A Strategic Theory of Policy Diffusion via Intergovernmental Competition*

Brady Baybeck
Associate Professor
Department of Political Science
University of Missouri - St. Louis
Saint Louis, MO 63121
Baybeck@umsl.edu

William D. Berry
Syde P. Deeb Eminent Scholar
Department of Political Science
Florida State University
Tallahassee, FL 32306-2230
wberry@fsu.edu

David A. Siegel
Assistant Professor
Department of Political Science
Florida State University
Tallahassee, FL 32306-2230
dsiegel@fsu.edu

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ABSTRACT

Scholars have hypothesized that policy choices by national, state and local governments often have implications for "location choices" made by residents (e.g., tax policies affect where firms set up business, welfare benefits influence where the poor live, government restaurant smoking restrictions influence where people eat). We develop a spatially-explicit strategic theory of policy diffusion driven by intergovernmental competition over residents' location choices. The theory assumes that governments' decisions constitute a strategic game in which governments are influenced by their neighbors. We suggest a variety of policy contexts in which the theory is applicable. For one such context—the adoption of lotteries by American states—we use the theory to generate several hypotheses, and then test them using event history analysis. The results provide substantial support for the theory, and indicate that states compete for lottery business in a much more sophisticated fashion than has been previously recognized.

The policy discretion available to states in the American federal system creates an opportunity for states to learn from one another by observing the consequences of a policy in another state before adopting the policy themselves. At the same time, policies adopted by one state frequently have economic effects on other states, thereby encouraging competition among the American states. In particular, when a state suffers negative externalities due to the policies of other states, it has an incentive to choose policies aimed at shielding itself from these effects. Although *learning* and *economic competition* are fundamentally different forms of intergovernmental relations, both result in the diffusion of policy across states—i.e., in a process in which the policy choices of one state are influenced by the choices made by others.

Scores of studies—dating back 40 years—have confirmed that public policies diffuse across the American states (e.g., Walker 1969; Gray 1973). The vast majority of these studies have detected this diffusion using an event history analysis (EHA) statistical model having the probability that a state will adopt a policy as dependent variable, and including among the independent variables the number (or percentage) of neighboring states that have previously adopted (e.g., Berry and Berry 1990; Mintrom 1997; Balla 2001). Although this "neighbors variable" specification of diffusion may successfully identify *whether* a policy diffuses, it clearly is incapable of determining *why* policies diffuse.

In the last five years, however, a few state politics scholars have begun testing distinct learning and economic competition explanations for the diffusion of policy. Boehmke and Witmer (2004) test both explanations for the diffusion of Indian gaming across the states, Berry and Baybeck (2005) do so for the interstate diffusion of both the lottery and welfare benefit levels, and Shipan and Volden (2008) test whether each of learning and economic competition is responsible for the diffusion of anti-smoking policies across U.S. cities. These authors have significantly advanced the study of policy diffusion by adding insights about the policy-making processes responsible for diffusion to the voluminous evidence that policies diffuse.

Occurring alongside this recent attention on identifying the mechanisms by which policies diffuse have been increasingly sophisticated theories and specifications of the process of learning (e.g., Volden, Ting and Carpenter 2008; Volden 2006; Grossback, Nicholson-Crotty, and Peterson 2004; Nicholson-Crotty 2004). In our view, this progress in studying learning has not been matched in research about economic competition. Even the most sophisticated recent studies of diffusion via competition test theories that fail to do justice to the complexity of the process. For example, when modeling competition, recent studies of lottery and welfare benefit diffusion across states focus exclusively on what we might call *defensive* behavior, in which governments make a decision motivated by the desire to prevent something "bad" from happening: a loss of revenue or increased costs for service provision. When a state has a large number of residents living near the border of states with a lottery, the state adopts one to try to discourage these residents from traveling to another state to play (Berry and Baybeck 2005; Erekson et al. 1999; Alm, McKee and Skidmore 1993). Similarly, when a state has a large number of poor persons near its border living in other states with lower welfare benefits, it should be expected to lower its benefits to discourage these individuals from migrating (Berry and Baybeck 2005; Bailey and Rom 2004; Berry, Fording and Hanson 2003; Peterson and Rom 1989).

