“Causal effect of lottery promotions on post-win payments: Evidence from a large field experiment”

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CAUSAL EFFECT OF LOTTERY PROMOTIONS ON POST-WIN PAYMENTS: EVIDENCE FROM A LARGE FIELD EXPERIMENT

Abstract

This study aims to investigate how different incentive sizes in multi-shot lottery promotions, including large and small prizes, influence subsequent consumer payments. Multi-shot lottery promotions allow repeated opportunities to win incentives and are widely used across various industries. Understanding the relationship between the cost of implementing the promotions, such as incentives for winning, and subsequent consumer payments, which drive revenue, is essential for improving cost-effectiveness. This study analyzes large-scale field data from over one million mobile payment service users and employs a stratified randomized experiment method that addresses user-initiated transaction bias. The results show that, during the promotion, winning any prize increases the total transaction amount (by \$26.97–\$32.80), the number of transactions (by 1.17–1.27), and the average transaction amount (by \$8.81–\$9.38). Notably, a small prize with a 0.2% return rate yields a return on investment of 1078.8%, surpassing the 5.6% and 8.6% from larger prizes. However, after the promotion, these differences in incentive size have negligible effects on consumer payments. Further analysis, which also examined whether the effects of winning vary depending on users' frequency of use, reveals that these effects are most pronounced among light users across all outcomes. The findings suggest that allocating multiple small prizes may be more cost-effective than focusing on a few large prizes, especially for lower-usage segments, and offer valuable insights for designing successful multi-shot lottery promotions.

Keywords uncertainty, lottery, promotion, mobile payment, field experiment, loyalty program

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INTRODUCTION

Lottery promotions, in which participants win prizes through random lotteries, are prevalent in various industries. For example, Starbucks offered promotions where winning customers can win rewards such as a free drink for a specific period or a gift card[1]. Similarly, China's mobile payment providers, such as WeChat Pay and Alipay, distributed discounts and coupons through lotteries with each transaction (Ho et al., 2022). These companies believe that lottery promotions in which consumers can participate in multiple lotteries during promotion periods (defined as multi-shot lottery promotions) attract consumers and stimulate their payments. These promotions are considered attractive to consumers; although they can be risky, as consumers do not always provide the best results.

To make these promotions more attractive to consumers while keeping costs to a minimum and increasing profitability, it is critical to understand how the winning incentives of different sizes affect subsequent consumer payments during and after the promotions. Considering these effects is important for two main reasons. First, understanding

1 https://starbucks.promo.eprize.com/holiday2022/public/fulfillment/rules.pdf

the relationship between the volume of incentives consumers earn, representing costs to companies, and the subsequent revenue-generating payments allows companies to implement highly profitable promotions. Second, determining whether these effects are transient or persistent allows companies to design future promotions that improve long-term customer loyalty, which is closely related to long-term profitability (Zhang et al., 2010).

1. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

This literature review is organized into three main categories – lottery promotions, diagnosticity, and flexibility. Examination of these dimensions identifies the key insights and remaining gaps that inform the investigation of multi-shot lottery promotions with varying incentive sizes.

Although uncertainty promotions, such as lottery promotions where results are revealed post-participation, have been widely examined (Kovacheva & Nikolova, 2023), there remains considerable debate about their effectiveness. Several studies have questioned the effectiveness of lottery promotions (Eskinazi et al., 2024; Gneezy et al., 2006; Hardisty & Pfeffer, 2017; Newman & Mochon, 2012; Rydval et al., 2009; Simonsohn, 2009). These findings suggest that consumers often perceive the unpredictability of earning incentives as risky and prefer promotions with guaranteed rewards.

In contrast, other studies have investigated the effectiveness of lottery promotions in consumer decision-making processes (De Vries & Zhang, 2020; Goldsmith & Amir, 2010; Laran & Tsiros, 2013; Shen et al., 2015), promotion types (Laporte & Laurent, 2015; Lee & Qiu, 2009; Mazar et al., 2017; Tang et al., 2022), discount structures and lottery probabilities (Attari et al., 2022), and product categories (Ailawadi et al., 2014). These studies suggest that, although the effectiveness of lottery promotions depends on specific contextual factors, consumers may still prefer them to certain promotions in which incentives are guaranteed. While most research focuses on single-shot promotions, which typically allow only one lottery participation per period, multi-shot promotions, which permit multiple participations, remain largely unexplored. Furthermore, the impact of varying incentive sizes on consumer payments, especially during and after multi-shot promotions, remains unexamined.

