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Nonlinear Effect of Business Cycle on Lottery Sales Stability

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Abstract

This paper constructs a panel smooth transition autoregression model to evaluate the impact of the U. S. business cycle on the stability of lottery sales. We find that the impact is nonlinear and time-varying, depending on the level of the leading indicator. The persistence of lottery sales locates between 0.7779 and 0.8539, implying that current lottery sales are influenced by about 15%-23% of current disturbance, and the stability of the lottery sales is relatively high. An increase in the leading indicator would lead to a higher persistence of lottery sales and then more stable lottery sales in the next period.

JEL classification numbers: C23, L83, E32
Keywords: Sales persistence, stability of lottery sales, panel smooth transition autoregression (PSTAR) model, lagged leading indicator

1 Introduction

In the U.S., revenue from legalized lottery operations has been playing an important role in states' overall revenues and remaining the largest source of gambling revenue to governments. Up to now, 44 states have legalized state lotteries to raise revenues. According to the statistics of the Census Bureau and the Rockefeller Institute of Government, overall state revenues from lotteries more than doubled from $10.5 billion in 1993 to $20.5 billion in 2014. This revenue shared about 2.1%-2.8% of states' own-source revenues. However, the revenues fell in three years - 2001, 2002, and 2009 due to the dot-com crisis and the

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European financial crisis. Evidently, the paths of the lottery sales might be ***nonlinear*** and influenced by ***business cycle*** or ***specific economic crisis***.

In fact, states' shares of nationwide revenue from lotteries varied significantly in the period. In 2015, about 40% of total lottery revenue was collected in California, Florida, Pennsylvania, New York, and Texas. About 80% of total lottery revenues were collected in 15 states, and the remaining 28 states collected only one-fifth of total lottery revenues. Thus, in investigating the paths of the revenues, one cannot ignore the ***heterogeneity problem*** among states' lottery revenues.

Several aspects of gambling have been investigated; however, the literature on the relationships between gambling and business cycle is limited (Li et al. 2010). Only very few studies examine how gambling sales are influenced by specific economic crises. For example, Gu (1999) finds that the Asian financial crisis in 1997–1998 had a severe impact on Asian players' gaming propensity for Las Vegas casino drops of baccarat and pai gow. However, Raab and Schwer (2003) find a temporary decline in the gaming propensity for both games and this effect dies out over time. Richard (2010) finds that economic development needs, measured by general unemployment rates, are associated with the casino legalization decisions by national governments. Casino legalization decisions are more likely to occur in the years with high unemployment. Unemployment is a lagging index and the result of a country's business cycle. That is, ***investigating changes in lottery sales from different stages of the business cycle is crucial***. The investigation results help gambling industries execute the optimal allocation of their resources during the downturn, including decisions about personnel and promotional activities. They also assist state governments in predicting the evolvement of the lottery sales during the downturn and provide support for decisions on expanding their gambling operations for balancing their budgets (Dadayan and Ward 2009).

While earlier studies have paid attention to analyzing the possible consequences of macroeconomic conditions on gambling or lottery sales, the approaches and data they use have several shortcomings. First, most of them use linear structural models and time series models to estimate lottery sales. These approaches ignore the probable nonlinear transition process and the heterogeneity in lottery sales for different states. That is, the impact of regressors on lottery sales may be nonlinear and different among states. Second, their results rely on single one economic crisis and rather short sample period (e.g., DeBoer 1990; Mikesell 1994). Thus, one is unable to evaluate the differential lottery sales for a country in prosperity stages and recession stages, and neglects the dynamic characteristics of the lottery sales. Most importantly, they do not apply proper techniques to investigate the nonlinear impact as mentioned above.

