臺灣經濟預測與政策
中央研究院經濟研究所
37:1 (2006), 49–67

Number Selection Strategy of Lottery Players: An Empirical Study of the Taiwan Lottery

Jue-Shyan Wang*
Department of Public Finance
National Chengchi University

Mei-Yin Lin
Department of Finance and Taxation
Aletheia University

Keywords: Lottery demand, Conscious selection, Random selection
JEL Classification: D12, L83

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* Correspondence: Jue-Shyan Wang, Department of Public Finance, National Chengchi University, Taipei 116, Taiwan. Tel: (02) 2939-3091 ext. 51538; Fax: (02) 2939-0074; E-mail: jswang@nccu.edu.tw.
We thank Professor Chang, Ching-Cheng, the managing editor and three anonymous reviewers for their comments and suggestions.

ABSTRACT

This paper focuses on the change in the selection behavior of lottery players in Taiwan. First, we test the structural change in the time series of the sales to find the break point of the selection strategy. By estimating a generalized rollover probability function set by Scoggins (1995), we indicate that the lottery players initially pick numbers by way of conscious selection and later change their behavior to random selection. The results also show the demand elasticity under conscious selection is significantly larger than that under random selection, and both are larger than 1.

1. INTRODUCTION

There has been some literature that focuses on the decision-making of lottery players. Quiggin (1991) and Garrett and Sobel (1999) model the lottery player's expected utility to determine a lottery player's behavior. Jullien and Salanié (2000) and Bradley (2003) consider prospect theory to assess risk attitudes of lottery players. In this paper, we study this issue from the lottery demand side, which may have more policy implications.

There have been a number of studies to estimate demand functions for lottery games. The most popular empirical approach to lottery demand employs effective price, computed as the face value of a ticket minus the expected value of prize payments per ticket, to explain the variation in lottery sales. Cook and Clotfelter (1993), Gulley and Scott (1993), Mason et al. (1997), Walker (1998), and Forrest et al. (2000) all follow this approach. These researchers compute the expected value under the assumption that the lottery players pick numbers at random. However, many lottery players select their combinations through some other process. In other words, they believe there are some combinations that are much more popular than others. Cook and Clotfelter (1993) refer to this behavior as "conscious selection".

When selection is conscious, the probability distribution of numbers chosen by lottery players does not follow a uniform distribution. Therefore, the coverage rate, defined as the proportion of possible combinations purchased at least once, is less than which would result from random selection. Furthermore, the expected value function is different from earlier studies.

To allow for possibility of nonrandom selection, Scoggins (1995) specifies a generalized form to estimate the probability function of not winning the jackpot on a draw. Consequently, the hypothesis that the lottery players pick numbers randomly is rejected. Conscious selection provides for an unbiased estimate of expected revenue, and this bias is approximately ten percent. Farrell et al. (2000) also found strong evidence showing that lottery players choose their numbers nonrandomly. Under the assumption of conscious selection, however, the estimated demand elasticity is not significantly different from the result of random selection.[1] Similarly, Walker (1998) noted that conscious selection has little effect on expected value and the estimated price elasticity.

In this paper, we take into account the possibility that lottery players will shift their selection strategies. We argue that lottery players may change their behavior from conscious selection to random selection (or vice versa) through a learning process. Furthermore, we investigate the effect on demand elasticities under these two selection strategies. Our empirical study uses data of the Taiwan lottery because it has not been in operation for very long.[2] It is reasonable to assume that the learning process of lottery players is short and quick because of the availability of information. Therefore, using fresh data from a new lottery is more appropriate to our study. Many previous studies on the Taiwan lottery, however, focused on the influence of demographic factors such as sex, age, and income. There is very little literature that follows the effective price approach. Thus, it is meaningful to model the Taiwan lottery demand from the viewpoint of effective price as has been widely applied in foreign lottery studies.

