease from the 5.27 level to the 8.09 level. Figures 3 and 4 depict the same phenomenon. Overall, the results were as expected and consistent across the three simulation conditions.
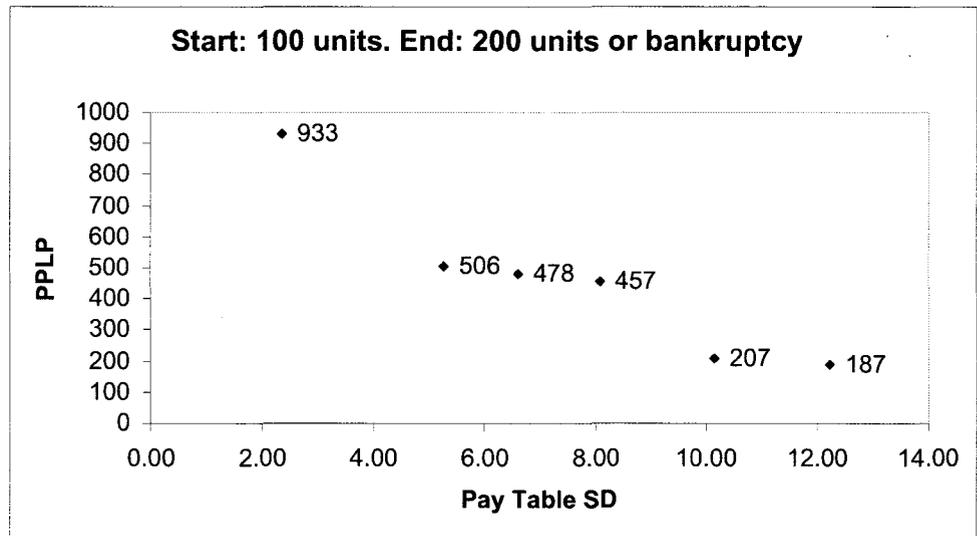

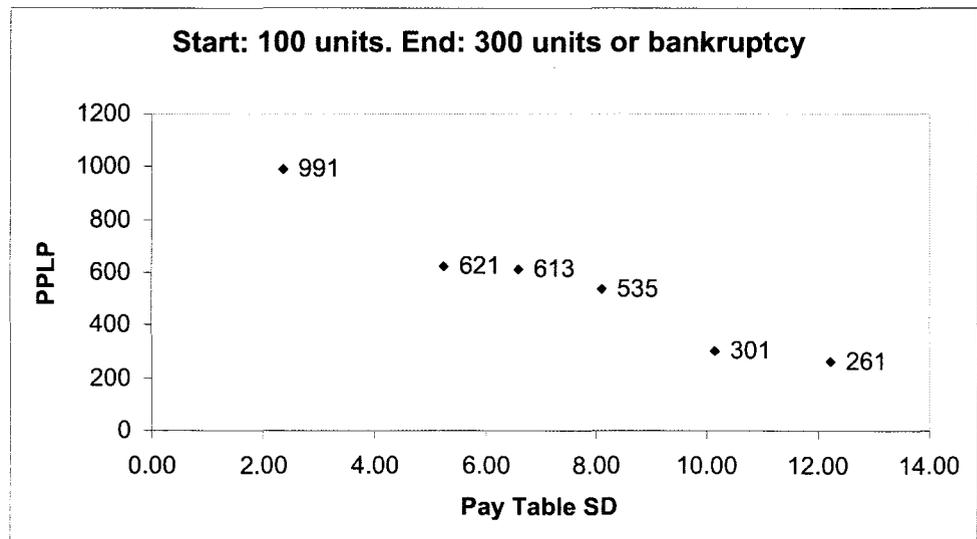*Figure 2.* Simulation results: Double-or-bankruptcy condition (100-unit bankroll).

Figure 3. Simulation results: Triple-or-bankruptcy condition.

