Department of Economics
Seminar Series

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“Local Price Variation and the Tax Incidence of State Lotteries”

Friday,
February 25, 2011
3:30 p.m.
211 Middlebush
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Working Paper 2010-035A

October 2010

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Local Price Variation and the Tax Incidence of State Lotteries

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Abstract

This paper explores the seemingly innocuous practice of ignoring the local price vector in empirical models of lottery demand. We argue using consumer theory that local consumption prices should be included and that the failure to consider local prices results in income elasticity of lottery demand estimates that are biased downward. Using a sample of MSAs, we find that, in accordance with our theory, local prices are a significant determinant of lottery sales and the income elasticity of demand for lotteries is greater in magnitude when the local price vector is considered. The degree of lottery regressivity is thus overstated when local prices are omitted. One notable finding is that the tax incidence of lotteries changes from regressive to progressive once the local price vector is included.

Keywords: state lotteries, local prices, tax incidence, regressivity  
JEL Codes: H7, H22, L83

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Local Price Variation and the Tax Incidence of State Lotteries

I. Introduction

Beginning with New Hampshire’s introduction of the first modern-day state lottery in 1964, forty-three states and the District of Columbia have now legalized state-sponsored lotteries. State lotteries are often characterized as a voluntary tax since state governments retain a portion of ticket sales (about 30 to 35 percent, on average).\(^1\) Lottery sales in the United States topped $55 billion in fiscal year 2008, of which state governments retained nearly $18 billion (roughly 1 percent of total state government revenue) for spending on education, infrastructure, and other social programs.\(^2\) The growth in lottery sales over the past several decades is not only a result of more states offering lotteries, but by ever evolving and expanding product lines that are designed to attract and retain customers through higher jackpots.

The growth of the lottery industry has sparked much academic research on various aspects of the industry.\(^3\) The issue that has received the most attention in the academic literature on state lotteries is the distribution of lottery expenditures across different income groups (see, for instance, Clotfelter and Cook 1987, 1989; Scott and Garen, 1994; Farrell et al., 1999; Price and Novak, 1999; Forrest et al., 2000; and Garrett and Coughlin, 2009).\(^4\) Because states retain a portion of all lottery sales, the issue is commonly framed in terms of the tax incidence (or tax burden) of state lotteries. The specific question asked in the literature is whether lower income

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\(^1\) Whether a lottery ticket constitutes a tax is a point of debate since lottery participation is strictly voluntary.

\(^2\) Lottery sales and tax revenue numbers for 2008 suggest an average tax rate of 33 percent. The average tax rate for lotteries has historically been much higher than that of other state excise taxes (Clotfelter and Cook, 1987).

\(^3\) Filer et al. (1988), Davis et al. (1992), and Alm et al. (1993) have explored the determinants of a state’s decision to adopt a lottery. The optimal design of lottery games in terms of maximizing sales was studied by Quiggin (1991), Cook and Clotfelter (1993), and Garrett and Sobel (1999). Whether lottery ticket purchases are substitutes or complements for other consumer goods has been explored by Borg et al. (1993) and Kearney (2005). The revenue impact of cross-border lottery shopping has been studied by Garrett and Marsh (2002) and Tosun and Skidmore (2004). Similarly, Brown and Rork (2005) examined the strategic interaction between state lotteries using a model of tax competition. Several studies have explored whether earmarked lottery revenues increase spending on targeted programs (Borg and Mason, 1990; Spindler, 1995; Novarro, 2005). Finally, Guryan and Kearney (2008) examine whether lottery sales increase in stores that have recently sold a large-jackpot lottery ticket.

\(^4\) This, of course, is only a small listing of the dozens of studies on the subject.
individuals spend a greater percentage of their income on lottery tickets than do wealthier individuals, i.e. whether a state lottery (and thus the lottery tax) is regressive. The majority of research has shown that state lotteries can generally be characterized as a regressive form of taxation; however, some research has suggested that the degree of regressivity can be different for different lottery games, and some lottery games may be even be progressive.⁵ Although other state taxes such as sales taxes and excise taxes are also regressive, the tax incidence of state lotteries has received much more critical attention given the revenue maximization objective of state lottery agencies and the moral opposition some groups have toward state-sponsored gambling. As more states continue to adopt lotteries and other states expand lottery operations, the tax incidence of state lotteries will likely remain at the forefront of the policy debate over state lottery adoption and expansion.

To determine the tax incidence of state lotteries, researchers estimate an equation where the demand for lottery tickets is a function of income and other demographic characteristics, with all variables transformed to natural logarithms. The cross-sectional unit of observation varies across studies, but generally it is a zip code, a city, a county, or a state. The estimated income elasticity from the demand equation provides evidence on the tax incidence of the lottery: a lottery is regressive (progressive) if the estimated income elasticity is less (greater) than one.

The empirical methodology described above has been the traditional way of estimating lottery demand (and the income elasticity of demand) in the literature. However, we argue that the traditional lottery demand equation omits a critical component of demand, namely the prices of other goods. Consumer theory tells us that the quantity demanded of a good is a result of an individual’s utility maximization calculus that considers not only income, but a vector of all prices as well. As such, consumption of lottery tickets is not only a function of income but is

also a function of the purchasing power of a given level of income. Even at an aggregated level (e.g. city, county), location-specific prices for other goods should appear in any empirical model of lottery demand in order to be consistent with microeconomic theory. In addition, if local prices do play a role in lottery demand as suggested by theory but prices are not included in demand equation estimation, then the coefficient estimates – including the estimate of the income elasticity of demand – will be biased.

It should be of little surprise that consumption prices vary widely across regions. For example, according to data from the 2000 Census, the median price of a house in San Francisco was five times greater than the median price of a house in Pittsburgh. There exists significant cross-city variation in housing prices even after adjusting for the quality of housing (Gabriel and Rosenthal, 2004; Chen and Rosenthal, 2008). In addition, various cost of living indices (which we present in the next section of the paper) indicate that prices of other consumption goods (groceries, utilities, transportation, health services) vary across cities as well.

