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How Changes in the House Advantages of Reel Slots Affect Game Performance

Anthony F. Lucas[1] and Katherine Spilde[2]

Abstract

In two-game pairings of otherwise identical reel slot machines, the games with greater pars outperformed those with lesser pars. This finding held across five pairings, three casinos, three gaming markets, three game titles, three differences in pars, and five bank locations. These findings help clarify an important and polarizing issue within the literature and among casino operators. Many believe that increasing pars would be perceived as increasing prices, potentially driving customers to competitors. This concern takes on an exaggerated importance for operators catering to a frequently visiting, highly involved clientele. Over time, many believe such players would detect the increased pars, leading to an unwanted exodus of play. To the contrary, the findings did not support the ability of players to detect even egregious increases in the pars, suggesting a considerable insensitivity to changes in the obfuscated price. With pay tables featuring identical awards, there was no rational justification for playing the games with the greater pars. In spite of this clear disincentive, the games with the greater pars produced more theoretical win than their paired counterparts in each of five, two-game pairings. This suggested that an opportunity to increase operating profits may be available to those willing to buck conventional wisdom.

Keywords

casino operations analysis, casino management, slot machine pars, product positioning strategy, pricing strategy

Introduction

Casino operators typically position their slot floors via the casino advantage, which is known in the industry as the par. For example, in Las Vegas, there are clear demarcations between markets. It can be inferred from long-term aggregated results that the Strip's megaresorts offer the greatest pars, the downtown casinos feature the next greatest pars, and the casinos catering to the local clientele provide the least pars (Nevada Gaming Control Board, 2017). At the casino level, further demarcations can occur within each of these markets.

The casinos catering to a clientele comprised of frequent visitors routinely advertise their gaming value via low par messages. Operators in these markets do not want to be perceived as having a "tight" slot floor or high price point (Lucas & Singh, 2011). In large part, this strategy is based on the assumption that regular players can detect even slight differences in pars, which could affect their patronage decisions (Anderer, 2010; Higgins, 2010; Klebanow, 2006, 2014; Velotta, 2009). For casino operators, the fear is that detection of higher pars will create negative value perceptions, which will lead to fewer customer visits and ultimately to declines in slot revenues.

This study aims to empirically examine how changes in pars affect game performance. In addition, this focus provides an opportunity to examine whether the wagering behavior of reel slot players supports their alleged ability to detect differences in pars over time. This issue takes on exaggerated importance for casinos catering to a frequently visiting clientele, as these valuable repeat customers experience the games over long stretches of time. The relevance of time is anchored in the belief that the ability to detect changes in pars improves with time (Frank, 2017; Gallaway, 2014). General par detection abilities have been cited as a primary cause of declining slot win in U.S. casinos (Applied Analysis, 2015; Gallaway, 2014, 2016) most of which cater to a local repeat clientele. If this is true, then casino operators should expect to earn less on slot machines that offer

[1]University of Nevada, Las Vegas, USA
[2]San Diego State University, CA, USA

Corresponding Author:
Anthony F. Lucas, William F. Harrah College of Hospitality, University of Nevada, Las Vegas, 4505 Maryland Parkway, Box 456021, Las Vegas, NV 89154-6021, USA.
Email: AFL2@cox.net

higher pars, provided these savvy players have a sufficient amount of time to detect these higher "price" points.

Why would frequent gamblers choose to play reel games with higher pars, assuming the games featured identical pay tables, identical game characteristics, and comparable game locations? One reason may be that these players cannot detect the difference between the pars, at least within modest ranges. Reel slot machines generally produce remarkably skewed outcomes distributions, which makes such detection difficult (Lucas & Singh, 2011). If this is true, then casino operators may be able to improve game performance by *increasing* par. At a minimum, the efficacy of popular price- or value-based par positioning strategies would be challenged, especially as they relate to revenue optimization efforts.

Notwithstanding notable exceptions such as casinos in the Macao and Singapore markets, most gaming properties rely heavily on slots for casino operating profits (Lucas & Kilby, 2012; Lucas & Spilde, 2017a). For many of these properties, profits from slots represent the supermajority of the total operating profit for the entire enterprise (Lucas & Kilby, 2012; Lucas & Spilde, 2017a). These critical contributions stem from the combination of substantial revenues and low operating costs. Because of this exaggerated reliance on slot operations, any research results that aid in the optimization of slot revenues would make an important contribution to the industry. Understanding how changes in pars affect game performance is especially useful to operators targeting local customer bases, as well as game makers selling machines to these casinos. Positioning strategies, marketing communications, gaming experiences, and game design would all benefit from this insight.

Literature Review

Industry Positions on Detection

Many on the operations side of the industry contend that frequent slot players are able to detect differences in pars as slight as 1 to 2 percentage points (Higgins, 2010; Klebanow, 2006, 2014; Meczka,2017), with general detection abilities enhanced by factors such as time (Frank, 2017; Gallaway, 2014) or gaming experience (Meczka, 2017). The game supplier side of the business has blamed downturns in slot revenues on increasing floor pars, suggesting that lower pars would produce increases in gaming value perceptions via increased play time (Applied Analysis, 2015; Pollack, 2007; Rutherford, 2015; Stutz, 2015). Still, there remains something of a divide between operators and suppliers regarding the demand for reel slots featuring greater pars, with many operators continuing to rely on such games (Rutherford, 2015).

In part, this divide likely exists due to the absence of sound empirical research supporting the claims made by those on both sides of the debate. Even if these opinions were supported by well-designed analysis, the methodological details are rarely if ever disclosed within the trade publications. This makes it difficult to ascertain the veracity of these claims, which likely serves to preserve the long-standing debate. The next two sections describe studies that have addressed this issue, while also describing the methodology behind the findings.

Support for the Ability to Detect Differences

From the problem gambling literature, Harrigan and Dixon (2010) simulated play on two versions of the same reel slot machine, with substantially different payback percentages. Specifically, the payback percentage of one game was set at 85%, with the second one set at 98%. They conducted a simulation featuring 2,000 virtual players who each wagered US$3.75 per spin. These "players" each started with a bankroll of US$1,000 and wagered until their balance was zero.

Most key metrics such as the mean number of total spins per player and the mean number of winning spins per player were clearly greater for the 98% game; however, the authors were careful to note that these differences were dramatically reduced when looking at the median outcomes for these same metrics.

They further concluded that the typical (median) player's experience did not appear importantly different under their simulation parameters. The 98% game simply created more players with balances above the starting bankroll condition, which drove the observed differences in the means of the performance measures. Alternatively stated, the differences in the means were created by differences in the experiences of the few lucky players in the upper tails of each outcome distribution (i.e., outliers).

