



## DETERMINANTS OF DEMAND FOR SPORTS LOTTERY: INSIGHTS FROM A MULTILEVEL MODEL

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### ABSTRACT

*Sports lottery, as a distinct sport product, has gained increasing popularity throughout the world. Drawing upon various theories developed over the years explaining the lottery gaming behavior, this study empirically examined the demand for the Shengfu lottery game, a popular soccer betting lottery in China. Specifically, this study examined the relationships between lottery demand and socio-demographic variables, and lottery attributes through a multilevel modelling procedure. The main findings are that (a) ticket composition has considerable impact on demand; (b) easiness of winning a game is positively related to the demand; (c) the provinces with higher income levels have higher demand for sports lotteries; (d) people with higher financial and social burdens tend to buy more lottery tickets; (e) venue accessibility has a positive impact on sales.*

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**Keywords:** Sports lottery, Gambling, Consumption, Demand, Multilevel model.

### Contribution/ Originality

This study is one of very few studies which have investigated the relationships between sport lottery demand and socio-demographic variables and lottery attributes through a multilevel modelling framework.

## 1. INTRODUCTION

Sports lottery, as an offspring of lottery games, comes into being as a compromise between traditional lottery games and sports betting. It is a type of lottery gambling involves bets on the results of preselected sports events regardless of its own characteristics (Mao *et al.*, 2014). Most

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sports lotteries, including *La Quiniela* in Spain, and the *Shengfu* Game in China, are organized in an adapted pari-mutuel form, where the payoff is calculated by sharing the pool among all winning bets without considering betting odds. Alternative, in the North America, sports lotteries, such as *sportselect* in Canada and the Delaware Sports Lottery in the United States, are organized in a fixed-odds betting form, where betters are promised a fixed payoff according to the odds posted by the lottery organizations. Because of the unpredictability of competition results, sporting event has always been an attractive medium for betting. Therefore, capitalizing on the general appealing of sports betting, sports lottery becomes a significant public financing avenue in some countries and states where sports lotteries have been legalized (Li *et al.*, 2012).

Sports lotteries are often to raise funds for social welfares courses, including orphanages, nursing homes, medical care, education, legal assistance, and etc. Particularly, Sports lotteries are often earmarked for sports development. For instance, in China, 60% of the revenue is earmarked for the implementation of “National Fitness Plan”, and the rest 40% is complementary financial source for “Olympic Glorious Program” (Li *et al.*, 2012). The revenue may be used for promoting sports for all programs, building sports infrastructures for mass participation, hosting mega sporting events, and sports development in the regions under poverty line.

Sports lotteries, as a revenue source for the governments, are essentially implicit taxes (DeBoer, 1986; Clotfelter and Cook, 1987; Clotfelter and Cook, 1990). The institution of lotteries is often based on the notion that an unhealthy but not necessarily evil course can be allowed with regulation if it can be used to raise funds for good courses (McGowan, 1994). Despite of their positive contribution to advancement of public courses, lottery gaming can also be a type of gambling behavior and at times cause serious social problems (Li *et al.*, 2012; Li *et al.*, 2012). It is therefore critical to examine factors determining the demand function for sports lottery. This study focused on the demand for the *Shengfu* lottery game, a soccer betting lottery established in October 2001 and the most popular sports betting game in China. A panel data containing sales of 211 draws of 30 provinces in 2011 and 2012 was obtained from the Chinese Sports Lottery Administration Center. Through a multilevel modelling procedure, this study examined the relationships between lottery demand and socio-demographic variables, and lottery attributes.

