A DYNAMIC SPACE-TIME PANEL DATA MODEL OF STATE-LEVEL BEER CONSUMPTION

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Abstract

A dynamic space-time panel data model containing random effects is used to examine state-level beer consumption over the period of 1970 to 2007 for the 48 contiguous US states and the District of Columbia. A valuable aspect of dynamic space-time panel data models is that the parameter estimates from these models can be used to quantify dynamic responses over time and space as well as space-time diffusion impacts. We examine the impact of state-level taxes on beer on home (own) state and outside (other) state consumption of beer. The model allows for this situation since buyers of beer near state borders can purchase in neighboring states if there is a tax advantage for doing so.

KEYWORDS: Dynamic space-time panel data model, Markov Chain Monte Carlo estimation, dynamic responses over time and space.

1 Introduction

Following the definition of a microeconomic demand equation, we are able to construct a demand equation for beer as a function of several explanatory variables, such as individual income and the price of beer. Economic theory predicts that buyers would adjust their consumption behavior based on changes in their income, the price of beer, and consumption of related goods such as liquor. Therefore, observed variation in beer consumption across states and over time should be explained by these variables. In this thesis, we are interested in modeling state-level demand for beer, which we measure using the quantity consumed in each state over many years. Clearly, beer consumption is persistent since beer demand should depend on the consumption from the previous year, which is known as time dependence. We also allow for consumption in neighboring states to influence beer consumption in each state since, if neighboring states sell beer at a lower price, buyers can cross the state-borders to purchase the lower priced beer. This leads to a situation known as spatial dependence, where consumption in one state may depend on that in neighboring states. Our ultimate objective is to incorporate both time and spatial dependence in a regression model.

Several studies use spatial econometric regressions to determine the influence on dependent variables of explanatory variables in situations involving neighboring regions or spatial spillover effects. This thesis uses a dynamic space-time panel data model from Debarsy, Ertur and LeSage (2010) to examine state-level beer consumption over the period 1970 to 2007 for the 48 contiguous US states and the District of Columbia. For our purpose of analyzing the neighboring state effects, Alaska and Hawaii are excluded since they are not neighbors to the other 49 regions in our sample which are the lower 48 states and the District of Columbia. A valuable aspect of dynamic space-time panel data models is that the parameter estimates of each explanatory variable from these models can be utilized to quantify dynamic responses over time and space as well as space-time diffusion impacts associated with changes in these variables. We examine the impact of state-level taxes on beer on own-state and other-state consumption of beer. The model allows for this situation since buyers of beer near state borders can purchase in neighboring states if there is a tax advantage to doing so. Own-state quantity of beer consumed exhibits time dependence meaning consumption is related to the quantity consumed from the previous year. Beer consumption also exhibits spatial dependence due to cross-border shopping. This combination of space and time dependence results in diffusion effects, where changes in taxes on beer in state i can over time influence beer consumption in many other states, not simply neighboring states.

We begin with a traditional demand equation for beer, where the quantity consumed depends on price, income, and complementary or substitute goods as shown in (1),

$$Q_{it} = f(Q_{it-1}, I_{it}, P_{it}, S_{it}), i = 1, \ldots, N, t = 1, \ldots, T \tag{1}$$

where Q_{it} represents the quantity of beer sold in state i at time t. The past period quantity Q_{it-1} is included to model time dependence or persistence in consumption. The explanatory variables are: I_{it} representing income per capita, P_{it}, the beer tax in state at time t and S_{it} the quantity of spirits (a complement) consumed. Income changes can certainly impact the consumption of beer, positively if beer is a normal good or negatively in the case of an inferior good.[1] Taxes, P, represent a proxy for price, since variation in taxes on beer are much greater than variation in prices across the states. Price is treated as constant across the states having no impact on beer consumers' decision-making, so that taxes can be viewed as equal to the price. Although we include spirits consumed in our empirical implementation of the model, we ignore this variable in some of the theoretical discussion. Ignoring the variable of spirits consumption simplifies the mathematical notation because we only include the explanatory variables P_{it}, I_{it} in our equations.

Econometric models are usually based on a *cross-section* of observations, say a sample of states, households, or firms at one point in time, or on *time-series* observations which follow a single state, household, or firm over time. Our model in (1) represents a combination of both cross-sections and time-series, since we have observations on all states over many time periods. This combination is known as a *panel data model*, where we observe the same panel of observations (the states) over many time periods.

In addition to time dependence, there is also a reason to believe that each neigh-

[1] Microeconomic theory predicts that as income increases the quantity of normal goods demanded increases and that for inferior goods decreases.

boring state's beer consumption may influence Q_{it}. Consumers living near state borders can cross borders and make beer purchases in neighboring states. As noted, the quantity of beer consumed depends on consumers' income and the price. Given this, consumers near state borders could be sensitive to the price of beer between their state and neighboring states. Consistent with utility maximization, consumers will search for lower priced beer. Suppose a neighboring state has different policies on alcohol sales and offers the consumers a lower price (tax) on beer, consumers will cross the state border to purchase the lower priced beer. Consequently, own-state consumers can satisfy their needs and this consumer reaction to the tax can influence neighboring states' beer sales.

Debarsy, Ertur and LeSage (2010) introduces this consumer reaction as the "bootlegging phenomena" in the context of cigarette sales and taxes. This consumer behavior motivates the significance of neighboring state taxes. Since consumers are allowed to participate in the neighboring state market, changes in taxes will impact both the own-state beer consumption and that of neighboring states. Thus, our regression model should incorporate the neighboring values of beer consumption as influential elements of the model.

The next section explains how spatial regression models incorporate neighboring state beer consumption into standard regression relationships like that in equation (1). We will introduce a spatial matrix W representing the spatial configuration of states as they would appear on a map.

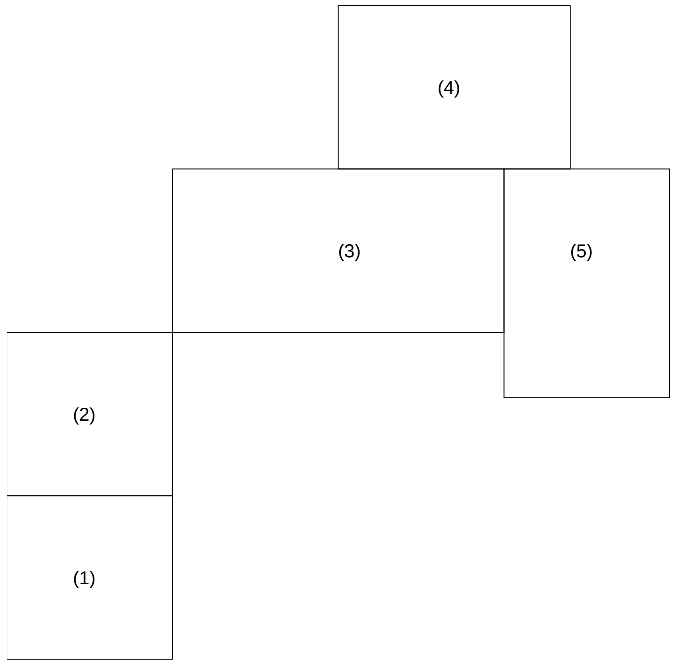

Figure 1: State Contiguity Relationship

1.1 Modeling neighboring states

In spatial regression models, each observation represents a region, in our case, the N states, where N is the number of regions. An $N \times N$ spatial weight matrix W is used to describe the spatial (map) configuration of the N state-level observations. This matrix is used in spatial regression models to incorporate neighboring state information, in our case, beer consumption.

Figure 1 showing five states (regions) are used to describe how a map could be used to create a 5×5 weight matrix W.

Each region $i = 1, \ldots, 5$ on the map is represented by the ith row in Table 1. For example, state 1 shares a border with state 2, so we place a 1 in the second column,

Table 1: Contiguity configuration

	State 1	State 2	State 3	State 4	State 5
State 1	0	1	0	0	0
State 2	1	0	1	0	0
State 3	0	1	0	1	1
State 4	0	0	1	0	1
State 5	0	0	1	1	0

first row of the table. We define a shared border as borders touching, so in Figure 1 states 2 and 3 have a shared border. We continue in this way to weight the first-order neighbors 1 and non-neighbors 0. From the figure we see that state 5 has borders touching states 3 and 4, resulting in ones in the 3rd and 4th columns of row 5. Utilizing this table, we can create a matrix D that represents the state contiguity relationships.

$$D = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 & 0 \end{pmatrix} \tag{2}$$

We can use a normalized version of the spatial weight matrix D (which we label W) which has the sum of the weights for each row equal to one. This W matrix can be used to create an average of neighboring state beer consumption.

$$W = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 1/2 & 0 & 1/2 & 0 & 0 \\ 0 & 1/3 & 0 & 1/3 & 1/3 \\ 0 & 0 & 1/2 & 0 & 1/2 \\ 0 & 0 & 1/2 & 1/2 & 0 \end{pmatrix} \qquad (3)$$

For example, in the third row of the matrix D (the own-state is state 3), there are three ones for state 2, state 4, and state 5. Therefore, on the third row of W, each 1 is replaced with 1/3 so that the sum of all three equals one.

The product W_iQ, where W_i is an $1 \times N$ vector containing the ith row of W and Q is the $N \times 1$ vector of beer consumption in all N states, produces an average of neighboring values in Q. As an example, consider the second observation (state) W_2Q:

$$W_2Q = \sum_{j=1}^{N=5} W_{2j}Q_j = 1/2Q_1 + 1/2Q_3$$

which is an average of the value of Q_1 and Q_3 representing beer consumed in the two neighboring states/observations. As we have discussed, the spatial lags play a significant role in capturing the neighboring effects on each state.