Dixon, Fugelsang, MacLaren, and Harrigan (2013) found that actual players were able to determine differences in payback percentages between two versions of a reel slot game. The two versions appeared identical to the participants, including the pay tables, but the payback percentages once again varied greatly (i.e., 85% vs. 98%). Specifically, the 85% game featured a house edge 650% greater than the 98% game (i.e., 15% vs. 2%). The participants played the two games in a laboratory setting, completing precisely 500-spins on each game, in each of 30 sessions. The amount wagered per spin was held constant. The researchers recorded the payback percentage for each player, on each game, for each session.

Independent-samples t tests were conducted using these session-level payback percentages. These results indicated a statistically significant difference in the session-level payback percentages for six of the seven participants who completed the study. When surveyed upon completion of the study, all seven of these participants were able to identify the game with the greater payback percentage.

Others have analyzed secondary data describing the relationship between actual payback percentages and actual win levels by state within the legal U.S. jurisdictions (Applied Analysis, 2015). Their study analyzed actual return-to-player (RTP) data from several states, as opposed to programmed slot machine payback percentages. The authors hypothesized that decreasing payback percentages played an important role in explaining why the recovery of slot revenues has lagged behind that of broader consumer spending patterns. The economic recovery period was defined as 2010 through 2014, which was intended to represent the period following the global financial crisis. Although the authors were careful to note multiple exceptions, their general conclusion was that decreasing payback percentages had not translated into incremental gaming revenues in the postrecession era. Moreover, they suggested that decreasing payback percentages were likely contributors to the decline in postrecession slot win.

The primary conclusion from Applied Analysis (2015) appeared somewhat equivocal, as it was refuted by data from several of the gaming jurisdictions included in their study. For example, the same secondary data set could be used to argue that actual hold percentage and actual slot win were not significantly correlated. In addition, for states such as Indiana and Pennsylvania, the legalization of gambling in Ohio would be a competing cause for decreased slot win. A similar argument has been made for states such as New Jersey, as it saw marked declines in revenues following the legalization of casino gambling in neighboring states (Miller, 2014; Paumgarten, 2015). Such critical factors were not accounted for in their study. Finally, even in the aggregate, their historical data showed substantial increases in U.S. slot win during long periods of both increasing and decreasing payback percentages. This suggested that a considerable force other than payback percentage could have been behind the changes slot win levels. For example, the impact of a newly emerged gaming jurisdiction. In addition, the potential effects of product-level factors such as increases in the minimum bet per spin, increases in volatility, and increases in game speed were not considered.

Support for the Inability to Detect Differences

Several quasi-experimental studies within the problem gambling literature feature results that failed to demonstrate sensitivity to slot machine payback percentages (Haw, 2008; Weatherly & Brandt, 2004; Weatherly, Thompson, Hodny, & Meier, 2009). In Haw (2008), the actual payback percentages experienced by participants in the initial phase of his study failed to influence their choice of games played in the second phase. This was notable, as the outcomes produced in the second phase of the study determined the extent of the incentives awarded to the participants.

Weatherly and Brandt (2004) failed to find a statistically significant relationship between the number of trials in a 15-minute gaming session and programmed payback percentage. They examined three different payback percentages: 75%, 83%, and 95%. Their results are consistent with the idea that players would not be able to detect differences in payback percentages, at least within the parameters of their study. Weatherly et al. (2009) also failed to find compelling evidence of sensitivity to programmed payback percentages. Both Weatherly and Brandt and Weatherly et al. featured very short gaming sessions (i.e., 15 and 20 minutes, respectively). Given the considerable variance in most slot machine pay tables, these short sessions likely impaired the ability of the gamblers to determine differences in the payback percentages.

Within the casino management literature, findings from several studies suggested that players were not able to detect differences in pars (Lucas & Brandmeir, 2005; Lucas & Singh, 2011). In Lucas and Brandmeir (2005), the pars on 38, US$5.00 reel slots were increased from 5.0% to 7.5% with no significant decrease in the average theoretical win. This was a year-over-year design featuring the same 3 to 4 months of daily observations for each game, in each of 2 consecutive years. Although their study featured a limited and staggered sample from a single property, the games were left in the same locations on the casino floor to mitigate location bias. Lucas and Singh (2011) performed 90 different simulations of a reel slot game at four different levels of par and three different levels of pay table variance. Although they created virtual players with no capacity for memory, their results indicated that very few players would be able to detect a significant difference in the pars of otherwise identical games. Their conclusion was based on two independent-samples *t* tests performed on the outcomes of play across several different game pairings. The game pairings manipulated the par while holding sigma constant. They tested differences in pars ranging from 3 to 9 percentage points.

Many in the industry have long contended that decreases in par lead to increases in play time for individual players, citing par as an effective proxy for time on device (Dunn, 2004). This belief has led to "price" positioning strategies based on overall floor par settings. Lucas and Singh (2008) challenged this paradigm when they were able to demonstrate that changes in pay table variance could obscure or overpower the effects of par on play time, when measured at the level of the individual gamer. They simulated play on five different games, each with a different par and different pay table variance. Their results indicated that the game with the lowest par actually produced the least amount of play, while the game with the greatest par produced the greatest amount of play. This counterintuitive result was due to the changes in the pay table variances. Specifically, the game with the least pay table variance produced the greatest play time, while the game with the greatest variance produced the least play time. Their aim was to demonstrate the relative power of each factor on the individual gaming experience.

Extension of the Literature

Although all of the studies mentioned in this section have made important contributions to the collective literature, the current study sought to extend it in the following ways. The comparative performance measures occurred within the same time period, eliminating the staggered year-over-year design limitation in Lucas and Brandmeir (2005). The performance measures resulted from live play in actual casinos with real bankrolls at stake. This addressed the virtual player/de novo condition in Lucas and Singh (2011) and Harrigan and Dixon (2010). In addition, players in this study were not aware of the experiment or its end goals, as they were in Dixon et al. (2013). Although their aims were different, Dixon et al. also conducted their study with a limited sample of players in a laboratory setting that did not feature play with actual bankrolls at stake. Furthermore, such a sample is not likely to represent the overall behavioral profile/characteristics of a casino's entire clientele. Finally, the donor casinos reported average visitation rates ranging from three to five gaming trips per week allowing for an examination of par sensitivity within a highly involved clientele. These visitation rates would produce a range of 78 to 128 trips every 180 days, addressing concerns of ample time to discover differences in the pars of games located in actual casinos.

Method

This field experiment approached the par sensitivity-performance question from a practical and operations-based perspective. We tested whether the performance of otherwise identical games would vary by the par settings. This design also allowed us to better understand the ability of players to detect the difference in pars, as the games with the lower pars offered real and undeniable value. If pars can be detected by frequent gamblers, then the performance of the low par game should exceed that of its high par counterpart within each two-game pairing. That is, these players should prefer to risk and ultimately lose their bankrolls on the low par game.