This paper rewrites the panel smooth transition regression (PSTR) model, recently developed by González, et al. (2005), as a panel smooth transition autoregression (PSTAR) one to simultaneously resolve the above problems and to evaluate the nonlinear impact of business cycles on lottery sales and their stability. A basic PSTR model contains two linear components connected by a nonlinear transition function and allows the series under investigation to move smoothly within two regimes. This model is useful for situations where the nonlinear dynamics are driven by a common regime-switching component, but where the response to this component may be different across variables (González et al. 2005). For example, the lottery sales of the U.S. states may be disturbed by the worldwide recessions, but some states may enter into recessions earlier than others. Besides, in conducting the estimation of the PSTR model, a panel data set that simultaneously covers time series and cross-sectional data is used. That is, a panel data set considers the heterogeneity of cross-sectional units and includes enough observations and lengths of time series. The PSTAR model used in this study is formed by replacing the exogenous explanatory variables in the PSTR model with lagged dependent variables.

In sum, employing the PST(A)R model to estimate lottery sales persistence has the following traits. First, we select lagged lottery sales as the explanatory variables (or regressors); therefore, we do not need to determine what variables should be used as the regressors and to find the expected values of the selected regressors (Andrews and Cynthia 2003; Olson et al. 2003; Worthington et al. 2007). Second, it can deal with the problems of nonlinearity and heterogeneity (Hsiao 2003). The characteristics of nonlinearity and heterogeneity can be used to interpret the probable nonlinear process of the lottery sales and the differential impacts of economic condition (measured by business cycle in this paper) on the lottery sales. More importantly, the sum of the estimated coefficients in the lagged lottery sales can measure the persistence of lottery sales, which provides useful information for lottery industry and state governments. A standard design to measure the persistence of the dependent variable is to estimate an autoregressive (AR) model and the estimated coefficient of the one-period lagged dependent variable is the persistence of the dependent variable (Dechow and Ge 2006). However, we extend the persistence effect to include more lagged terms of the dependent variable.

To conduct the empirical estimation, this paper selects 37 states in the U.S. as sample objects. The reason is that they have similar incomes and different paths of lottery sales, which can satisfy the heterogeneity of cross-states effects on lottery sales. This paper contributes to the existing literature in three distinct ways. First, we provide a more proper econometric model to resolve the estimation problems of lottery sales confronted by previous studies. Second, through the linearity test on the PSTAR model, we further investigate whether lottery sales and their stability demonstrate a nonlinear, smooth transition process. This is especially important for the governmental authority to use the estimated model for evaluating and forecasting the changes of lottery sales. Finally, using leading indicators as the transition variable in the PSTAR model, we can interpret the differentiated persistence of lottery sales and prove whether business cycle can nonlinearly influence current lottery sales, as business cycle locates in different stages. These advantages are particularly crucial for lottery industry and state authorities to modify suitable policies for improving revenues from lottery sales.

The remainder of this paper is organized as follows. Section 2 introduces the lottery sales model of a PSTAR specification for evaluating the threshold effects of the leading indicator on lottery sales when a leading indicator is assigned as the transition variable and located in different regimes. Section 3 shows the procedures for testing the stationarity of the variables under investigation and for testing and estimating the PSTAR model, including nonlinear unit root test, nonlinearity test, and no remaining nonlinearity test. Section 4 presents the data source and empirical results, and the final section provides several policy suggestions.

2 Empirical model

To evaluate the threshold effect of the business cycle on lottery sales and their stability, we need first to construct the PSTR model. The basic PSTR model with a single transition function can be written as follows (González et al 2005):

$$y_{i,t} = \alpha_i + \beta_0' x_{i,t} + \beta_1' x_{i,t} W(z_{i,t}; \gamma, c) + \varepsilon_{i,t} \tag{1}$$

where i = 1,2,...,N is the number of states and t = 1,2,...,T is the number of periods. $y_{i,t}$ is a dependent variable (i.e., the lottery sales) and $x_{i,t}$ is a K-dimensional vector of regressors. α_i represents a individual fixed effect. $W(z_{i,t};\gamma,c)$ is the transition function with the value between 0 and 1, depending on time- and cross-section-varying transition variable $z_{i,t}$. γ is the transition parameter, describing the switching speed of the transition variable between different regimes. c is the threshold of the transition variable. Both γ and c are estimated endogenously. $\varepsilon_{i,t}$ is a residual.