## 2. DETERMINANTS OF DEMAND FOR SPORTS LOTTERY

Traditional demand analysis starts with the assumptions about the nature of gambling behavior. To account for the paradoxical phenomenon of the coexistence of gambling and insurance purchase, multiple theories have been proposed over the years by economists, sociologists, psychologists, and other scholars. Most notably are expected utility theory and its generalizations (Friedman and Savage, 1948) indivisibility in expenditure (Ng, 1965) gambling as strategic labor supply (Nyman *et al.*, 2008) gambling as consumption (Conlisk, 1993) and cognitive theories (Griffiths, 1990; Rogers, 1998). However, they are not incompatible. These theories proffer us critical insights and predications about the gambling behavior of lottery players from

different angles. Various demand models have been constructed based on different assumptions about gambling behavior. The main empirical question from the expected utility theory is whether consumer demand for lottery games responds to true expected returns, as EUT predicts. These works lead to the construction of effective price in estimating lottery demand (Gulley and Scott, 1993; Forrest *et al.*, 2000). The indivisibility in consumption hypothesis and strategic labor supply (i.e., “something for nothing”) hypothesis can be tested based on their specific predictions about the relationship between demand and certain socio-demographic variables, such as income, population age composition, and profession (Nyman *et al.*, 2008; Weinbach and Paul, 2008). The gambling as consumption examined how the attractiveness of the game impact the demand (García and Rodríguez, 2007; Humphreys *et al.*, 2013; Paul and Weinbach, 2013; Mao *et al.*, 2014). From cognitive perspective, previous studies have examined how the possibility of dreaming impact the demand, which was often call as jackpot pool model (Cook and Clotfelter, 1993; Garrett and Sobel, 1999; Forrest *et al.*, 2002) how the rollover induced the lottomania, an excessive demand for lottery (Beenstock and Haitovsky, 2001) and how the heuristics of representation impact the dynamic nature of gambling behavior (Mao *et al.*, 2014)

## 2.1. Effective Price

There are two different prices in the market for lottery games. The nominal price of a lottery ticket, usually fixed at a very small value, say, \$1 in US, or two *yuan* in China, is what the players actually pay for a chance of winning a prize. The actual price of a ticket, known as effective price in literature, defined as “the cost of buying a probability distribution of prizes that has expected value of one dollar” (Clotfelter and Cook, 1987). Effective price of a unit price lottery ticket can be measured by the difference between its face value and the expected value of the prize, which tends to converges to the takeout rate with sufficiently long periods of time (Gulley and Scott, 1993). Modeling demand in terms of the effective price describes the effect of the implicit cost (i.e., the effective price) on the amount of tickets players choose to purchase. It is consistent with the logic of the expected utility theory and rests on the assumption that players form rational expectation of effective price and use this information in the process of purchase decision. However, this is a strong assumption. The calculation of the effective price is complex. It is unlikely that players actually have the cognitive capability or motivation to forecast the effective price when they wager given the nominal cost of ticket is often very low.

## 2.2. Jackpot Pool

Instead it seems more likely that players are motivated by a heuristic of the prospective size of jackpot pool (Cook and Clotfelter, 1993; Garrett and Sobel, 1999; Forrest *et al.*, 2002). Forrest *et al.* (2002) argued that lottery players may be simply motivated by the enjoyment of the dream of spending the largest prize that could be won from holding the ticket, rather than the expectation of winning the prize. The jackpot pool was defined as the largest amount that anyone could win as a

single winner. Modeling demand in terms of the jackpot describes the halo effect of the grand prize on the amount of tickets players choose to purchase. It is also consistent with an information account proposed by [Shugan and Mitra \(2009\)](#) that under adverse environments favorable outcomes convey more information than unfavorable outcomes. In this case, the maximum data (jackpot) may contain more information than the average data (effective price). However, under certain circumstances, for instance, when there is a cap on the prize one can win at any draw, the jackpot pool will become irrelevant in the demand function. This is exactly the case with Shengfu game.

### 2.3. Game Attractiveness

The notion of gambling as consumption suggests that the attractiveness of the lottery game will have an impact on the demand for the sports lottery. [Breuer et al. \(2009\)](#) acknowledge that sports betting products apparently offer nonmonetary utility for bettors because some individuals have utilized sports betting to hedge the disappointment of an unsuccessful outcome of an event they are emotionally attached to. Indirect evidence also comes from [Paul and Weinbach \(2010\)](#) and [García et al. \(2008\)](#). Through an analysis of the betting volumes of the National Basketball Association (NBA) and National Hockey League (NHL) obtained and aggregated across three on-line sportsbooks for the 2008-09 season, [Paul and Weinbach \(2010\)](#) found that betting behavior is much like fan behavior as key fan-attributes, such as the quality of teams and the availability of television coverage, were shown to have a positive and significant effect on betting volume. [García et al. \(2008\)](#) examined the impact of having a professional football team in the Spanish First or Second Division in a certain province on the amount of sales of football pools in Spain (La Quiniela). Their results showed that having a club in the top divisions has a significant effect on sales of La Quiniela.