Data Sources

Performance data were gathered from slot machines located within three different casinos described as AUS, LV1, and LV2. All three properties catered to and relied on a frequently visiting clientele. This was an important criterion for participation in the study, as highly involved players were most likely to detect differences in pars.

AUS was an Australian slot club located in the suburbs of Sydney. LV1 and LV2 both resided in suburban Las Vegas, nowhere near the Strip. The Australian venue offered no table games, no hotel, and approximately 300 slot machines. Two hundred ten of these machines were either penny video reels or multidenomination video reels with the penny option. These 210 games were located across 31 banks. LV1 and LV2 both featured less than 500 hotel rooms and less than 50 table games. LV1 operated approximately 800 slot machines, including 355 units that were either penny video reels or multidenomination video reels with the penny option. These 355 games were located across 55 banks. LV2 offered approximately 1,000 slot machines, with 440 games that were either penny video reels or multidenomination games with the penny option. All slot machine unit and bank counts are approximations, to protect the anonymity of the data donors and to acknowledge that these totals oscillated over the course of the study. The penny reel slot counts are relevant because US$0.01 is the dominant betting unit for most venues, and the games examined herein were penny video reels.

Only AUS did not offer live table games, as regulations prohibit them within the Australian club market. All three properties offered an array of dining options ranging from gourmet/specialty restaurants to quick-service outlets. No further property-level details could be provided, as all of the data donors wished to remain anonymous.

With respect to pars, different versions of most reel slots appear identical to the players (Harrigan & Dixon, 2009, 2010). The pay table that is visible to the players is usually identical across the multiple versions of the game. It is the probabilities that underlie the outcomes of each spin that are altered to produce the different pars/versions. These probabilities are manipulated by pay symbol distributions which are concealed from the players (Harrigan & Dixon, 2010). This was the case for all of the games examined in the current study.

The game-level performance data were collected from two different banks of games located within AUS (AUS-A and AUS-B), one bank within LV1 (LV1-A), and two different banks within LV2 (LV2-A and LV2-B). All game pairings comprised two identical games, save the difference in pars. The paired games featured the same visible pay table, the same theme/title, the same credit value (i.e., US$0.01), and the same cabinet design. Table 1 provides additional details for the specific pairings.

From Table 1, the far right column indicates the percentage increase in price, assuming pars are perceived as prices. LV1-A and LV2-B both represented substantial increases in price, with both pairings featuring an 86.55% bump. Even LV2-A's relatively modest increase of 24.97% represents a considerable jump in price. The increases in pars within each pairing were affected by (a) the availability of the licensed par options for each title and (b) the experimental

Table 1.
Par Comparisons Within Two-Game Pairings.

Two-Game Pairing	Game Theme/Title	Par 1	Par 2	Par Differences (% Points)	Par Differences (%)
AUS-A	Tokyo Rose	10.03%	14.93%	4.90	48.85
AUS-B	Dragon's Fortune	10.03%	14.93%	4.90	48.85
LV1-A	Buffalo	5.28%	9.85%	4.57	86.55
LV2-A	Buffalo	9.85%	12.31%	2.46	24.97
LV2-B	Buffalo	5.28%	9.85%	4.57	86.55

Note. AUS = Australia; LV = Las Vegas.

willingness of the casino operators. The latter concern stems from the fact that these experiments were conducted in live casino environments, with real customer experiences and real operating profits at stake.

All paired games were located on the lateral ends of the same bank of machines to mitigate potential location bias. This was an important experimental control, as researchers have found bank-level location characteristics to be associated with changes in individual game performance (Lucas & Dunn, 2005). All two-game pairings accumulated chronological performance data over the same dates. For AUS, the daily observations were collected from June 10, 2016, through December 6, 2016 (n = 180). The daily results for the games located in LV 1 and LV 2 were gathered from July 13, 2016, through October 10, 2016 (n = 90), and July 13, 2016, through January 8, 2017 (n = 180), respectively.

Casino operators were permitted to limit their participation in the study to 90 days. This option was exercised by LV1. After talking to several slot managers and game makers, 90 days was deemed a sufficient length of time for regular customers to detect a difference in the selected pars. The 90-day minimum was based on the assumption that a regular slot player in a repeater market would visit an average of 3 times per week, resulting in nearly 40 visits during the 90-day period (i.e., 38.57 visits, to be precise). This assumption was supported by proprietary visitation data provided by the data donors. Participation in the study was capped at 180 days. This cap was invoked for AUS and LV2. Given the challenges of gaining access to live gaming performance data, some flexibility in the sample size was necessary. Operators are naturally protective of live customer experiences, subjecting any form of experimentation to a variety of concerns.

There were other games on the floor with the same title as the experimental units, which were not part of the experiment. AUS offered one additional Tokyo Rose game and two additional Dragon's Fortune games. LV1 offered 10 additional Buffalo games, while LV2 offered eight additional Buffalo games.

Hypothesis Testing

Two-tailed, paired-samples t tests were conducted using the daily coin-in for each game, for each of the five, two-game pairings shown in Table 1. Because this experiment was conducted within a live commercial setting, there were limitations on the number and type of par comparisons. All hypothesis testing was to be conducted at the .10 alpha level, as this was an exploratory study; however, a Bonferroni adjustment was applied, given the repeated performance of t tests (Hair, Black, Babin, Anderson, & Tatham, 2006). This adjustment reduced the effective alpha to .02 (i.e., .10 / 5).

The first null hypothesis for all five, two-game pairings was as follows:

$$H_0 1 = \mu_{low} = \mu_{high}.$$

Here, μ_{low} represented the mean, daily coin-in for the low par game within each two-game pairing, while μ_{high} represented the same for the high par game within the same pairing. Daily coin-in represented the total dollar-value of wagers placed in each machine over the course of each 24-hour gaming day. Within each two-game pairing, the low and high par games featured the same game titles/themes, pay tables, denomination, and cabinet design.

Two-tailed, paired-samples t tests were also conducted using the daily T-win for each game, for each of the five, two-game pairings shown in Table 1. This second hypothesis was advanced under the same test conditions as $H_0 1$ and expressed as follows:

$$H_0 2 = \mu_{low} = \mu_{high}.$$

Here, μ_{low} represented the mean, daily T-win for the low par game within each two-game pairing, while μ_{high} represented the same for the high par game within the same pairing. On reel slots, theoretical win represents both the casino's positive expected value and the player's negative expected value, given the game's wagering activity. For example, if a player wagered US$1.00 on a game with a 5%

par, then the T-win would be US$0.05, regardless of the actual outcome. T-win considers both the dollar amount wagered and the par. Of course, management seeks to maximize its positive expected value, while the players seek to minimize their negative expected value. Therefore, if players could detect a difference in the pars of the paired games, ceteris paribus, we would expect the T-win to be greater on the low par game. This is because there is a compelling disincentive to play its paired counterpart.