However, the same reasoning that leads these authors to assume that policy makers take action defensively to avoid a loss of revenue or an increase in costs prompts an expectation that policy makers will also compete *offensively* by making decisions aimed at securing an increase in revenue or a decrease in costs. If we expect a state to adopt a lottery to prevent a loss of revenue when it has a large number of residents living near other states with lotteries, we should also expect the state to adopt to try to increase revenue when a large number of individuals who might be lured across the border to play reside nearby in other states without lotteries. Similarly, if a state seeking to control costs is expected to decrease welfare benefits in order to discourage the poor living nearby in other states from moving in, the state should also be expected to decrease benefits to encourage its own poor residents near its border to emigrate to other states.

Furthermore, we should expect governments that compete defensively and offensively to anticipate that other governments will behave similarly, and factor this into their policy choices. Put differently, each government should behave *strategically*; its decision about whether to adopt a policy should take into account not only the current policies of other governments, but its expectations about how these other governments would respond to its own policy change. However, with rare exception, research on economic competition has failed to recognize the strategic nature of interaction among governments.

Below, we seek to overcome this limitation of previous work by developing a spatially-explicit strategic theory of policy diffusion via intergovernmental competition over residents' location choices. The theory assumes that each government must decide whether to adopt a policy, and that these decisions constitute a strategic game among governments in which each government competes with those that are geographically proximate.[1] We then specialize the theory to the case of the diffusion of the lottery across American states. This specialization yields a set of testable hypotheses, which are evaluated empirically using pooled cross-sectional time-series data and measures constructed with the geographical information systems (GIS) technology introduced by Berry and Baybeck (2005). We find substantial support for the theory.

A Spatially-Explicit Strategic Theory of Policy Diffusion via Interstate Competition

There are two groups of actors in our theory. The first is a set of *n* spatially-distributed and non-overlapping government jurisdictions, each of which has policy makers that behave as a unitary actor. Anticipating our specialization of the theory to the case of lottery adoptions by American states, we call these actors *states*, but they could also be, for example, cities in a metropolitan area, or countries in Europe. The second group of actors is the set of persons or firms—spatially distributed within the *n* states—that are interested in acquiring some good or service provided by the states (or produced privately but regulated by the states). We call these persons or firms *interested individuals*, and refer to the good or service that they seek to acquire as the *target good*.

We assume that the target good is dispensed at fixed locations, and interested individuals must be at one of these locations to acquire the good. Further, we assume that whether or not the target good is acquired within a state has fiscal consequences for the state; these consequences can be positive (increased revenue, or decreased spending obligations) or negative (decreased revenue, or increased spending obligations). Since the location choices of interested individuals have fiscal consequences for states, each state, *s*, has a preference about whether interested individuals—its own, and those of other states—acquire the target good within *s* or outside.

A variety of substantive contexts arguably satisfy these assumptions. For example, the interested individuals might be (*i*) persons in the U.S. interested in playing the lottery (which requires purchasing a ticket from the state running the lottery at a location within that state) or in casino gambling, (*ii*) poor individuals seeking to reside in an American state in which they would be eligible for generous welfare benefits, (*iii*) smokers interested in eating in a restaurant in a city that does not ban smoking in restaurants (Shipan and Volden 2008), (*iv*) persons seeking to reside in a U.S. state in which their overall tax burden would be low, or to purchase gasoline in a state in which the gasoline tax would be low, or (*v*) firms wanting to be in a jurisdiction in which they would receive generous subsidies or be subject to lax regulation. All these examples reflect cases in which the acquisition of target goods by interested individuals have fiscal consequences for states. In some cases (e.g., playing the lottery), the consequences are positive (increased revenues) and each state would prefer that interested individuals acquire the target good within. In other cases (e.g., eligibility for generous welfare assistance), there are negative consequences for a state when the target good is acquired within (increased spending obligations), and states would prefer that interested individuals acquire the good elsewhere.

For simplicity, henceforth, we develop our theory assuming that the acquisition of the target good within a state has positive consequences for the state, and therefore, that the state would prefer that interested individuals acquire the good within its borders. However, only minor adjustments would be required to deal with a case in which consequences are negative.