In this paper we explore the seemingly harmless practice of ignoring the general price vector in models of lottery-ticket demand. We expand traditional empirical models of lottery demand by including local consumption prices and we examine how this affects the inferences regarding the demand for lottery tickets. Our objective is to demonstrate that for a given sample local prices are a significant determinant of lottery demand, as predicted by consumer theory. The implication is that local prices should be included in any lottery demand equation, regardless of the unit of observation chosen by the researcher. Furthermore, we demonstrate that the omission of local prices from our lottery demand models results in biased income elasticity estimates. This point is of particular importance since the income elasticity of demand provides

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6 Differences in local prices, namely housing prices, were shown to explain locational differences in the educational wage premium (Black et al., 2009) and in the demand for children (Black et al., 2010).
evidence on the tax incidence of state lotteries, and suggests that previous studies that have not included local prices may have produced biased estimates of lottery tax incidence. Our results suggest that a failure to include local consumption prices results in a downward bias in the income elasticity of demand for lottery tickets which thus overstates the degree of lottery regressivity.

Our paper proceeds in several steps. The next section contains the theoretical motivation for including the local price vector in models of lottery demand. Based on the theoretical discussion, we arrive at the conclusion that the omission of local prices from empirical lottery demand models should yield income elasticity estimates that are biased downward. Section III of the paper discusses our data and empirical methodology. Our results are presented and discussed in Section IV. The final section of the paper is reserved for discussion and concluding comments.

II. Conceptual Motivation

The income elasticity of demand for lottery tickets (β) is traditionally obtained by estimating the following equation

\[ \ln(X_i) = \beta \cdot \ln(\text{Income}_i) + \theta \cdot Z_i + \varepsilon_i \]  

(1)

using observed data on per capita lottery sales (X) and income for each unit of observation i, where i typically represents either a zip code, a county, or a state, depending on the study. The matrix Z includes demographic and economic variables, such as education levels, unemployment rates, the age of the population, and poverty rates. The price of lottery tickets is generally

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7 We are not suggesting that our income elasticity estimates provide the final say on the tax incidence of state lotteries, as any estimate for the tax incidence is dependent upon the sample used by the researcher. Rather, we claim that ignoring differences in local prices in any cross-sectional sample will result in biased income elasticity estimates.
omitted from equation (1) because most lottery tickets cost $1 (thus, lottery sales = quantity of tickets sold).\(^8\) Most importantly, the prices of other goods in region \(i\) are typically not included in equation (1). As a result, researchers implicitly assume that the effect of other prices on the demand for lottery tickets is zero.

However, consumer theory tells us that the quantity of \(X\) is not only a function of income, but also of own price and the prices of other goods. Thus, the quantities of \(X\) observed across regions are a function of regional income and other local prices (recall that the price of \(X\) is more or less constant across regions). If prices of other goods are not constant across regions, as suggested by the data, then price variation by location is expected to influence the quantity demanded of \(X\) across regions.

The income elasticity of demand is, of course, a useful measure that shows how the demand responds to a change in income when everything else is held constant. In the empirical studies of the demand for lotteries, the “change in income” comes from the locational variation in income. In this setting, the necessary condition of “holding everything else constant” is almost inevitably violated and the only way for the empirical exercise to be valid is to account for differences in local consumption prices.

As an extreme case, assume that the quantity demanded for lotteries is the same in two cities but income and all consumption prices in city 1 are twice as large as those in city 2. If we ignore consumption prices when calculating the income elasticity, we might conclude that lottery demand in this society is absolutely income inelastic. This is, however, an erroneous conclusion.

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\(^8\) Two issues are worth clarifying. First, here we refer to the dollar price of a lottery ticket, not the expected return which is calculated using the probability of winning each prize. The overall expected return of lotteries (i.e. the average expected return per ticket from all lottery games) does vary across states depending upon the odds of winning and the prizes offered, but the variation across state in the overall expected return of lotteries is small. Second, although some instant (‘scratch-off’) lottery tickets cost more than $1, we do not have game-level sales data. We thus following the existing literature and explicitly model the demand for lottery sales rather than the demand for the quantity of tickets.
as we really cannot say anything about the income elasticity of lottery demand by observing these two cities since there is no variation in purchasing power between the two cities.

In reality, of course, locational incomes and prices are not as perfectly proportional as in the above example, but as long as other prices are not included in the regression model, the income elasticity estimate in equation (1) will be biased. An important issue is the direction of bias in the estimated income elasticity of demand for lotteries. Based on the above theoretical motivation, the more appropriate empirical specification is:

\[ \ln(X_i) = \beta \cdot \ln(\text{Income}_i) + \theta \cdot Z_i + \alpha \cdot \ln(P_i) + \varepsilon_i, \tag{2} \]

where \( P_i \) is the price of the composite commodity in region \( i \). If the true \( \alpha \) is not zero and equation (1) is estimated rather than equation (2), then \( \beta \), the income elasticity of demand, will be biased.

The direction of the bias is determined by the product of the sign of \( \alpha \) and (in part) the sign of the correlation between income and price \( P \) (Greene, 2000; Jargowsky, 2005). With respect to the correlation between income and \( P \), our data reveal a positive and statistically significant correlation of 0.52 between metropolitan area income and prices, i.e. higher income cities have higher prices. Regarding the relationship between \( P \) and \( X \) in equation (2), the coefficient \( \alpha \) will be positive (negative) if lottery tickets (\( X \)) and the composite good (\( Y \)) are gross substitutes (complements). Because lottery tickets are a very small part of individuals’ consumption bundles and we are considering the price \( P \) of all others goods in a region, it seems reasonable that the substitution effect from a higher \( P \) will be dominated by a negative income

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9 The bias in \( \beta \) is also determined by the correlation between income and the other variables in \( Z \). The average correlation between income and our other independent variables is 0.18. Because income is positively correlated with local prices (see text) and, on average, with the other independent variables, there is no ambiguity in the final determination of the degree of bias once the sign of \( \alpha \) is known.
effect resulting from a higher P. Thus, lower real income leads to a reduction in lottery tickets from a higher P, suggesting $\alpha$ is negative.$^{10}$

Therefore, a negative (and statistically significant) $\alpha$ and a positive correlation between income and P suggests that estimating equation (1), as has been done in previous research, will result in an income elasticity of demand that is biased downward. Estimating equation (2) that accounts for regional price variation should yield an income elasticity that is larger than that obtained from equation (1).

As discussed earlier, the income elasticity of demand for lottery tickets has been used to evaluate the tax incidence of state lotteries. Previous studies on the tax incidence of state lotteries have not accounted for the importance of local price variation in their empirical models. We have demonstrated above that ignoring local price variation may result in income elasticity estimates that are biased downward and thus overstate (understate) the regressivity (progressivity) of state lotteries. The degree to which the income elasticity of demand is biased is an empirical question which we address in the next section.