For this study, win (aka actual win) would be a potentially misleading measure of daily game performance, due to the substantial amount of machine-level variance in the outcome distribution of daily wagering activity. For example, on the Tokyo Rose game examined herein, a single wager could produce a payout ranging from zero to 2,500 credits. If only one game in a pairing were to incur a top award payout, it would almost certainly appear as the worst performer for that day, regardless of its par. Over the course of a day (i.e., the short run), games often produce outcomes that are not representative of their long-term/true earning capacity. This is due to the heavily skewed outcome distributions of the games (Singh, Lucas, Dalpatadu, & Murphy, 2013). Even minor differences in the number of infrequent top award payouts could have a material effect on the mean daily win of a game, especially over the sample periods examined in this study. Alternatively stated, the luck component inherent in actual win data degrades its utility as a performance measure. Cardno, Thomas, and Sawyer (2015) note these and other limitations associated with the use of actual win data in the analysis of slot performance.

Results

Descriptive statistics for both daily coin-in and daily T-win were reviewed prior to hypothesis testing (see Table 2). AUS-A and AUS-B values were expressed in Australian dollars (i.e., Aus$). All other values were expressed in US$. All statistics were derived from daily observations. Histograms and Q-Q Plots of the difference scores for each pairing were also reviewed. Although some outliers were revealed, investigation of the observations that produced them verified the legitimacy of the data points.

As shown in Table 2, the mean coin-in was greater for the game with the lower par in four of five pairings. To the contrary, mean daily T-win was greater for the high par game in all five pairings. From Table 3, the daily coin-in observations were significantly correlated within each two-game pairing, supporting the use of the dependent-samples t test. Because each game's coin-in observations were multiplied by a constant (i.e., its par), identical correlation coefficients were produced by the T-win data for each of the same two-game pairings.

Coin-in Tests

Table 4 summarizes the results of the paired-samples t tests of daily coin-in observations. From the "All Observations" section of Table 4, the null hypothesis ($H_0 1$) was rejected in three of the five, two-game pairings. With the Bonferroni adjusted alpha of .02, both LV1-A and LV2-A failed to reject the null hypothesis ($t = -1.693$, $p = .094$, $df = 89$ and $t = 2.052$, $p = .042$, $df = 179$, respectively). LV1-A was the only pairing in which the game with the greater par produced a greater mean daily coin-in.

As outliers were identified in the data screening process, Table 4 was expanded to include the results of the same hypothesis tests, without the influence of these cases. These results appear in the section of Table 4 titled "Outliers Omitted." With the outliers removed, three of the five, two-game pairings failed to reject the null hypothesis ($H_0 1$). The p values for all three of these two-game pairings increased considerably from the levels posted in the "All Cases" section. In all but one of the five pairings, the magnitude of the mean difference declined. Only LV2-B remained relatively flat in this regard. AUS-B was the most notable change from the all-cases scenario, failing to maintain a statistically significant difference ($t = 1.181$, $p = .239$, $df = 169$).

Although the differences were not consistently significant, the low par games did produce means in excess of their paired counterparts in four of five pairings. Given the exploratory nature of this study, these daily differences were further examined with respect to time. Specifically, time series plots were reviewed to determine whether the mean difference for each pairing was constant over the sample period. For example, if the magnitude of the positive differences were to increase over time, it would support the idea that at least some players were able to recognize a difference in the pars.

The time series plots of daily coin-in differences failed to reveal a clear increase in any of the mean differences. In spite of this result, time series regression analysis was employed to test the effects of linear trend variables on daily coin-in differences. These trend variables were set to 1 on the first day of the sample period, with their value increasing by 1 on each successive day. Other explanatory variables included outlier dates (binary format), autoregressive terms, and moving-average terms, all of which were employed on an as-needed basis. None of the five trend variables posted a statistically significant result, indicating that the mean difference in daily coin-in was stable over time, for each of the five, two-game pairings. Table 5 summarizes these results.

As a final step, nonparametric tests were employed to measure the proportion of positive difference scores. Sign tests were conducted on the full data sets, as they do not require symmetric distributions. Positive differences reflected a greater daily coin-in observation for the low par

Table 2.
Descriptive Statistics by Two-Game Pairing.

Two-Game Pairing	*M*	Median	*SD*	Minimum	Maximum
AUS-A: Tokyo Rose (*n* = 180)					
Daily coin-in					
10.03%	2,400.06	1,973.56	2,149.80	532.66	25,240.63
14.93%	1,843.47	1,653.21	922.62	465.28	6,700.31
Daily T-win					
10.03%	240.73	197.95	215.63	53.43	2,531.64
14.93%	275.23	246.82	137.75	69.47	1,000.36
AUS-B: Dragon's Fortune (*n* = 180)					
Daily coin-in					
10.03%	2,105.42	1,629.60	1,614.71	393.15	12,110.41
14.93%	1,829.17	1,630.60	1,082.52	444.43	6,974.24
Daily T-win					
10.03%	211.17	163.45	161.95	39.43	1,214.67
14.93%	273.10	243.45	161.62	66.35	1,041.25
LV1-A: Buffalo (*n* = 90)					
Daily coin-in					
5.28%	1,240.25	1,193.67	558.47	298.05	2,599.04
9.85%	1,437.26	1,053.53	1,124.19	287.04	6,116.73
Daily T-win					
5.28%	65.49	63.03	29.27	15.74	137.23
9.85%	141.57	103.77	110.73	28.27	602.50
LV2-A: Buffalo (*n* = 180)					
Daily coin-in					
9.85%	3,270.35	2,955.72	1,365.63	1,142.51	8,309.77
12.31%	3,039.82	2,920.73	1,133.30	943.37	6,535.21
Daily T-win					
9.85%	322.26	291.26	134.60	112.58	818.84
12.31%	374.29	359.63	139.54	116.16	804.68
LV2-B: Buffalo (*n* = 180)					
Daily coin-in					
5.28%	4,517.27	4,259.35	1,671.09	1,447.74	9,919.12
9.85%	4,047.35	3,705.17	1,703.69	972.84	13,802.96
Daily T-win					
5.28%	238.33	224.72	88.17	76.38	523.33
9.85%	398.83	365.11	167.88	95.86	1,360.14

Note. All descriptive statistics associated with the performance of the AUS-A and AUS-B games are in terms of Australian dollars. The descriptive statistics associated with the performance of all other games are in terms of U.S. dollars. AUS = Australia; LV = Las Vegas.

Table 3.
Correlation Coefficients: Daily Coin-in by Two-Game Pairing.