González et al. (2005) and Bessec and Fouquau (2008) indicate that the logistic function with m location parameters can be used as the transition function in Eq. (1):

$$W(z_{i,t};\gamma,c) = \left[1 + \exp\left(-\gamma \prod_{j=1}^{m} \left(z_{i,t} - c_j\right)\right)\right]^{-1} \tag{2}$$

where $\gamma > 0$ and $c_1 \le c_2 \le \Lambda \le c_m$. When $\gamma \to \infty$, the PSTR model converges towards a panel threshold regression model (Hansen 1999). Contrarily, when $\gamma \to 0$, the transition function $W(z_{i,t};\gamma,c)$ is constant and the PSTR estimation becomes a panel with fixed effects. Following the suggestion of González et al. (2005), we consider only the cases of m = 1 and 2 to capture the nonlinearities caused by smooth regime-switching processes. The cases of m =1 and 2 correspond to a logistic PSTR model and a logistic quadratic PSTR specification, respectively. In addition, the basic PSTR model can be extended to (r+1) different regimes:

$$y_{i,t} = \alpha_i + \beta_0' x_{i,t} + \sum_{j=1}^{r} \beta_j' x_{i,t} W_j\left(z_{i,t};\gamma_j, c_j\right) + \varepsilon_{i,t} \tag{3}$$

where $W_j(z_{i,t};\gamma_j,c_j)$, j = 1,…,r, are the transition functions.
In our constructed lottery sales model of a PSTAR specification, the regressors in Eqs. (1) and (3) are k-period lagged lottery sales, where k=1,2,…,K. In this specification, we do not need to determine what variables influence lottery sales. The PSTAR model with a single transition function can be expressed as follows:

$$LOT_{i,t} = \alpha_{i0} + \sum_{k=1}^{K} \alpha_k LOT_{i,t-k} + \sum_{k=1}^{K} \alpha'_k LOT_{i,t-k} W(LI_{t-d};\gamma,c) + \varepsilon_{i,t} \tag{4}$$

where α_{i0} is the individual fixed effect. α_k and $\alpha'_k, k = 1,2,...,K$, are the estimated coefficients of the lottery sales $LOT_{i,t-k}$ in two different regimes. $W(LI_{t-d};\gamma,c)$ is the transition function describing the smooth switching process of lottery sales. LI_{t-d} is the d-period lagged leading indicator, representing the business cycle of the U.S. Different from the specification in González et al. (2005) and Fouquau et al. (2008), we allow the probable lagged influence of the transition variable (i.e., business cycle in this study) on lottery sales. Based on this consideration, this paper specifies the maximum lag length of the transition variable to be six (i.e., d = 0,1,…,6).
Eq. (4) can display two traits in describing the process of lottery sales. First, it can measure the indirect influence of the business cycle on lottery sales through lagged lottery sales. That is, the U.S. business cycle has spillover effects on lottery markets. Second, the transition parameter *m* can describe the speculation behavior of lottery markets. The larger the transition speed γ is, the higher the speculative behavior in the lottery markets would be. This reason is that the lottery sales change more quickly as the leading indicator approaches its threshold value.
In Eq. (4), the effect of the k-th regressor on lottery sales for state i at time t is $\alpha_k + \alpha'_k W(LI_{t-d};\gamma,c)$, $k = 1,2,...,K$. Obviously, the effect is a weighted average of parameters α_k and α'_k and depends on the level of the transition variable LI_{t-d}. Additionally, the persistence effect of lottery sales is measured by $\sum_{k=1}^{K} \alpha_k + \sum_{k=1}^{K} \alpha'_k W(LI_{t-d};\gamma,c)$.[3] Clearly, both the marginal effect and persistence effect vary with time, which extremely differs from the time-invariant effects obtained in previous linear models. Most previous studies only used one-period lagged dependent variable to assess the persistence of the dependent variable (e.g., Dichev and Tang 2009; Frankel and Litov 2009). Cheng and Wu (2013) argue that this treatment may be inadequate for companies with volatile or irregular sale streams. Because companies can have volatile sale streams, their sale persistence may be insignificant if only a one-period lagged dependent variable is employed. However, this flaw can be avoided by considering more the lag lengths for explanatory variables to trace earnings persistence. Thus, we use more lagged