<u>The Choice by States</u>

Each type of actor in our theory confronts a choice. Each state, s, at each time, t, considers a policy that—if adopted—would increase the likelihood that interested individuals acquire the target good in s. The state then makes a binary, strategic choice: adopt the policy, or not. For one example above, the policy choice would be whether to adopt a lottery. We denote the choice of state s at time t by $X_{s,t}$, with $X_{s,t}=1$ if s adopts the policy, and $X_{s,t}=0$ if it does not. The *action vector*—denoted by $X_t=(X_{1,t},\ldots, X_{n,t})$—describes the behavior of all states (i.e., whether each adopts the policy) at time t.

<u>The Choice by Interested Individuals</u>

We assume that at each time, t, each interested individual decides whether to acquire the target good, and if is to be acquired, at what location. The individual assesses both the cost and the benefit of acquiring the good from each state that makes it available. If the net benefit of acquisition is negative for all states, she chooses not to acquire it; if the net benefit is positive for at least one state, she acquires it in the state offering her the greatest net benefit. However, for simplicity, we do not explicitly model the strategic behavior of interested individuals. Rather we view the travel distance required to acquire the target good as a reasonable proxy for the cost of acquiring it. We assume that an interested individual's willingness to acquire the good is a declining function of the travel distance required, with willingness reaching zero when the distance surpasses some threshold, D miles. The aggregate decisions of interested individuals determine states' economic payoffs in a manner described below.

Defining States' Neighbors

We define the *target individuals* of state s as all interested individuals within D miles of s's border on either side. We define a *neighbor* (or *neighboring state*) of s as a state that shares at least one target individual with s. Thus, s's neighbors are not limited to adjacent states; a nonadjacent state with a border less than D miles away can also be a neighbor. We denote the subset of states consisting of s's neighbors at time t by $L_{s,t}$, and call the action vector for these states s's *regional action vector*, denoted $X_{L_{s,t},t}$. When deciding whether to adopt the policy, a state seeking to maximize its fiscal position must take into account the adoption choices of each of its neighbors. This is because the choices made by these neighbors influence the choices by s's target individuals about where to acquire the target good and, thus, have direct fiscal consequences for s.

States' Costs of Adoption

For any state, adopting the policy entails a cost for policy makers. In the case of the lottery, for example, this cost might be that occasioned by having to overcome political interests opposed to legalized gambling. The cost of adoption is time-dependent, and may vary as political, economic, or social circumstances change. It may be a one-time cost realized only upon the state's initial adoption, or it may be a continuing cost that must be paid for as long as the policy is in place. We denote the *cost of adoption* for state s at time t by $c_{s,t}$.

States' Economic Payoffs

We must also consider economic payoffs for states. (In the case of the lottery, the payoff to a state can be equated with the revenues it collects.) The payoff for state s is determined by (*i*) its adoption decision (whether it adopts or not) ($X_{s,t}$), (*ii*) the adoption decisions of s's neighbors ($X_{L_{s,t},t}$), and (*iii*) the spatial distribution and location choices of target individuals. Although each state's payoff is directly influenced by the policy choices only of its neighbors, its payoff is indirectly determined by the decisions of non-neighbors as the consequences of states' decisions propagate across space; this is the essence of diffusion.

Establishing some terminology regarding states' payoffs will be useful. We denote the *payoff for s if it adopts* (i.e., if $X_{s,t}$=1), conditional on the behavior of its neighbors, as $b_{s,t}^{A}(X_{L_{s,t},t})$; *s's payoff if it does not adopt* is denoted $b_{s,t}^{\sim A}(X_{L_{s,t},t})$. However, for simplicity, we will often refer below to $b_{s,t}^{A}$ and $b_{s,t}^{\sim A}$, making the conditionality on a state's regional action vector implicit. We define the *net payoff for s from adopting* as its payoff if it adopts less its payoff if it does not: $b_{s,t}^{A}(X_{L_{s,t},t}) - b_{s,t}^{\sim A}(X_{L_{s,t},t})$. Finally, we define the *net* benefit *to s from adopting* as its net payoff from adopting less its cost of adoption: $b_{s,t}^{A}(X_{L_{s,t},t}) - b_{s,t}^{\sim A}(X_{L_{s,t},t}) - c_{s,t}$.