	AUS-A	AUS-B	LV1-A	LV2-A	LV2-B
	10.03%	10.03%	5.28%	9.85%	5.28%
AUS-A: 14.93% (*n* = 180)	.206	—	—	—	—
AUS-B: 14.93% (*n* = 180)	—	.452	—	—	—
LV1-A: 9.85% (*n* = 90)	—	—	.284	—	—
LV2-A: 12.31% (*n* = 180)	—	—	—	.284	—
LV2-B: 9.85% (*n* = 180)	—	—	—	—	.250

Note. All bivariate correlation coefficients were significant at .01 alpha (two-tailed tests). AUS = Australia; LV = Las Vegas.

Table 4.
Results of Paired-Samples *t* Tests on Daily Coin-in for Each Two-Game Pairing.

Two-Game Pairing (Pars)	*M* Difference	*SE* Difference	*t*	*p*	*df*
All cases					
AUS-A (10.03% vs. 14.93%)	Aus$556.59	Aus$160.83	3.461	.001	179
AUS-B (10.03% vs. 14.93%)	Aus$276.25	Aus$110.53	2.499	.013	179
LV1-A (5.28% vs. 9.85%)	US$-197.00	US$116.39	−1.693	.094	89
LV2-A (9.85% vs. 12.31%)	US$230.52	US$112.34	2.052	.042	179
LV2-B (5.28% vs. 9.85%)	US$469.92	US$154.00	3.051	.003	179
Outliers omitted					
AUS-A (10.03% vs. 14.93%)	Aus$284.30	Aus$67.40	4.218	<.0005	170
AUS-B (10.03% vs. 14.93%)	Aus$82.76	Aus$70.09	1.181	.239	169
LV1-A (5.28% vs. 9.85%)	US$-14.49	US$88.69	−0.163	.871	84
LV2-A (9.85% vs. 12.31%)	US$107.20	US$100.94	1.062	.290	174
LV2-B (5.28% vs. 9.85%)	US$493.08	US$122.57	4.023	<.0005	172

Note. A positive mean difference indicates a greater mean for the game with the game with the *lesser* casino advantage (i.e., par). AUS = Australia; LV = Las Vegas.

Table 5.
Summary of Results for Linear Trend Variables.

Difference Series	Trend Coefficient	*SE B*	*t*	*p*
AUS-A (*n* = 180)	Aus$0.42	Aus$1.43	0.2948	.768
AUS-B (*n* = 180)	Aus$1.05	Aus$1.45	0.7251	.469
LV1-A (*n* = 90)	US$-0.06	US$2.46	−0.0228	.982
LV2-A (*n* = 180)	US$-1.89	US$2.16	−0.8755	.383
LV2-B (*n* = 180)	US$-2.21	US$2.45	−0.9025	.368

Note. "Difference Series" refers to daily coin-in differences for each two-game pairing (i.e., low par coin-in – high par coin-in). Aus$ indicates Australian dollars. Dependent variable = daily coin-in difference; AUS = Australia; LV = Las Vegas.

game. The results of these tests matched those from the "Outliers Omitted" section in Table 4. Specifically, the proportion of positive differences for both AUS-A and LV2-B was significantly greater ($Z = -4.994$, $p < .0005$, $n = 180$ and $Z = -2.758$, $p = .006$, $n = 180$, respectively). AUS-B, LV1-A, and LV2-A each failed to reject the null hypothesis of equal proportions of positive and negative differences ($Z = -0.820$, $p = .412$, $n = 180$; $Z = -0.820$, $p = .412$, $n = 180$; and $Z = -0.105$, $p = .916$, $n = 90$, respectively). To verify, AUS-B and LV1-A posted identical results for the sign test.

Post Study

Upon review of the results, it was brought to our attention that the observed differences in performance within the pairings could have been affected by the position of the games within the experimental banks. For example, it is possible that all of the low par games could have been located on the end of the bank that featured a location-based advantage. Although researchers have identified performance advantages related to aisle locations for banks and end-unit locations for units within banks (Lucas & Dunn, 2005), no one has tested for game-level performance differences in the opposite lateral end locations of banks. With a data set collected from AUS, we were able test for such differences in performance. We performed a paired-samples *t* test on the coin-in from games located on the opposite lateral ends of the same banks. The data were collected over a 90-day period in 2016, so the unit of analysis was total coin-in for each game over the 90-day period. Although we were able to control for differences in denomination and cabinet design, most matched pairs differed on par, volatility, and game theme. Data from 63 matched pairs were collected, but two pairs were identified as outliers and omitted from the final analysis. The results of the paired-samples *t* test indicated no statistically significant difference in the performance of games located on the opposite lateral ends of the same bank ($t = -0.329$, $p = .744$, $df = 60$).

T-Win Tests

Table 6 summarizes the results of the paired-samples *t* tests of daily T-win observations. From the "All Observations" section of Table 6, the null hypothesis (H_02) was rejected in

Table 6.
Results of Paired-Samples *t* Tests on Daily T-Win for Each Game Pairing.

Two-Game Pairing (Pars)	*M* Difference	*SE* Difference	*t*	*p*	*df*
All cases					
AUS-A (14.93% vs. 10.03%)	Aus$34.50	Aus$17.20	2.006	.046	179
AUS-B (14.93% vs. 10.03%)	Aus$61.92	Aus$12.62	4.905	<.0005	179
LV1-A (9.85% vs. 5.28%)	US$76.08	US$11.19	6.797	<.0005	89
LV2-A (12.31% vs. 9.85%)	US$52.03	US$12.23	4.254	<.0005	179
LV2-B (9.85% vs. 5.28%)	US$160.50	US$12.59	12.745	<.0005	179
Outliers omitted					
AUS-A (14.93% vs. 10.03%)	Aus$49.65	Aus$8.91	5.571	<.0005	173
AUS-B (14.93% vs. 10.03%)	Aus$61.92	Aus$12.62	4.905	<.0005	179
LV1-A (9.85% vs. 5.28%)	US$58.30	US$8.35	6.984	<.0005	84
LV2-A (12.31% vs. 9.85%)	US$52.03	US$12.23	4.254	<.0005	179
LV2-B (9.85% vs. 5.28%)	US$147.34	US$10.07	14.627	<.0005	176

Note. All positive mean differences indicate a greater mean for the game with the *greater* casino advantage. AUS-B and LV2-A contained no outliers. AUS = Australia; LV = Las Vegas.

Table 7.
Summary of Results for Linear Trend Variables.