III. Data and Methodology

The Data

We conduct our analysis using data on lottery sales, local prices, personal income, and demographic characteristics for 111 Metropolitan Statistical Areas (MSAs) for the year 2000. We chose an MSA as a unit of analysis because it provides the lowest level of aggregation for which local price data are available. The MSAs used in the analysis are listed in the Appendix. The sample and year of study was dictated by the greatest availability of local price and lottery sales data.

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$^{10}$ The majority of studies have found that lottery tickets are normal goods.
Price data for each of the 111 MSAs are from The Council for Community and Economic Research’s *Cost of Living Index (COLI).*\(^\text{11}\) The COLI measures relative price levels for consumer goods and services, and has been used by previous studies to capture price variation across locations.\(^\text{12}\) The various price indices for each MSA are each interpreted as a percentage of the average for all urban areas (where the average is set to 100). For each MSA, we obtained the composite price index as well as separate price indices for groceries, housing, utilities, transportation, healthcare, and miscellaneous expenditures.\(^\text{13}\) The composite index is a weighted average of the six separate price indices and we use the composite index as the price of the composite consumption commodity in each MSA.\(^\text{14}\) The individual price indices are highly correlated with each other as well as with the composite price index, as seen in Table 1. Their use in our empirical models will allow us to explore which specific prices, if any, influence lottery demand and the bias in the income elasticity of demand for lottery tickets if the respective price index is omitted. Descriptive statistics for the price indices are shown in the top portion of Table 2.

[Table 1]

Lottery-ticket sales at the MSA level are not readily available and therefore had to be constructed from county-level lottery sales data. To do so, we first obtained a list of all counties that are within each MSA (for which we had obtained local price data) by using the 2000 Census MSA boundary definitions and component (county) names.\(^\text{15}\) We then contacted state lottery

\(^{11}\) See [www.coli.org](http://www.coli.org/) for a description of how the price indices are calculated and for a list of all commodities included in each price index.

\(^{12}\) See, for example, Cebula and Coombs (2008) and Nonnemaker et al. (2009).

\(^{13}\) Several issues involving the price data are discussed in the Appendix.

\(^{14}\) The weights for the individual indices are as follows: Groceries – 12.5%, Housing – 29.8%, Utilities - 9.9%, Transportation – 10.7%, Health care – 4.1 percent, and Miscellaneous good and services – 32.9%. The sum of weights does not equal 100 due to rounding.

agencies and obtained county-level sales data for the year 2000. Lottery sales at the county-level were then summed to arrive at lottery sales at the MSA-level.

We also obtained MSA-level sales for instant lottery games (“scratch-offs”) and online lottery games (e.g. Lotto or PowerBall) separately in a manner identical to that of total lottery sales (the sum of instant game sales and online game sales) in order to explore the role of local prices in explaining the demand for different lottery products.\textsuperscript{16} In addition, considering different types of lottery games gives us more ways to test our hypothesis. Research has shown that the income elasticities of demand for online games and instant games can be quite different, with the former having a higher income elasticity of demand (even suggesting progressivity).\textsuperscript{17} Descriptive statistics for lottery sales are shown at the bottom of Table 2.

\begin{table}
\centering
\caption{Descriptive statistics for lottery sales}
\begin{tabular}{lrr}
\hline
\multicolumn{1}{p{8cm}}{Variable} & \multicolumn{1}{p{2cm}}{Mean} & \multicolumn{1}{p{2cm}}{Standard Deviation} \\
\hline
Per capita personal income & \$X,000 & \$Y,000 \\
Population density & \text{people/sq mi} & \text{people/sq mi} \\
Percentage of population with a bachelor’s degree & \% & \% \\
\hline
\end{tabular}
\end{table}

We follow past literature and include several economic, demographic, and game characteristic variables in our models of lottery demand. In particular, the economic and demographic variables we include are per capita personal income, population density, and the percentage of the population that has a bachelor’s degree or higher.\textsuperscript{18} Past research has shown that lottery sales are higher in more densely-populated areas and inversely related to education levels.\textsuperscript{19}

\textsuperscript{16} Online games and instant games are considered different lottery products because online lottery games offer much higher jackpots than instant lottery games and the potential frequency-of-play for online games is less than that of instant games as drawings for online games are aired on television only several times a week.

\textsuperscript{17} Research by Mikesell (1989), Oster (2004), and Garrett and Coughlin (2009) suggests that large jackpot online lottery games may attract a wealthier player than lower jackpot instant games, and as a result the income elasticity of demand for some online games can be greater than that for instant lottery games. These studies find evidence that online games can be progressive. Ghent and Grant (2010) use data on the income distribution rather than income levels and find that the degree of regressivity can differ by the type of lottery game.

\textsuperscript{18} Personal income, population density, and the percentage of the population with a bachelor’s degree or higher were gathered from the 2000 U.S. Census.

\textsuperscript{19} Studies have considered other economic and demographic variables as well, including the unemployment rate, the age of the population, and the percent of the population living below the poverty level. A confounding issue in modeling lottery demand is that many of these variables tend to be highly correlated with each other as well as
Lottery game characteristic variables include the age of the lottery in years, an indicator dummy variable for whether the state participates in multi-state lottery games, the number of years the state has participated in multi-state lottery games, and an indicator variable for whether the state has commercial casino gambling.\textsuperscript{20} The values for these variables are the same for each MSA in a state since the lottery is state-wide. The age of the lottery is included to capture the differences in each state lottery’s life-cycle (Mikesell, 1994). Because we are comparing different state lotteries in different stages of their life-cycles, the expected sign on age is ambiguous. Multi-state games (like PowerBall and Mega Millions) generate the largest jackpots to date, and thus states that participate in these games are expected to have higher sales (Garrett and Sobel, 1999). The casino dummy variable will capture any effects of competition between casino gaming in the state and the state lottery (Elliot and Navin, 2002).

\textit{Methodology}

We estimate equation (1) and equation (2) using per capita total lottery sales, instant lottery sales, and online lottery sales as our dependent variables. All equations contain the aforementioned economic, demographic, and game characteristic variables.\textsuperscript{21} We also separately estimate equation (2) using each of the seven local price variables. As we wish to obtain the income elasticity of demand, lottery sales and per capita income are converted to natural logarithms before estimation. We also transform local prices into natural logarithms so that the resulting coefficient on prices in equation (2) will reflect the cross-price elasticity of demand.

\textsuperscript{20} Lottery game characteristic data were obtained from Lafluer’s (2009). A list of the states having commercial casino gaming was provided by the American Gaming Association at www.americangaming.org.