Relevant for this study in terms of multi-shot lottery promotions are the findings of Ho et al. (2022) and Shen et al. (2019), which emphasize the potential importance of larger incentives in influencing consumer payments. Ho et al. (2022) examined some multi-shot lottery promotions of mobile payments and found that cashback promotions, with a higher median value than discounts, had a stronger marginal effect on mobile payment adoption. However, their analysis, based on Point of Sales data combined with the promotion time collected from leaflets published by mobile payment providers, did not account for whether users participated in the promotion or how much incentive they earned, and the impact of incentive size on subsequent consumer payments remains unclear. Shen et al. (2019) introduced the reinforcing-uncertainty effect and demonstrated, through field experiments including a running event and a pay-by-task survey platform, that lottery promotions drive repeated behavior through the outcome acquisition utility – namely, how one feels about the outcome itself – and the uncertainty resolution utility – namely, how one feels about knowing the unknown. Although insightful, their findings were based on field experiments that do not involve actual consumer payments, and the effect of these utilities on actual consumer payments remains unclear. In contexts involving actual payments, consumers are known to experience psychological pain associated with payment (Soman, 2003; Zellermayer, 1996), and the pain of payment may influence the effectiveness of promotions depending on whether a payment is required. However, these insights still emphasize the potential importance of understanding how larger incentives can influence consumer payments.

Winning a prize in the multi-shot lottery promotion can reinforce subsequent consumer payments. In the multi-shot lottery promotion analyzed in

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this paper, the incentives consumers can win are proportional to the transaction amount at the time of winning. This reinforcement is measured by two indicators: the causal effect on the number of transactions, which reflects how frequently consumers participate in subsequent lotteries, and the causal effect on the payment amount per transaction, which reflects consumers' attempts to increase the incentives gained on winning. Therefore, it is hypothesized that in multi-shot lottery promotions where the incentive amount depends on the payment amount, winning a larger prize influences subsequent consumer payments by encouraging both their number of transactions and payment amount per transaction to secure larger incentives in future lotteries.

The difference in the size of incentives obtained in multi-shot lottery promotions may not have a substantial impact after the promotions, according to the concept of diagnosticity. Diagnosticity refers to the extent to which people use information as a cue for judgment based on its perceived relevance (Feldman & Lynch, 1988; Lynch et al., 1988). This concept has been widely applied in marketing (Akdeniz et al., 2013; Herr et al., 1991; Byun et al., 2021; Suk et al., 2010) and extended to lottery promotions (Alavi et al., 2015; Tan et al., 2019). Alavi et al. (2015) used diagnosticity to demonstrate that while certain promotions negatively affect reference prices, lottery promotions do not, and this effect is robust to variations in discount rates and winning probabilities. Tan et al. (2019) applied diagnosticity to show that lottery promotions mitigate the negative effects of promotions on perceived quality linked to long-term customer loyalty. Both studies attributed these findings to reduced diagnosticity in lottery promotions, as uncertain discounts discourage consumers from inferring appropriate price levels.

Unlike price discounts for specific products examined in the prior studies, discounts in promotions such as mobile payments, which apply broadly rather than targeting specific products, are less likely to serve as cues for inferring appropriate price levels and can further weaken their connection to specific price points. Thus, it is hypothesized that the size of the incentive won in a lottery promotion does not affect consumer payments after the promotion.

In multi-shot lottery promotions, the effect of winning during the promotions may vary depending on the user's intensity of use, based on the concept of flexibility. When individuals have flexibility, their intention to act increases, as they perceive greater control over their ability to choose their actions (Breugelmans & Liu-Thompkins, 2017; Dellaert & Dabholkar, 2009; March, 1978). Breugelmans and Liu-Thompkins (2017) identified usage levels as a key factor influencing this flexibility. Light users, with lower usage levels, have a greater capacity to increase their purchases than heavy users due to greater flexibility (Breugelmans & Liu-Thompkins, 2017; Liu, 2007). In contrast, the usage volume only tends to rise when it remains below a certain threshold. As heavy users, who had already used the service extensively before promotion, experience a consumption ceiling effect (Lal & Bell, 2003; Liu, 2007; Uncles et al., 2003), their ability to further increase usage can be restricted. While these findings focus on certain promotions, they may also apply to multi-shot lottery promotions.