Our empirical study follows three stages. The first stage is to find the break date when lottery players shift their selection strategies. In the second stage, we compute the expected values before and after the break date found previously. Comparing the expected value in these two periods helps us to explain why lottery players change their behavior. Last, we estimate the demand functions for the lottery during these two periods separately and propose to test whether the demand elasticities are significantly different. The empirical result of our study shows that the lottery players initially pick numbers by way of conscious selection and later change their behavior to random selection. Moreover, the results also show the demand elasticity under conscious selection is significantly larger than that under random selection, and both are larger than 1. This conclusion that the demand elasticities are significantly different between these two strategies will have some implications for policy makers. It implies that the Taiwan lottery agencies should raise the percentage of stakes allocated to the jackpot, and the extent of the raise could be less when the lottery players pick numbers by random selection.

The rest of the article is as follows. In the next section, we set the probability function of not winning the jackpot and then describe the expected value function.

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[1] Farrell et al. (2000) compared their estimated result with that of Cook and Clotfelter (1993). The latter have stated the possibility of nonrandom selection. Their estimation, however, is under the assumption of random selection.

[2] The Taiwan lottery was launched in January 2002.

The third section is the result of our empirical study. The last section summarizes our conclusions.

2. THE MODEL

2.1 Rollover Probability Function

For each draw, the lottery player selects n different numbers from one through m. The probability of any one ticket winning the jackpot, π, is $\pi = n!(m-n)!/m!$.

Therefore, the probability of any one ticket not winning the jackpot is $1-\pi$. We assume the probability of rollover follows a binomial distribution when the lottery players pick numbers randomly, and thus we employ the probability function introduced by Scoggins (1995).

$$P_t = (1-\pi)^{S_t}, \tag{1}$$

where P_t is the rollover probability, S_t is the number of tickets sold, and t denotes period t. Scoggin generalizes equation (1) to allow for the probability of conscious selection as follows:

$$P_t = (1-\pi)^{\alpha+\beta S_t}. \tag{2}$$

We can estimate equation (2) to test the joint hypothesis $\alpha = 0$, $\beta = 1$. If the joint hypothesis is accepted, it implies the lottery players select numbers randomly. On the other hand, the joint hypothesis will be rejected when the lottery players select numbers by way of conscious selection.

2.2 The Expected Value and Lottery Demand

To simplify our problem, we assume there is a single prize pool.[3] If there is no matching ticket to win the jackpot on a given draw, the jackpot is rolled over into the jackpot of the next period. Consequently, the jackpot is constituted by the sales revenue net of the take-out rate (proportion of stakes not returned in prizes) and the rollover (if any)

[3] Walker (1998) and Mason et al. (1997) suggest that this assumption is harmless provided smaller prize pools do not roll over. The small prize pools are unlikely to roll over in theory and unheard of in practice. This simplified assumption is common in most literature.

from the previous draw. Furthermore, the jackpot, J_t, is determined by the following rule:

$$J_t = (1 - \tau)kS_t + R_{t-1}, \tag{3}$$

where τ is take-out rate, k is the face value and R_{t-1} is rollover amount from previous draw.

The expected value, EV_t, of a ticket can be written as:

$$\mathrm{EV}_t = \frac{J_t\,(1 - P_t)}{S_t}, \tag{4}$$

Thus, the effective price of a ticket is $k - \mathrm{EV}_t$. We specify a short-run lottery demand function in which the drawing demand is determined largely by the effective price. The demand function can be represented in log-linear form as:

$$S_t = a_0 + a_1 \times \mathrm{LT}_t + a_2 \times \ln(k - \mathrm{EV}_t) + \varepsilon_t, \tag{5}$$

where LT_t is a log-linear time trend and ε_t is an error term. The notation of ln indicates natural logarithm. The time trend, an explanatory variable, is designed to capture other factors that systematically affect the sales over time.[4] All the variables are transformed to natural logarithmic form, which allows us to measure the demand elasticity by the absolute value of coefficient a_2.

3. THE EMPIRICAL RESULTS

We use the above model to analyze the Taiwan lottery, which is operated by the Taipei Bank. The Taiwan lottery is a 6/42 game played twice a week, and the face value is fifty N.T. dollars a ticket. Therefore, the probability of winning the jackpot, π, is 1/5,245,786 ($= 6!36!/42!$). Our data are from the first 203 draws that started on January 22, 2002 and ended on December 30, 2003, when a new lottery game was introduced.[5] All the data are found on the Taipei Bank Web site.[6]

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[4] Mikesell (1987), Clotfelter and Cook (1989), and Miers (1996) find that lottery sales decline as a lottery game grows older. Therefore, it is reasonable to include the time trend in the regressions.