\textsuperscript{21} We retain the multi-state lottery game variables in the instant lottery game regressions in order to capture any substitutability or complementarity between instant and online lottery games (Clotfelter and Cook, 1989).
For each lottery sales category and price level we then compare the income elasticity estimates from equation (1) and equation (2). If local prices are inversely related to lottery sales, as our previous theoretical discussion suggests, we should then find that the income elasticity coefficient from equation (1) is smaller than the coefficient estimate from equation (2). This would support our hypothesis that local prices play an important role in explaining cross-sectional differences in lottery demand, and that the failure to include local prices in models of lottery demand can result in income elasticity estimates that are biased downward.

IV. Empirical Results

*Composite Commodity Prices*

The empirical results from our models of lottery demand (total sales, instant sales, and online sales) are shown in Table 3. For each lottery game category we estimate the demand model with and without the composite price level for each MSA. All equations were estimated by GLS using White’s heteroscedasticity-corrected standard errors.

We find that local prices have a negative and statistically significant influence on all three categories of lottery sales (columns 2, 4, and 6 in Table 3). Higher-price MSAs thus have lower lottery sales. This supports our hypothesis that lower real income due to higher consumption prices leads to a reduction in lottery ticket sales (i.e., across MSAs, a dominant income effect exists from higher overall prices). The size of each coefficient reveals that the cross-price elasticity of demand for lottery tickets is high, and there appears to be little variation in the size of the cross-price elasticity across lottery game category (-1.84 to -1.99). The price coefficients are interpreted as meaning that an MSA with a price level that is ten percent higher is expected to have lottery ticket sales 18 to 20 percent lower, ceteris paribus.
More importantly, though, Table 3 reveals that the inclusion of local prices significantly improves the overall fit of each model, as is evident from the $F$-statistics (bottom of Table 3) that test the null hypothesis that the $R^2$ from the model without price is equal to the $R^2$ from the model with prices. For all three game categories, the adjusted $R^2$ is significantly higher in the models that include local prices. The difference in the adjusted $R^2$ for each game category is large – for total lottery sales the adjusted $R^2$ is nearly 13 percentage points (39 percent) higher, for instant lottery sales the adjusted $R^2$ is nearly 12 percentage points (88 percent) higher, and for online lottery sales the adjusted $R^2$ is over 6 percentage points (14 percent) higher.

Our theoretical discussion suggested that if local prices are a negative and significant determinant of lottery sales, then models of lottery demand that fail to consider local prices should produce income elasticities of demand that are biased downward. The downward bias in the income elasticity of demand for each category of lottery sales is evident in Table 3.22 For total lottery sales, the income elasticity of demand increases from 0.94 to 1.17 (an increase of 24 percent) when local prices are included in the model. Based on the point estimates, the tax incidence of lottery tickets in our sample of MSAs changes from slightly regressive to slightly progressive (although neither elasticity is statistically significantly different from one). For instant lottery tickets, the income elasticity changes from 0.36 and not statistically different from zero when local prices are omitted to 0.57 and significantly different from zero when local prices are included. Finally, we find that online tickets are progressive in both online lottery models, but the degree of progressivity is higher when local prices are considered. The income elasticity of demand for online tickets increases from 1.51 to 1.73, an increase of 15 percent.

22 Our income elasticity estimates from the models that do not include local prices fall within the range of estimates found in numerous previous studies.
A summary of our results thus far is useful. In agreement with our theory, we find that in our sample of MSAs local prices have a negative and statistically significant impact on lottery sales. We find that the inclusion of local prices significantly increases the $R^2$ of each lottery demand model. Also in agreement with our theory, the empirical results reveal that the inclusion of local prices increases the income elasticity of demand (and decreases the regressivity in the case of instant and total lottery sales), as the latter is biased downward when local prices are omitted from the model. The increase in the magnitudes of the income elasticities is non-trivial, and in the case of total lottery sales the point-estimates suggest a change in the tax incidence from slightly regressive to slightly progressive. Thus, the overall price level has been shown to play an important role in the demand for lottery tickets and in determining the income elasticity of demand. In the next section we consider the effect of the six specific-commodity price indices on the demand for lottery tickets.

Specific Commodities’ Prices

We now estimate our models of lottery demand using the six specific-commodity prices rather than the composite price index. Doing so allows us to compare the performance of specific-commodity price indices with that of the composite commodity price index (which, recall, is a weighted average of the six component indices). Although we are now considering the prices of specific consumption goods rather than composite consumption, we still expect that the substitution effect from higher prices will be dominated by a negative income effect resulting from higher prices since lottery consumption, for most individuals, remains lower than consumption of each of the specific goods. Thus, we expect negative coefficients on the specific-commodity price variables.
Our first exercise involves including all six price indices in the models for total lottery sales, instant lottery sales, and online lottery sales. The results from these regressions are shown in column (2) of Tables 4, 5, and 6, respectively. The results from the regressions that omit local prices (columns 1, 3, and 5 from Table 3) are re-presented in column (1) of Tables 4, 5, and 6 for comparison. For brevity in presentation, the coefficients on the economic, demographic, and game characteristic variables are not shown in Tables 4, 5, and 6.

The six specific prices indices are all jointly significant (based on $F$-tests) in the models of total lottery sales, instant lottery sales, and online lottery sales. As did the inclusion of the composite price index, the inclusion of the six prices significantly increases the explanatory power of each model. In comparison with the models without local prices, the inclusion of the six price indices increases the adjusted-$R^2$ by roughly 22 percentage points in the total lottery demand model, 30 percentage points in the instant lottery demand model, and 10 percentage points in the online lottery demand model. These percentage point improvements in each adjusted-$R^2$ are larger than those obtained with the inclusion of the composite price index, suggesting that, jointly, the specific commodity-prices indices have greater explanatory power than the weighted average composite price index.

All of the prices indices’ coefficients that are individually statistically significant have a negative sign, as predicted by theory (however, caution should be exercised in evaluating the individual coefficients given that the high collinearity (see Table 1) between the specific price indices likely generates larger standard errors and questionable coefficient estimates). The cross-
price elasticities for grocery and healthcare prices are negative and statistically significant in the total demand model; the cross-price elasticities for grocery and transportation prices are negative and significant in the instant demand model; and the cross-price elasticity for healthcare prices is negative and significant in the online demand model.\textsuperscript{23}

As was the case with the composite price index, the estimated income elasticity of demand is larger in the models that contain the six specific-commodity price indices compared with the models that omit local prices. In addition, the estimated income elasticities from the models that contain the six specific-commodity price indices are larger than the income elasticities from the models that contain the composite price index. Specifically, the income elasticity of demand for total lottery sales increases from 0.94 to 1.28 (compared with 1.17 when the composite price index was used); the income elasticity for instant lottery sales increases from 0.36 and not significant to 0.70 and significant (compared with 0.57 with the composite index was used); and the income elasticity for online sales increases from 1.51 to 1.78 (compared with 1.73 when the composite index was used).