Consequently, the product of the 5×5 matrix W and a 5×1 vector Q can produce a spatial lag vector WQ which is 5×1 vector containing the average values of neighboring states/observations. It might be more appropriate to use an unequal weighting scheme in our application, where the length of borders in common between the states provides the basis for the spatial weighting matrix W. A neighboring state with a longer common border would receive more weight in this approach. This border effect is an issue for future exploration. Another point is that states bordering Canada and Mexico will not be treated the same as other states since we do not have information on beer consumed in these bordering regions. However, there would be extra import tariffs associated with cross-border shopping in these cases.

We also examine time dependence which means that beer consumed in previous periods influences current period beer consumed. Time dependence might reflect habit formation in our regression model which will be introduced in the following section.

1.2 Space-time model

The current period consumption of beer for each state typically involves persistence or habit formation. Beer consumers in state i will slowly change their behavior over time, so beer consumption from the previous year should influence current year consumption. This persistence leads us to include beer consumption from the past period, Q_{it-1} in equation (4).

From the previous section using the matrix W, we can construct explanatory variables W_iQ_t, which represents the average of beer consumption at time t from states neighboring i, where W_i represents row i of the matrix W, and Q_t is the vector of beer consumed in all states at time t. As already noted, bootlegging purchases will be made in neighboring states to avoid taxes or take advantage of overall lower prices. This motivates the variable $\sum_{j=1}^{N} W_{ij}Q_{jt}$ in (4). We expect persistence in bootlegging behavior which is the reason for use of $W_{ij}Q_{jt-1}$ in equation (4), which defines a linear combination of spatially weighted values of beer consumed in neighboring states during the previous time period. In Chapter 7 of their book, LeSage and Pace (2009) introduce a spatiotemporal adjustment model that specifies the dependent variable as an outcome of its previous value, in our case Q_{it-1} as well as the previous neighboring values WQ_{t-1}.

We also include the price and income variables which are both lagged in (4) as indicated by P_{it-1} and I_{it-1}. Use of previous period values for these variables in our regression model avoids simultaneity issues[2]. Another motivation for using lagged values of price and income is that alcohol consumption may respond slowly to price and income changes because consumers require time to change drinking behavior.

$$
\begin{aligned}
Q_{it} &= \alpha + \phi Q_{it-1} + \rho \sum_{j=1}^{N} W_{ij}Q_{jt} + \theta \sum_{j=1}^{N} W_{ij}Q_{jt-1} \\
&+ \beta P_{it-1} + \gamma I_{it-1} + \varepsilon_{it}
\end{aligned}
\tag{4}
$$

In the relationship (4) between the beer consumption and its price and consumers'

[2]Econometric simultaneity arises when one or more of explanatory variables is jointly determined with the dependent variable through an equilibrium mechanism.

income. The scalar parameter α is an intercept term of the demand equation, ϕ is a parameter of time dependence, and ρ is a parameter of spatial dependence. The parameter θ measures space-time persistence or diffusion. The parameter β represents the coefficient on the price level (tax) variable. According to the "Law of Demand" in economic theory, as price decreases quantity of beer consumed increases. In other words, the quantity of beer demanded and the price of beer have an inverse relationship. Therefore, β should be a negative coefficient. Since we use logged quantity of beer consumed and logged prices/taxes, the coefficient β also represents the own-price elasticity of demand. The coefficient γ on income per capita of state residents should be positive if beer is a normal good and negative if beer is an inferior good. Based on the log transformations to quantity of beer consumed and income and the definitions of normal and inferior goods, γ also can be interpreted as the income elasticity of beer demand.

To summarize, expression (5) below shows our ultimate model that will be used to estimate beer consumption:

$$
\begin{aligned}
Q_{it} &= \alpha + \phi Q_{it-1} + \rho \sum_{j=1}^{N} W_{ij} Q_{jt} + \theta \sum_{j=1}^{N} W_{ij} Q_{jt-1} \\
&+ \beta_1 P_{it-1} + \beta_2 \sum_{j=1}^{N} W_{ij} P_{jt-1} + \gamma_1 I_{it-1} + \gamma_2 \sum_{j=1}^{N} W_{ij} I_{jt-1} \\
&+ \psi_1 S_{it-1} + \psi_2 \sum_{j=1}^{N} W_{ij} S_{jt-1} + \varepsilon_{it} \qquad (5) \\
\varepsilon_{it} &= \mu_i + \eta_{it}
\end{aligned}
$$

Since spatial diffusion can arise from changes in these price and income variables, spatial lags of both the price and income variables representing averages of neighboring values have been added to the model. The last term, ε_{it} includes random effects $\mu_i, i = 1, \ldots, N$ which implies a different intercept term for each state, and η_{it} is an independent, identically distributed error term with zero mean and constant variance across both time and space.

Parent and LeSage (2010b) discuss how to estimate the parameters of this type of model, and their MATLAB routines[3] were used to estimate the model for a panel of the 49 states for each annual time period over the 1970-2007 period. Panel estimation procedures produce a single set of estimates for the parameters on the explanatory variables β, γ, ψ as well as the space-time dependence parameters ρ, ϕ, θ based on all data. In essence, these could be considered average responses of beer consumption to changes in the explanatory variables over all states and time periods.

In the next section, we examine how the model estimates can be used to calculate spatial spillover (bootlegging) effects. For simplicity, this discussion ignores the panel data nature of the model and considers the cross-section of 49 states for just a single time period.

1.3 Spatial Spillovers

In this discussion of spillovers, we ignore the time dimension and consider a simple cross-section of states as shown in (6). The vector $y = Q_t$ is beer consumption in our

[3] LeSages's econometrics toolbox is available at: http://www.http://spatial-econometrics.com/.

states for a single year, and Wy is the average consumption in neighboring states. The explanatory variables matrix $X = \begin{pmatrix} P_{t-1} & I_{t-1} & S_{t-1} \end{pmatrix}$, contains price, income and spirits consumption (lagged).

$$
\begin{aligned}
y &= \rho W y + X\beta + \varepsilon && (6)\\
y &= (I_n - \rho W)^{-1}(X\beta + \varepsilon) && (7)\\
y &= \left(I_n + \rho W + \rho^2 W^2 + \ldots\right)(X\beta + \varepsilon) && (8)
\end{aligned}
$$

Solving for y in (6) assuming the matrix inverse exists and that $|\rho| < 1$, we obtain (7).[4] The matrix inverse $(I_n - \rho W)^{-1}$ in (7) can be written as an infinite series: $(I_n + \rho W + \rho^2 W^2 + \ldots)$. As already noted, W represents the first-order neighbors, while W^2 identifies second-order neighbors, and higher-order neighbors are represented by W^3, W^4 etc. Recall that second-order neighbors refer to regions that are neighbors to the first-order neighbors. For example, in Figure 1, region 2 is a first-order neighbor to region 1, and region 3 is a second-order neighbor to region 1 because it neighbors region 2.

Expression (8) allows us to consider the own- and cross-partial derivatives, $\partial y / \partial x_r'$, which show how changes in variable x_r impact the dependent variable vector y. Specifically, how changes in the price of beer, x_r (or income) in state i influence beer consumption in states i and j.

[4] See LeSage and Pace (2009) for conditions necessary for inverting $(I_n - \rho W)$.

$$\partial y/\partial x_{r'} = (I_N - \rho W)^{-1} I_N \beta_r \tag{9}$$

Expression (9) is an $N \times N$ matrix because changes in state i price, x_{ir} can influence beer consumption y_j in the own- and neighboring states due to bootlegging. That is, changes in x_{ir} result in an $N \times 1$ vector of responses $y_j, j = 1, \ldots, n$. Since we could change $x_{ir}, i = 1, \ldots, n$, we have an $n \times N$ matrix of partial derivatives in (9).

LeSage and Pace (2009) propose scalar summary measures of the the $N \times N$ matrix of partial derivatives, based on averages of the diagonal and off-diagonal elements. The diagonal represents the magnitude of direct effects or own-partials: $\partial y_i/\partial x_{ir}$, or own-state impacts. The indirect effects are represented by the cross-partials: $\partial y_j/\partial x_{ir}$, or other-state bootlegging impacts. An average of the main diagonal elements of the $N \times N$ matrix in (9) is used to summarize the own-partial derivatives (or direct effect) as a single number. Similarly, averaging the off-diagonal elements allows us to have a single number representing the cross-partial derivatives, or spatial spillover (bootlegging) effects. We have these two scalar summaries for each of the r explanatory variables.

Debarsy, Ertur and LeSage (2010) extend this approach to the case of space and time dependence modeled by dynamic space-time data panel models. This leads us to introduce the dynamic space-time panel model in the next section. Our dynamic panel data model allows us to quantify changes in taxes and income on beer consumption in own- and other-states over time. This model allows us to obtain the dynamic responses arising from changes in the explanatory variables at time t as well as future time periods, $t+T$, in own- and other-states.

2 The dynamic space-time panel

A number of studies show that dynamic space-time data panel models allow us to estimate both space and time dependence using cross-sections for the states over many time periods, rather than the single period models for spatial dependence that we have presented so far, for example Parent and LeSage's (2010b) study. Given sample data on our variables Q, P, I, S over many years for all states, we are able to extend (4) as a dynamic spatial lag model. We also extend the model to include spatially lagged exogenous (explanatory) variables for price and income. Using matrix notation this extension of beer demand in (4) can be written for a single time period as shown in (10).

$$\begin{aligned} Q_t &= \alpha + \phi Q_{t-1} + \rho W Q_t + \theta W Q_{t-1} \\ &+ \beta_1 P_{t-1} + \beta_2 W P_{t-1} + \gamma_1 I_{t-1} + \gamma_2 W I_{t-1} + \psi_1 S_{t-1} + \psi_2 W S_{t-1} + \varepsilon_t \end{aligned} \quad (10)$$

where Q_t is the N-dimensional vector of the dependent variable (current period t beer consumption), and the added spatially lagged price and income variables are: WP_{t-1}

and WI_{t-1}, with associated parameters β_2, γ_2. We recall that the matrix product Wz produces an average of $z-$values from neighboring regions, so the spatial lags of price and income represent neighboring states prices and income in the previous time period. In (10), α is an intercept parameter and β_1, γ_1 are the own-state prices and income coefficients.