### 2.4. Consumer Characteristics

**Income:** There is evidence that the demand for lottery is likely to depend on the socio-demographic structure of the population. Previous studies have sought to explore the impact of socio-demographic factors on lottery demand, particularly income. The estimated effects of income on lottery demand in previous studies have been mixed, but the collective evidence suggests that lottery expenditures do not systematically depend on income, and the lottery tax generally is regressive but with substantial differences in the degree of regressivity across different lottery games. The regressivity of tax means that the percentage of total tax burden consistently exceeds the corresponding percentage of total income all the way through the income scale.

**Financial burden:** In line with the indivisibility in expenditure reasoning, financial burden is hypothesized to be positively correlated with the demand. [Weinbach and Paul \(2008\)](#) investigation of the relationship between the amount of lottery tickets purchased across the United States and the distribution of government transfer payments also lend evidence to the interplay between

consumption indivisibility and limited accessibility of credit market. Using weekly lottery sales data, they demonstrated an increase in lottery activity during weeks in which transfer payments are distributed. They also found that spending increases during check week are relatively more concentrated in games with lower jackpots, indicating differences in preferences for the transfer recipient group (i.e., low income group) from the population at large. The Pick 3 and Pick 4 games are found to exhibit significant increases in sales during check week, while Pick 5 and Pick 6 games do not. They suggested that the choice of lottery games is at least partially influenced by wealth and accessibility to credit markets, a conclusion consistent to indivisibility hypothesis.

**Education:** The level of education is an important determinant of one's earning function. It has been confirmed by hundreds of studies that better-educated individuals earn higher wages than their less-educated counterparts (Card, 1999). With understanding that lottery participation is generally negatively associated with income level, it is also likely to be true with education. Additionally, there is some evidence to support the notion that certain courses received from formal education may improve one's rationality, thus better-educated individuals may fall less to those cognitive misconceptions frequently identified in gambling. Although never demonstrated empirically in the lottery gambling literature, it is rather plausible that education has an additional impact on lottery expenditure beyond its effect through income.

**Accessibility:** Venue distribution plays a fundamental role in marketing gambling products. Several studies have examined the relationship between gambling venue accessibility and the demand for gambling products. Shiller (2000) contended that an individual's geographical whereabouts may induce gambling, when considering the greater availability of gambling facilities in urban areas that provides more opportunities to buy tickets. The availability of gambling opportunities, particularly with regard to facility density and venue proximity to home, work or other convenient locations, was found to be associated with demand for gambling products and the prevalence of program gamblers (Welte *et al.*, 2004; Hing and Haw, 2009). Sleight *et al.* (2002) reported a case about how Camelot managed to optimize its outlets to increase venue accessibility for its customers. The effects of venue accessibility on lottery demand, however, has not yet empirically documented in the literature.

## 4. METHOD

### 4.1. The Setting

The current investigation focused on the Shengfu game (Win-Tie-Lose Game). Each lottery ticket contains 14 football (soccer) matches selected from a wider range of football competitions. These include but are not limited to the English Premier League, German Bundesliga, Italian Series A, Spanish Primere League, the UEFA Champions League, and the Asian Cup. The Chinese domestic football leagues are not allowed to be used in sports lottery betting. The players have the possibility of choosing the final result of each of the 14 matches from among three alternative results: home team win (3), tie (1), and away team win (0). The Shengfu game is a pari-mutuel

game where prizes represent a share of sales revenue. Currently, only two prizes are awarded for each drawing. To win the first prize, players have to correctly choose all of the 14 matches listed in the ticket. Those correctly predicting 13 of the 14 results win a second prize. If there are no winners of the first and/ or second prize, this money rolls over to the jackpot pool of the next drawing. The rollover is not allocated to the second prize. 35% of the sales is taken by the governments (among which, 1% goes to an adjustment fund), and up to 65% of sales is returned to players. Additionally, Chinese lottery administration voluntarily sets a 5 million yuan prize cap for a single stake. Lottery players can, therefore, only win a maximum of 5 million yuan for each winning ticket. In the case of a prize cap, any unallocated prize money will roll over to the next draw.