From these findings, when comparing light users with relatively low pre-promotion usage levels and heavy users with relatively high pre-promotion service usage levels during multi-shot lottery promotions, it is anticipated that light users, due to their greater flexibility and the ceiling effect constraining heavy users, will respond more strongly to winning a lottery.

This study aims to empirically investigate how winning incentives of different sizes in multi-shot lottery promotions affect subsequent consumer payments during and after these promotions. Based on the literature review, it is hypothesized that:

H1: *In multi-shot lottery promotions where the incentives obtained from winning depend on the payment amount at the time of winning, winning a prize with larger incentives leads to an increase in both the number of transactions and the transaction amount per transaction.*

H2: *Winning a prize with varying incentive sizes has no substantial impact on consumer payments after multi-shot lottery promotions.*

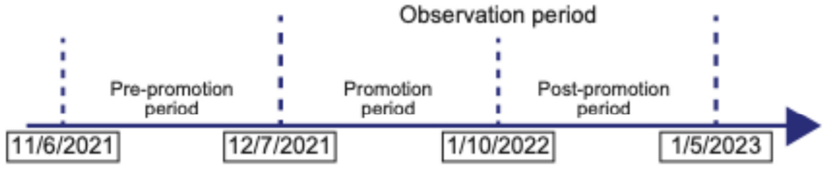

Figure 1. Timeline of the data set

H3: The effect of winning a lottery is more effective for light users with a low intensity of service use than for heavy users with a high intensity of service use during multi-shot lottery promotions.

2. METHODOLOGY

This study analyzes the mobile payment history of a mobile payment provider and lottery promotion data, including user participation records and details of incentives won through the lottery. In 2021, the mobile payment service provided by a mobile payment provider in East Asia had more than 35 million users and had established partnerships with numerous stores, including supermarkets, drugstores, restaurants, electronics retailers, and department stores. Therefore, consumers could widely use the service as a regular means of payment in their daily lives. The provider implemented a comprehensive lottery promotion from December 7, 2021, to January 10, 2022. In this promotion, a lottery was conducted for each payment transaction of $3.85 or more[2], and all users who made the transactions automatically participated in the promotion. The lottery results were immediately communicated through the mobile payment application, but the exact amount of winnings remained undisclosed until the drawing. Although the provider revealed an overall winning probability of 20%, the specific probabilities for individual prizes were not disclosed.

For each transaction, four possible outcomes were available: win the first, second, or third prize or no prize. The winners were awarded points equivalent to a percentage of their transaction amount at the winning timing: 50% for the first, 25% for the second, and 0.2% for the third. The first and second prizes were large, while the third prize was a small. These points, issued through a coalition loyalty program with a linear reward structure (Stourm et al., 2015), could be used in multiple stores or exchanged for cash at a rate of 0.008 dollars per point. The participants could win multiple times, but the maximum number of points earned per win was capped at 10,000.

Figure 1 outlines the timeline for the data set. The mobile payment history was collected from participants before and after the promotion to identify variations in consumer payments. Specifically, pre-promotion data helped capture baseline consumer payments, while post-promotion data, spanning 360 days, were used to analyze the long-term effects of different incentive sizes on consumer payments after the promotion. Lottery promotion data were collected during the promotion period to identify the effects of winning incentives of different sizes on consumer payments during the promotion.

The data set included consumers who won a single prize and those who never won. This study focuses on the sole winners, as they represent the largest group among prize recipients. To maintain consistency, the analysis was limited to winners who

Table 1. Sample size and average incentive from winning for each prize

Prize	Return rate [%]	Sample size	Average incentive from winning [dollars]
First	50	5,682	11.785
Second	25	5,794	7.108
Third	0.2	500,000	0.054
Non-winners	0	500,000	0

2 A rate of 130 yen/dollar was used for the conversion.

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participated between one and ten times before winning, as the sample size was smaller among the most frequent participants, according to the stratified randomized experiment method detailed in the following subsection. Additionally, due to the large number of third-prize winners and non-winners, 500,000 users were randomly sampled from each group. Table 1 summarizes the sample sizes and the average incentives for each prize level.