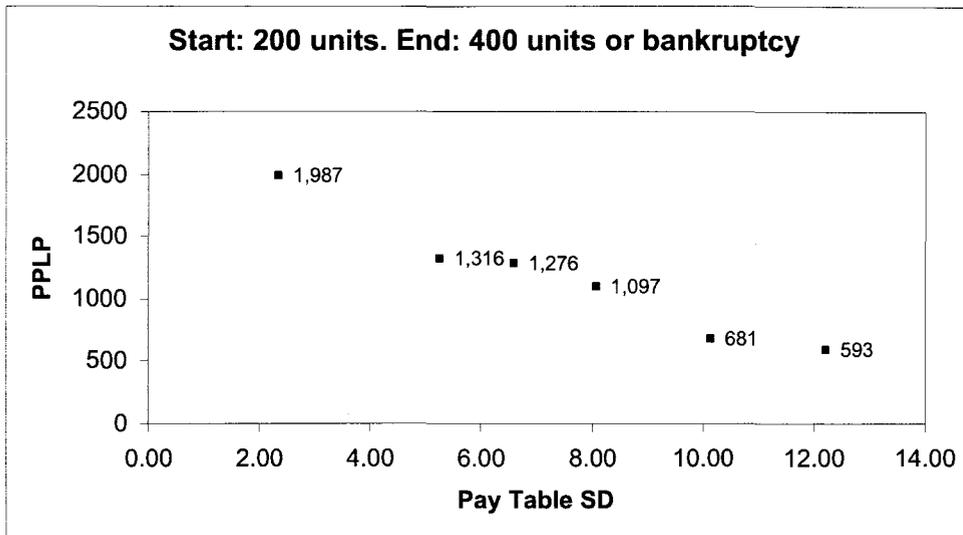**Start: 200 units. End: 400 units or bankruptcy**

Figure 4. Simulation results: Double-or-bankruptcy condition (200-unit bankroll).

With only six observations the chance of estimating a true population parameter is greatly diminished; however, the correlation coefficients (Pearson's R) associated with Tables 2 through 4 were equal to -0.95, -0.97, -0.98, respectively. Despite the low number of observations, all three of these coefficients were significant at the 0.01 alpha level. Both the graphic results and the correlation coefficients indicated a strong relationship between PPLP and the standard deviation. However, Pearson's R is a measure of linear association. While the graphic results did appear appropriately ordered, they did not illustrate a relationship as decidedly linear as the one indicated by the correlation coefficients. Spearman's Rho, the nonparametric version of Pearson's R, was equal to -1.0 in all three simulation scenarios, with all reported p-values below 0.001. Spearman's Rho substitutes ranks for the actual data values. In each simulation, an increase in the standard deviation rank produced a corresponding decrease in the PPLP rank, hence the perfect negative correlation (i.e., Rho's = -1.0).

Similar to the results described in Kilby, Fox, and Lucas (2004), the bankruptcy rate associated with the simulations varied greatly across the different pay tables. Under the double-or-bankrupt condition, the bankruptcy rate ranged from 80.7% to 96.8% of the 50,000 virtual players (100-unit scenario). The 200-unit scenario produced a broader bankruptcy range, from a low of 71.5% to a high of 99.8%. Under the triple-or-bankrupt condition, the bankruptcy rate varied much less, posting a low of 92.5% and a high of 92.6%.

Discussion

As expected, the results indicated an inverse relationship between pulls per losing player and the pay table standard deviation. This result is consistent with the previous findings of the performance – potential researchers (Lucas & Dunn, 2005; Lucas et al., 2004) as well as the work of Lucas and Brandmier (2005) on the effect of par changes. The result of the current study, taken with that produced by Kilby, Fox, and Lucas (2004), further supports the notion that the standard deviation of the pay table is a much better proxy of time on device than hit frequency. That is, the graphs produced in the current study clearly show that increases in standard deviation lead to decreases in PLLP. To the contrary, the graph in Kilby, Fox, and Lucas (2004) provided no evidence that increases in hit frequency produce increases in PPLP.

Managerial Implications

Regarding the managerial implications of this basic finding, casino managers must consider managing and positioning their slot floors according to the standard deviation of the games. For many years, par has been the key positioning metric, despite its limited effect on short-term encounters. However, it is the short-term encounter of the player that has brought standard deviation to the forefront of the satisfaction challenge. That is, the bankroll limitations of nearly all players greatly diminish their ability to detect changes in par over a session of play. To the contrary, varying degrees of the standard deviation are capable of producing a profound effect on the short-term encounter of slot players.