The dynamic aspect of the model is reflected in the variables Q_{t-1} and WQ_{t-1}. The variable Q_{t-1} and associated autoregressive time dependence parameter ϕ allows past beer consumption to influence current period consumption due to habit persistence. The variable WQ_{t-1} and associated parameter θ allows for spatiotemporal diffusion impacts. Since the dependent variable Q_t depends on WQ_t, there is an influence on own-state beer consumption from neighboring states. LeSage and Pace (2009) note that cross-sectional spatial dependence can arise from a diffusion process working over time. These diffusion impacts are accounted for by WQ_{t-1}, which allows past consumption in neighboring states to influence current period own-state consumption.

We can use matrix notation to describe our dynamic panel data model. Given data for the states for each time period (in our case 38 years), we place all $Q_t, t = 1, \ldots, 38$ into a vector Y and the explanatory variables P_{t-1} and I_{t-1} for each t into Z as in (11).

$$Y = \begin{pmatrix} Q_1 \\ Q_2 \\ \vdots \\ Q_T \end{pmatrix}, \quad Z = \begin{pmatrix} P_0, I_0, S_0 \\ P_1, I_1, S_1 \\ \vdots \\ P_{T-1}, I_{T-1}, S_{T-1} \end{pmatrix} \tag{11}$$

Parent and LeSage (2010a) define a framework for modeling specific "space-time dynamic dependence" that uses both space and time filter expressions. Following Parent and LeSage (2010a) and Debarsy, Ertur and LeSage (2010), we let A be $(T+1) \times (T+1)$ matrix for time dependence, where we apply $T+1$, instead of T to ignore the issues of initial period values. Debarsy, Ertur and LeSage (2010) show that we can express this time dependence filter as $A = (I_{T+1} - \phi L)$, where L is a matrix time lag operator. The spatial dependence filter is defined as an $N \times N$ matrix B which is equal to $B = (I_N - \rho W)$. As noted, the W matrix with normalized rows classifies neighboring cross-sectional dependence.

The Kroneker product of the matrices A and B that they introduce is the essential component to identify space-time dependence.

$$\begin{aligned} A \otimes B &= (I_{T+1} - \phi L) \otimes (I_N - \rho W) \\ &= I_{N,T+1} - \rho I_{T+1} \otimes W - \phi L \otimes I_N + (\rho \times \phi) L \otimes W \end{aligned} \tag{12}$$

$$= \quad I_{N,T+1} - \rho I_{T+1} \otimes W - \phi L \otimes I_N - \theta L \otimes W, \tag{13}$$

This Kroneker product of spatial and temporal dependence filters ($A \otimes B$) creates an $(NT+1) \times (NT+1)$ dynamic matrix. As noted, ϕ is the parameter of the first order time dependence and ρ is the spatial dependence parameter. The matrix L represents a time lag operator that can be expressed as $LQ_t = Q_{t-1}$. In addition, we have covariance between space and time represented by $L \otimes W$. The matrix product in (12) implies a restriction on the covariance term coefficient $\theta = -\rho \times \phi$. Parent and LeSage (2010a) implement this restriction in an applied model, but we will follow Debarsy, Ertur and LeSage (2010) and do not impose this restriction. This restriction forces space and time to be separable in the model, whereas our model is more general.

Given the definitions in (11), Y is an $NT \times 1$ vector and Z is an $NT \times 3$ matrix containing the explanatory variables P, I and S for all states and time periods. Applying the spatial-temporal filter, $A \otimes B$, our dependent variable of beer consumed is specified as below, where ι_T is a $T \times 1$ vector of ones:

$$(A \otimes B)Y \quad = \quad Z\beta + WZ\gamma + \iota_T \otimes \mu + \eta \tag{14}$$

We assume the parameters β and γ are constant throughout time and over spatial units, and the $N \times 1$ random effects parameter vector μ allows for N state-specific effects. The spatial-temporal filter and matrix notation in (14) represents our dynamic space-time model. In order to find the expression for the partial derivatives associated with changes in the price and income variables contained in Z, it is useful to isolate the vector Y. This can be done using the matrix inverse shown in (15).

$$Y = (A \otimes B)^{-1}[Z\beta + WZ\gamma + \iota_T \otimes \mu + \eta] \tag{15}$$

Recall from our discussion of spatial spillovers, our approach is to quantify the direct effects (own-partials): $\partial y_{it}/\partial Z^r_{it}$ and the indirect effects (cross-partials): $\partial y_{jt}/\partial Z^r_{it}$. The own-partial derivatives represent the magnitude of impacts on y_{it} from a change in the rth variable in state i at time t. For example, the own-partial tells us how changes in the tax of beer in state i impacts the beer consumption in state i. Similarly, the cross-partial derivative measures bootlegging effects. For example, how the changes in the price in state i influences beer purchased in state j, or bootleg effects.

Since we use a dynamic model, we consider $\partial y_{it+k}/\partial Z^r_{it}$, that is the impact of time t price changes on the future consumption in time $t+k, k = 1, \ldots, T$.

For example, the own-partial $\partial y_{it+k}/\partial Z^r_{it}$ measures how quantity consumed in future periods in, say, Texas responds to changes in the price of beer within the state at time t. Also, the cross-partial $\partial y_{jt+k}/\partial Z^r_{it}$ in this example might quantify the changes in beer consumption in Louisiana or New Mexico, to changes in the price of beer in Texas. If we consider the price changes to be permanent, then we can cumulate the responses over time to find the long run impacts. We will illustrate this in our application.

Debarsy, Ertur and LeSage (2010) show that the matrix inverse $(A \otimes B)^{-1}$ can be written as in (16).

$$(A \otimes B)^{-1} = \begin{pmatrix} B^{-1} & 0 & \dots & & 0 \\ D_1 & & & & \vdots \\ D_2 & D_1 & \ddots & & \\ \vdots & & \ddots & & 0 \\ D_{T-1} & D_{T-2} & \dots & D_1 & B^{-1} \end{pmatrix} \tag{16}$$

$$\begin{aligned} C &= -(\phi I_N + \theta W) \\ B &= (I_N - \rho W) \\ D_s &= (-1)^s (B^{-1}C)^s B^{-1}, \quad s = 0, \dots, T-1 \end{aligned} \tag{17}$$

The structure of the matrix inverse (16) makes it easy to consider future time period impacts, e.g., $t+1$ associated with changes in the explanatory variables Z_t, as shown in (18). Debarsy, Ertur and LeSage (2010) have shown that this panel allows us to analyze impacts for any k-period ahead horizon, as well as the cumulative impacts that arises from a permanent change in Z at time t for a future horizon $t+k$.

$$\partial Y_{t+1} / \partial Z_t^{r'} = \left(D_1 + B^{-1}\right) [I_N \beta_r + W \gamma_r] \tag{18}$$

Working with an $N \times N$ matrix makes it difficult to analyze impacts associated with changes in beer taxes. LeSage and Pace (2009) suggest using average of main diagonal as a scalar summary of direct effects for single period cross-sectional models, since the diagonal represents direct effects or own-partials: $\partial Y_{t+1,i}/\partial Z^r_{t,i}$, or own-state impacts. Since (18) is a single period $N \times N$ matrix of impacts, we can use the same summary scheme for single period impacts. Similarly, indirect effects: $\partial Y_{t+1,j}/\partial Z^r_{t,i}$, or other-state bootlegging impacts can be converted to a single number representing the cross-partial derivatives or spatial spillover (bootlegging) effects by averaging the off-diagonal elements. We have these two scalar summaries for each of the r explanatory variables.

To cumulate the impacts over future horizons, we can use expression (19). Debarsy, Ertur and LeSage (2010) point out that this is equivalent to summing down the first column of the matrix inverse $(A \otimes B)^{-1}$. We note that (18) and (19) are $N \times N$ matrices. The $N \times N$ matrix (19) represents effects with respect to both time and spatial dependencies. Doing this only requires working with $N \times N$ matrices B and C as shown in (20).

$$\partial Y_{t+k}/\partial Z^{r'}_t = \sum_{s=0}^{k} D_s[I_N \beta_r + W\gamma_r] \tag{19}$$

$$D_s = (-1)^s (B^{-1}C)^s B^{-1}, \quad s = 0, \dots, T-1 \tag{20}$$

We can use the same approach described above for the one period ahead impacts with the $N \times N$ matrix sums shown in (19), to produce the scalar summary measures. The main diagonals for each time period reflect the own-state impacts over future time periods, due to both time and spatial dependence. The sum of off-diagonal elements $\sum_{s=0}^{k} D_s$ reflect both spatial spillover effects and diffusion effects over time. By diffusion effects, we refer to the idea that a change in Texas at time t would affect the neighboring state Louisiana at time $t+1$, and neighbors to Louisiana, such as Mississippi at time $t+2$, and continue to spread to other states in future time periods. The highly non-linear nature of (20) which appears in (19) means that we cannot separate time and space impacts in this model. However, Parent and LeSage (2010a) show how to separate time and space impacts in a simpler model. This technique allows us to examine if $\theta = -\phi \times \rho$ holds in any application of a dynamic model. Thus, space-time separability is considered in our sample data. In the next section, we employ these partial derivatives using coefficient estimates from the dynamic model of state-level beer consumption.