This study addresses the potential limitations of the data set. While restricted to a single provider's promotion and transaction history, the data set offers valuable insights with broad managerial and scholarly relevance. Its promotional format, resembling those of other companies with multiple prize opportunities (Ho et al., 2022; Mazar et al., 2017), supports generalizability to similar lottery promotions. Additionally, targeting all users who transacted during the promotion minimizes systematic consumer bias. The data set's inclusion of diverse business types, such as supermarkets, drugstores, and department stores, reflects routine consumer payments and avoids store-related biases, making it applicable to various businesses and valuable for academic research.

This study uses mobile payment and lottery promotion data to examine the impact of winning various prize values in a multi-shot lottery promotion. Non-winners – participants who never won a prize – were selected as the control group to quantify the effects of winning. While there is a potential risk that disappointment from not winning could suppress payments and overestimate winning effects, this bias is likely minimal for three reasons. First, consumers making payments of $3.85 or more were automatically entered into the lottery, regardless of their awareness, and non-winning results were not explicitly communicated, reducing the likelihood of disappointment affecting all non-winners. Second, participation incurred no additional costs, as entry was a by-product of routine payments, limiting spending reductions due to non-winning. Finally, non-winners are a consistent baseline for comparing prize effects, as lottery randomization ensures that observed payment differences are directly attributable to winning specific prizes. Therefore, using non-winners as the control group is appropriate, with minimal bias resulting from non-winning effects.

Estimating these effects involves three challenges. The first challenge is the endogenous bias arising from differences in the number of lottery entries between winners and non-winners. Since the probability of winning increases with the number of entries, failing to control for this leads to biased comparisons, even when winners are randomly determined. To address this, a stratified randomized experimental method motivated by Imbens and Rubin (2015) was developed. Users are stratified based on the number of lotteries they entered before winning. For the *j*-th stratum ($j \geq 1$), users who participated in *j* lotteries before winning are compared to non-winners who entered at least *j* lotteries. This method leverages the randomness of lottery results and users' inability to predict outcomes, ensuring unbiased comparisons within each stratum.

The second challenge is integrating non-winners as a control group within each stratum. To address this, non-winners in the *j*-th stratum are defined as users who have not won during the promotion and participated in at least *j* lotteries. This ensures their non-winner status after the *j*-th lottery and adjusts for the effect of lottery participation before the *j*-th stratum. The causal effect of winning each prize in the *j*-th stratum is then estimated using the potential outcomes framework (Imbens & Rubin, 2015; Rubin, 1974) (see equation (1)):

$$\tau_{prize}(j) = E\left[Y^{(j)} | prize = 1\right] - E\left[Y^{(j)} | prize = 0\right], \tag{1}$$

where $Y^{(j)} \in \mathcal{Y} \subset R$ denotes an outcome of interest within the *j*-th stratum, and $prize$ is a binary indicator signifying whether or not a particular prize, for instance, the first, second, or third prize, is secured. To quantify the causal effect of different prize values in lottery promotions, stratum-specific effect estimates are combined using a weighted average based on the sample size of each stratum, as shown in equation (2):

$$\tau_{prize} = \frac{1}{N} \sum_{j=1}^{J} N_{prize}(j) \tau_{prize}(j), \tag{2}$$

where $N_{prize}(j)$ is the total number of consumers of winners of $prize$ in the *j*-th stratum for $i = 1, \ldots, J$, and $N_{ctrl}(j)$ is the total number of consumers of non-winners in the *j*-th stratum.

Here, $$N_{prize} := \sum_{j=1}^{J} N_{prize}(j) + N_{ctrl}(j).$$

The integrated estimate τ_{prize} is the estimate of the causal effect of securing each prize.

Third, the overlap of non-winners across different strata complicates the calculation of the weighted average variance. This issue is addressed using the non-parametric bootstrap method (Efron & Tibshirani, 1994) to derive standard errors for the causal effects of winning each prize. Bootstrap samples are constructed by randomly drawing m users with replacement from the data set, and causal effects are estimated for each prize. This process is repeated B times, and the empirical distribution of these estimates is treated as the approximate population distribution, allowing for the calculation of standard errors and confidence intervals.

To measure the performance of the lottery promotion, the ROI for each prize is calculated as follows:

$$ROI_{prize} = \frac{Profit\_ratio \cdot Amount_{prize}}{Incentive_{prize}}, \tag{3}$$

where $Amount_{prize}$ is the causal effect of the total transaction amount by prize, which means the increase in the total transaction amount due to winning the prize. $Profit\_ratio$ is the ratio of profit to total transaction amount, and $Incentive_{prize}$ is the average incentive to win.