[5] The introduction of a new game leads to substitution effect that is beyond the scope of this paper.

[6] The web site is at http://www.roclotto.com.tw.

3.1 Test of Selection Strategy

Data on the distribution of numbers chosen is seldom published and thus researching popular combinations is difficult. Consequently, we suggest analyzing the lottery players' selection strategies by examining the time series data of the sales. In other words, the switch in selection behavior will include some relationship with the change in the sales. Suppose lottery players select numbers nonrandomly and they prefer certain combinations of numbers. Thus the expected value of a ticket with a popular combination will be lower than that with an unpopular combination.[7] Consequently, the players may change their behavior to random selection. Moreover, some lottery players may even withdraw from the game because of the frequent rollovers generated by the selection of unpopular combinations. Therefore, we conjecture that when the players shift their selection strategies, the sales will result in a structural change as well. In this section, we will prove this conjecture by some empirical results. First, we find the structural change point in the sales. If this point is really the break date that players, on average, change their behavior, the roll probability function before and after this point will be different. Moreover, we will show the shift in roll probability function is correlated with the change of expected value.

We simplify the test developed by Bai (1999) to investigate structural change. His method is implemented by Papell (2002), and we follow Papell's setting. Suppose there is one break,[8] we start by estimating the following regression:

$$\ln S_t = b_0 + b_1 \times \mathrm{LT}_t + b_2 \times \mathrm{DT}_t + \sum_{j=1}^{n} b_{3,j} \times \ln S_{t-j} + \varepsilon_t, \tag{6}$$

where the break occurs at time TB and the slope dummy variable $\mathrm{DT}_t = (t - \mathrm{TB})$ if $t > \mathrm{TB}$; 0 otherwise. This setting allows the slope of $\ln S_t$ to be different before and after the break point. If the coefficient of the slope dummy variable, b_2, is positive, it implies that the change in the sales is intensified. On the other hand, the negative of b_2 indicates that the change in the sales becomes more moderate.

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[7] This is because the return on a winning ticket will be diluted by the shares of other lottery players.

[8] Bai and Papell apply this method to test multiple structural changes. In this paper, we discuss the shift between two selection strategies. It is more convenient to assume only one break to explain our problem more precisely.

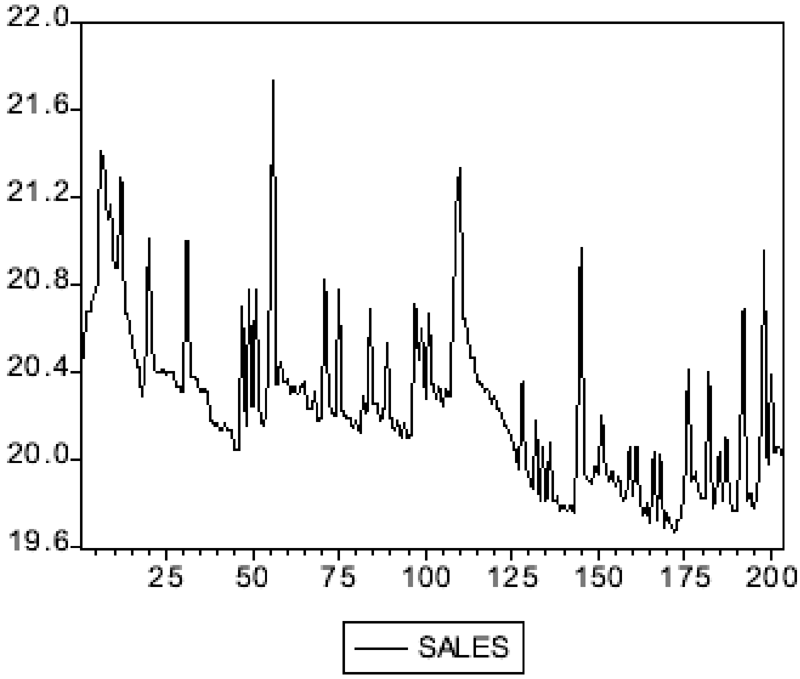

Figure 1 Log of the sales

The optimal location of the break, TB, is chosen globally by minimizing the sum of squared residuals (SSR) of equation (6). We take the natural log of the sales as the dependent variable and use ordinary least squares to estimate equation (6). The optimal lag length n is 2, which is chosen by the Schwarz Information Criteria.