In our second exercise we wish to see which commodity price indices can serve as suitable proxies for the composite price index if the latter is not available to researchers. The motivation comes from the fact that there exists a high correlation between the specific price indices and the composite price index. We include each specific commodity price index in a separate regression, with the results presented in columns (3) through (8) in Table 4 (total sales), Table 5 (instant sales), and Table 6 (online sales).

\textsuperscript{23} While we do not address in this paper why prices of different goods have different effects on lottery demand, it is interesting to note that the majority of lottery tickets are sold at grocery stores, convenience stores, and gas stations (Lafleurs, 2009). Perhaps then it is not surprising that movements in prices of groceries and gasoline have larger effects on individuals’ buying behavior of lottery tickets than do other prices.
The majority of the estimated cross-price elasticities are negative and statistically significant, again in accordance with theory. Only utilities prices and miscellaneous prices (except in the case of instant lottery sales) do not significantly explain lottery sales. Each category of lottery sales is most responsive to differences in grocery prices, healthcare prices, and transportation prices, although the importance of each differs by game category. As with our previous results, the adjusted $R^2$ is significantly higher in each model that contains a significant price coefficient compared with the models that omit local prices. However, the adjusted $R^2$s from the models that included the six price indices are greater than the adjusted $R^2$s from the single price index regressions, thus suggesting that the six price indices together provide greater explanatory power than each individual price index despite their high correlations with each other.

V. Summary and Discussion

The tax incidence of state lotteries is the most researched aspect of the lottery industry over the past several decades. Given that the use of state lotteries as a means of public finance is more controversial than traditional revenue sources, there is a continued effort to estimate as precisely as possible the income elasticity of demand for lottery tickets. In this paper we visited the seemingly harmless practice of ignoring local consumption prices in empirical models of lottery demand, as has been the norm in dozens of previous studies. We demonstrated using consumer theory that a vector of local prices should be included in cross-sectional demand models and that the failure to include local consumption prices in lottery demand equations can result in a downward bias in the income elasticity of demand for lottery tickets, resulting in misleading conclusions regarding the tax incidence of state lotteries.
Our empirical results, based on a sample of 111 MSAs, supported our theory. We find that the income elasticity of demand for lottery tickets (all games, instant games, and online games) is larger when local prices are included in the models - the omission of local prices therefore overstated (understates) the regressivity (progressivity) of state lotteries. This finding is robust to the use of overall price indices as well as commodity-specific price indices.

We do not claim that our income elasticity estimates provide the final say on the tax incidence of lotteries, but rather our results demonstrate that ignoring differences in local prices in any cross-sectional sample can result in misleading conclusions regarding the tax incidence of lotteries. Two of our findings in particular highlight the importance of local prices in models of demand. First, the income elasticity of demand for instant lottery games is not statistically different from zero when local prices are omitted from demand equations, but when local prices are included the income elasticity of demand for instant games is roughly 0.60. We argue this is a significant decrease in the degree of instant game regressivity. Second, we find that the tax incidence of all lottery games changes from slightly regressive to slightly progressive (based on the income elasticity point estimates) when local prices are included. The inclusion of local prices can thus change conclusions regarding the overall tax incidence of lotteries.

Our results have several implications for policy as well as future academic research. From a policy perspective, the regressivity of state lotteries has been (and likely will continue to be) the greatest argument against them. Although one can take the view that regressivity is bad regardless of the degree of regressivity, we argue that there is a significant difference in the policy discussion of state lotteries with regards to a lottery having an income elasticity of, say, 0.10 versus 0.80. Certainly the weight of the regressivity argument is dependent upon the degree of regressivity rather than absolute regressivity, and our results have shown that the degree of
regressivity may be overstated if local prices are not included in cross-sectional models of lottery demand.

Our results suggest several avenues for future research. First, local prices should be considered when estimating the income elasticity of other tax bases, such as income taxes, sales taxes, and excise taxes. Consumer theory also predicts that the size of tax bases (quantity) in each location is a function of local prices as well. A similar argument can be made for alternative forms of gambling, such as casinos and horseracing. Second, the income elasticity of demand is commonly used to forecast revenue or sales growth over the business cycle. Our results suggest that more accurate forecasts can be obtained if local price variation is included in forecasting models.
Appendix

The following MSAs are used in the analysis (2000 U.S. Census definitions).

Abilene, TX
Akron, OH
Albuquerque, NM
Amarillo, TX
Austin-San Marcos, TX
Beaumont-Port Arthur, TX
Bellingham, WA
Binghamton, NY
Bloomington, IN
Bloomington-Normal, IL
Boise City, ID
Bremerton, WA
Brownsville-Harlingen
-San Benito, TX
Bryan-College Station, TX
Buffalo-Niagara Falls, NY
Cedar Rapids, IA
Champaign-Urbana, IL
Chicago, IL
Cincinnati, OH-KY-IN
Cleveland-Lorain-Elyria, OH
Columbia, MO
Columbus, OH
Dallas, TX
Davenport-Moline-
Rock Island, IA-IL
Daytona Beach, FL
Dayton-Springfield, OH
Decatur, IL
Des Moines, IA
Detroit, MI
El Paso, TX
Elkhart-Goshen, IN
Eugene-Springfield, OR
Evansville-Henderson, IN-KY
Fort Myers-Cape Coral, FL
Fort Walton Beach, FL
Fort Worth-Arlington, TX
Fresno, CA
Glens Falls, NY
Grand Rapids-Muskegon-
Holland, MI
Houston, TX
Indianapolis, IN
Jacksonville, FL
Joplin, MO
Kansas City, MO-KS
Killeen-Temple, TX
Lafayette, IN
Lansing-East Lansing, MI
Las Cruces, NM
Lexington, KY
Lima, OH
Longview-Marshall, TX
Los Angeles-Long Beach, CA
Louisville, KY-IN
Lubbock, TX
Lynchburg, VA
Mansfield, OH
McAllen-Edinburg
-Mission, TX
Miami, FL
Modesto, CA
Muncie, IN
Nassau-Suffolk, NY
New York, NY
Newark, NJ
Oakland, CA
Odessa-Midland, TX
Olympia, WA
Orlando, FL
Panama City, FL
Pensacola, FL
Peoria-Pekin, IL
Phoenix-Mesa, AZ
Portland-Vancouver, OR-WA
Richland-Kennewick-
Pasco, WA
Richmond-Petersburg, VA
Riverside-San
Bernardino, CA
Roanoke, VA
Rochester, MN
Rockford, IL
Sacramento, CA
Salem, OR
San Antonio, TX
San Diego, CA
San Francisco, CA
Santa Barbara-
Santa Maria-Lompoc, CA
Santa Fe, NM
South Bend, IN
Spokane, WA
Springfield, IL
Springfield, MO
St. Cloud, MN
St. Joseph, MO
St. Louis, MO-IL
Syracuse, NY
Taco, WA
Tallahassee, FL
Tampa-St. Petersburg-
Clearwater, FL
Terre Haute, IN
Toledo, OH
Topeka, KS
Tucson, AZ
Tyler, TX
Visalia-Tulare-
Porterville, CA
Waco, TX
Waterloo-Cedar Falls, IA
West Palm Beach-
Boca Raton, FL
Wichita Falls, TX
Wichita, KS
Yakima, WA
Youngstown-Warren, OH
Yuma, AZ