We make two other assumptions about payoffs that we believe are reasonable given the previously stated assumptions that (*i*) adopting the policy increases the likelihood that interested individuals acquire the target good in the state that adopts, and (*ii*) a state benefits from target individuals' acquisition of the good within the state. The first assumption is that an adoption by a state exerts a negative externality on all its neighbors. That is, the payoff for each state, *s*, is decreasing in its neighbors' adoptions, regardless of whether *s* adopts itself. More formally,

<u>Assumption 1</u>: $b^{A}_{s,t}(X^{+1}_{L_{s,t},t}) < b^{A}_{s,t}(X_{L_{s,t},t})$ and $b^{\sim A}_{s,t}(X^{+1}_{L_{s,t},t}) < b^{\sim A}_{s,t}(X_{L_{s,t},t})$, where $X^{+1}_{L_{s,t},t}$ is the same as $X_{L_{s,t},t}$, except that the first regional action vector indicates one additional neighbor has adopted.

To justify this assumption, we need only consider the alternative. Together, (*i*) and (*ii*) in this paragraph imply that adopting the policy tends to have positive economic consequences for a state. Thus, if contrary to Assumption 1, a state's adoption were to induce *positive* externalities for its neighbors, adoptions would make further adoptions even *more* beneficial for supposedly competing states. Adoption would spur more adoption, and all states except those with very high costs or surrounded by states with very high costs would adopt cooperatively in a cascade of adoptions (Siegel 2009). This strikes us as very unlike the typical conception of competition.

The second assumption is that each state's net payoff from adopting is positive for any configuration of other states' adoption decisions. Formally, for each state, *s*:

<u>Assumption 2</u>: $b^{A}_{s,t}(X_{L_{s,t},t}) > b^{\sim A}_{s,t}(X_{L_{s,t},t})$ for any regional action vector for *s*, $X_{L_{s,t},t}$.

This flows directly from the presumed beneficial nature of individuals acquiring the target good within the state. If contrary to Assumption 2, *s*'s net payoff from adopting were negative for some configuration of other states' adoption decisions, *s* would not want to adopt in this situation regardless of the cost, and regardless of future consequences. This would suggest that in some cases, acquiring the target good in the state would not have positive consequences for the state, which is different from the scenario we want to explore.

In the on-line appendix, we complete the specification of a general strategic theory of economic competition assuming that states make rational decisions in continuous time based on their costs and payoffs. We hope this theory will provide a jumping-off point for further work. In the next section, in order to derive testable hypotheses, we specialize our theory to the case of lottery adoptions by American states.

Specializing the Strategic Theory to the Case of Lottery Adoptions

Lottery adoptions by American states have been the focus of many studies of policy diffusion (Berry and Berry 1990; Alm, McKee and Skidmore 1993; Erekson et al. 1999; Berry and Baybeck 2005). This extensive previous work makes the lottery an excellent policy for evaluating our theory empirically. First, the previous research has established many of the variables that determine the cost of adoption ($c_{s,t}$), thereby simplifying the specification of a portion of the theory that is not our central focus. Second, Berry and Baybeck (2005) find evidence that economic competition is a mechanism for the diffusion of the lottery, suggesting that our theory is relevant to this case.

Our specialization to the case of the lottery has two notable features. First, because our theory assumes common knowledge of all costs and payoffs, all diffusion occurs due to competition and learning does not occur. We have little doubt that a theory incorporating both competition and learning would better reflect the true process by which lotteries diffuse across the American states. However, we exclude learning from the model because (*i*) our theoretical interest is in competition, (*ii*) other scholars have already developed strategic theories of government learning (e.g., Carpenter 2004; Volden, Ting, and Carpenter 2008), and (*iii*) allowing learning in the model would dramatically increase its complexity and push the length of this paper well beyond the limits of *The Journal*. Second, to reflect the difficulty of solving the complex spatial problem states face in deciding whether to adopt (Carpenter 2004), we allow for bounded rationality in states' decision-making via a Quantal Response Equilibrium concept.

Our theory translates quite readily to the case of the lottery. The 48 continental American states are the theory's states. Playing the lottery is the target good, and persons living within D miles of a state's border who would like to play the lottery are the state's target individuals. We presume that each state, s, must choose whether to adopt a lottery in each year, t. As in the general theory, we let $X_{s,t}=1$ if state s adopts a lottery, and $X_{s,t}=0$ if it does not. In turn, each interested individual, i, that has access to a lottery (in either i's own state or a neighboring state) must decide whether to play the lottery, and if it is to be played, in which state.[2] For any state, s, the set of neighbors is static; thus we can drop the time subscript from $L_{s,t}$—the subset of states consisting of s's neighbors—and simply write L_s. We equate the payoff to a state with the total revenue it collects (from a lottery or any other source). Therefore, $b_{s,t}^{A}$ denotes the revenue of state s in year t if it adopts a lottery and $b_{s,t}^{\sim A}$ denotes this revenue if s does not adopt a lottery.