#### 4.2. Empirical Model

A panel data containing sales of 211 draws of 30 provinces in 2011 and 2012 was obtained from the Chinese Sports Lottery Administration Center. To examine the demand function of Shengfu game, an empirical regression model was constructed. The main regression of interest is a multilevel model given by:

$$y_{it} = \gamma_1 y_{i,t-1} + \dots + \gamma_4 y_{i,t-4} + \mathbf{x}'_{it} \beta + \alpha_i + \varepsilon_{it}, \quad i = 1, 2, \dots, 30; \quad t = 5, 6, \dots, 211,$$

where  $y_{it}$  is the natural logarithm transformed aggregate sales of province  $i$  at draw  $t$ ,  $\log(\text{SALES})$ ; four lags of  $\log(\text{SALES})$  were included in the model based on a previous auto-correlation analysis to capture the dynamic nature of gaming behavior;  $\mathbf{x}'_{it}$  are explanatory variables;  $\alpha_i$  are random individual-specific effects; and  $\varepsilon_{it}$  is an idiosyncratic error.

Table 1 lists all the variables included in the analyses. To capture the game attractiveness, six derived dummy variables (EPL&GB, ISA&SLL, MAJOR4, 1TIER, 2TIER, 3TIER) and one continuous variable (NUM) were derived to represent lottery ticket compositions, and a post-hoc prediction difficulty variable (PDC) and its square (PDCSQ) were derived to represent the difficulty of winning a prize. To capture the province characteristics, the following variables were included: population of a province in 2010 (POP), income (INCOME), total dependence rate (TDR) as a proxy of financial burden, proportion of population with completed higher education (HER) and proportion of population who are illiterate (ILR), and venue accessibility as measured by number of sports lottery outlets (NTER). POP, INCOME, and NTER were natural logarithm transformed. Information on HER and ILR were directly obtained from the Sixth National Population Census of the People's Republic of China, which was conducted in 2010. The information on NTER was obtained from the Yearbook of the Chinese Lotteries 2011. All the rest explanatory variables were constructed.

Ticket composition: English Premier League, German Bundesliga 1, Italian Series A, and Spanish La Liga have been four major leagues for sports betting in China. More than half of all draws are composed of matches selected from these four leagues. Particularly, one third of all draws are involved the combination of English Premier League and German Bundesliga 1 (EPL&GB), and the combination of Italian Series A and Spanish La Liga (ISA&SLL). Two

dummy variables EPL&GB and ISA&SLL were generated to represent these two combinations. A third dummy variable MAJOR4 was generated to represent any other combinations of these four leagues. Furthermore, dummy variable 1TIER was generated to represent combinations of matches from the following most popular leagues: FIFA World Cup, European Championship, and UEFA Champions League. Dummy variable 2TIER represents the combinations of matches from the following less popular leagues: Ligue 1, and AFC Champions League AFC Cup, FIFA Women World Cup, Copa America, Olympic Men Soccer, European National Teams Qualifying Games, Championship, FA Cup, and Asian National Teams Qualifying Games. Dummy variable 3TIER represents the combinations of matches from the least popular leagues. Finally, a dummy variable OTHER which serves as the baseline was generated, which represent the rest combinations that were not accounted by previous dummy variables. Additionally, because sometimes matches are selected from one league, and other times they are selected from multiple leagues. Variable NUM captures the number of different leagues a given draw involves.

**Prediction difficulty:** The difficulty level associated with correctly predicting 14 matches varies draw by draw, which may have an impact on consumer purchasing behavior. Specifically, a moderately easy game will sell more because players have greater probability to win a prize. However, when the game became extremely easy, consumers may lose their interests in predicting those results. Therefore, in addition to EP, adding a variable capturing this draw-specific difficulty factor may increase the explanation power of the demand equation. A prediction difficulty (easiness) coefficient (PDC) is constructed and given by  $\log(\text{Actual number of second prize winners} / \text{Number of second prize winners assuming random selection})$ . PDC actually measures the easiness of a draw because the greater the value the easier the game is. The reason using second prize instead of first prize is because there were few undefined data points. Furthermore, PDC can be approximated by a normal distribution (Figure 1). Additionally, to examine a potential quadratic effect of PDC, the square of PDC is also included in the regression analyses.