MSA Price Indices - Notes

There are several issues regarding the MSA-level price indices that we had to address.

First, the Council for Community and Economic Research’s MSA cost-of-living index definitions are based on the U.S. Census’s 2003 revised MSA boundary definitions, some of
which differ slightly from the 2000 Census MSA boundary definitions. In these cases, we attempted to match MSA definitions to ensure that the price indices and other data covered the same geographic area as closely as possible. We will gladly provide a list of all matched non-identical MSAs upon request. See http://www.coli.org/surveyforms/SampleData.zip for more information.

Second, the C2ER cost-of-living indices are quarterly in frequency, but indices for each quarter are not available for all MSAs. The annual price indices we use in the paper are quarterly averages of all quarters available for each MSA in 2000. There is little difference in the cost-of-living index in each MSA from one quarter to the next, and as such the findings regarding the impact of prices on lottery demand were not qualitatively different when we used price indices for a specific quarter rather than the average of all available quarters in the year.
References


Lafleur’s 2009 World Lottery Almanac, eds. Teresa LaFleur and Bruce LaFleur, TLF Publications, Boyds, Maryland, 2009.


Table 1: Correlations - COLI Price Indices

<table>
<thead>
<tr>
<th></th>
<th>Composite</th>
<th>Grocery</th>
<th>Housing</th>
<th>Utilities</th>
<th>Transportation</th>
<th>Healthcare</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grocery</td>
<td>0.75</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Housing</td>
<td>0.98</td>
<td>0.65</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Utilities</td>
<td>0.49</td>
<td>0.49</td>
<td>0.40</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transportation</td>
<td>0.67</td>
<td>0.71</td>
<td>0.57</td>
<td>0.39</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Healthcare</td>
<td>0.79</td>
<td>0.71</td>
<td>0.74</td>
<td>0.25</td>
<td>0.70</td>
<td></td>
</tr>
<tr>
<td>Miscellaneous</td>
<td>0.79</td>
<td>0.66</td>
<td>0.70</td>
<td>0.39</td>
<td>0.62</td>
<td>0.70</td>
</tr>
</tbody>
</table>

Note: Sample size is 111 MSAs for the year 2000. See Appendix for a list of MSAs.
### Table 2: Descriptive Statistics

<table>
<thead>
<tr>
<th>Price Indices</th>
<th>Mean</th>
<th>Standard Error</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Composite</td>
<td>103.40</td>
<td>19.36</td>
<td>88.90</td>
<td>242.70</td>
</tr>
<tr>
<td>Grocery</td>
<td>100.89</td>
<td>9.59</td>
<td>81.50</td>
<td>143.30</td>
</tr>
<tr>
<td>Housing</td>
<td>108.04</td>
<td>53.01</td>
<td>80.50</td>
<td>499.00</td>
</tr>
<tr>
<td>Utilities</td>
<td>103.64</td>
<td>18.75</td>
<td>70.40</td>
<td>177.00</td>
</tr>
<tr>
<td>Transportation</td>
<td>101.66</td>
<td>8.20</td>
<td>82.30</td>
<td>130.60</td>
</tr>
<tr>
<td>Healthcare</td>
<td>105.85</td>
<td>16.21</td>
<td>81.40</td>
<td>177.90</td>
</tr>
<tr>
<td>Miscellaneous</td>
<td>100.78</td>
<td>6.53</td>
<td>90.80</td>
<td>136.40</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lottery Sales ($)</th>
<th>Mean</th>
<th>Standard Error</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Per Capita Total</td>
<td>116.40</td>
<td>49.27</td>
<td>33.88</td>
<td>263.23</td>
</tr>
<tr>
<td>Per Capita Online</td>
<td>57.96</td>
<td>36.70</td>
<td>13.24</td>
<td>177.58</td>
</tr>
<tr>
<td>Per Capita Instant</td>
<td>58.44</td>
<td>23.87</td>
<td>20.64</td>
<td>131.33</td>
</tr>
</tbody>
</table>

Note: Sample size is 111 MSAs for the year 2000. See Appendix for a list of MSAs.
### Table 3: Estimated Lottery Demand – With and Without Local Price Variation