The overall performance of the lottery promotion is also evaluated in terms of ROI. The ROI of the lottery promotion is calculated by weighting the ROI of each prize. Specifically, the ROI of the lottery promotion is expressed as follows:

$$ROI_{total} = Profit\_ratio \times \frac{\sum_{prize} Amount_{prize} \cdot N_{prize}}{\sum_{prize} Incentive_{prize} \cdot N_{prize}}, \tag{4}$$

where $$N_{prize} := \sum_{j=1}^{J} N_{prize}(j).$$

The parameter settings used in this analysis are detailed further. For this investigation, the parameters are set as follows: $N = 1,011,476$, $J = 10$, $B = 1,000$, and $Profit\_ratio = 2\%$.

3. RESULTS

H1 and *H2* are tested by examining the effects of winning each prize on consumer payments during and after promotion, and *H3* is tested by analyzing the heterogeneous winning effects across heavy, middle, and light users. In this study, a stratified randomized experimental method was used to quantify the causal effects of winning the first, second, or third prizes, each with different return rates, on consumer payments during and after the promotion. The in-promotion section of Table 2 shows the causal effects of winning each prize on post-winning payments during the promotion, specifically the total transaction amount, the number of transactions, and the average amount per transaction. As shown in Table 2, the causal effects on the total transaction amount were \$32.80 for the first prize, \$30.58 for the second prize, and \$26.97 for the third prize (all $p<0.05$). The causal effects on the number of transactions were 1.27 for the first prize, 1.22 for the second prize, and 1.17 for the third prize (all $p<0.05$). Furthermore, the causal effects on the average amount per transaction were \$9.38 for the first prize, \$9.23 for the second prize, and \$8.81 for the third prize (all $p<0.05$). These results support *H1*. Moreover, comparing the effect sizes between the number of transactions and the average amount per transaction reveals that the effect on the number of transactions is more significant, regardless of the prize type. This indicates that for all prizes, the effect of winning on increasing the frequency of lottery participation is more prominent than the effect of increasing the payment amount per transaction.

Next, the analysis results for the effects after promotion are presented. The post-promotion section of Table 2 shows the causal effects of winning each prize on post-winning payments after the promotion. As shown in Table 2, statistical significance was not observed at the level of 5% for causal effects on the total transaction amount, the number of transactions, and the average amount per transaction, except for the total transaction amount of the second prize and the number of transactions of the first prize. Furthermore, the effect sizes for all these causal effects ranged from 0.01 to 0.05. Based on the effect size guidelines provided by Fey et al. (2023), these effects can be considered negligible. These findings support *H2*.

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Given that winning different prizes has no substantial effect on post-promotion payments, the ROI for each prize and the overall ROI were calculated based on consumer payments during the promotion. Specifically, the ROI for each prize was calculated using equation (3), and the overall ROI was calculated using equation (4). Here, $Amount_{prize}$ was derived from the causal effects of each prize's total transaction amount during the promotion shown in Table 2, $Incentive_{prize}$ was based on the incentives for each prize shown in Table 1, and N_{prize} was determined by the sample sizes for each prize shown in Table 1. Thus, the ROI was 5.6% for the first prize, 8.6% for the second prize, and 1078.8% for the third prize, with the overall ROI calculated at 208.0%. These findings reveal that the ROI for the third prize, a small prize with a return rate of 0.2%, greatly exceeded the ROIs for the first (50%) and second (25%), classified as large prizes. This result demonstrates that a small prize significantly contributes to the overall improvement of ROI in the promotion.

An empirical analysis was conducted to examine the impact of winning different incentive sizes on post-winner payments among users with varying levels of mobile payment usage prior to promotion. Specifically, all users were classified into three groups (heavy users, middle users, and light users) based on their total transaction amount before the promotion, and the causal effects of winning prizes with different return rates on consumer payments within each group were analyzed.

Table 3 presents the causal effects of winning each prize on post-winning payments during the promotion. As shown in Table 3, winning any prize led to statistically significant increases in all outcomes, regardless of the level of user usage or the type of prize. From the perspective of effect size, the causal effects were greater for light users, followed by middle users, and then for heavy users, for all outcomes and prize types. These findings support *H3*.