Our interest is in understanding strategic incentives of states in adopting lotteries, not in the vicissitudes of population movement, lottery administration, or political pressure. Thus, we simplify our theory in several respects when specializing it to the case of lottery adoptions. First, we assume simplified costs. Two types of costs imposed by a lottery adoption on policy makers are relevant. One is the political cost of adopting a lottery. For example, there may be constituencies who view the lottery as institutionalized gambling and object to it for religious or ethical reasons. This cost is most relevant before s's initial adoption, and is likely to decline rapidly after adoption, as the lottery becomes the new status quo to which people are accustomed. For simplicity, we assume that after a state's adoption the decline in the political cost of adopting is immediate and to zero.

The second cost lies in administering the lottery itself, which is in addition to the usual state tax apparatus. This cost varies with the competitive effort put into the lottery: the amount of advertising done to attract players, and the share of revenues returned to winners. This cost may, however, equivalently be conceived as a reduction in the payoff from the lottery rather than an independent cost, and so to simplify the model, we include a state's cost of administering the lottery as a factor offsetting the revenue to the state if a lottery is adopted, $b^A_{s,t}(X_{L_s,t})$. Thus, political factors that serve as a barrier to an initial adoption of a lottery by s constitute the sole cost we consider in $c_{s,t}$.

We also assume simplified payoff functions. Specifically, we presume that within a given year, s's payoff (i.e., revenue) varies due only to the adoption choices of neighboring states. This requires assuming that interested individuals have constant preferences for lotteries during a year, conditional on the behavior of neighboring states, and that changes in states' populations are small compared to the overall size of these populations.

We assume that states may enact policy only once per year, matching the constraints imposed by legislative sessions in most American states. We also presume that states do not "disadopt" after any adoption of a lottery. This reflects the observation that of the 42 states that have adopted a lottery (since the first adoption by New Hampshire in 1964), none has abandoned it. Finally, we assume that states consider only prior adoptions and the possibility of adoptions in the current year when making decisions. Accordingly, while states are not forward-looking (to future years), they are also not myopic; they behave strategically, attempting to account for other states' responses to their own actions within any given year.[3]

Even with these simplifications, states face a difficult problem in our model. Because all other states' adoption decisions alter its payoffs, each state must consider the expected decisions of all other states. When the number of states grows large, this is a nontrivial problem. To account for the likelihood that states will fail to optimize their behavior with perfect precision, we incorporate bounded rationality in the model: we utilize a Quantal Response Equilibrium (QRE) solution concept that allows for imperfect, though still rational, expectations on other states' behavior. Consequently, each state responds to an equilibrium probability distribution over other states' adoption decisions, and correspondingly engages in equilibrium behavior that assigns a probability to adopting a policy in equilibrium (McKelvey and Palfrey 1995).

In addition to allowing states to make errors in calculation, an advantage of the QRE is that its equilibria are probabilities of adoption rather than point predictions, which offers a better fit with our empirical tests below. The Logit Equilibrium correspondence assigns a probability of adoption,

$$\pi_s = \frac{e^{\lambda u_s^A(\pi)}}{e^{\lambda u_s^A(\pi)} + e^{\lambda u_s^{\sim A}(\pi)}} , \tag{2}$$

to each state, s, where $\pi = (\pi_1,\ldots,\pi_n)$ is the vector of adoption probabilities for all states, λ (≥ 0) is inversely proportional to the level of error in states' utility assessments, and $u_s^A(\pi)$ and $u_s^{\sim A}(\pi)$ are state s's expected utilities for adopting and not adopting, respectively, given all other states' equilibrium behavior. There are no time subscripts in this expression—as it reflects behavior within a year—but the vector π can be calculated for any year to produce probabilities of adoption for that year. The terms in equation (2) can be rearranged to yield the following expression for π_s:

$$\pi_s = \frac{1}{1 + e^{-\lambda \Delta_s(\pi)}} , \tag{3}$$

where $\Delta_s(\pi)$ is the utility gain to s for adopting (relative to not adopting): $u_s^A(\pi) - u_s^{\sim A}(\pi)$. Note that the probabilistic nature of states' actions in equilibrium implies that states' adoptions will be staggered over time. McKelvey and Palfrey (1995) characterize the properties of the Logit

(Quantal Response) Equilibrium correspondence we use here; for our purposes it is sufficient to note that it is well defined.