The estimated result shows the SSR is minimum when TB=108, and the value of SSR at this point is 13.4375. The estimated coefficient of LT_t is -0.1113, and DT_t is -0.0012. The time series data of the sales in natural log form is presented in Figure 1. The negative trend is obvious, and the change of the sales becomes moderate after about the middle of the period, which are both correlated with the negative coefficients of LT_t and DT_t.

Next, we split the sample periods into two parts: period 1 includes the first 108 draws and period 2 contains the last 95 draws. We estimate the rollover probability function stated in equation (2) during these two periods. Equation (2) is like a limited-dependent-variable model. We can estimate the coefficients by maximizing the log-

Table 1 Estimation of rollover probability function

	Period 1	Period 2
α	0.4951×10^7 (0.4732×10^7)	-0.6855×10^7 (0.7853×10^7)
β	0.3426 (0.3282)	1.6154^{**} (0.9208)
Log-likelihood	-44.4493	-43.8656

Note: 1. Standard errors are in parentheses.
2. ** denotes significance at 10%.

likelihood function ($\ln L$) set by the following equation:

$$\ln L = \sum_{t=1}^{T} \left[RP_t \times \ln P_t + (1 - RP_t) \times \ln(1 - P_t) \right], \tag{7}$$

where RP_t is a latent variable: $RP_t = 1$ when the jackpot rolls over in period t, and $RP_t = 0$ otherwise. The estimated result of equation (7) is presented in Table 1.

We test the joint hypothesis $\alpha = 0, \beta = 1$ by conducting a likelihood ratio test. The resulting χ^2 statistics is 10.2588 in period 1 and 2.8735 in period 2. The 95 percent critical value with two degrees of freedom is 5.9915. Consequently, the hypothesis that the lottery players pick numbers randomly is rejected in period 1 and is accepted in period 2. According to these results, we conclude that the lottery players initially select numbers by way of conscious selection and later change their behavior to random selection.

Why do the players change their selection strategies? The answer can be found in the differences of expected value between these two periods. We compute the expected value as stated in equation (4) and summarize the statistics in Table 2.

The statistics suggest that the expected value under conscious selection in period 1 is lower than that under random selection. The lottery players realize that picking numbers nonrandomly will result in a lower return. Thus, they change their strategies to random selection. We also find that the expected value under random selection is more volatile. Lottery players that pick their combinations by random selection face more uncertainty and risk than conscious selection lottery players. There has been

Table 2 Summary statistics of expected value

	Period 1	Period 2
Mean	19.6470	19.8069
Standard error	2.0799	2.9398
Minimum	17.9067	16.4566
Maximum	26.1439	28.3079
Skewness	1.7633	1.0575
Kurtosis	1.8197	0.0341

some literature that discusses why risk-averse individuals take unfair gambles (see Garrett and Sobel, 1999; Bradley, 2003). This issue requires a more complicated model that is beyond the scope of our paper. Hence, this paper only describes the uncertainty that the lottery players face.

3.2 Estimation of Demand Function

We note that the sales depend on the effective price, $k - \mathrm{EV}_t$. Moreover, the expected value (i.e., jackpot) defined in equation (4) is determined by the sales. To avoid the simultaneity problem, we estimate this model by two-stage least squares with expected value endogenous. We generate an expected effective price series in the first stage. This price series will be included as a regressor of demand function in the second stage. The coefficient of expected price is used to measure the demand elasticity.