To verify the robustness of hypotheses *H1* and *H2*, it was examined whether these hypotheses hold for heavy, middle, and light users individually. Regarding *H1*, the results in Table 3 show mixed results: while the hypothesis was confirmed for heavy users, it did not hold for light users. This suggests that the effects of winning prizes with different incentive sizes may vary depending on the user's level of mobile payment usage. However, as shown in the previous subsection, the general trend that higher incentives stimulate consumer payments supports the validity of *H1*.

Finally, Table 4 shows the causal effects of winning each prize on post-promotion payments, includ-

Table 2. Effect of winning each prize on transactions during and after the promotion

Phase	Outcome	Prize	Mean	S.E.	C.I.	ES
In-promotion	Total transaction amount	First	32.80	2.52	[28.08, 37.77]	0.32
		Second	30.58	2.14	[26.40, 34.82]	0.30
		Third	26.97	0.29	[26.36, 27.53]	0.25
	Number of transactions	First	1.27	0.05	[1.17, 1.38]	0.45
		Second	1.22	0.05	[1.12, 1.31]	0.44
		Third	1.17	0.01	[1.16, 1.19]	0.42
	Average amount per transaction	First	9.38	0.88	[7.80, 11.11]	0.24
		Second	9.23	0.66	[7.95, 10.52]	0.24
		Third	8.81	0.10	[8.61, 9.01]	0.22
Post-promotion	Total transaction amount	First	29.66	16.69	[–1.64, 63.73]	0.04
		Second	39.08	16.66	[5.63, 74.06]	0.04
		Third	–1.89	3.15	[–8.64, 3.98]	0.01
	Number of transactions	First	2.63	1.23	[0.40, 5.27]	0.04
		Second	2.33	1.28	[–0.14, 4.85]	0.05
		Third	0.10	0.23	[–0.33, 0.53]	0.01
	Average amount per transaction	First	–0.48	0.28	[–1.01, 0.05]	0.04
		Second	0.15	0.36	[–0.50, 0.90]	0.04
		Third	–0.05	0.05	[–0.15, 0.05]	0.01

Notes: S.E.: Standard error. C.I.: 95% Confidence interval. ES: Effect size. Results are considered statistically significant (*p*<0.05) if the 95% confidence interval constructed using the bootstrap method does not include 0 and are highlighted in bold.

Table 3. Effect of winning each prize on transactions for heavy, middle, and light users during the promotion

Outcome	Segment	Prize	Mean	S.E.	C.I.	ES
Total transaction amount	Heavy	First	32.05	3.97	[24.68, 40.22]	0.26
		Second	25.41	3.14	[19.43, 31.73]	0.22
		Third	21.06	0.49	[20.10, 22.02]	0.17
	Middle	First	21.55	2.56	[16.76, 26.91]	0.29
		Second	22.31	2.54	[17.86, 27.80]	0.29
		Third	19.94	0.39	[19.15, 20.70]	0.25
	Light	First	28.40	3.19	[22.49, 35.48]	0.36
		Second	37.10	6.35	[26.18, 51.32]	0.47
		Third	31.17	0.56	[30.11, 32.24]	0.36
Number of transactions	Heavy	First	1.05	0.09	[0.88, 1.23]	0.31
		Second	0.95	0.08	[0.79, 1.11]	0.28
		Third	0.90	0.01	[0.87, 0.93]	0.26
	Middle	First	1.05	0.06	[0.92, 1.18]	0.52
		Second	1.10	0.06	[0.98, 1.22]	0.54
		Third	1.01	0.01	[0.99, 1.02]	0.49
	Light	First	1.21	0.07	[1.08, 1.34]	0.75
		Second	1.20	0.06	[1.08, 1.32]	0.74
		Third	1.22	0.01	[1.20, 1.23]	0.74
Average amount per transaction	Heavy	First	6.12	0.95	[4.35, 8.07]	0.16
		Second	5.47	0.74	[4.11, 6.97]	0.15
		Third	5.39	0.13	[5.14, 5.65]	0.15
	Middle	First	8.44	1.56	[6.00, 12.05]	0.25
		Second	7.87	0.90	[6.28, 9.75]	0.23
		Third	7.88	0.18	[7.54, 8.22]	0.21
	Light	First	15.34	2.34	[11.37, 20.42]	0.36
		Second	18.06	2.56	[13.37, 23.61]	0.41
		Third	15.77	0.30	[15.17, 16.39]	0.34

Notes: S.E.: Standard error. C.I.: 95% Confidence interval. ES: Effect size. Results are considered statistically significant (p<0.05) if the 95% confidence interval constructed using the bootstrap method does not include 0 and are highlighted in bold.