The expected utilities, u_s^A and $u_s^{\sim A}$, and their difference, Δ_s (the notation for which we simplify by making their dependence on π implicit), grow substantially more complex the more states there are. To simplify the analysis and more cleanly derive theoretical implications, below we will restrict attention to the case in which there are just two states. This simplification makes it so that the regional action vector for each state, *s*, has only two possible values: the other state has not adopted (making *s* a monopoly provider of the lottery), or the other state has adopted. Even though our theory assumes just two states, our hypotheses are generalized to reflect states having multiple neighbors, thereby permitting an empirical test using data from the American states.

An equilibrium of the interaction is a vector $\pi = (\pi_s, \pi_r)$ for which the Logit Equilibrium correspondence holds for all states. Although we are not able to derive a closed-form solution, we are able to derive comparative statics for the model. In particular, we determine the marginal effect of six variables on the probability that one of the states, say *s*, adopts a lottery (π_s): *s*'s cost of adoption (c_s), *r*'s cost of adoption (c_r), and four variables reflecting a state's conditional revenue gain from adopting a lottery. For each state, *i* (= *s* or *r*), let $\delta_i(1) = b_i^A(1) - b_i^{\sim A}(1)$ be *i*'s revenue gain from adopting a lottery when *i*'s neighbor has a lottery, i.e., *i*'s *revenue gain under competition*.[4] Similarly, let $\delta_i(0) = b_i^A(0) - b_i^{\sim A}(0)$ be *i*'s revenue gain from adopting a lottery when *i*'s neighbor does not have a lottery, i.e., *i*'s *revenue gain as a monopoly provider*. We derive the marginal effect on π_s of $\delta_s(0)$, $\delta_s(1)$, $\delta_r(0)$, and $\delta_r(1)$. The precise comparative statics for the model are presented—along with their derivation—in Part I of the on-line appendix. However, we can easily summarize the general results:

- π_s is increasing in $\delta_s(1)$ and decreasing in c_s; $\pi_s(0)$ is additionally increasing in $\delta_s(0)$;
- when $\delta_s(1) > \delta_s(0)$ (i.e., when s's revenue gain from adopting a lottery under competition exceeds its revenue gain from adopting as a monopoly provider), $\pi_s(0)$ is increasing in $\delta_r(1)$ and $\delta_r(0)$, and decreasing in c_r;
- when $\delta_s(0) > \delta_s(1)$ (i.e., when s's revenue gain from adopting as a monopoly provider exceeds its revenue gain under competition), $\pi_s(0)$ is decreasing in $\delta_r(1)$ and $\delta_r(0)$, and increasing in c_r.

Some comparative statics are not surprising. s's probability of adopting a lottery decreases with its cost of adoption, and rises with the amount of revenue it would gain by adopting (both when its neighbor has a lottery and when its neighbor does not). The effects of the cost and revenue characteristics of s's neighbor on s's probability of adoption depends on s's revenue gain from adopting a lottery under competition relative to its revenue gain from adopting as a monopoly provider. When s's revenue gain from adopting under competition exceeds its revenue gain as a monopoly provider, s's probability of adoption increases with the variables that increase its neighbor r's probability of adoption (r's cost and revenue gain from adoption). When s's revenue gain from adopting as a monopolist exceeds its revenue gain under competition, s's probability of adoption decreases with the variables that increase r's probability of adoption (r's cost and revenue gain from adoption).