3 The state-level beer demand application

3.1 The sample data

We use a panel of the lower 48 states and the District of Columbia covering 38 years from 1970-2007 to model a simple demand equation for quantity of beer consumed as a function of the taxes per gallon, state-level personal income per capita, and consumption of spirits, high alcohol content beverages (e.g. liquor but not wine).[5] Taxes represent a proxy for price since variation in taxes on beer are much greater than variation in prices across the states. Price is treated as constant across the states, so that taxes can be viewed as equal to the price. The state-level tax rates on beer were from the Tax Foundation.[6]

Alcohol consumption is measured as standardized alcohol consumption per person age 14 and older for each state from the National Institute on Alcohol Abuse and Alcoholism (NIAAA), part of the National Institutes of Health and Department of Health and Human Services.[7] NIAAA uses per capita alcohol consumption that controls for the fact that beers vary in alcohol content by type and brand. The same is true for spirits consumption that we use as a control variable in the regression relationship. Since cultural differences arise across the US, inclusion of spirits consumption help control for spatial variation in alcohol consumption patterns across the states. Microeconomic theory also suggests spirits may act as substitutes or complements to beer consumption.

Microeconomic theory also suggests that consumers' income should be an important determinant of the quantity of any good consumed. Annual personal income and population data were used to construct personal income per capita for each state

[5] All of the variables, quantity beer consumed, personal income, and spirits consumption, are logged values.

[6] Tax Foundation Special Report, No. 134, "State Tax Collections and Rates"; which utilized various sources: State Revenue Departments; Commerce Clearing House; Federation of Tax Administrators; Department of Agriculture, American Petroleum Institute.

[7] Alcohol data are available at: http://www.niaaa.nih.gov/

over the period 1970 to 2007.[8]

As Parent and LeSage (2010a) introduced in their dynamic model, we employ Bayesian Markov Chain Monte Carlo (MCMC) procedures to estimate each parameter of model conditional on the others. We report estimates for the model parameters in Table 2 based on 125,000 MCMC draws with the first 100,000 discarded to account for burn-in of the MCMC sampler. The table reports the posterior mean as well as lower 0.05 and upper 0.95 percentiles representing Bayesian confidence intervals using the 25,000 retained draws. Large variances were assigned to the prior distributions so these estimates should reflect mostly sample data information and be roughly equivalent to those from maximum likelihood estimation.

In Table 2, we see positive space and time dependence as evidenced by ϕ and ρ parameters that are statistically different from zero according to the lower and upper 0.05 and 0.95 confidence intervals.

Negative space-time covariance as shown by θ which is consistent with the space-time filter theory, since θ is predicted to equal $-\rho \times \phi$, and both ρ and ϕ are positive leading to negative θ. However, $-\rho \times \phi = -0.2767$, which is different from our estimate for $\theta = -0.2908$. Nevertheless, this estimate has lower and upper 0.05 and 0.95 bounds of -0.3426 and -0.2415. Respectively, the upper-lower confidence intervals hold the predicted value of $-\rho \times \phi = -0.2767$. Thus, we can conclude that our estimate of θ is not statistically significantly different from that predicted by the

[8]Source: Regional Economic Information System, Bureau of Economic Analysis, US Department of Commerce SA04H State income summary (historical) http://www.bea.gov/regional/, Bureau of Economic Analysis.

filter specification.[9]

Table 2: Dynamic space-time model parameter estimates

Parameters	Mean	std dev.	lower 0.05	upper 0.95
ϕ	0.8657	0.0118	0.8426	0.8884
ρ	0.3197	0.0270	0.2681	0.3796
θ	-0.2908	0.0259	-0.3426	-0.2415
σ_μ^2	0.0009	0.0002	0.0005	0.0014
σ_ε^2	0.0009	0.3e-04	0.0008	0.0010
constant	-0.0458	0.0288	-0.0955	0.0116

We note that estimates for coefficients on Z, WZ are not reported since they are not interpretable. The coefficients associated with price, income, spirits consumption and their spatial lags cannot be directly interpreted as if they were partial derivatives that measure the response of the dependent variable to changes in the regressors. As already noted, the partial derivatives as in (19) take the form of $N \times N$ matrices for each time horizon and are non-linear functions of these coefficient estimates and the space-time filter parameters.

We will discuss results of direct and indirect effects for variables in Z, tax/price, income and quantity of spirits consumed which acts as a control variable in the relationship between beer consumption and the other variables. The direct and indirect effects from the dynamic model were calculated for each future horizon from $T = 0, \ldots, 29$. These reflect short-run (small values of T) and long-run elasticity (large values of T) responses, since our variables are transformed using logs.

[9] While the estimates are not statistically different, numerical differences will lead to different numerical values for the effects estimates. The practical significance of these differences is a subject for future research.

3.2 The dynamic space-time panel model results

Table 3, shows direct effect estimates (the own-partial) for the price (tax) elasticity based on our data. The table reports individual mean estimates and cumulative means associated with the future horizons T. Confidence intervals for 95 and 99 percent levels are also shown in the table. We use the same format in Tables 4 to 10 which report direct and indirect effects estimates for all of our explanatory variables.

First, Table 3 shows the mean direct or own-state effects arising from a change in the tax or price of beer. The time zero horizon shows the immediate period effect, within the year when the tax/price change takes place. Other time horizons 1 to 29 show the impact of the tax change in future years, which arises because the relationship exhibits positive time dependence. This means that changes in the current time period will have a lasting impact on future periods. The table also shows lower and upper 0.01 and 0.99 as well as 0.05 and 0.95 confidence intervals, which can be used to determine if the mean effects are statistically significant (different from zero).

The first column of the table shows the cumulative effects over time that arise from the tax change. Since the percentage change in the tax rate is a persistent change to a higher tax level, consumers will adjust their consumption behavior in both the short- and long-run. The cumulative changes ultimately stabilize to represent the long-run elasticity response to the tax change.

Economic theory predicts that the beer consumption response to an increase in the tax/price should be negative, and we see that this is true for the nine years following the tax change using the 95% confidence intervals. After nine years, the direct effect is no longer statistically significant.

The short-run one year elasticity of -0.011 means that a 10 percent increase in the beer tax would lead to a 0.11 percent decrease in beer consumption. The long-run elasticity is around -0.041, meaning that the long-run response of beer consumption to a 10 percent increase in the tax would be a decrease of 0.41 percent. These are very small responses that economists would label as *inelastic*, meaning that changes in taxes would not have a very big impact on the amount of beer consumed.

Table 4 shows the direct effects on beer consumption arising from a change in personal income (per capita) of consumers in a state. The mean estimates for the income elasticity are negative, suggesting beer is an inferior good based on microeconomic theory, However, none of the income elasticity estimates are significantly different from zero based on the lower and upper 0.05 and 0.95 confidence intervals. Therefore, our data does not show a significant relationship between beer consumption and changes in individual income in the short or long run.

Table 5 shows the direct effects arising from a change in (logged) state-level spirits consumption (per capita). The mean estimates for the elasticity response of beer consumption to a higher level of spirits consumption are positive, which suggests that beer and spirits are compliments. Microeconomic theory defines complementary goods are those whose consumption is positively related. This positive relationship between consumption of the goods indicates that increases in consumption of one of the two goods leads to an increase in consumption of the other good.

The estimates are significant using the 0.01 and 0.99 confidence intervals. The short-run (one-year) elasticity is 0.063 and the long-run elasticity is around 0.25, meaning that a 10 percent increase in spirits consumption in a state would lead to a 0.6 percent short-run increase in beer consumption and a 2.5 percent long-run increase in beer consumption. This suggests that state-level beer consumption is much more responsive to spirits consumed than to the tax on beer, or to income of consumers.

For the next three tables, we discuss the results on indirect effects associated with the cross-partials of each tax of beer, individual income, and spirits consumption in a state. These effects cumulate over all neighboring states, and neighbors to the neighboring states and so forth. That is, they sum up the spatial spillover effects on all other states, including space-time diffusion impacts that arise over time. The impact on an individual neighboring state would be smaller than the direct effects estimates, consistent with the notion that spatial spillovers are second-order effects. However, when we cumulate these smaller effects over all neighboring states and states where diffusion impacts have occurred, we observe effects that are likely to be larger than the direct effects.

In Table 6, the mean indirect or other-state effects arising from a percentage change in beer taxes that fall on all other states as a result of an increase in the beer tax in one state are negative. The effects are significantly different from zero using the 0.01 and 0.99 confidence intervals out to a time horizon of 15 years, and 23 years based on the 0.05 and 0.95 intervals. The short-run (one-year) elasticity is around -0.04 and the long-run elasticity is around -0.13, consistent with the notion that long-run responses are more elastic as consumers adjust their behavior over time.

The negative indirect impacts from an increase in beer taxes is a surprising result indicating that tax increases discourage border crossing sales in neighboring states. There are around 4.5 neighboring states on average for each state in our sample of 49 US regions. A short-run negative elasticity for border crossing sales slightly less than -0.01 for each of the 4.5 neighbors would produce the -0.04 cumulative short-run elasticity response. Over time the indirect effects cumulate to a long-run elasticity of -0.132, but this includes diffusion effects to neighbors to the neighboring states. A possible explanation for the negative spatial spillovers and diffusion effects is that states compete when setting their excise taxes on cigarettes, beer, wine, spirits and gasoline. There are a great many studies regarding regional tax competition. The tax competition that Allers and Elhorst (2005) and Deskings and Hill (2010) discuss establishes positive spatial dependence between neighboring states tax setting behavior. This means that a rise in state i taxes on beer is likely accompanied by increased beer taxes in states that neighboring state j.

The fact that spatial spillovers play such a large role in reducing beer consumption as a result of tax increases has important policy implications. From the perspective of society at large, the impact of individual state beer taxes reduce consumption in the own-state and neighboring states. Ignoring the neighboring state impacts would lead to a downward bias in the assessment of tax impacts on beer consumption. The direct effects point to a long-run reduction of 0.41 percent in beer consumption for every 10 percent increase in taxes. The long-run total effects which include the direct and indirect effects (see Table 9) equal a 1.7 percent reduction in beer consumption for every 10 percent increase in taxes. Economists would classify beer consumption as having a long-run inelastic response to taxes/price, since the elasticity is less than unity. An elasticity of one would mean that a 10 percent increase in taxes/price would lead to a 10 percent decrease in consumption.