Difference Series	Trend Coefficient	*SE B*	*t*	*p*
AUS-A (*n* = 180)	Aus$-0.13	Aus$0.18	−0.6969	.487
AUS-B (*n* = 180)	Aus$-0.13	Aus$0.24	−0.5392	.590
LV1-A (*n* = 90)	US$0.18	US$0.34	0.5260	.600
LV2-A (*n* = 180)	US$0.02	US$0.03	0.6017	.548
LV2-B (*n* = 180)	US$0.22	US$0.19	1.1288	.261

Note. "Difference Series" refers to daily coin-in differences for each two-game pairing (i.e., high par T-win – low par T-win). Aus$ indicates Australian dollars. Dependent variable = daily T-win difference; AUS = Australia; LV = Las Vegas.

four of the five, two-game pairings. With the Bonferroni adjusted alpha of. 02, only AUS-A narrowly failed to reject the null hypothesis ($t = 2.006$, $p = .046$, $df = 179$).

Like the coin-in differences, outliers within each series of daily T-win differences were investigated and verified as legitimate. Histograms of the difference scores for each pairing were reviewed to identify these extreme cases. The "Outliers Omitted" section of Table 6 includes the results of the same paired-samples *t* tests, after removing the outlier observations.

With the outliers removed, the null hypothesis ($H_0$2) was rejected in all five, two-game pairings. The mean differences remained relatively stable with respect to those found in the "All Cases" section of Table 6. AUS-A was the most notable change, recording a statistically significant difference in daily T-win, once the outliers were removed. This particular pairing included the greatest outlier value among all five pairings, with a T-win difference of Aus$-2,229. One of AUS's best players happened to play the low par game on September 19, producing coin-in in excess of Aus$25,000.

To better understand how the difference in daily T-win was affected by time, the same time series regression analyses were conducted to measure the effects of the previously described trend variables. Prior to these analyses, time series plots of daily T-win differences were reviewed to visually gauge the stationarity of each series. These plots failed to reveal a clear and/or meaningful increase in any of the mean differences over the sample periods. From Table 7, the results of the time series regression analyses indicated that none of the five trend variables posted a statistically significant effect. This demonstrated that the mean difference in daily T-win did not change over time for each of the five, two-game pairings.

Sign tests were also performed on the daily T-win differences produced by each two-game pairing. Positive differences reflected a greater daily T-win observation for the high par game. The null hypothesis of equal proportions was rejected in all five of the two-game pairings, as the number of positive differences were significantly greater within each pairing. The results of these tests matched those from the "Outliers Omitted" section in Table 6. More specifically, the results of the sign tests were as follows: AUS-A ($Z = -5.888$, $p < .0005$, $n = 180$), AUS-B ($Z = -6.634$, $p < .0005$, $n = 180$), LV1-A ($Z = -4.743$, $p < .0005$, $n = 90$), LV2-A ($Z = -4.330$, $p < .0005$, $n = 180$), and LV2-B ($Z = -10.472$, $p < .0005$, $n = 180$).

Discussion

Coin-in Results

The results produced by the paired-samples *t* tests on daily coin-in observations were not consistent with respect to statistical significance. The null hypothesis ($H_0$1) could not be rejected for three of five pairings, in the outliers-omitted condition. The sign tests corroborated these outcomes. In spite of these inconsistent results, the low par games did produce a greater mean coin-in in four of five pairings (see Table 4). One reason could be that some players could detect a difference in the pars. Alternatively, such differences could be the result of the declines in pars. That is, coin-in is a function of par. All else held constant, decreases in par will generate more coin-in, on average. Therefore, we would expect coin-in to be greater for the low par game.

Consider the example of two players who each have a US$100 bankroll. Player A wagers until bankrupt on Game A, which has a 5% par. Player B wagers until bankrupt on Game B, which features a 10% par. Other than the difference in pars, the games are identical. On average, or over the long run, gamblers such as Player A will generate US$2,000 in coin-in (US$100 / 0.05) before losing their US$100 bankroll. Given the same context, gamblers such as Player B will generate US$1,000 in coin-in (US$100 / 0.10) before losing their US$100 bankroll. This process follows a geometric distribution, with respect to total coin-in produced by the US$100 bankroll. Therefore, we would expect Game A to generate more coin-in, on average, even though both games produced the same win (i.e., US$100).

The previous example does assume that no players are waiting to play each game. If there were such players, the high par game could potentially accommodate more play within a gaming day, which could bolster its coin-in level. Given the low average occupancy percentages of most slot floors, this was not a critical concern.

Most importantly, the time series plots and time series regression analyses failed to provide evidence of a significant and positive increase in the daily coin-in differences. If frequent players were able to divine differences in the pars of the paired games, we would expect to see a clear increase in coin-in differences over time. Specifically, we would expect to see an increase in coin-in on the low par game and a corresponding decrease on the high par game.

All things considered, it was difficult to make a compelling case for the ability of players to detect differences in pars over time via the coin-in data. The results produced by the T-win data only added to the difficulty of making this argument.

T-Win Results

For operators, the T-win results provided critical operations-related insight. Specifically, they offered a start position for understanding the effects of par on unit-level revenue, highlighting a potential growth opportunity. T-win was the most relevant performance metric within the context of this study, as it embodied the willingness to both risk and lose bankroll to the game. In the outliers-omitted condition, the null hypothesis ($H_0$2) was rejected in each of the five pairings, with the high par game outperforming its low par counterpart in each case. This result held across samples gathered in three casinos, three gaming markets, three game titles, three differences in pars, and five bank locations.

The paired-samples *t* test results did not support the notion that players could detect the differences in the pars over extended periods of time. That is, there was no economic incentive to risk and lose their bankroll on the game with the greater par. Although undisclosed to the players, there was a considerable disincentive to do so (i.e., the greater par).

The time series plots of daily T-win differences and the results of the time series regression analyses also failed to provide support for the ability of players to detect differences in pars over time. Specifically, these results provided no compelling evidence of increasing differences in the daily T-win over time, within any of the pairings. Such increases would be expected if players were able to detect differences in the pars.

The T-win findings supported increasing the pars to improve game performance. Moreover, the increased performance of the games featuring the greater pars countered widespread concerns within the industry that increasing pars are damaging slot revenues, as noted in Gallaway (2016). Similarly, the T-win results confounded the premise of the Applied Analysis (2015) study in that they did not support the ability of a repeat clientele to detect differences in pars. Moreover, these results failed to provide evidence of a collective and negative reaction to steep increases in pars. It follows that frequent players would not decrease their slot play based on their alleged objection to a gradual and undisclosed increase in pars. The results of the current study also failed to support popular positions within the industry related to the ability of players to detect even slight increases in pars (Gallaway, 2014; Higgins, 2010; Klebanow, 2006, 2014; Meczka, 2017; Velotta, 2009). These general concerns for "price" sensitivity should be somewhat allayed, at least within the parameters tested herein.