Table 4. Effect of winning each prize on transactions for heavy, middle, and light users after the promotion

Outcome	Segment	Prize	Mean	S.E.	C.I.	ES
Total transaction amount	Heavy	First	65.56	29.24	[8.96, 122.98]	0.07
		Second	77.21	28.10	[22.08, 130.37]	0.08
		Third	2.61	5.83	[–8.64, 14.21]	0.01
	Middle	First	–4.87	20.60	[–44.76, 36.64]	0.07
		Second	46.64	20.75	[6.77, 86.06]	0.07
		Third	–1.16	3.70	[–8.83, 5.97]	0.01
	Light	First	0.14	25.17	[–48.76, 50.14]	0.06
		Second	–28.23	23.20	[–71.88, 20.12]	0.06
		Third	–6.54	4.07	[–14.74, 1.23]	0.01
Number of transactions	Heavy	First	4.02	2.06	[0.11, .8.06]	0.08
		Second	2.52	2.07	[–1.61, 6.74]	0.08
		Third	0.70	0.41	[–0.09, 1.47]	0.01
	Middle	First	2.19	1.80	[–1.42, 5.81]	0.08
		Second	5.50	1.85	[1.92, 9.13]	0.09
		Third	–0.20	0.32	[–0.83, 0.41]	0.01
	Light	First	–0.04	1.86	[–3.52, 3.85]	0.06
		Second	–1.39	1.82	[–4.86, 2.14]	0.08
		Third	–0.30	0.31	[–0.89, 0.31]	0.01
Average amount per transaction	Heavy	First	0.01	0.43	[–0.75, 0.93]	0.06
		Second	0.37	0.45	[–0.43, 1.24]	0.07
		Third	–0.08	0.07	[–0.22, 0.05]	0.01
	Middle	First	–1.01	0.28	[–1.55, –0.37]	0.09
		Second	–0.56	0.31	[–1.13, 0.05]	0.07
		Third	0.03	0.07	[–0.09, 0.15]	0.01
	Light	First	–0.61	0.68	[–1.83, 0.77]	0.06
		Second	0.69	1.06	[–1.30, 2.93]	0.06
		Third	–0.09	0.15	[–0.37, 0.22]	0.01

Notes: S.E.: Standard error. C.I.: 95% Confidence interval. ES: Effect size. Results are considered statistically significant (p<0.05) if the 95% confidence interval constructed using the bootstrap method does not include 0 and are highlighted in bold.

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ing the total transaction amount, the number of transactions, and the average amount per transaction. As shown in Table 4, the effect sizes for all outcomes ranged between 0.01 and 0.09. Based on the effect size guidelines provided by Fey et al. (2023), these effects can be considered negligible. These findings support *H2*, further strengthening the validity of the hypothesis.

4. DISCUSSION

This study offers three primary theoretical contributions. First, this study complements the reinforcement-uncertainty effect proposed by Shen et al. (2019) through empirical evidence from a large-scale field experiment in the context of mobile payments involving actual monetary transactions. Although they conducted field experiments in running events and survey tasks, they did not investigate lottery promotions involving actual consumer payments and did not compare the effects of different incentives within such promotions. By analyzing the mobile payment lottery promotion, this study compares the impact of different incentive sizes on repeated participation and demonstrates that larger incentives, which increase the outcome acquisition utility, more effectively promote repeated participation. This complements their findings.

Second, this study contributes to the theory of diagnosticity in multi-shot lottery promotions by examining the long-term effects after the promotion. The existing literature (Alavi et al., 2015; Tan et al., 2019) has used the concept of diagnosticity to explain that, in lottery promotions related to specific products, the uncertainty of price discounts prevents consumers from associating those discounts with the quality of the product, thus avoiding impacts on reference prices. The lottery promotions analyzed in this study are unrelated to discounts on specific products and involve random lotteries for each payment. Similar to previous research findings, the results suggest that consumers are unlikely to associate discounts with product quality. Consequently, even when consumers win prizes of varying incentive sizes, no substantial long-term effects are observed after the promotion, thus extending the diagnosticity theory in the context of lottery promotions.