Another interesting implication of the negative indirect effect is that tax revenues in neighboring states collected from beer sales would decrease, whereas tax revenues in the own-state would increase as a result of a ceteris paribus tax increase. This is because with neighboring states tax rates held constant but consumption lower, tax revenue would fall. However, in the own-state, the increased tax rates lead to an inelastic decrease in beer consumption that increases tax revenue from beer sales.

Table 7 and Table 8 show the (cumulative over all states) indirect or other-state effects arising from a percentage change in own-state personal income per capita and change in own-state consumption of spirits per capita. According to the results, however, the spatial spillovers associated with an increase in both own-state income and consumption of spirits are not statistically significant. Since spatial spillovers associated with an increase in own-state spirits consumption are not statistically significant, increased income or increased consumption of spirits in state i has no impact on beer consumption in neighboring states.

Tables 9 to 11 show the total responses of beer consumption to changes in taxes, income and spirits consumption. These responses are the sum of the direct plus indirect effects reported in Tables 3 to 8.

There are a number of possible scenarios that arise in terms of the statistical significance of the total responses. One is that positive (negative) direct effects can be offset or canceled out by negative (positive) indirect effects leading to total effects that are not statistically significant. Another situation would be where direct (indirect) effects were significant while indirect (direct) were not significant which could produce significant or insignificant total effects depending on the relative magnitudes involved. Of course, the two types of effects could have the same sign and be reinforcing in terms of magnitude leading to significant total effects, even if the direct, indirect or both effects were not significant individually.

From Table 9 we see negative and significant (at the 0.01 and 0.99 levels) total effects (at all time horizons) associated with tax/price increases. This is an example where the direct and indirect effects are both negative, with the indirect effects not significant at the 0.01 and 0.99 levels. However, the signs of the two types of effects are the same producing a reinforcing of the two impacts that leads to highly significant total effects.

Table 10 shows the total effects associated with the income elasticity. Here we see a total effect that is positive and significant at the 0.05 and 0.95 levels for all time horizons. This is despite the fact that neither the direct or indirect effects were statistically significant. However, we note that the effects are quite small having a long-run total elasticity of only 0.048, and significant only at the 0.05 and 0.95 level.

The total effects of spirits consumption are positive and significant at the 0.01 and 0.99 levels, despite the fact that the spatial spillovers (indirect effects) were not significant. This is a case where the large direct effects long-run elasticity magnitude of 0.25 dominates and accounts for most of the total effect long-run elasticity equal to 0.285.

Table 12 shows the mean random effects estimates along with standard deviations and the ratio of the mean to standard deviation which represents a $t-$statistic. Lower and upper 0.05 and 0.95 confidence intervals are also presented.

The random effects can be viewed as an addition to the intercept term of the model that creates a state-specific intercept. If the random effect for state i is positive, this indicates that forces are at work that lead to higher levels of beer consumption in state i over all time periods than would be predicted by our models explanatory variables. In contrast, a negative random effect for state i points to lower than expected beer consumption in state i (for all time periods) than would be predicted by the model.

Some of the random effects estimates appear to make intuitive sense. For example, Utah has a large negative (and significant) random effect estimate which might be explained by the presence of the large Mormon population which forbids alcohol consumption. Kentucky is another state with a large negative and significant effect. This state has only 32 “wet counties” where alcohol sales are allowed, 46 “dry counties” where alcohol sales are outlawed and restrictions of some type in all other counties in the state. Wisconsin has a large positive effect estimate, which makes sense given its history of beer production. Texas has the largest positive effect estimate despite the fact that there are a number of counties in west Texas that are “dry counties”.

Figure 2 presents a map with an accompanying legend in Figure 3 showing the significant negative and positive effects estimates. From the map legend we see there are 8 states that had negative and significant effects estimates, mostly on the east coast (Connecticut, Maryland, Massachusetts, New Jersey, New York, and Virginia) as well as Utah, mentioned previously, and California. The positive effects estimates are almost all southern and western states that border Mexico, with the exception of Wisconsin and Montana.

4 Conclusion

A number of studies discuss regression models that incorporate spatial as well as time dependence. In this thesis we use a dynamic space-time panel model to examine cross-border shopping for beer (bootlegging) to avoid high beer taxes implemented by some states.

A valuable aspect of dynamic space-time models is that parameter estimates can be used to quantify dynamic responses over time and space as well as space-time diffusion impacts arising from changes in taxes. By measuring own- and cross partial derivatives, this dynamic space-time panel data model allows us to estimate direct effects (own state effects) and indirect effects (bootlegging effects).

Our examination of state-level beer consumption over the period of 1970 to 2007 for the 48 contiguous US states and the District of Columbia shows that spillover effects of beer tax rates are statistically significant. However, the greatest impact on beer consumption is from changes in spirits consumption, a complementary good. The short- and long-run direct or own-state impact of beer tax rates on beer consumption are negative and significant but small, while the indirect or spillover effects are negative and around three times as large as the direct effect. This implies that neglecting spillover effects of beer taxes would cause large biases when examining the impacts of taxes on beer consumption.

Our findings indicate that the largest impact on beer consumption is spirits consumption, which has a positive short- and long-run direct effect on beer consumed that is almost twice as large as the negative impact from beer taxes. The spatial spillover impact of spirits consumption is small, so the total effects of spirits consumed on beer consumption consists mostly of the direct effects. The positive relationship suggests that reducing consumption of spirits would have a greater impact on reducing the consumption of beer than raising beer taxes by the same amount.

Examining the random effects estimates for individual states that are part of the model of beer consumption, the signs and significance are consistent with what we know about some states in the US. For example, random effects on the east coast are negative suggesting lower levels of beer consumption in these states after controlling for other variables in our model. Utah has a negative and significant random effect estimate which is consistent with important Mormon religious influences in this state. On the other hand, positive random effects tend to appear in states where beer production takes place such as Wisconsin, pointing to higher levels of beer consumption all else equal. This was also true of southern states.

In our study of state-level beer consumption, we are able to obtain interesting results from utilizing a dynamic space-time data panel model, incorporating time and spatial dependence in our regression model. Our results suggest that the dynamic model can reduce possible biases and quantify the influence of both direct/indirect effects for each explanatory variable.