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[3] The introduction of persistence effect can see, for example, Cheng and Wu (2013).

terms of lottery sales as the regressors to provide more information for measuring the persistence of lottery sales. Considering the probable cycle period of monthly data used in this paper, we allow k up to six, and the optimal k-period lagged lottery sales is decided by applying a stepwise regression method at 5% significance level.

3 Relevant testing

Unit root tests are used to confirm the stationarity of the variables under study. This study applies the panel unit root test, recently proposed by Emirmahmutoglu and Omay (2014), to test the stationarity. This test improves over the traditional testing procedures that assume linearity, symmetry, and cross-sectional independence. That is, our testing procedure incorporates nonlinearity, asymmetry within a heterogeneous panel context via the sieve bootstrap method.

The cross-sectional dependence (CD) test proposed by Pesaran (2004) is first employed to examine the cross-sectional dependence. The dependence test is given as follows:

$$CD = \sqrt{2T/N(N-1)}\left(\sum_{i=1}^{N}\sum_{j=i+1}^{N}\hat{\rho}_{i,j}\right) \tag{5}$$

where $\hat{\rho}_{i,j}$ is the estimated correlation coefficient between error terms for the individuals i and j.

Regarding Emirmahmutoglu and Omay (2014) test, it is expressed as follows:

$$\Delta y_{i,t} = G_{i,t}(\gamma_{1,t}, y_{i,t-1})\{S_{i,t}(\gamma_{2,t}, y_{i,t-1})\rho_{1,i} + (1 - S_{i,t}(\gamma_{2,t}, y_{i,t-1}))\rho_{2,i}\}y_{i,t-1} + \varepsilon_{i,t} \tag{6}$$

where $y_{i,t}$ is a series and Δ is the difference operator.

$G_{i,t}(\gamma_{1,t}, y_{i,t-1}) = 1 - \exp(-\gamma_{1,t} y_{i,t-1}^2)$, $\gamma_{1,t} > 0$ and $S_{i,t}(\gamma_{2,t}, y_{i,t-1}) = [1 + \exp(-\gamma_{2,t} y_{i,t-1})]^{-1}$, $\gamma_{2,t} > 0$。

Applying the Taylor expansion, the estimation form can be rewritten as follows:

$$\Delta y_{i,t} = \phi_{1,i} y_{i,t-1}^3 + \phi_{2,i} y_{i,t-1}^4 + \sum_{j=1}^{P_i}\delta_{i,j}\Delta y_{i,t-j} + \varepsilon_{i,t} \tag{7}$$

To test Eq. (7), the null hypothesis with unit root is specified as $H_0 : \phi_{1,i} = \phi_{2,i} = 0$. If the null hypothesis is rejected, then we test the null hypothesis of nonlinear, symmetric ESTAR against the alternative hypothesis of nonlinear, asymmetric ESTAR, i.e., $H_0 : \phi_{2,i} = 0$ against $H_1 : \phi_{2,i} \neq 0$.