**Total dependence rate:** In China, intergenerational-support family-based care has been at the core of the typical family. A majority of the elderly live with one of their children and rely on their support. TDR is the total dependence rate, which is calculated by the following equation:

$$\text{TDR} = (\text{AGE0-14} + \text{AGE65+})/\text{AGE15-64},$$

Where AGE0-14 is the proportion of age group 0-14 in the population, AGE15-64 proportion of age group (15-64) in the population, and AGE65+ proportion of age group (15-64) in the population. Information on AGE0-14, AGE15-64, AGE65+, HER, and ILR were obtained from the Sixth National Population Census of the People's Republic of China.

**Income:** The National Bureau of Statistics of China does not provide the information about household income, but the Per Capita Annual Income of Urban Households (PCIUH) and Per Capita Income of Rural Households (PCIRH) are reported by the Sixth National Population Census of the People's Republic of China. Further, the proportions of rural and urban residents in the population are reported by the China Population and Employment Statistics Yearbook 2011.

Therefore, INCOME is the per capita income of urban household and per capita income of rural household weighted by the proportion of urban and rural residents in the population. It is derived by the following equation:

$$\text{INCOME} = \text{PCIUH} \times \%(\text{Urban Population}) + \text{PCIRH} \times \%(\text{Rural Population})$$

#### 4.3. Method of Estimation

For panel data, dependent variables and regressors can potentially vary over both time (i.e., within variation) and individuals (i.e., between variation). There are two major characteristics associated with this data set, which in turn determine the estimation strategy to be employed. First,  $T$  (i.e., 211) is large relative to  $N$  (i.e., 30). It is not possible to obtain standard errors that control for serial correlation in the error without explicitly stating a model for serial correlation (e.g., OLS using cluster-robust standard errors, or population averaged estimator (also known as Pooled FGLS estimator)). A model for serial correlation in the error, such as ARMA model for the errors, thus needs to be specified. On the other hand, given  $N$  is fixed, it is often possible to relax the assumption of independence across individuals (Cameron and Trivedi, 2010). Yet, it is possible to obtain standard errors that allow autocorrelated errors of general form by applying the method of Driscoll and Kraay (1998). Second, given the existence of time-invariant regressors (i.e., zero within variation), they cannot be identified by estimators using only within variations (e.g., OLS on the mean-difference data, or Fixed Effects Estimator). A possible approach is using Hausman and Taylor (1981) estimator, which estimates coefficient of time-invariant regressors by two-stage least squares, using those elements of time-averaged time-variant regressors that are uncorrelated with individual-specific part of the error term as instruments for time-invariant regressors (Hsiao, 2003). However, estimates of Hausman and Taylor's instrumental variable approach will be biased under dynamic model specification. Arellano and Bond (1991) proposed an IV approach using first-difference that provides unbiased and consistent estimation for dynamic models, but the time-invariant regressors will be removed by first differencing. An alternative strategy often adopted in empirical research is to use random effects models, if stronger assumptions can be made. The crucial distinction between fixed and random effects is not in the nature of the effect, but whether to make inference with respect to the population characteristics or only with respect to the effects that are in the sample (Hsiao, 2003). Finally, if the individual provinces are considered as a sample from a population of sports lottery jurisdictions, and the draws are a sample from a population of all draws, then it would make sense to associate random effects with both these factors. Unlike most application of mixed effects models (also known as hierarchical linear models), the covariance structure in this study is nonnested, because individual is not nested in time and time is not nested in individual. The random intercept for provinces is shared cross all draws for a given province  $i$ , whereas the random intercept for draws is shared by all provinces in a given draw  $t$ . This type of completely crossed effects model can be estimated by the xtmixed procedure in STATA, following suggestions of Rabe-Hesketh and Skrondal (2012).