<table>
<thead>
<tr>
<th>Variable</th>
<th>Dependent Variable: Per Capita Total Sales (ln)</th>
<th>Dependent Variable: Per Capita Instant Sales (ln)</th>
<th>Dependent Variable: Per Capita Online Sales (ln)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Per Capita Income (ln)</td>
<td>0.939**</td>
<td>1.169**</td>
<td>1.506**</td>
</tr>
<tr>
<td></td>
<td>(3.88)</td>
<td>(5.31)</td>
<td>(4.94)</td>
</tr>
<tr>
<td>Composite Price Index (ln)</td>
<td>------</td>
<td>-1.992**</td>
<td>------</td>
</tr>
<tr>
<td></td>
<td>(3.74)</td>
<td>(3.74)</td>
<td>(3.80)</td>
</tr>
<tr>
<td>Population Density</td>
<td>0.108**</td>
<td>0.363**</td>
<td>0.166**</td>
</tr>
<tr>
<td></td>
<td>(2.47)</td>
<td>(4.22)</td>
<td>(2.73)</td>
</tr>
<tr>
<td>% Pop. with ≥ 4yr. degree</td>
<td>-0.030**</td>
<td>-0.021**</td>
<td>-0.032**</td>
</tr>
<tr>
<td></td>
<td>(4.38)</td>
<td>(3.54)</td>
<td>(4.32)</td>
</tr>
<tr>
<td>Age of lottery</td>
<td>0.118*</td>
<td>0.014**</td>
<td>0.020**</td>
</tr>
<tr>
<td></td>
<td>(1.82)</td>
<td>(2.54)</td>
<td>(2.63)</td>
</tr>
<tr>
<td>Age of multi-state lottery</td>
<td>-0.066**</td>
<td>-0.072**</td>
<td>-0.093**</td>
</tr>
<tr>
<td></td>
<td>(3.33)</td>
<td>(3.30)</td>
<td>(3.62)</td>
</tr>
<tr>
<td>Multi-state dummy variable</td>
<td>0.408**</td>
<td>0.339**</td>
<td>0.433**</td>
</tr>
<tr>
<td></td>
<td>(3.36)</td>
<td>(2.59)</td>
<td>(2.82)</td>
</tr>
<tr>
<td>Casino dummy variable</td>
<td>-0.140</td>
<td>-0.174</td>
<td>-0.160</td>
</tr>
<tr>
<td></td>
<td>(1.20)</td>
<td>(1.61)</td>
<td>(1.18)</td>
</tr>
<tr>
<td>Constant</td>
<td>-4.127*</td>
<td>2.514</td>
<td>-10.542**</td>
</tr>
<tr>
<td></td>
<td>(1.77)</td>
<td>(0.79)</td>
<td>(3.56)</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.326</td>
<td>0.452</td>
<td>0.451</td>
</tr>
</tbody>
</table>

\[ H_0: R^2_{price} = R^2_{no\ price} \]

\[ F = 24.71** \]  \[ F = 16.92** \]  \[ F = 13.99** \]

Notes: * denotes significance at 10 percent, ** at 5 percent or better. Absolute t-statistics are in parentheses and are based on White’s heteroskedasticity-consistent standard errors. The coefficient on population density is multiplied by 1,000.
<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Per Capita Income (ln)</td>
<td>0.939** (3.88)</td>
<td>1.284** (5.95)</td>
<td>1.154** (5.62)</td>
<td>1.224** (5.31)</td>
<td>0.945** (3.92)</td>
<td>1.165** (4.82)</td>
<td>1.040** (4.77)</td>
<td>0.923** (3.96)</td>
</tr>
<tr>
<td>Grocery Prices (ln)</td>
<td>------</td>
<td>-1.828** (3.15)</td>
<td>------</td>
<td>-2.844** (6.26)</td>
<td>------</td>
<td>------</td>
<td>------</td>
<td>------</td>
</tr>
<tr>
<td>Housing Prices (ln)</td>
<td>------</td>
<td>-0.196 (0.97)</td>
<td>------</td>
<td>-0.874** (3.88)</td>
<td>------</td>
<td>------</td>
<td>------</td>
<td>------</td>
</tr>
<tr>
<td>Utility Prices (ln)</td>
<td>------</td>
<td>0.213 (0.84)</td>
<td>------</td>
<td>0.194 (0.68)</td>
<td>------</td>
<td>------</td>
<td>------</td>
<td>------</td>
</tr>
<tr>
<td>Transportation Prices (ln)</td>
<td>------</td>
<td>-0.612 (1.05)</td>
<td>------</td>
<td>------</td>
<td>------</td>
<td>-2.073** (4.24)</td>
<td>------</td>
<td>------</td>
</tr>
<tr>
<td>Healthcare Prices (ln)</td>
<td>------</td>
<td>-0.881** (2.29)</td>
<td>------</td>
<td>------</td>
<td>------</td>
<td>------</td>
<td>-1.580** (6.21)</td>
<td>------</td>
</tr>
<tr>
<td>Miscellaneous Prices (ln)</td>
<td>------</td>
<td>1.098 (1.16)</td>
<td>------</td>
<td>------</td>
<td>------</td>
<td>------</td>
<td>------</td>
<td>-1.345 (1.66)</td>
</tr>
<tr>
<td>Constant</td>
<td>-4.127* (1.77)</td>
<td>2.553 (0.71)</td>
<td>6.689** (2.68)</td>
<td>-3.139 (1.36)</td>
<td>-5.057** (2.02)</td>
<td>3.156 (1.06)</td>
<td>2.112 (0.90)</td>
<td>2.122 (0.46)</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.326</td>
<td>0.543</td>
<td>0.490</td>
<td>0.432</td>
<td>0.324</td>
<td>0.427</td>
<td>0.485</td>
<td>0.342</td>
</tr>
</tbody>
</table>

H₀: R²_price = R²_no_price

| Observations (MSAs) | 111 | 111 | 111 | 111 | 111 | 111 | 111 | 111 |

Notes: * denotes significance at 10 percent, ** at 5 percent or better. Absolute t-statistics are in parentheses and are based on White’s heteroskedasticity-consistent standard errors. Dependent variable is the natural logarithm of per capita total lottery sales. All regressions also include the economic, demographic, and game characteristic variables. See text for details.
Table 5: Estimated Instant Lottery Demand – Local Price Variation by Specific Commodity