González et al. (2005) suggest using a three-step procedure to estimate Eq. (4). First, the linearity test is conducted to examine whether lottery sales follow linear processes. No remaining nonlinearity test in the transition function is performed as the null hypothesis of linearity is rejected. In this procedure, the number of transition functions (or regimes) is determined. Finally, after demeaning the variables under investigation, nonlinear ordinary least squares are used to estimate

the parameters in Eq. (4).
In executing the linearity testing of Eq. (4), the transition function $W(LI_t;\gamma,c)$ is replaced with its first-order Taylor expansion at $\gamma = 0$ (see van Dijk et al., 2002). Therefore, the following auxiliary equation is constructed:

$$e_{i,t} = \eta_{0i} + \sum_{k=1}^{K} \eta_k LOT_{i,t-k} + \sum_{k=1}^{K} \eta'_k LOT_{i,t-k} LI_{t-d} + \nu_{i,t} \tag{8}$$

where $e_{i,t}$ is the residual of the linear component in Eq. (4). η_{0i} is the time-invariant fixed effect. η_k and η'_k, k=1,2,…,K, are estimated parameters in two different regimes. The null hypothesis of the linearity testing is $H_0 : \eta'_1 = \eta'_2 = ... = \eta'_K = 0$. In previous studies, three approaches are used to conduct the linearity test and no remaining nonlinearity test, including the Wald (*LM*), Fisher (*LMF*) and likelihood ratio tests (*LRT*) (see, e.g., Fouquau et al 2008). [4]

Let $PSSR_0$ be the panel sum of squared residuals under H_0 : the linear panel model with individual effects, and $PSSR_1$ be the panel sum of squared residuals under H_1 : the PSTAR model with two regimes (i.e., r=1). Then, the corresponding *LM* and *LMF* statistics are expressed as follows:

$$\begin{gathered} LM = TN(PSSR_0 - PSSR_1)/PSSR_0 \\ LMF = [(PSSR_0 - PSSR_1)/mK]/[PSSR_0/(TN - N - m(K+1))] \end{gathered} \tag{9}$$

where *K* is the number of regressors and *m* is the number of location parameters. Under the null hypothesis, the *LM* statistic has a chi-square distribution, and *LMF* statistic has an approximate $F[mK, TN - N - m(K+1)]$ distribution.

When H_0 is rejected, we perform the no remaining nonlinearity test whether there is one transition function (H_0 : r=1) against there are at least two transition functions (H_1 : r≧ 2). The procedure is similar to the one used to conduct the linearity test. If the null hypothesis (H_0 : r=1) is rejected, we test a three-regime model, i.e., H_0 : r=2 vs. H_1 : r≧ 3. The testing procedure continues until the first acceptance of the null hypothesis of no remaining heterogeneity.

[4] van Dijk et al. (2002) indicate that the Fisher test has better size properties in small samples than the other two tests.

4 Empirical results

Empirically, this paper uses a panel data of lottery sales in 37 U.S. states during the period of January 2000 through December 2015. We exclude the remaining 8 states due to unavailable data. These states have experienced different lottery sales, which can satisfy the heterogeneity of cross-country. The data come from the North American Association of State and Provincial Lotteries (NASPL) and the OECD database.

The gaming industry has generally been considered as recession proof. The recession may cause an increase in gambling opportunities. When normal revenue growth decreases during economic recessions, state governments often consider expanding their gambling operations for balancing their budgets (Dadayan and Ward 2009) by efforts to keep gambling revenues (and the concomitant gambling taxes) within the state, to reduce unemployment and to attract tourism (Calcagno et al. 2010; Richard 2010). However, as the gaming industry has expanded it has increased its exposure to the lodging and convention industries. This is supported by the fact that the gaming industry is struggling alongside these industries. In addition, Coughlin and Garrett (2009) find no evidence that the income elasticity of demand for lottery tickets is different in recession and boom periods. Evidently, the impact of business cycles on lottery sales is ambiguous or may be nonlinear. Thus, this study selects the change rate of leading indicator, a representative proxy for the business cycle, as the transition variable in the PSTAR model.