In the first double-or-bankrupt simulation, as the standard deviation moved from 2.37 to 12.21, the average PPLP decreased from 933 to 187. The 200-unit scenario saw the average PPLP decrease from 1,987 to 593, across the same pay tables. Similarly, in the triple-or-bankrupt simulation, as the standard deviation increased from 2.37 to 12.21, the average PPLP decreased from 991 to 261. With par held constant, these results demonstrated the substantial effect of standard deviation changes on the session-level experience of slot players.

For those executives operating casinos in repeater markets, managing the gaming experience may be particularly crucial to success. Most riverboat and Indian gaming jurisdictions, as well as the Las Vegas locals' market, cater to frequently visiting and involved gamblers. This type of gambler is likely to have well formed expectations related the slot experience, especially with regard to time on device. With bankruptcy rates ranging from 71.5% to 99.8%, time on device may be one of the few ways of communicating value to this crucial market segment. Further, gaming value has been found to significantly influence satisfaction ratings, with regard to the slot experience (Lucas, 2003). This linkage underscores the importance of the results from the current study.

For those executives operating casinos in repeater markets, managing the gaming experience may be particularly crucial to success.

For those operating casinos in destination markets, the time required to obtain a player's bankroll has been advanced as a management concern (Lucas & Brandmier, 2005). That is, the acquisition cost of players is great, and some gaming executives do not want to decrease their chances of acquiring their associated bankrolls. Assuming that hotel guests play at the host property first, some executives would prefer that the first shot at the bankroll be the last shot 'fired,' in effect. These executives would prefer to win the bankroll before the player decides to try his luck elsewhere. After all, the loss rate for the typical slot player is staggering. However, it is important to remember that only increases in par will increase the aggregate casino win, as increases in standard deviation will also produce great payouts. The standard deviation only affects the rate at which individual wins or losses occur. It does not directly affect the aggregate win.

Additionally, with the recent expansion of attractive amenities in US gaming destinations, casino managers often garner less of a customer's time and money. There are many other desirable options for would-be gamblers, such as gourmet restaurants, shows, shopping, spas, or nightclubs. For those casino managers with limited time to earn revenue, understanding the effect of pay table standard deviation may be a very helpful insight.

Limitations

The results of the simulation do not prove that an inverse relationship exists between PPLP and pay table standard deviation. However, the results do strongly support the idea. Although only reel games were examined here, there is no reason to believe that changes in the standard deviation would not produce a similar effect on other games, such as video poker. However, to test this hypothesis, researchers would first need to derive the optimal strategy for each video poker game. This expected-value driven strategy can vary across games, resulting from changes in the pay tables.

Future Research

The varying degree of change with regard to the increase in standard deviation and the corresponding decrease in PPLP gives rise to further research. That is, plateaus may exist with regard to the effect of standard deviation on PPLP. To address this issue, a much tighter field of pay tables would need to be simulated. Although this effect may have been caused by the design of the pay tables simulated in this study, there also remains a chance that the relationship between PPLP and standard deviation is curvilinear.

Additionally, replication of this research would be beneficial as would a study designed to examine the effects of standard deviation on video poker outcomes, at the session level. Further, as many players select games within relatively narrow par ranges (i.e., price points), it would be beneficial measure the relative effects of changes in par against changes in standard deviation. That is, examine the relative effects of each variable on session-level outcomes such as PPLP.

Finally, Lucas and Brandmier (2005) analyzed the changes in unit-level win after substantial increases in the par. In large part, that study sought to understand the sensitivity of players to increases in par. Similarly, research aimed at identifying the sensitivity of changes in the standard deviation would be equally valuable. This could be accomplished via quasi-experimental design, in either a gaming lab, or in the field. The lab design could feature two otherwise identical reel slot machines with different levels of standard deviations. Participants could be assigned a fixed number of credits (i.e., bankroll) and asked to place constant-amount wagers until the initial bankroll is either doubled or lost. This process would be repeated on the second game. After both rounds are completed, the participants would be asked to identify the game with the greater standard deviation, thus assessing the ability of players to sense changes in the game's standard deviation, at the session level. Of course this general approach could be tailored to specific research goals.

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