## 5. RESULTS

### 5.1. Fixed Effects Models

The first class of models is fixed effects models, which explicitly consider the individual-specific effects. The first FE model (FE1) is static model fitted with Least Squares Dummy Variables (LSDV) approach of including a set of dummy variables, here for each province. The second model (FE2) is a dynamic version of FE1. To examine the coefficients of time-invariant variables, the fourth model (FE3) is estimated by Hausman and Taylor (1981) approach. And the fifth model (FE4) is estimated by Arellano and Bond (1991) approach to account for dynamic specification. Column 4-7 of Table 2 report the results of these four models. As discussed, the FE1, FE2, and FE4 were unable to identify time-invariant regressors. The coefficient estimates of those time-variant variables of FE1 and FE3 are same as those of PM1 and PM2. The coefficient estimates of FE2 and FE4 are generally consistent. The key insight is that the intra-class correlation (IC) of FE1 is 0.856, suggesting that 85.6% variances of sales are due to differences across provinces. The IC of FE2 is 0.664, suggesting that even after controlling historical sales level (i.e., four lags of sales), 66.4% variances are still attributable to regional differences. FE3 does not account for dynamics but includes time-invariant variables. The IC of FE3 is 0.747, meaning about 10.9% (i.e.,  $0.856-0.747$ ) variances are explained by those time-invariant variables. The key insight from FE4 is that including four lags of sales in the model is likely appropriate. Arellano-Bond test for zero autocorrelation in first-differenced errors reject the null of no autocorrelations at order 1 ( $z=-2.41$ ,  $p=.016$ ) but not at higher orders ( $z=.11$ ,  $p=.91$  at order 2;  $z=-.67$ ,  $p=.50$  at order 3). Therefore, we can conclude that after including four lags, there is no serial correlation in the error as desired.

### 5.2. Two-Way Random-Effects Model

The second class of models is a dynamic two-way random-effects model (RE1) using MLE via EM algorithm (Rubin and Szatrowski, 1982; Rabe-Hesketh and Skrondal, 2012). Column 8 of Table 2 reports the results of the model. The coefficient estimates of RE1 are generally consistent with previous studies: (a) Ticket combination variables have significant impact on the demand. Specifically, tickets composed of popular matches sell more than those composed of less popular matches; (b) Prediction difficulty coefficient is marginally significant at 10% confidence level, and the magnitude is rather small (0.03); (c) The square term of PDC was not significant but in the direction of prediction across all the regressions; (d) Diversifying the draw by including matches from one more league has a negative impact on sales, reducing sales by about 7.7% (i.e.,  $\exp(-0.08)-1$ ); (e) Population was not found a significant predictor of sales after controlling all the other variables; (f) Dependence rate is significantly related to sales, one percent increase in TDR is associated with about 2.0% increase in sales (i.e.,  $\exp(0.02)-1$ ); (g) The demand elasticity with regard to income is about 0.40, quite different from previous models; (h) HER, ILR, and NTER were found not significant related to sales. The estimated residual standard deviation between

provinces was 0.15, and the estimated residual standard deviation between draws was 0.40. The remaining residual standard deviation, not due to additive effects of provinces and draws, was estimated as 0.20. The residual intra-class correlation (ICC) for provinces was estimated as

$$\hat{\rho}(\text{province}) = \frac{0.15^2}{0.15^2 + 0.40^2 + 0.20^2} = 0.10$$

and the residual ICC for draws was estimated as

$$\hat{\rho}(\text{draw}) = \frac{0.40^2}{0.15^2 + 0.40^2 + 0.20^2} = 0.72$$

Hence, there is a high correlation over draws within provinces and a small correlation over provinces within draws.

## 6. DISCUSSION

Despite that sports lottery gambling has become a prevalent economic and recreational activity, it remains an under-researched area in sports management literature. Drawing upon a set of panel data of the Shengfu game, the most representative sports lottery in China, and through multilevel modeling, this study examined the relationship between sport lottery demand and game attributes and consumer characteristics. Because the lottery administrator sets a prize cap for both first prize and second prize winners- no winner can win more than 5 million RMB in each draw. It seems that the jackpot size becomes irrelevant in players' decisions, therefore, we exclude jackpot pool in this study. Furthermore, we did not consider effective price as we did in a previous study (Mao *et al.*, 2014) because it makes a strong assumption about gaming behavior. We argued that it is unlikely that players have the capability and motivation to calculate the effective price. Instead, this study focused on game attributes and consumer characteristics.