Descriptive statistics of the data are reported in Table 1. In Table 2, we reject the null hypothesis of no cross-sectional dependence at 1% significance level. This result supports the decision to use a panel data framework rather than a pure time series structure to test the unit root properties in all the variables. Table 3 reports the result of the panel unit test using the sieve bootstrap method outlined in Emirmahmutoglu and Omay (2014). We use the empirical distributions of the tests generated by 5000 replications to obtain their *p*-values. For all tests, we choose the lag length using the Swartz information criterion (SIC). The testing results reveal that the data generating processes of the variables under study follow a nonlinear and asymmetric process. That is, the two series are stationary at level values. In other words, panel unit root tests that do not incorporate nonlinearity, asymmetry, and cross-sectional dependence may generate misleading findings.

Table 1: Descriptive statistics

Variable	Mean	Max.	Min.	Std. Dev.	Jarque-Bera	p-value
LOT	1325.337	9226.49	28.231	1520481	823.15	0.000
LI	99.7	101.3	95.6	1.4145	304.02	0.000

Note: *LOT* and *LI* denote lottery sales and the leading indicator, respectively. The amounts of *LOT* are in millions.

Table 2 Cross-sectional dependence test by Pesaran (2004)

Variable	Test statistic	p-Value
LOT	250.378	0.000
LI	56.781	0.000

Note: *LOT* and *LI* denote lottery sales and the leading indicator, respectively.

Table 3 Panel Unit Root Tests by Emirmahmutoglu and Omay (2014)

	$\bar{t}_{AE}^{as}$	$\overline{F}_{AE}$
LOT	1.955*	2.218**
LI	2.227**	3.215***

Notes: Schwarz information criterion (SIC) is used to determine the optimum lag length. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively, based on the sieve bootstrap p-values.

Before performing the estimation of Eq. (4), we need to employ the stepwise regression to determine the regressors. The chosen regressors include one- and two-period lagged lottery sales. The test and estimation results for Eq. (4) using the PSTAR model are reported in Tables 4 through 6. In Table 4, the linearity tests lead to a rejection of the null hypothesis of linearity for all PSTAR specifications with different numbers of location parameters (m=1,2). Evidently, the lottery sales of 37 states in the U.S. display nonlinear dynamic paths, and the relationships between current lottery sales and lagged lottery sales are nonlinear. Thus, employing a nonlinear PSTAR approach to model lottery sales is proper, and a linear approach may distort the influence of the leading indicator on lottery sales.

Table 4: Linearity test

H_0: Linear model (r=0)					
H_1: PSTAR model with at least one transition function (r≧ 1)					
LI_{t-d}	Testing statistic	Number of location parameters (m)			
		m=1		m=2	
d=0	*LM*	9.495	[0.009]	11.614	[0.020]
	LMF	4.472	[0.012]	2.735	[0.028]
	LRT	9.583	[0.000]	11.746	[0.000]
d=1	*LM*	16.262	[0.000]	53.199	[0.000]
	LMF	7.762	[0.000]	13.649	[0.000]
	LRT	16.522	[0.000]	56.133	[0.000]
d=2	*LM*	4.011	[0.135]	49.640	[0.000]
	LMF	1.869	[0.155]	12.639	[0.000]
	LRT	4.026	[0.018]	52.182	[0.000]

Notes: the transition variable is change rate of (lagged) leading indicator, LI_{t-d}. The PSTAR models with LI_{t-d}, d=3,4,5,6 cannot pass the linearity test; therefore, we omit the testing results in the Table. *LM*, *LMF*, and *LRT* are the Wald test, Fisher test, and likelihood ratio test, respectively. The significance level is specified at 5%. r denotes the number of transition functions.

Table 5 displays the results of the no remaining nonlinearity tests. van Dijk et al. (2002) indicate that F versions of the LM test statistics have better size properties in small samples than do the χ^2 variants. Thus, this study uses LMF as the selection criterion for the number of transition functions. In case of one location parameter (m=1), the PSTAR models with d=0,1,2, have at least two transition functions (i.e., r≧ 2). Moreover, in the case of two location parameters (m=2), except for the PSTAR model with d=1, the remaining two cases have only one transition function (i.e., r=1).