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Figures

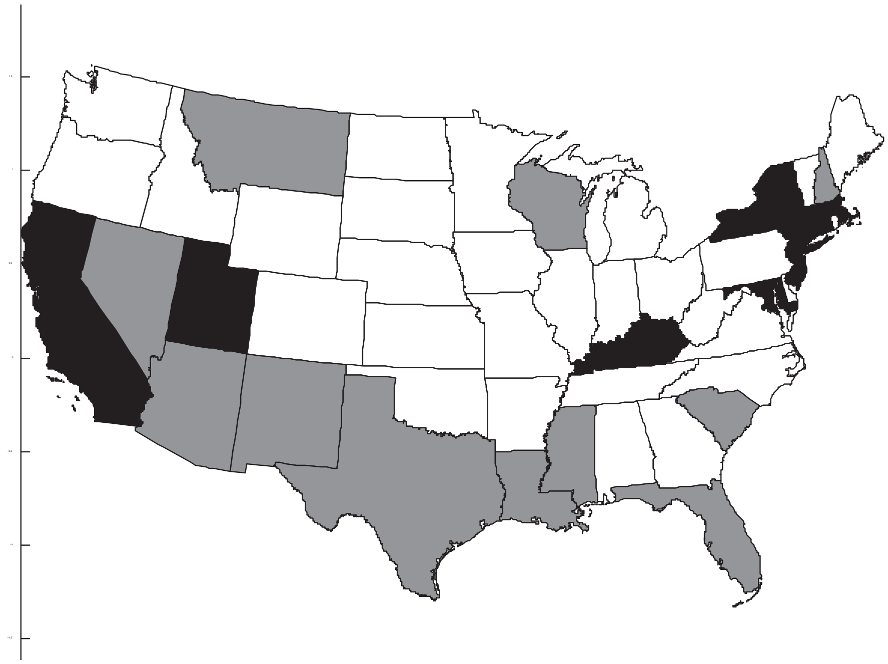

Figure 2: Random effects estimates for the states

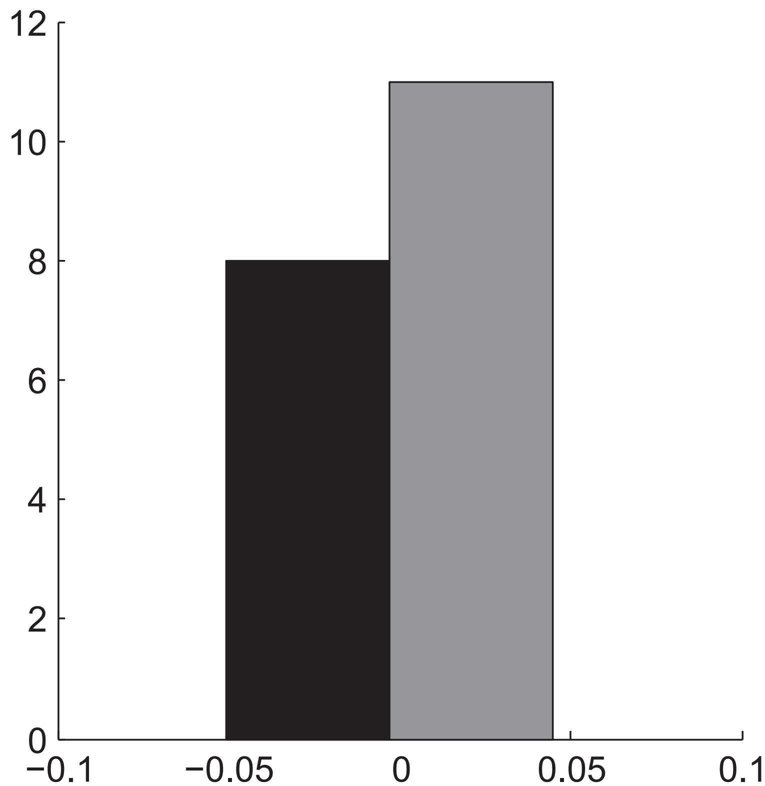

Figure 3: Random effects map legend

Tables

Table 3: Space-time direct effect estimates for (logged) price/taxes

	Price/tax (elasticity)					
Horizon T	Cumulative	lower 0.01	lower 0.05	mean	upper 0.95	upper 0.99
0	-0.006172	-0.013464	-0.011692	-0.006172	-0.000796	0.000927
1	-0.011431	-0.011519	-0.009965	-0.005259	-0.000627	0.000877
2	-0.015913	-0.009820	-0.008503	-0.004481	-0.000488	0.000789
3	-0.019733	-0.008439	-0.007295	-0.003820	-0.000372	0.000738
4	-0.022990	-0.007239	-0.006246	-0.003257	-0.000272	0.000694
5	-0.025768	-0.006217	-0.005357	-0.002778	-0.000189	0.000639
6	-0.028138	-0.005363	-0.004614	-0.002370	-0.000127	0.000598
7	-0.030161	-0.004642	-0.003969	-0.002022	-0.000074	0.000555
8	-0.031887	-0.004031	-0.003423	-0.001726	-0.000033	0.000526
9	-0.033361	-0.003493	-0.002954	-0.001474	-0.000002	0.000498
10	-0.034619	-0.003036	-0.002551	-0.001259	0.000025	0.000464
11	-0.035694	-0.002636	-0.002205	-0.001075	0.000047	0.000425
12	-0.036613	-0.002296	-0.001912	-0.000918	0.000057	0.000395
13	-0.037397	-0.001994	-0.001659	-0.000785	0.000067	0.000372
14	-0.038068	-0.001740	-0.001440	-0.000671	0.000073	0.000347
15	-0.038642	-0.001519	-0.001249	-0.000574	0.000076	0.000320
16	-0.039132	-0.001321	-0.001086	-0.000491	0.000078	0.000294
17	-0.039552	-0.001160	-0.000943	-0.000420	0.000077	0.000272
18	-0.039911	-0.001018	-0.000820	-0.000359	0.000077	0.000246
19	-0.040218	-0.000897	-0.000715	-0.000307	0.000075	0.000227
20	-0.040481	-0.000789	-0.000623	-0.000263	0.000073	0.000209
21	-0.040706	-0.000693	-0.000545	-0.000225	0.000070	0.000192
22	-0.040899	-0.000605	-0.000476	-0.000193	0.000066	0.000176
23	-0.041064	-0.000534	-0.000416	-0.000165	0.000062	0.000164
24	-0.041205	-0.000470	-0.000364	-0.000141	0.000058	0.000150
25	-0.041326	-0.000415	-0.000318	-0.000121	0.000054	0.000139
26	-0.041430	-0.000365	-0.000278	-0.000104	0.000050	0.000130
27	-0.041519	-0.000321	-0.000243	-0.000089	0.000047	0.000119
28	-0.041595	-0.000284	-0.000213	-0.000076	0.000043	0.000107
29	-0.041660	-0.000250	-0.000187	-0.000065	0.000040	0.000098

Table 4: Space-time direct effect estimates for (logged) personal income per capita

	Income (elasticity)					
Horizon T	Cumulative	lower 0.01	lower 0.05	mean	upper 0.95	upper 0.99
0	-0.009804	-0.059422	-0.047478	-0.009804	0.028189	0.039686
1	-0.018389	-0.052113	-0.041432	-0.008585	0.024390	0.034320
2	-0.025908	-0.045550	-0.036215	-0.007519	0.021057	0.029772
3	-0.032494	-0.039870	-0.031578	-0.006587	0.018254	0.025805
4	-0.038265	-0.034911	-0.027603	-0.005771	0.015814	0.022344
5	-0.043322	-0.030719	-0.024172	-0.005057	0.013736	0.019384
6	-0.047755	-0.027097	-0.021112	-0.004432	0.011906	0.016836
7	-0.051640	-0.023732	-0.018500	-0.003886	0.010339	0.014657
8	-0.055047	-0.020980	-0.016199	-0.003407	0.008981	0.012753
9	-0.058035	-0.018603	-0.014243	-0.002988	0.007802	0.011111
10	-0.060656	-0.016338	-0.012511	-0.002621	0.006751	0.009671
11	-0.062956	-0.014476	-0.011008	-0.002299	0.005875	0.008462
12	-0.064973	-0.012839	-0.009690	-0.002018	0.005113	0.007408
13	-0.066744	-0.011365	-0.008529	-0.001771	0.004473	0.006470
14	-0.068299	-0.010099	-0.007492	-0.001555	0.003891	0.005658
15	-0.069664	-0.008941	-0.006616	-0.001365	0.003374	0.004985
16	-0.070863	-0.008001	-0.005846	-0.001199	0.002934	0.004359
17	-0.071916	-0.007099	-0.005150	-0.001053	0.002561	0.003803
18	-0.072841	-0.006297	-0.004533	-0.000925	0.002232	0.003318
19	-0.073654	-0.005593	-0.003994	-0.000813	0.001943	0.002900
20	-0.074369	-0.004994	-0.003541	-0.000715	0.001693	0.002541
21	-0.074998	-0.004430	-0.003132	-0.000628	0.001477	0.002244
22	-0.075550	-0.003951	-0.002765	-0.000553	0.001289	0.001961
23	-0.076036	-0.003525	-0.002450	-0.000486	0.001127	0.001722
24	-0.076464	-0.003123	-0.002168	-0.000428	0.000983	0.001514
25	-0.076840	-0.002786	-0.001918	-0.000376	0.000858	0.001337
26	-0.077171	-0.002480	-0.001698	-0.000331	0.000749	0.001177
27	-0.077463	-0.002222	-0.001504	-0.000292	0.000657	0.001033
28	-0.077720	-0.001981	-0.001334	-0.000257	0.000574	0.000909
29	-0.077946	-0.001769	-0.001183	-0.000226	0.000502	0.000807

Table 5: Space-time direct effect estimates for (logged) spirits consumption per capita

	Spirits consumption (elasticity)					
Horizon T	Cumulative	lower 0.01	lower 0.05	mean	upper 0.95	upper 0.99
0	0.033839	0.015514	0.019838	0.033839	0.047827	0.051964
1	0.063085	0.013361	0.017139	0.029246	0.041288	0.044912
2	0.088370	0.011522	0.014774	0.025285	0.035702	0.038781
3	0.110238	0.010010	0.012742	0.021868	0.030966	0.033661
4	0.129158	0.008608	0.010981	0.018920	0.026884	0.029374
5	0.145534	0.007391	0.009463	0.016375	0.023407	0.025600
6	0.159711	0.006382	0.008157	0.014178	0.020405	0.022419
7	0.171991	0.005468	0.007022	0.012279	0.017799	0.019644
8	0.182630	0.004700	0.006031	0.010639	0.015550	0.017211
9	0.191850	0.004050	0.005187	0.009221	0.013638	0.015073
10	0.199845	0.003467	0.004453	0.007995	0.011957	0.013275
11	0.206779	0.002984	0.003814	0.006934	0.010496	0.011694
12	0.212794	0.002544	0.003260	0.006016	0.009223	0.010306
13	0.218016	0.002185	0.002795	0.005221	0.008096	0.009107
14	0.222549	0.001869	0.002391	0.004533	0.007129	0.008063
15	0.226486	0.001592	0.002043	0.003937	0.006281	0.007140
16	0.229906	0.001364	0.001743	0.003420	0.005540	0.006336
17	0.232879	0.001163	0.001486	0.002973	0.004890	0.005622
18	0.235463	0.000990	0.001266	0.002584	0.004319	0.005000
19	0.237711	0.000837	0.001080	0.002248	0.003814	0.004456
20	0.239666	0.000711	0.000919	0.001955	0.003366	0.003975
21	0.241368	0.000604	0.000785	0.001702	0.002977	0.003531
22	0.242849	0.000514	0.000669	0.001481	0.002635	0.003136
23	0.244139	0.000437	0.000569	0.001290	0.002336	0.002802
24	0.245263	0.000371	0.000483	0.001124	0.002073	0.002506
25	0.246242	0.000313	0.000411	0.000979	0.001838	0.002245
26	0.247096	0.000267	0.000350	0.000854	0.001633	0.002007
27	0.247840	0.000227	0.000298	0.000744	0.001449	0.001808
28	0.248489	0.000192	0.000253	0.000649	0.001288	0.001619
29	0.249056	0.000162	0.000214	0.000567	0.001144	0.001456