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Per Capita Income (ln)</td>
<td>0.355</td>
<td>0.699**</td>
<td>0.630**</td>
<td>0.576**</td>
<td>0.351</td>
<td>0.641**</td>
<td>0.441*</td>
<td>0.335</td>
</tr>
<tr>
<td></td>
<td>(1.34)</td>
<td>(2.68)</td>
<td>(2.74)</td>
<td>(2.09)</td>
<td>(1.33)</td>
<td>(2.45)</td>
<td>(1.71)</td>
<td>(1.36)</td>
</tr>
<tr>
<td>Grocery Prices (ln)</td>
<td>-2.982**</td>
<td>-3.639**</td>
<td>-2.492**</td>
<td>-3.639**</td>
<td>-0.675**</td>
<td>-2.623**</td>
<td>-1.346**</td>
<td>-1.676*</td>
</tr>
<tr>
<td></td>
<td>(4.94)</td>
<td>(7.52)</td>
<td>(4.96)</td>
<td>(7.52)</td>
<td>(2.49)</td>
<td>(5.36)</td>
<td>(4.47)</td>
<td>(1.92)</td>
</tr>
<tr>
<td>Housing Prices (ln)</td>
<td>0.133</td>
<td>-0.675**</td>
<td>-1.262</td>
<td>-0.675**</td>
<td></td>
<td>-0.675**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.52)</td>
<td>(2.49)</td>
<td>(0.47)</td>
<td>(2.49)</td>
<td></td>
<td>(0.47)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Utility Prices (ln)</td>
<td>0.046</td>
<td>-0.126</td>
<td>-0.420</td>
<td>-0.420</td>
<td>-0.420</td>
<td>-0.126</td>
<td>-0.420</td>
<td>-0.420</td>
</tr>
<tr>
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<td>(1.04)</td>
<td>(1.04)</td>
<td>(0.47)</td>
<td>(1.04)</td>
<td>(1.04)</td>
</tr>
<tr>
<td>Transportation Prices (ln)</td>
<td>-1.141*</td>
<td>-1.141*</td>
<td>-1.141*</td>
<td>-2.633**</td>
<td>-1.346**</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td>(1.86)</td>
<td>(1.86)</td>
<td>(1.86)</td>
<td>(5.36)</td>
<td>(4.47)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Healthcare Prices (ln)</td>
<td>-0.420</td>
<td>-0.420</td>
<td>-0.420</td>
<td>-0.420</td>
<td>-0.420</td>
<td>-0.420</td>
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<tr>
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<tr>
<td>Miscellaneous Prices (ln)</td>
<td>0.781</td>
<td>0.781</td>
<td>0.781</td>
<td>0.781</td>
<td>0.781</td>
<td>0.781</td>
<td>-1.676*</td>
<td>-1.676*</td>
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<td></td>
<td>(0.83)</td>
<td>(0.83)</td>
<td>(0.83)</td>
<td>(0.83)</td>
<td>(0.83)</td>
<td>(0.83)</td>
<td>(1.92)</td>
<td>(1.92)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.903</td>
<td>13.919**</td>
<td>14.743**</td>
<td>1.667</td>
<td>1.509</td>
<td>10.121**</td>
<td>6.218**</td>
<td>8.688*</td>
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<tr>
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<td>(0.36)</td>
<td>(3.32)</td>
<td>(5.52)</td>
<td>(0.64)</td>
<td>(0.57)</td>
<td>(3.13)</td>
<td>(2.33)</td>
<td>(1.70)</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.129</td>
<td>0.424</td>
<td>0.418</td>
<td>0.193</td>
<td>0.123</td>
<td>0.304</td>
<td>0.249</td>
<td>0.157</td>
</tr>
<tr>
<td>H₀: R²_price = R²_no price</td>
<td>F = 10.99**</td>
<td>F = 52.24**</td>
<td>F = 9.10**</td>
<td>F = 0.25</td>
<td>F = 26.98**</td>
<td>F = 17.51**</td>
<td>F = 4.41**</td>
<td></td>
</tr>
<tr>
<td>Observations (MSAs)</td>
<td>111</td>
<td>111</td>
<td>111</td>
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</table>

Notes: * denotes significance at 10 percent, ** at 5 percent or better. Absolute t-statistics are in parentheses and are based on White’s heteroskedasticity-consistent standard errors. Dependent variable is the natural logarithm of per capita instant lottery sales. All regressions also include the economic, demographic, and game characteristic variables. See text for details.
Table 6: Estimated Online Lottery Demand – Local Price Variation by Specific Commodity

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Per Capita Income (ln)</td>
<td>1.506**</td>
<td>1.778**</td>
<td>1.640**</td>
<td>1.813**</td>
<td>1.521**</td>
<td>1.668**</td>
<td>1.619**</td>
<td>1.491**</td>
</tr>
<tr>
<td></td>
<td>(4.94)</td>
<td>(5.98)</td>
<td>(5.54)</td>
<td>(5.94)</td>
<td>(5.17)</td>
<td>(5.24)</td>
<td>(5.68)</td>
<td>(4.89)</td>
</tr>
<tr>
<td>Grocery Prices (ln)</td>
<td>-0.372</td>
<td>-1.781**</td>
<td>-1.781**</td>
<td>-1.781**</td>
<td>-1.781**</td>
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<tr>
<td></td>
<td>(0.47)</td>
<td>(3.06)</td>
<td>(3.06)</td>
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<td>(3.06)</td>
<td>(3.06)</td>
<td>(3.06)</td>
<td>(3.06)</td>
</tr>
<tr>
<td>Housing Prices (ln)</td>
<td>-0.350</td>
<td>-0.942**</td>
<td>-0.942**</td>
<td>-0.942**</td>
<td>-0.942**</td>
<td>-0.942**</td>
<td>-0.942**</td>
<td>-0.942**</td>
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<tr>
<td></td>
<td>(1.30)</td>
<td>(3.79)</td>
<td>(3.79)</td>
<td>(3.79)</td>
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<tr>
<td>Utility Prices (ln)</td>
<td>0.346</td>
<td>0.476</td>
<td>0.476</td>
<td>0.476</td>
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<tr>
<td></td>
<td>(1.05)</td>
<td>(1.37)</td>
<td>(1.37)</td>
<td>(1.37)</td>
<td>(1.37)</td>
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<tr>
<td>Transportation Prices (ln)</td>
<td>-0.129</td>
<td>-1.485**</td>
<td>-1.485**</td>
<td>-1.485**</td>
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<td>(0.16)</td>
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<tr>
<td>Healthcare Prices (ln)</td>
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<td>(3.07)</td>
<td>(5.42)</td>
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<td>(5.42)</td>
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<tr>
<td>Miscellaneous Prices (ln)</td>
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<tr>
<td></td>
<td>(3.56)</td>
<td>(1.89)</td>
<td>(1.09)</td>
<td>(3.32)</td>
<td>(4.03)</td>
<td>(1.46)</td>
<td>(1.19)</td>
<td>(1.02)</td>
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</tbody>
</table>

Adjusted R²        0.452  0.555  0.482  0.516  0.462  0.476  0.558  0.456

H₀: R²_price = R²_no price

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
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<tbody>
<tr>
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<tr>
<td></td>
<td>5.07**</td>
<td>6.92**</td>
<td>14.59**</td>
<td>2.83*</td>
<td>5.66**</td>
<td>25.50**</td>
<td>1.76</td>
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</tbody>
</table>

Notes: * denotes significance at 10 percent, ** at 5 percent or better. Absolute t-statistics are in parentheses and are based on White’s heteroskedasticity-consistent standard errors. Dependent variable is the natural logarithm of per capita online lottery sales. All regressions also include the economic, demographic, and game characteristic variables. See text for details.