Table 5: Test of no remaining nonlinearity

H_0: PSTAR model with one transition function (r=1)

H_1: PSTAR model with at least two transition functions (r≧ 2)

LI_{t-d}	Testing	Number of location parameters (m)			
		m=1		m=2	
d=0	*LM*	12.394	[0.002]	6.974	[0.137]
	LMF	5.822	[0.003]	1.614	[0.170]
	LRT	12.545	[0.002]	7.021	[0.135]
d=1	*LM*	63.675	[0.000]	25.879	[0.000]
	LMF	33.286	[0.000]	6.218	[0.000]
	LRT	67.942	[0.000]	26.548	[0.000]
d=2	*LM*	41.861	[0.000]	1.862	[0.761]
	LMF	20.880	[0.000]	0.427	[0.789]
	LRT	43.649	[0.000]	1.865	[0.761]

Notes: the transition variable is (lagged) change rate of leading indicator, LI_{t-d}. *LM*, *LMF*, and *LRT* are the Wald test, Fisher test, and likelihood ratio test, respectively. As indicated by González et al. (2005), the significance level is specified at 1%. r denotes the number of transition functions.

Stability of Lottery Sales

Based on the test results in Table 5, the PSTAR models have at least one transition functions. To ascertain the optimal model for evaluating the nonlinear dynamics of lottery sales, we use the AIC and BIC. To save space, we only display the results of the optimal estimation model; however, the remaining estimation results are available upon request. As a result, the PSTAR model with one transition function (*r*=1), one location parameter (*m*=1), and one-period lagged lottery sales, LI_{t-1}, (*d*=1) is the optimal one. Table 6 displays the parameter estimates of the optimal PSTAR model.

In Table 6, the estimated threshold c and transition parameter γ are 100.24 and 35.177, respectively, revealing that the lottery sales display a slowly smooth and nonlinear movement between two different regimes, the lower regime (i.e., the value of the transition function approaches to 0) and the upper regime (i.e., the value of the transition function approaches to 1). This result can interpret why the lottery sales do not display a linear process, explored in the previous studies (e.g., Olson et al 2003).

The persistence effect on lottery sales is significantly and permanently positive, i.e., $0.6811+0.1728*W(LI_{t-1};35.177,100.24)>0$. Since one-period lagged leading indicator LI_{t-1} varies with time, the persistence effects of lottery sales also display this characteristic. The transition function adjusts toward the upper regime as the leading indicator LI_{t-1} is above the threshold 100.24; therefore, the persistence effect of lottery sales rises. Contrarily, as the leading indicator is below the threshold, the transition function adjusts toward the lower regime; therefore, the persistence effect of lottery sales declines. In the two extreme cases of $W(LI_{t-1}; 35.177, 100.24)$=0 and 1, the effects are 0.6811 (=0.7097-0.0286, or 68.11%) and 0.8539 (=0.6811+0.0682+0.1046 or 85.39%), respectively.

In addition, the larger (smaller) the one-period lagged lottery sales LI_{t-1} is, the higher (lower) the persistence effect and sales stability, and the lower (higher) disturbance of current information, measured by the residual ε_{it}, would be. One of the reasons is that an increase in LI_{t-1} stands for an improvement in economic conditions in the previous period, which causes buyers to have an optimistic expectation in future income, and then forces them to have a more active investment in the lottery market in the current period. Thus, the persistence of lottery sales becomes higher, and the current lottery sales are less influenced by current information. For example, when the leading indicator is at a relatively high level (e.g., above its threshold, 100.24), the lottery sales display a high persistence (0.8539) and previous information about lottery sales becomes more important. In this situation, the seller of lottery ticket has to pay more attention to previous information about lottery sales for stabilizing lottery markets.