Substituting the jackpot rule and the probability function into equation (4), the expected value depends on the previous rollover and the current sales. We take the previous sales as predicted value for the current sales, and we transform the formula for expected value into a linear reduced form written as the following equation:

$$\mathrm{EV}_t = c_0 + c_1 \times \mathrm{Trend}_t + c_2 \times R_{t-1} + \sum_{j=1}^{m} c_{3,j} \times S_{t-j} + \varepsilon_t, \qquad (8)$$

where Trend_t is the linear time trend. Equation (8) describes expected value as a function of the previous rollover, R_{t-1}, and the relevant previous sales, S_{t-j}. The lag length of the previous sales m is chosen by the significance of the coefficient estimate. All the variables are in level form because the logarithm of rollover is missing when the value

Table 3 The estimation of expected value

	Period 1	Period 2
Constant	18.0584^* (0.3136)	18.9200^* (0.7766)
Trend_t	-0.3336×10^{-2} (0.2531×10^{-2})	-0.0169^* (0.3883×10^{-2})
R_{t-1}	$0.3834 \times 10^{-7*}$ (0.1382×10^{-8})	$0.7513 \times 10^{-7*}$ (0.2603×10^{-7})
S_{t-1}	$0.2530 \times 10^{-7*}$ (0.1128×10^{-7})	$0.7279 \times 10^{-7*}$ (0.2561×10^{-7})
S_{t-2}	$0.3913 \times 10^{-7*}$ (0.1129×10^{-7})	$0.5811 \times 10^{-7*}$ (0.2603×10^{-7})
S_{t-3}		$0.5811 \times 10^{-7*}$ (0.2603×10^{-7})
$\bar{R}^2$	0.8854	0.9008
DW	1.9302	1.6092
SSR	48.1921	76.3315
Log-likelihood	−108.1030	−124.4070

Note: 1. Standard errors are in parentheses.
2. * denotes significance at 5%.

is zero. Equation (8) is estimated by ordinary least squares method and the result is shown in Table 3.

The optimal lag, S_{t-2}, for previous sales is 2 in period 1 and is 3 in period 2. The negative trend in the sales is significant in period 2. However, this trend effect is insignificant in period 1. Hence, people stop playing the lottery because they are discouraged by the frequent rollovers. The previous rollover and the previous sales all have significantly positive relations with the current sales.

The fitted value, denoted by $\widehat{\text{EV}}_t$, generated in equation (8) and the predicted effective price, $k - \widehat{\text{EV}}_t (k = 50)$, as an explanatory variable are used to estimate the demand function. Before we begin this estimation, it is necessary to test whether the time series is stationary to avoid a spurious regression problem.[9]

We use the Augmented Dickey-Fuller test to identify the order of integration of the data. The results reject the null hypothesis of a unit root for the sales and the expected

[9] See Granger and Newbold (1974).

value (both in log form).[10] Therefore, the two time series are stationary, and it is valid to estimate the demand function using these variables.

Gulley and Scott (1993) and Forrest et al. (2000), by means of a dummy variable, test the difference in sales between Wednesday drawings and Saturday drawings. Forrest et al. (2002) also set a dummy variable to study the influence of the increased ticket sales. To capture such factors that may affect the lottery demand, we add some dummy variables into the estimation of equation (5). Day_t is a dummy variable that takes the value of one for the drawings scheduled for Tuesday and zero for Friday. The four types of drawings promoted by the Taipei Bank are denoted as $\mathrm{D1}_t$, $\mathrm{D2}_t$, $\mathrm{D3}_t$, and $\mathrm{D4}_t$. $\mathrm{D1}_t$ is a dummy variable set equal to one for the jackpot of the specific draws with sales of one hundred million N.T. dollars. $\mathrm{D2}_t$ is a dummy variable that is equal to one for the jackpot of specific draws to increase sales by 15% as the special number is larger than the other six numbers. $\mathrm{D3}_t$ is a dummy variable that takes the value of one for the jackpot of specific draws to increase the sales by 15% without any condition. $\mathrm{D4}_t$ is a dummy variable set equal to one for the jackpot of specific draws guaranteed to reach one hundred million N.T. dollars. The first and the second promotions, $\mathrm{D1}_t$ and $\mathrm{D2}_t$, are only carried out in period 1. The third and the fourth promotions, $\mathrm{D3}_t$ and $\mathrm{D4}_t$, are performed in period 2. To avoid the singularity, only Day_t, $\mathrm{D1}_t$ and $\mathrm{D2}_t$ are included as the regressors in the estimation for demand function in period 1. Day_t, $\mathrm{D3}_t$ and $\mathrm{D4}_t$ are included as the dependent variables in the estimation for demand function in period 2. Table 4 reports results of the estimation for the demand function.