Table 6: Space-time indirect effect estimates for (logged) price/taxes

	Price/tax (elasticity)					
Horizon T	Cumulative	lower 0.01	lower 0.05	mean	upper 0.95	upper 0.99
0	-0.021254	-0.038795	-0.034729	-0.021254	-0.007827	-0.004237
1	-0.039088	-0.032160	-0.028850	-0.017834	-0.006602	-0.003540
2	-0.054057	-0.026712	-0.024079	-0.014969	-0.005532	-0.002885
3	-0.066626	-0.022331	-0.020177	-0.012570	-0.004605	-0.002372
4	-0.077185	-0.018807	-0.016977	-0.010559	-0.003819	-0.001909
5	-0.086058	-0.015941	-0.014340	-0.008873	-0.003155	-0.001532
6	-0.093517	-0.013611	-0.012201	-0.007459	-0.002578	-0.001207
7	-0.099790	-0.011748	-0.010395	-0.006273	-0.002099	-0.000952
8	-0.105068	-0.010179	-0.008886	-0.005278	-0.001727	-0.000735
9	-0.109510	-0.008850	-0.007638	-0.004442	-0.001408	-0.000556
10	-0.113250	-0.007683	-0.006551	-0.003740	-0.001132	-0.000396
11	-0.116401	-0.006703	-0.005652	-0.003151	-0.000904	-0.000286
12	-0.119056	-0.005872	-0.004892	-0.002655	-0.000726	-0.000194
13	-0.121294	-0.005160	-0.004235	-0.002238	-0.000570	-0.000108
14	-0.123182	-0.004527	-0.003677	-0.001888	-0.000442	-0.000052
15	-0.124775	-0.003990	-0.003199	-0.001593	-0.000341	-0.000008
16	-0.126119	-0.003515	-0.002787	-0.001344	-0.000258	0.000036
17	-0.127255	-0.003111	-0.002423	-0.001135	-0.000190	0.000067
18	-0.128214	-0.002740	-0.002106	-0.000959	-0.000135	0.000087
19	-0.129024	-0.002422	-0.001837	-0.000811	-0.000093	0.000100
20	-0.129710	-0.002141	-0.001598	-0.000686	-0.000060	0.000108
21	-0.130290	-0.001909	-0.001392	-0.000580	-0.000034	0.000118
22	-0.130781	-0.001691	-0.001217	-0.000491	-0.000017	0.000121
23	-0.131197	-0.001498	-0.001059	-0.000416	-0.000002	0.000122
24	-0.131549	-0.001334	-0.000924	-0.000352	0.000008	0.000119
25	-0.131847	-0.001187	-0.000807	-0.000298	0.000015	0.000114
26	-0.132100	-0.001055	-0.000707	-0.000253	0.000020	0.000109
27	-0.132315	-0.000940	-0.000618	-0.000215	0.000023	0.000102
28	-0.132497	-0.000838	-0.000540	-0.000182	0.000026	0.000096
29	-0.132652	-0.000744	-0.000471	-0.000155	0.000026	0.000091

Table 7: Space-time indirect effect estimates for (logged) personal income per capita

	Income (elasticity)					
Horizon T	Cumulative	lower 0.01	lower 0.05	mean	upper 0.95	upper 0.99
0	0.017553	-0.032220	-0.020799	0.017553	0.055314	0.068576
1	0.032643	-0.028089	-0.018239	0.015090	0.047965	0.059217
2	0.045625	-0.024428	-0.015911	0.012982	0.041617	0.051588
3	0.056801	-0.021334	-0.013870	0.011176	0.036160	0.045015
4	0.066429	-0.018747	-0.012091	0.009628	0.031449	0.039261
5	0.074728	-0.016340	-0.010532	0.008299	0.027371	0.034240
6	0.081888	-0.014199	-0.009191	0.007159	0.023786	0.030060
7	0.088067	-0.012447	-0.008026	0.006180	0.020739	0.026325
8	0.093405	-0.010821	-0.007054	0.005338	0.018093	0.023172
9	0.098018	-0.009486	-0.006186	0.004613	0.015793	0.020397
10	0.102008	-0.008332	-0.005402	0.003990	0.013836	0.017989
11	0.105461	-0.007336	-0.004723	0.003453	0.012090	0.015765
12	0.108451	-0.006433	-0.004156	0.002990	0.010600	0.013960
13	0.111041	-0.005622	-0.003633	0.002591	0.009284	0.012273
14	0.113287	-0.004926	-0.003178	0.002246	0.008150	0.010801
15	0.115236	-0.004309	-0.002793	0.001948	0.007168	0.009562
16	0.116927	-0.003768	-0.002445	0.001691	0.006292	0.008463
17	0.118396	-0.003318	-0.002149	0.001469	0.005529	0.007521
18	0.119672	-0.002913	-0.001880	0.001276	0.004864	0.006625
19	0.120782	-0.002561	-0.001650	0.001110	0.004286	0.005884
20	0.121747	-0.002266	-0.001446	0.000966	0.003770	0.005229
21	0.122588	-0.002000	-0.001273	0.000840	0.003322	0.004654
22	0.123320	-0.001771	-0.001119	0.000732	0.002931	0.004134
23	0.123958	-0.001554	-0.000981	0.000638	0.002589	0.003675
24	0.124514	-0.001375	-0.000859	0.000556	0.002285	0.003249
25	0.124999	-0.001207	-0.000750	0.000485	0.002022	0.002903
26	0.125422	-0.001064	-0.000662	0.000423	0.001783	0.002593
27	0.125792	-0.000936	-0.000580	0.000370	0.001577	0.002292
28	0.126115	-0.000832	-0.000508	0.000323	0.001394	0.002047
29	0.126397	-0.000734	-0.000445	0.000282	0.001236	0.001828

Table 8: Space-time indirect effect estimates for (logged) spirits consumption per capita

	Spirits consumption (elasticity)					
Horizon T	Cumulative	lower 0.01	lower 0.05	mean	upper 0.95	upper 0.99
0	0.011003	-0.021792	-0.013321	0.011003	0.035137	0.042441
1	0.019521	-0.019111	-0.011970	0.008518	0.028671	0.034761
2	0.026052	-0.016724	-0.010807	0.006531	0.023486	0.028801
3	0.030998	-0.014782	-0.009769	0.004946	0.019327	0.024069
4	0.034686	-0.013209	-0.008917	0.003688	0.016099	0.020133
5	0.037380	-0.011818	-0.008130	0.002694	0.013397	0.016823
6	0.039293	-0.010555	-0.007432	0.001913	0.011199	0.014178
7	0.040596	-0.009554	-0.006770	0.001303	0.009348	0.012023
8	0.041426	-0.008652	-0.006173	0.000831	0.007882	0.010219
9	0.041895	-0.007744	-0.005685	0.000469	0.006648	0.008758
10	0.042089	-0.007038	-0.005202	0.000194	0.005639	0.007531
11	0.042078	-0.006326	-0.004748	-0.000011	0.004806	0.006552
12	0.041917	-0.005764	-0.004347	-0.000161	0.004078	0.005687
13	0.041650	-0.005271	-0.003968	-0.000267	0.003481	0.004930
14	0.041311	-0.004792	-0.003613	-0.000340	0.003002	0.004335
15	0.040925	-0.004365	-0.003293	-0.000386	0.002585	0.003825
16	0.040512	-0.003968	-0.003003	-0.000413	0.002215	0.003382
17	0.040088	-0.003603	-0.002731	-0.000424	0.001904	0.002973
18	0.039665	-0.003290	-0.002479	-0.000423	0.001638	0.002622
19	0.039250	-0.002978	-0.002257	-0.000415	0.001418	0.002320
20	0.038850	-0.002710	-0.002057	-0.000400	0.001233	0.002051
21	0.038468	-0.002462	-0.001865	-0.000382	0.001071	0.001812
22	0.038107	-0.002246	-0.001687	-0.000361	0.000925	0.001600
23	0.037769	-0.002046	-0.001532	-0.000338	0.000804	0.001421
24	0.037454	-0.001865	-0.001389	-0.000315	0.000704	0.001260
25	0.037163	-0.001704	-0.001256	-0.000292	0.000614	0.001123
26	0.036894	-0.001561	-0.001135	-0.000269	0.000536	0.000993
27	0.036647	-0.001414	-0.001030	-0.000247	0.000472	0.000883
28	0.036421	-0.001284	-0.000927	-0.000226	0.000413	0.000785
29	0.036216	-0.001167	-0.000837	-0.000206	0.000361	0.000698

Table 9: Space-time total effect estimates for (logged) price/taxes

	Price/tax (elasticity)					
Horizon T	Cumulative	lower 0.01	lower 0.05	mean	upper 0.95	upper 0.99
0	-0.027426	-0.048015	-0.042941	-0.027426	-0.012231	-0.007817
1	-0.050519	-0.039601	-0.035630	-0.023092	-0.010447	-0.006711
2	-0.069969	-0.032712	-0.029603	-0.019451	-0.008891	-0.005704
3	-0.086359	-0.027236	-0.024740	-0.016390	-0.007534	-0.004867
4	-0.100175	-0.022911	-0.020840	-0.013816	-0.006389	-0.004109
5	-0.111826	-0.019360	-0.017577	-0.011651	-0.005410	-0.003446
6	-0.121655	-0.016484	-0.014918	-0.009829	-0.004566	-0.002902
7	-0.129951	-0.014167	-0.012676	-0.008296	-0.003848	-0.002435
8	-0.136955	-0.012205	-0.010820	-0.007004	-0.003241	-0.002047
9	-0.142871	-0.010569	-0.009292	-0.005916	-0.002734	-0.001716
10	-0.147869	-0.009206	-0.007985	-0.004999	-0.002287	-0.001435
11	-0.152095	-0.008066	-0.006900	-0.004226	-0.001918	-0.001200
12	-0.155668	-0.007110	-0.005967	-0.003573	-0.001607	-0.000993
13	-0.158692	-0.006254	-0.005177	-0.003023	-0.001339	-0.000834
14	-0.161250	-0.005495	-0.004489	-0.002559	-0.001113	-0.000697
15	-0.163417	-0.004851	-0.003901	-0.002166	-0.000923	-0.000579
16	-0.165252	-0.004278	-0.003388	-0.001835	-0.000764	-0.000480
17	-0.166806	-0.003784	-0.002947	-0.001555	-0.000635	-0.000401
18	-0.168125	-0.003336	-0.002574	-0.001318	-0.000525	-0.000336
19	-0.169242	-0.002951	-0.002246	-0.001118	-0.000433	-0.000278
20	-0.170191	-0.002606	-0.001953	-0.000948	-0.000357	-0.000228
21	-0.170996	-0.002304	-0.001706	-0.000805	-0.000294	-0.000186
22	-0.171679	-0.002032	-0.001489	-0.000684	-0.000240	-0.000152
23	-0.172260	-0.001799	-0.001300	-0.000581	-0.000198	-0.000126
24	-0.172754	-0.001602	-0.001132	-0.000493	-0.000162	-0.000103
25	-0.173173	-0.001424	-0.000989	-0.000420	-0.000133	-0.000084
26	-0.173530	-0.001265	-0.000864	-0.000357	-0.000109	-0.000068
27	-0.173834	-0.001122	-0.000755	-0.000304	-0.000089	-0.000056
28	-0.174092	-0.000994	-0.000663	-0.000258	-0.000073	-0.000046
29	-0.174312	-0.000887	-0.000580	-0.000220	-0.000059	-0.000038