Although the T-win results were not consistent with the findings of Harrigan and Dixon (2010) and Dixon et al. (2013), both of those laboratory-based studies featured a 13 percentage point difference in the pars. This difference was well beyond those examined in the current study. In addition, the focus of Harrigan and Dixon and Dixon et al. was on actual win data for individual players, as opposed to game-level performance expressed in terms of T-win. Staying within the problem gambling literature, the T-win results from the current study did generally support extant findings related to the inability of players to detect differences in pars (Haw, 2008; Weatherly & Brandt, 2004; Weatherly et al., 2009).

The T-win findings were consistent with those produced in Lucas and Singh (2011) who suggested that few players would be able to detect differences in pars up to 9 percentage points. Their conclusions were also based on actual win results for individual players, at the gaming session level. The current T-win findings were consistent with Lucas and Brandmeir (2005) to the extent that game-level performance was not negatively impacted by increased pars. They also found the daily, game-level T-win to increase with a 50% increase in par, but their observed US$54-gain was not statistically significant.

Managerial Implications

Ultimately, gaming executives are charged with optimizing slot revenues. They must manage a variety of variables to achieve this goal, not the least of which is choosing the optimal par setting. Many decide to offer lower par settings, assuming players will be able to detect the gaming value (Dunn, 2004). This value position anchors a marketing strategy designed to ultimately increase slot revenues, most likely based on the belief that such games will noticeably increase play time and/or the number of gaming visits (Dunn, 2004; Meczka, 2017). The results of this study did not support this popular revenue optimization strategy, as the T-win for the games with the greater pars outperformed their paired counterparts. This challenged the assumption that players are able to perceive even considerable differences in pars and would, therefore, not necessarily perceive gaming value as theorized. The time series plots and the results from the time series regression analyses bolstered this position, failing to provide evidence of progressive play migration to the low par games.

The lack of support for player sensitivity to pars is also useful to those who manage their slot floor yield via server-based gaming. One of the major advantages of server-based gaming technology is the ability for management to increase pars during peak demand periods, providing an opportunity to increase revenues (Pollack, 2007). With this comes concern for player perceptions of “price” gouging (Lucas & Kilby, 2012; Pollack, 2007). The results of the current study suggest that players would not notice substantial increases in pars during high-demand periods such as weekends, holidays, and special event days. Of course, this position is at least limited to the increases in reel pars tested herein and the duration of the sample periods.

By increasing pars, operators may be able to improve overall slot revenues. In addition, these resulting revenue gains would be associated with very little incremental operating costs, leading to strong gains in departmental profit margins. For properties with a heavy reliance on slots, such gains could translate to important increases in overall earnings before interest, taxes, depreciation and amortization (EBITDA). The mean differences shown in Table 6 illustrate this point, highlighting the unit-level gains for the high par games in terns of T-win dollars. Such contributions represent considerable growth potential when extrapolated to additional game locations. Although the parameters of any extrapolation remain unknown, the potential benefits are certainly worthy of serious consideration and further inquiry.

Exposure Factors

This study measured performance in terms of daily wagering metrics at the unit or individual game level. This approach likely included play from several individual players on each game, over the course of a single day. This design facilitated an understanding of the reaction to changes in pars at the level of the overall clientele. This was an important distinction for operators, as that is the level for which they are ultimately responsible. This distinction was also the basis for their proposed 90- to 180-day sample size recommendation. Specifically, they felt that this allowed for a sufficient duration for the unit-level results to reflect any material detection/reaction by their clientele.

The visitation rate supported the sample size recommendation, estimated at three to five visits per week across the three different venues. At an average of four visits per week, the estimated number of visits per player would be just over 102, for a 6-month sample period (i.e., 180 / 7 × 4). This calculation is intended to provide a general framework for understanding player visitation rates. We are not suggesting that an individual player would necessarily interface with the experimental units on each of the 102 visits.

Notwithstanding the calculations in the previous paragraph, it is possible that an individual gambler could have played a treatment machine only once, preventing that player from detecting a difference in the pars of the paired games. As described in “Data Sources,” there were many penny video reel games in each of the three casinos. If one were to assume that players are indifferent to game title and location, the availablity of these additional penny video reels would reduce the chance of any single player interfacing with the experimental units. This concern was mitigated by the following player tendencies: (a) limiting play to a small, evoked set of titles; (b) limiting play to preferred areas of the slot floor; and (c) playing multiple games within a single visit.

To further frame the chances of an individual player interfacing with the test units, it is important to know more about each casino’s game inventory. As described in “Data Sources,” there were additional games with the same title that were not part of the experiment. AUS featured one additional Tokyo Rose game and two additional Dragon’s Fortune games, LV1 offered 10 additional Buffalo games, and LV2 operated eight additional Buffalo games. The additional Tokyo Rose and Dragon's Fortune games were not located in the same section of the slot floor as the experimental games, nor were any of these additional units on the floor for the entire sample period. For the most part, two of the additional Buffalo games were located in the same sections of the slot floor as the experimental units, in both LV1 and LV2. This number did oscillate throughout the sample periods, as games are often moved, removed, and added to slot floors. Within the experimental sections of the floor, there were no games with the same title as the paired games that featured a par below that of the low par game.

Cross-talk among players is described in both Lucas and Kilby (2008) and Lucas and Spilde (2017b), as it relates to discussions between players about play incentives they have or have not received. This phenomenon could also play a role in the par discovery process. For example, consider a clientele characterized by frequent visitation. Many of the players will know one another, engaging in conversations related to topics such as promotional offers and gaming experiences. Discovery of a high or low par game by one player is likely to be communicated to others. This information-sharing process is also likely to continue throughout player networks, potentially exposing the presence and location of the discovered par(s) to a multitude of players. Any cross-talk effect would expand the level of exposure from the isolated individual experience to a broader player base.

It would be difficult to know the precise chances of an individual player's exposure to the test units, as this was not a laboratory experiment with a focus on individual participants. Some assumptions would be necessary to estimate exposure. For an individual player looking for a Tokyo Rose or Dragon's Fortune game within the experimental section of the AUS floor, the chances of playing at least one of the experimental games on a particular visit would have been 100%. In LV1 and LV2, given the same scenario, the estimated likelihood for play on at least one of the experimental games would have been 50%. Of course, these estimates do not account for the aforementioned proclivity of gamblers to play multiple games per visit, the overall inventory of penny video reels, and the cross-talk effect. All of these factors could further affect the chances of an individual player's exposure.

What we do know is that all of the games received considerable play over the sample periods (see Table 2). Furthermore, the results from the T-win *t* tests suggested that these players (collectively) did not detect/object to a difference in pars over the course of the sample periods. That is, these results failed to indicate any form of mass flocking to the game with the lower house edge, in spite of the fact that is was located 2 feet away from its paired counterpart. Time series regression results from both the coin-in and T-win data supported this position, failing to provide evidence of progressive play migration.