The results indicate the decline trend of the natural log of the sales is significant in period 1 and is insignificant in period 2. This is consistent with our previous finding that structural change of the sales becomes more moderate in period 2. The demand elasticities measured by the absolute value of coefficients on predicted effective price are both larger than 1 in these two periods. Consequently, reducing the take-out rate will increase the sales revenue. Moreover, the demand elasticity under conscious selection is larger than that under random selection.[11] The reason is that the effective price under conscious selection is higher than that under random selection.

The dummy variable Day_t is not significant. Hence, the sales are not different between the drawings on Tuesday and Friday. This result differs from that of Gulley

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[10] The test statistics for $\ln S_t$ is -6.8885 which is run with a constant, a trend and four augmenting lags. The test statistics for $\ln \mathrm{EV}_t$ is -4.8452 which is also run with a constant, a trend but with three augmenting lags.

[11] This result is similar to that of Lin and Wang (2004).

Table 4 The estimation of the demand function

	Period 1	Period 2
Constant	27.7162* (0.5596)	22.9374* (2.3292)
LT_t	−0.1684* (0.0348)	−0.0481 (0.4544)
$\ln(k - \widehat{EV}_t)$	−3.0989* (0.1632)	−1.9447* (0.0555)
Day_t	0.0174 (0.0165)	−0.0338* (0.0080)
$D1_t$	0.2545* (0.1044)	
$D2_t$	0.0178 (0.0628)	
$D3_t$		0.7145* (0.0833)
$D4_t$		0.1678* (0.0378)
ρ		0.8814* (0.0521)
$\bar{R}^2$	0.8384	0.9408
SSR	1.6158	0.4845
Log-likelihood	68.9877	114.2150

Note: 1. Standard errors are in parentheses.
2. *denotes significance at 5%.
3. The estimation uses the Cochrance-Orcutt method to correct for the first order serial correlation.

and Scott (1993) and Forrest et al. (2000) where the Wednesday drawings have lower popularity. The dummy variables indicate the promotions are positively significant for $D1_t$, $D3_t$, and $D4_t$. Thus, these promotions, except the second promotion, are effective.

We test the null hypothesis that the demand elasticities in these two periods are equal. The demand function is rewritten as the following form:[12]

[12] We could not test this null hypothesis directly from the result of Table 4 because the estimations for these two periods do not have the same regressors.

$$\ln S_t = a_0 + a_1 \times \mathrm{LT}_t + a_2 \times \ln\left(k - \widehat{\mathrm{EV}}1_t\right) + a_2' \times \ln\left(k - \widehat{\mathrm{EV}}2_t\right) + a_3 \times \mathrm{Day}_t + \sum_{i=1}^{4} a_{4i} \times \mathrm{D}i_t + \varepsilon_t, \tag{9}$$

$k - \widehat{\mathrm{EV}}1_t$ is the effective price for period 1 and is set to zero in period 2. $k - \widehat{\mathrm{EV}}2_t$ is the effective price for period 2 and is equal to zero in period 1. We will estimate this equation for the whole period, not separately for two periods. Because of the nonexistence of the singularity problem, we include all the dummy variables in the estimation for demand function. The null hypothesis for our test is $a_2 = a_2'$. When the null hypothesis is true, the restricted regression can be expressed as:

$$\ln S_t = a_0 + a_1 \times \mathrm{LT}_t + a_2 \times \ln\left(k - \widehat{\mathrm{EV}}_t\right) a_3 \times \mathrm{Day}_t + \sum_{i=1}^{4} a_{4i} \times \mathrm{D}i_t + \varepsilon_t, \tag{10}$$

$k - \widehat{\mathrm{EV}}_t$ denotes the effective price in restricted regression. We set $k - \widehat{\mathrm{EV}}_t = (k - \widehat{\mathrm{EV}}1_t)$ in period 1 and $k - \widehat{\mathrm{EV}}_t = (k - \widehat{\mathrm{EV}}2_t)$ in period 2. The results for the restricted regression and unrestricted regression are presented in Table 5.