Finally, this study contributes to the flexibility theory by examining the heterogeneous effects of winning in multi-shot lottery promotions on consumer payments. Using the theory of flexibility, the study demonstrates that the effects of winning in the multi-shot lottery promotion are more pronounced for light users than for heavy users. Previous research (Breugelmans & Liu-Thompkins, 2017; Liu, 2007) has applied the concept of flexibility to show that the effects of promotions are more effective for light users of a service than for heavy users. However, these findings were limited to certain promotions. This study complements this theory by showing that the effects of winning in lottery promotions also align with the feasibility theory, where the promotional effects are more impactful for light users than for heavy users.

This study has several important managerial implications. First, multi-shot lottery promotions should be designed to allocate more small prizes with relatively smaller incentives rather than focusing solely on large prizes with larger incentives, especially within a finite budget. According to the analysis, in multi-shot lottery promotions that combine large and small prizes, a small prize plays a more critical role than large prizes in boosting consumer payments from an ROI perspective. Companies can achieve higher ROI by offering a larger number of small prizes while also including large ones to increase the likelihood of more customers winning within the constraints of a limited budget. Additionally, implementing a multi-shot lottery promotion design is essential for leveraging consumers' tendency to pursue further wins after their initial win.

Second, analysis of heterogeneous effects provides valuable insights for companies designing multi-shot lottery promotions. By targeting specific consumer groups, companies can improve the effectiveness of their promotions. The findings suggest that focusing on light users, defined by their usage levels before promotion, can significantly improve ROI.

Finally, this study evaluates the effectiveness of multi-shot lottery promotions implemented by mobile payment providers, a strategy widely accessible to retailers. The results indicate that these promotions are an effective marketing strategy to improve the ROI. Online platforms that offer services such as ticket sales, airline bookings, and hotel reservations have commission rates that exceed the commonly observed 2% among retailers. As such, these platforms are likely to achieve even higher ROI from lottery promotions than the results reported in this study.

CONCLUSION

This study aims to empirically investigate how winning incentives of different sizes in multi-shot lottery promotions affect subsequent consumer payments during and after these promotions. The findings revealed that during the promotion, winning any prize increased the number of transactions, the total transaction amount, and the average transaction amount, with the number of transactions showing a larger effect. The ROI for the third prize, a small prize with a return rate of 0.2%, greatly exceeded the ROIs for the first (50%) and second (25%), which were classified as large prizes. However, after the promotion, winning prizes with varying incentive sizes had no substantial effect on consumer payments. Further analysis by user groups (heavy, middle, and light users) showed that the effects of winning were most pronounced among light users across all outcomes. Overall, these findings suggest that allocating a larger number of smaller prizes is a more effective strategy within a limited budget than concentrating on a few large prizes, as it promotes repeated participation and increases ROI. Moreover, targeting light rather than heavy and middle users appears particularly beneficial.

This research has several limitations and offers opportunities for prospective studies. First, this study focused on the post-participation effects of lottery prizes, leaving their impact on initial consumer participation unexamined. Given that prize structures can influence the decision to participate, future research will investigate the interplay between these pre-participation factors and the post-participation behaviors highlighted here. Second, comparing winners against non-winning participants, rather than non-participants, could potentially lead to an overestimation of the winning effect due to losers' negative reactions. However, it can be argued that specific features of this promotion, such as automatic entry linked to routine payments and the implicit notification for non-winners, likely mitigate severe disappointment effects, lending reasonable validity to the comparison made in this context. Nevertheless, future research incorporating a non-participant control group could provide a more robust estimate of the true winning effect.

AUTHOR CONTRIBUTIONS

Conceptualization: Kohsuke Kubota, Keiichi Ochiai, Takahiro Hoshino.
Data curation: Kohsuke Kubota.
Formal analysis: Kohsuke Kubota.
Investigation: Kohsuke Kubota.
Methodology: Kohsuke Kubota, Keiichi Ochiai, Takahiro Hoshino.
Project administration: Kohsuke Kubota, Keiichi Ochiai.
Software: Kohsuke Kubota.
Supervision: Takahiro Hoshino.
Validation: Kohsuke Kubota.
Visualization: Kohsuke Kubota.
Writing – original draft: Kohsuke Kubota.
Writing – review & editing: Kohsuke Kubota, Keiichi Ochiai, Takahiro Hoshino.

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