Understanding Detection Difficulties

The difficulty in detecting differences in pars may lie in the basic mathematical structure of the games. House advantages are derived from the difference between the value of wagers placed and the value of the associated payouts, over the course of a game's cycle. For now, think of the cycle as the average number of trials required to produce all possible outcomes on a given game. Over the cycle, all payouts are a function of (a) the probability of the payout (i.e., lining-up the appropriate pay symbols) and (b) the value of the payout.

For example, assume a game has three reels with only one top award symbol on each of the three reels. Furthermore, each reel has 32 possible stop positions. In this case, the game would have a cycle length of 32,768 spins (i.e., 32^3). Assuming only one coin is wagered per spin, the game can be expected to take in 32,768 coins over the course of the cycle (i.e., coin-in = 32,768). If the game were programmed to payout 29,491 coins over the cycle (i.e., coin-out = 29,491), then it would be expected to retain approximately 10% of the coins wagered (i.e., [32,768 − 29,491] / 32,768). Therefore, this game would have a 10% par.

It would not be unusual if nearly half of this 29,491 of coin-out were associated with the game's top four or five jackpots. These jackpots occur very infrequently. For example, one of these awards/jackpots may occur, on average, once every 5,000 spins. Given that top awards are relatively great in value, the product of the award value and the probability of its occurrence can profoundly affect the game's coin-out and ultimately its house advantage. For example, what if the game were altered such that this same payout were to occur, on average, once every 5,500 spins? Would the players notice? Would the players notice the change from 20 to just over 18 of these jackpots every 100,000 spins? This frequency revision would certainly increase the game's par, that is, its long-term expected value.

Imagine similar subtle decreases in the probabilities of the other top awards. Taken together, such changes could substantially increase the game's par, even with the credit value of the top awards remaining unchanged. In addition, as jackpot values increase the same effects can be achieved with even smaller declines in their probabilities. The question now becomes, can players detect differences in subtle changes in the frequency of very infrequently occurring jackpots? When considered in this context, the inability of players to detect changes in pars may appear less abstract.

Due to the origin of changes to game pars, management may be able to increase them without consequence to player perceptions of gaming value. The results of this study failed to support the notion that such changes were perceived by the player bases of the donor casinos. Although the changes in pars examined herein may appear egregious at face value, the individual customer interfaces with the games are insufficient to ascertain the subtle changes in the probabilities that produced these changes. Therefore, paying out the top awards less frequently may represent low hanging fruit for operators. This benefit will certainly be noticed in the aggregated win/loss outcomes of thousands of slot machines, each accepting a great number of trials. Conversely, players are not afforded this long-term aggregated perspective. Therefore, such changes are far less likely to be noticed at the level of the individual player experience. For those wondering about a temporal or cumulative component of detection, this explanation was supported over a 6-month window within casinos with a frequently visiting clientele.

Marketing Communications

As previously noted, there is a popular school of thought within the gaming industry that believes that decreases in par lead to increases in time on device or play time (Dunn, 2004; Frank, 2017; Gallaway, 2014, 2016; Meczka, 2017). For those who subscribe to this belief, it is natural for marketing messages to correlate gaming value with par settings. The idea is to attract customers via communications that promise extended play times from low par settings. For reel slot players, this strategy would seem to hinge on their ability to detect changes in the pars. If they cannot, it is not clear how they would be able to make any meaningful assessment or determination of gaming value. Furthermore, these marketing messages likely contribute to expectations regarding play time. When actual play time falls short of these expectations, negative disconfirmation may occur. For most games, it is the pay table variance that is the primary determinant of play time (Lucas & Singh, 2008, 2011). Based on these results and those from the current study, it is recommended that operators consider other ways of conveying the idea of gaming value to reel slot players—ones they can more readily perceive.

Limitations and Future Research

The findings cannot be generalized to video poker games, video keno games, or the electronic versions of table games. The house advantage on these types of games can often be derived from the pay tables, offering players insight not afforded by reel slots. Although the focus of this work was exclusively on reel slot play, it is important to note that such games are clearly the preferred option within the broader category of electronic gaming devices even among Las Vegas residents (Las Vegas Convention and Visitors Authority, 2016). This is noteworthy, as Las Vegas residents comprise one of the world's most mature repeat-visitation markets, as well as its oldest video poker market. In addition, within the reel slot category, the results cannot be generalized beyond the specific titles, par differences, markets, game configuration (i.e., line games), and the penny denomination. Additional research expanding any of these parameters would lead to a broader understanding of the performance effects associated with changes in pars.

Harrigan and Dixon (2010) and Dixon et al. (2013) both produced results suggesting that reel slot players may be able to make distinctions between pars with a difference of 13 percentage points. Although this is well beyond the ranges tested in this study, it would be helpful to better understand game performance responses to par differences between 5 and 13 percentage points. This would be valuable information for operators and game makers alike.

To produce the different reel slot pars, the probabilities of the jackpots are altered by the game makers. Although standard practice, this usually results in minor changes to the standard deviation of the pay table. This is an artifact of the game-making process, as manufacturers do not hold a game's standard deviation constant across the different par options, with some omitting its actual value from the par sheet. As a result, casino operators must choose from the set of choices described in this article. For example, they must choose from the set of licensed pars for the Buffalo game (i.e., 5.28%, 9.28%, 12.31%, etc.). With their choice of par, operators must accept any associated change in the game's standard deviation. Generally, increases in the standard deviations of reel slots have been found to decrease coin-in (Lucas & Dunn, 2005; Lucas, Singh, & Gewali, 2007). In terms of individual game performance, a decrease in coin-in could, but does not necessarily, lead to a decrease in T-win. The ability of players to detect an increase in par could be impaired by a simultaneous decline in standard deviation. For any given title, the slight change in standard deviation for the different versions of licensed pars is an unavoidable real-world condition. This condition will exist for anyone interested in comparing performance across the pars found on actual slot machines.

Although the results suggest gains in slot win from increased par levels, the extent of these effects remains unknown. For example, would the effects dissipate as an expanded number of games on the slot floor featured increased pars? The results of such work would provide a deeper understanding of the wholesale effects of operating strategies anchored in increased reel slot pars. For now, it is our recommendation that interested operators increase pars on titles in a gradual or stepped fashion, appropriately measuring the results throughout the process.

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Author Biographies

Anthony F. Lucas, PhD, teaches casino management and casino marketing at the University of Nevada, Las Vegas. Dr. Lucas has received several awards for his research in these areas. He has also authored "Introduction to Casino Management", "Principles of Casino Marketing", and "Casino Management & Casino Marketing Case Studies".

Katherine Spilde, PhD, is a cultural anthropologist and an associate professor at the San Diego State University. She also serves as endowed chair of the Sycuan Institue on Tribal Gaming at San Diego State University.