This study revealed that ticket composition has considerable impact on the demand. We argue that this finding is consistent with the prediction of gambling as consumption account. If gambling is a financial decision, only information and expected value would matter. Although more popular leagues may have more information available, it would be an unwise decision to bet on these popular games because the probability of prize sharing would be much greater. Our empirical results actually showed that, on average, the ex-post winning probabilities were lower when the tickets were composed of EPL&GB and ISA&SLL. This also justifies the inclusion of an ex-post Prediction Difficulty Coefficient in the regression model. The coefficients estimates on the dummy variables therefore were effects after partialling out information contained in PDC. Another possibility is that the players forecast larger prizes when the tickets were composed of certain leagues. We did compare the prizes and winning probabilities between draws composed of EPL&GB with draws composed of ISA&SLL, and they were not statistically different. The question then is if the gambling properties were the same, then what drove the differences in the demand? Our answer was that they differed in consumption values. Popular leagues either attracted more sports fans or enticed existing fans to buy more.

The Prediction Difficulty Coefficient (PDC) was operationalized as  $\log(\text{actual number of second prize winners}/\text{number of second prize winners assuming random selection})$ . The inclusion of PDC is important because it serves as a proxy of information. Despite of post hoc nature of the construction, this variable had perfectly captured the actual difficulty of betting on each draw. As predicted, PDC was positively associated with demand. One percent increase in the PDC is associated with approximately three percent increase in sales. The quadratic term of PDC were negative and statistically significant in three out of eight regression models, which suggested that when a draw is perceived too easy, the demand will drop. Additionally, diversifying the draw by including matches from one more league has a negative impact on sales, reducing sales by about 7.7%. This is because having more leagues in a draw potentially increases the difficulty of betting as players may need to allocate more time to follow the matches or require broader knowledge about soccer betting.

Through multilevel modelling, this study revealed that some of the selected socio-demographic variables have significant impact on the demand for sports lottery, which is generally consistent with [Mao et al. \(2015\)](#) examination of the relationship between socio-demographic variables and demand for sports lotteries in China. First, the provinces with higher income levels had a higher demand for sports lottery. Although the estimations of income elasticity from the static and dynamic models differ drastically in terms of its magnitude, the sign remains positive. The income elasticity of Shengfu lottery is estimated around 2 in the static models, suggesting the demand is highly income elastic and can even be viewed as a “luxury” good for Chinese consumers. In the dynamic models, however, the income elasticity of Shengfu lottery is estimated around 0.4. This suggests that given the initial state of demand, the players are less responsive with regards to the change of income levels.

Second, using TDR as a proxy of financial and social burdens, this study found that TDR is positively related to demand, which is consistent with previous research that used transfer payment as a measure of financial and social burdens ([Weinbach and Paul, 2008](#)). This finding is consistent with the prediction of indivisibility in expenditure account, which suggested that under certain circumstances, people derive additional utility from risk seeking. Within the context of China, intergenerational-support family-based care has been at the core of Chinese families. A majority of the elderly live with one of their children and rely on their support. With the skyrocketing of real estate prices and living costs in China, many families encounter high financial and social burdens. Lottery has long been regarded as the only vehicle for them to buy hope. The finding in this study seems to be reflective on this social reality.

Third, the accessibility elasticity as measured by NTER is estimated around 0.32-0.58 in the static models, suggesting that the demand is positively related to accessibility of the game. However, the accessibility elasticity is no longer significant in the dynamic models, suggesting that given initial level of demand, accessibility did not have further impact on the demand. In addition, POP, HER and ILR in general were not significantly related to the demand.