Table 10: Space-time total effect estimates for (logged) personal income per capita

	Income (elasticity)					
Horizon T	Cumulative	lower 0.01	lower 0.05	mean	upper 0.95	upper 0.99
0	0.007749	-0.002399	0.000101	0.007749	0.015547	0.018175
1	0.014255	-0.002048	0.000087	0.006505	0.012904	0.014967
2	0.019718	-0.001767	0.000076	0.005463	0.010692	0.012410
3	0.024307	-0.001523	0.000066	0.004589	0.008884	0.010263
4	0.028164	-0.001328	0.000055	0.003857	0.007405	0.008545
5	0.031406	-0.001160	0.000047	0.003242	0.006189	0.007175
6	0.034133	-0.000998	0.000041	0.002727	0.005191	0.006025
7	0.036427	-0.000859	0.000035	0.002294	0.004362	0.005078
8	0.038357	-0.000743	0.000030	0.001931	0.003677	0.004287
9	0.039983	-0.000646	0.000026	0.001625	0.003110	0.003625
10	0.041352	-0.000567	0.000022	0.001369	0.002628	0.003079
11	0.042505	-0.000491	0.000019	0.001153	0.002224	0.002635
12	0.043477	-0.000427	0.000016	0.000972	0.001886	0.002260
13	0.044297	-0.000368	0.000014	0.000820	0.001611	0.001943
14	0.044988	-0.000313	0.000012	0.000691	0.001373	0.001662
15	0.045572	-0.000268	0.000010	0.000583	0.001173	0.001436
16	0.046064	-0.000232	0.000009	0.000492	0.001003	0.001247
17	0.046480	-0.000204	0.000008	0.000416	0.000861	0.001076
18	0.046831	-0.000177	0.000006	0.000351	0.000737	0.000934
19	0.047127	-0.000153	0.000005	0.000297	0.000632	0.000810
20	0.047378	-0.000134	0.000005	0.000251	0.000543	0.000702
21	0.047590	-0.000119	0.000004	0.000212	0.000468	0.000610
22	0.047770	-0.000103	0.000003	0.000179	0.000402	0.000525
23	0.047921	-0.000089	0.000003	0.000152	0.000347	0.000457
24	0.048050	-0.000077	0.000002	0.000129	0.000299	0.000398
25	0.048159	-0.000067	0.000002	0.000109	0.000258	0.000344
26	0.048251	-0.000058	0.000002	0.000092	0.000223	0.000301
27	0.048329	-0.000050	0.000002	0.000078	0.000192	0.000263
28	0.048395	-0.000043	0.000001	0.000066	0.000166	0.000231
29	0.048451	-0.000038	0.000001	0.000056	0.000143	0.000203

Table 11: Space-time total effect estimates for (logged) spirits consumption per capita

	Spirits consumption (elasticity)					
Horizon T	Cumulative	lower 0.01	lower 0.05	mean	upper 0.95	upper 0.99
0	0.044842	0.013351	0.021437	0.044842	0.068102	0.075383
1	0.082606	0.011421	0.018366	0.037764	0.056846	0.062656
2	0.114421	0.009855	0.015636	0.031816	0.047754	0.052708
3	0.141236	0.008483	0.013304	0.026814	0.040291	0.044448
4	0.163844	0.007358	0.011342	0.022608	0.034062	0.037782
5	0.182913	0.006232	0.009618	0.019069	0.028853	0.032255
6	0.199004	0.005245	0.008136	0.016091	0.024610	0.027750
7	0.212586	0.004477	0.006844	0.013582	0.020986	0.023882
8	0.224056	0.003790	0.005759	0.011470	0.017939	0.020574
9	0.233745	0.003192	0.004839	0.009689	0.015405	0.017814
10	0.241934	0.002665	0.004058	0.008189	0.013277	0.015477
11	0.248857	0.002247	0.003394	0.006923	0.011449	0.013484
12	0.254712	0.001902	0.002846	0.005855	0.009888	0.011747
13	0.259666	0.001589	0.002365	0.004954	0.008547	0.010228
14	0.263859	0.001339	0.001961	0.004193	0.007391	0.008981
15	0.267410	0.001123	0.001621	0.003551	0.006392	0.007874
16	0.270418	0.000934	0.001339	0.003008	0.005545	0.006912
17	0.272967	0.000772	0.001103	0.002549	0.004803	0.006130
18	0.275128	0.000637	0.000910	0.002161	0.004177	0.005410
19	0.276961	0.000523	0.000750	0.001833	0.003630	0.004755
20	0.278516	0.000432	0.000616	0.001555	0.003163	0.004176
21	0.279835	0.000356	0.000506	0.001320	0.002756	0.003688
22	0.280956	0.000289	0.000416	0.001121	0.002402	0.003251
23	0.281908	0.000237	0.000341	0.000952	0.002091	0.002873
24	0.282717	0.000192	0.000279	0.000809	0.001821	0.002535
25	0.283405	0.000155	0.000228	0.000688	0.001593	0.002231
26	0.283990	0.000126	0.000186	0.000585	0.001387	0.001969
27	0.284487	0.000102	0.000152	0.000498	0.001208	0.001737
28	0.284911	0.000084	0.000124	0.000424	0.001058	0.001536
29	0.285272	0.000068	0.000101	0.000361	0.000924	0.001362

Table 12: Random effect estimates for the states

States	μ mean	μ std	mean/std	lower 0.05	upper 0.95
AL	0.0106	0.0081	1.3027	-0.0054	0.0264
AZ	0.0166	0.0072	2.3091	0.0028	0.0308
AR	-0.0083	0.0076	-1.0909	-0.0235	0.0065
CA	-0.0237	0.0089	-2.6807	-0.0412	-0.0068
CO	0.0028	0.0077	0.3618	-0.0125	0.0180
CT	-0.0410	0.0088	-4.6737	-0.0583	-0.0239
DE	-0.0094	0.0084	-1.1236	-0.0252	0.0075
DC	-0.0177	0.0097	-1.8123	-0.0365	0.0016
FL	0.0261	0.0092	2.8425	0.0078	0.0439
GA	0.0065	0.0082	0.7942	-0.0098	0.0223
ID	-0.0020	0.0078	-0.2528	-0.0169	0.0138
IL	-0.0081	0.0081	-0.9967	-0.0241	0.0078
IN	-0.0095	0.0072	-1.3178	-0.0234	0.0049
IA	0.0127	0.0075	1.6991	-0.0017	0.0274
KS	-0.0031	0.0073	-0.4299	-0.0174	0.0112
KY	-0.0215	0.0080	-2.6834	-0.0371	-0.0056
LA	0.0264	0.0077	3.4314	0.0113	0.0414
ME	-0.0054	0.0125	-0.4376	-0.0300	0.0188
MD	-0.0284	0.0076	-3.7369	-0.0435	-0.0136
MA	-0.0184	0.0077	-2.3962	-0.0335	-0.0031
MI	-0.0134	0.0074	-1.8049	-0.0280	0.0013
MN	-0.0140	0.0075	-1.8656	-0.0290	0.0005
MS	0.0237	0.0081	2.9272	0.0078	0.0397
MO	0.0059	0.0075	0.7971	-0.0086	0.0208
MT	0.0179	0.0074	2.4241	0.0038	0.0328
NE	0.0103	0.0072	1.4246	-0.0036	0.0248
NV	0.0212	0.0103	2.0473	0.0013	0.0422
NH	0.0236	0.0096	2.4521	0.0047	0.0425
NJ	-0.0420	0.0085	-4.9174	-0.0589	-0.0252
NM	0.0322	0.0077	4.1542	0.0172	0.0476
NY	-0.0347	0.0078	-4.4772	-0.0497	-0.0193
NC	0.0096	0.0078	1.2374	-0.0056	0.0246
ND	0.0090	0.0070	1.2865	-0.0047	0.0228
OH	0.0133	0.0076	1.7610	-0.0015	0.0283
OK	-0.0093	0.0078	-1.1804	-0.0248	0.0062
OR	-0.0087	0.0076	-1.1502	-0.0233	0.0065
PA	0.0078	0.0079	0.9922	-0.0074	0.0235
RI	-0.0107	0.0089	-1.1985	-0.0275	0.0075
SC	0.0310	0.0092	3.3778	0.0129	0.0489
SD	0.0028	0.0074	0.3771	-0.0117	0.0176
TN	0.0059	0.0073	0.8107	-0.0084	0.0202
TX	0.0446	0.0083	5.3937	0.0283	0.0608
UT	-0.0509	0.0108	-4.7025	-0.0725	-0.0302
VT	0.0030	0.0087	0.3517	-0.0133	0.0206
VA	0.0012	0.0074	0.1611	-0.0132	0.0158
WA	-0.0141	0.0078	-1.8009	-0.0294	0.0013
WV	-0.0011	0.0087	-0.1243	-0.0181	0.0165
WI	0.0193	0.0076	2.5296	0.0048	0.0347
WY	0.0095	0.0089	1.0679	-0.0080	0.0271