The major conclusions for these coefficients are not different in quality from the results in Table 4. The estimated demand elasticities for unrestricted regression are 2.3198 in period 1 and 2.3723 in period 2. The estimated demand elasticity for restricted regression is 2.3377. All the estimated elasticities are significantly larger than one. The log-likelihood value for unrestricted regression and restricted regression are 137.933 and 134.562. The resulting likelihood ratio statistic is 6.742. The critical value for chi-squares statistic with one degree of freedom is significant at any conventional level. Thus, we reject the null hypothesis that $a_2 = a_2'$ on the basis of this test. It implies that the demand elasticities are significantly different for conscious selection and random selection. This conclusion is converse to the results of Farrell et al. (2000) and Walker (1998), which are both empirical studies of the U.K. game.

Table 5 The estimation of demand function for the whole period

	Period 1	Period 2
Constant	25.1668* (0.3313)	25.4444* (0.3183)
LT_t	−0.1974* (0.0362)	−0.2661 (0.0305)
$\ln(k - \widehat{EV}1_t)$	−2.3198* (0.0863)	
$\ln(k - \widehat{EV}2_t)$	−2.3723* (0.0866)	
$\ln(k - \widehat{EV}_t)$		−2.3377* (0.0849)
Day_t	−0.0013 (0.0107)	−0.0028* (0.0105)
$D1_t$	0.2003* (0.0991)	0.2050* (0.0977)
$D2_t$	0.0573 (0.0640)	0.0816 (0.0654)
$D3_t$	0.7667* (0.1065)	0.6552* (0.1011)
$D4_t$	0.1085** (0.0587)	0.1029** (0.0623)
ρ	0.6217** (0.0592)	0.6784* (0.0561)
$\bar{R}^2$	0.8950	0.8906
SSR	2.9455	3.0643
Log-likelihood	137.9330	134.5620

Note: 1. Standard errors are in parentheses.
2. *, ** denote significance at 5% and 10%.
3. The estimation uses the Cochrance-Orcutt method to correct for the first order serial correlation.

4. CONCLUSION

Our analysis focuses on the change in the selection strategies of lottery players. We find that lottery players in Taiwan initially pick numbers by way of conscious selection and later change their behavior to random selection. The lottery players change their behavior because they realize that conscious selection brings a lower return. This finding is interesting. To further our research, we can study the fresh lottery data from other countries to test whether this process of learning to select numbers is similar everywhere. It may help us to understand more about the behavior of lottery players.

In this paper, we compare the differences in demand elasticities under these two selection strategies. The results show the demand elasticity under conscious selection is significantly larger than that under random selection, and both are larger than 1. It implies that the Taiwan lottery agencies should raise the percentage of stakes allocated to the jackpot. In addition, the extent of the raise could be less than in previous studies because the lottery players have turned to random selection. Furthermore, we suggest that it is more realistic to take account of the possibility of change in selection strategy while studying the issue of lottery demand.

We try to find some factors to explain why the lottery players change their selection strategies. We argue that it results from some learning process and prove this conjecture by the empirical results in this paper. However, this explanation may not be completely satisfactory, and there must be more interesting factors that can better account for the change in selection strategies. Our paper is an initial study. A complete theoretical model should be established to address this issue.

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臺灣樂透彩券的選號策略之實證研究

王智賢*
國立政治大學財政學系

林玫吟
眞理大學財政稅務學系

關鍵詞: 樂透彩券之需求、自覺性選號、隨機選號
JEL 分類代號: D12, L83

* 聯繫作者: 王智賢, 國立政治大學財政學系, 臺北市 116 文山區指南路二段 64 號。電話: (02) 2939-3091 分機 51538; 傳眞: (02) 2939-0074; E-mail: jswang@nccu.edu.tw。作者感謝張靜貞教授、責任編輯委員與三位匿名審查教授的寶貴意見, 使得本文得以更加完整。

摘　要

本文主要研究臺灣樂透彩券參與購買者選號策略之轉變。首先, 從銷售量的時間序列資料來尋找結構轉變點, 並利用 Scoggins (1995) 所設定的累積頭彩機率密度函數進行實證資料的估計。結果發現初期彩券購買者偏好採用自覺性的選號策略, 隨之轉變爲隨機選號的購券方式。實證結果並顯示自覺性選號策略下的需求彈性顯著大於隨機選號下的需求彈性, 而且兩種選號策略下的需求彈性均大於1。