The current research has identified several interesting avenues for future research. These include, but are not limited to, investigation of the following questions: How to measure consumption value of sports gambling? What are the interrelationships between sports betting and sports spectatorship? How do players make decisions and how do they improve their betting skills? What are the implications of consumer learning on sports lottery administration? How do players respond to marketing activities, such as jackpot promotion, outlet expansion, and lottery advertising? Furthermore, there are many other types of sports betting products, such as office pools and parlay betting, that warrants future scholarly efforts.

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**Table-1.** Description of Variables Included in Regression Analyses

Variable	Definition
<i>Response Variables</i>	
SALES	Sales of <i>Shengfu</i> game for province i at draw t
<i>Explanatory Variables</i>	
L1.SALES	First lag of log(SALES).
L2.LSALES	Second lag of log(SALES).
L3.LSALES	Third lag of log(SALES).
L4.LSALES	Fourth lag of log(SALES).
EPL&GB	Matches selected from English Premier League & German Bundesliga.
ISA&SLL	Matches selected from Italian Series A League & Spanish La Liga.
MAJOR4	Matches selected from the four major leagues, and the combinations are other than EPL&GB and ISA&SLL.
1TIER	Matches selected from most popular leagues.
2TIER	Matches selected from less popular leagues.
3TIER	Matches selected from least popular leagues.
NUM	Number of different leagues in a given draw.
PDC	Prediction Difficulty Coefficient.
PDCSQ	Square of PDC.
POP	Total population of each province in 2010.
TDR	Total Dependence Rate.
HER	Proportion of population with completed higher education.
ILR	Proportion of population who are illiterate.
INCOME	A derived variable measuring average income level in the province.
NTER	The number of sports lottery outlets in each province.

Table-2. Results of regression models

	FE1	FE2	FE3	FE4	RE1
L.Isales		0.21** (0.01)		0.13** (0.06)	0.37** (0.01)
L2.Isales		0.05** (0.01)		-0.03 (0.08)	0.18** (0.01)
L3.Isales		0.12** (0.01)		0.05 (0.05)	0.13** (0.01)
L4.Isales		0.08** (0.01)		0.03 (0.04)	0.12** (0.01)
EPL&GB	0.40** (0.02)	0.39** (0.02)	0.40** (0.02)	0.41** (0.03)	0.39** (0.09)
ISA&SLL	0.24** (0.02)	0.11** (0.02)	0.24** (0.02)	0.17** (0.05)	0.04 (0.09)
MAJOR4	0.29** (0.02)	0.24** (0.02)	0.29** (0.02)	0.27** (0.04)	0.22** (0.09)
1TIER	0.27** (0.03)	0.20** (0.03)	0.27** (0.03)	0.18* (0.10)	0.12 (0.16)
2TIER	-0.10** (0.03)	-0.17** (0.03)	-0.10** (0.03)	-0.13 (0.12)	-0.21 (0.13)
3TIER	-0.63** (0.02)	-0.60** (0.02)	-0.63** (0.02)	-0.60** (0.05)	-0.57** (0.10)
NUM	-0.07** (0.01)	-0.08** (0.01)	-0.07** (0.01)	-0.08** (0.02)	-0.08** (0.03)
PDC	0.03** (0.00)	0.03** (0.00)	0.03** (0.00)	0.03** (0.01)	0.03* (0.02)
PDCSQ/100	-0.21** (0.10)	-0.11 (0.10)	-0.21** (0.10)	-0.11 (0.31)	-0.16 (0.49)
log(POP)			0.00 (0.00)		0.04 (0.08)
TDR			0.12** (0.04)		0.02** (0.01)
HER			0.02 (0.05)		0.00 (0.01)
ILR			-0.02 (0.08)		-0.00 (0.02)
log(INCOME)			1.95** (0.77)		0.40** (0.15)
log(NTER)			0.58** (0.21)		0.06 (0.09)
Constant	6.21** (0.02)	3.44** (0.09)	-20.67** (7.08)	5.12** (1.16)	-3.74** (1.36)

## Notes.

(a) FE1-Least Squares Dummy Variables (static); FE2-Least Squares Dummy Variables (including 4 lags);

FE3-Hausman-Taylor method; FE4-Arellano-Bond method; RE1-Two-way Random-effects models.

(b) Heteroskedasticity-robust standard errors in parentheses.

(c) \* p<0.10, \*\* p<0.05

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