Table 6: Estimation result of lottery sales

Model	PSTAR
Variable	*r*=*m*=1, *d*=1
LOT(1)	
θ_1	0.7097 [12.51]***
θ_1'	0.0682 [0.21]
LOT(2)	
θ_2	-0.0286 [-1.95]*
θ_2'	0.1046 [2.21]**
c	100.24
γ	35.177
AIC	23.684
BIC	23.733

Notes: The PSTAR model with r=m=1 and d=1 is the optimal one due to its minimum AIC and BIC. *r, m,* and *d* are the number of transition functions, the number of location parameters, and the lag length of transition variable, respectively. The digits in parentheses and brackets are the lag length of lottery sales and t-values, respectively. In estimating the PSTAR model we have exclude the mean of lottery sales; therefore, there is no individual fixed effects terms (i.e., the individual intercepts). *, **, and *** denote the significance level at 10%, 5%, and 1%, respectively.

According to the estimation results of the PSTAR model in Table 6, we can further analyze the dynamic paths of the estimated lottery sales persistence. All the sample states have faced at least one obvious switching points in their dynamic paths of the estimated lottery sales persistence. The turning point of lottery sales persistence occurred in 2011. Before 2011, the one-period lagged leading indicator located below the threshold (100.24); therefore, the persistence of lottery sales was 0.7779. In 2012, the one-period lagged leading indicator was slightly larger than the threshold, and then the persistence was 0.7943. After 2012, the one-period lagged leading indicator was significantly larger than the threshold, and then the persistence rose to 0.8539.

Policy Implications

According to the above empirical results, we provide the following policy suggestions. First, the sellers (or state governments) of lottery ticket can employ the PSTAR model with one- and two-period lagged lottery sales and one-period lagged leading indicator to forecast the lottery sales of the current period. That is, based on this forecasting model, the sellers (or state governments) just apply the published information about lottery sales and leading indicator, but not the expected regressors highlighted by traditional structural models, to project current lottery sales.

Second, the stability of lottery sales is nonlinear and varies with time, depending on the level of one-period lagged leading indicator in each period and in different regimes. Thus, the users of the PSTAR model need to measure the sales of lottery and their stability period by period, based on the lagged leading indicator.

Finally, the one-period lagged leading indicator has a nonlinear and positive impact on the stability of the lottery sales. The threshold of the leading indicator, 100.24, is a referenced index for the sellers to assess the stability of lottery sales and to make relevant policies for raising sales performance. For example, in the recession period of the European sovereign debt crisis, a relatively low leading indicator causes a smaller stability of lottery sales, implying that the lottery sellers should pay more attention to the current disturbance of social and economic environments on lottery sales. An available method that weakens the disturbance is to introduce new products.

5 Conclusions

This study constructs a PSTAR model using the leading indicator as the transition variable to estimate the lottery sales and their persistence effects in the U.S. state governments. This specified model can evaluate four characteristics of lottery markets, including the heterogeneity, nonlinearity, persistence, and spillover effects.

The empirical results can be summarized as follows. First, the lottery sales and their persistence display nonlinear dynamic paths that vary with time, depending on the one-period lagged leading indicator at different regimes. Second, the threshold of the leading indicator, 100.24, is a useful index for government authorities to evaluate the stabilization of lottery markets. Third, evidence also supports that business cycle, measured by the leading indicator, has a nonlinear spillover effect on the lottery market.

We provide the following policy propositions. First, under low leading indicators (e.g., during periods of catastrophic economic events), the persistence effect on lottery sales is 0.7779, implying that current lottery sales are influenced by 78% of lagged lottery sales, and the remaining 22% are disturbed by current exogenous shocks. Thus, in addition to the lagged lottery sales, the sellers of lottery should pay more attention to the current information influencing lottery demand. Second, the persistence effect of lottery sales rises to 0.8539, as the leading indicator increases over its threshold. In this situation, 15% of current lottery sales are still influenced by current exogenous shocks. An increase in leading indicator is not a useful instrument for state government to largely stabilize lottery markets. Third, for the sellers of lottery tickets, designing new lottery products is a more efficient method for stimulating current lottery sales, especially in economic recession periods.

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