Additional Assumptions About Lottery Competition

The previous section uses our strategic theory of diffusion via competition specialized to the case of the lottery to derive comparative statics concerning the effects of several variables on s's probability of adoption, π_s. In the next section, we derive expectations that form the basis for an empirical test of our theory. In order to derive these expectations, however, it is necessary to make some additional assumptions about the nature of competition between states. These assumptions help us connect states' revenue gains from adopting—the variables in the comparative statics—to suitable empirical proxies. We assume that interested individuals—those interested in playing the lottery—constitute the same share of the adult population in any region of either state, and that interested individuals are differentiated only by their cost of playing the lottery, which earlier we assumed increased with the distance required to play. This implies in particular that all individuals who choose to play "consume" equal quantities of the lottery, and no particular individual is more valuable to a state as a player than others. We also assume that in each state with a lottery, the density of locations at which to play is sufficiently great for the distance required for any state resident to play to be effectively zero. Thus, an individual must travel (*i*) no distance to play her own state's lottery, and (*ii*) her distance to the border with the other state to play a lottery in that state.

We presume that when both *s* and *r* have lotteries, these states compete over lottery sales among the border populations in both states via some combination of increased payouts to winners and/or advertising (Brown and Rork 2005; Garrett and Marsh 2002). Increased competition decreases both states' lottery revenue, and thus their conditional revenues given that both have adopted: $b_s^A(1)$ and $b_r^A(1)$. We assume that each state's decision about whether to adopt takes into account its willingness to compete, a willingness presumed to be captured by a single index reflecting the state's level of competitive effort: E_i ($i = s, r$).

These additional assumptions imply that the closer is an individual in one state (say *s*) to the states' shared border, the more costly it is for *s* to secure that individual's lottery play, and so the less incentive *s* has to compete over her play. Thus, in any competitive equilibrium in which states choose levels of competitive effort, there must be a cutline: a line that separates those that play the lottery in *s* from those that play the lottery in *r*. Since *D* denotes the maximum distance someone would travel to play the lottery, this cutline must be within *D* miles from the states' shared border, on one side or the other. Increasing a state's competitive effort may shift this line toward the other state, but adding another individual to the border region does not affect a state's revenue loss due to competition, unless it or its neighbor responds to this addition with a higher competitive level. Finally, we assume that $\delta_i(0) > \delta_i(1)$ for each state, i.e., each state's revenue gain from adopting when its neighbor does not have a lottery exceeds its revenue gain from adopting when its neighbor has a lottery. Substantively, this means that states' incentives to become monopoly lottery providers are greater than their incentives to enact a competitive lottery.[5]

Expectations from the Lottery Competition Model

One expectation derived from our theory is immediately evident from the comparative statics, since they indicate that regardless of whether *r* has adopted, increasing *s*'s cost of adoption decreases *s*'s probability of adoption:

> <u>Cost Hypothesis</u>: The probability that a state will adopt a lottery is negatively related to its cost of adoption.

The comparative statics regarding conditional revenue gains (i.e., the $\delta_i(\cdot)$ terms) are not directly useful for generating testable expectations because we cannot observe these variables—or even suitable proxies for them. However, the spatial distribution of population in *r* and *s* yields valuable information about the implications of a lottery on the states' revenues. For example, an increase in the proportion of the population in *s* living near *r* should reduce *s*'s revenue when *r* has a lottery but *s* does not have one, due to more residents of *s* playing *r*'s lottery. But this border population proportion should have no impact whatsoever on *s*'s revenue when *r* has no lottery. As a result, our theory yields expectations about the effects on *s*'s probability of adoption of the proportions of populations in *s* and *r* living close to their borders, and these populations can be observed directly.

First, assume *r* has a lottery but *s* does not. In this situation, *r* is able to "poach" revenue from *s*. This happens because some interested individuals in *s'*s border region, not being able to play at home, play *r*'s lottery, yielding revenue for *r*. Since a lottery is frequently a substitute for other goods subject to sales taxes, particularly entertainment (Kearney 2005; Borg, Mason and Shapiro 1993), *s* loses sales tax revenue. Even if *s* has no sales tax, the decline in spending contracts the state economy, decreasing *s*'s income tax revenue. Either way, *s*'s revenue declines. Moreover, the greater the share of *s*'s population near *r*, the greater the proportion of *s*'s residents that may cross the border to play, and thus the greater the incentive for *s* to adopt a lottery *defensively* to minimize the revenue loss.[6] This leads to our first expectation about the impact of border population on the probability of adopting a lottery:

> <u>Defensive Competition Expectation</u>: If *r* has a lottery, the probability that *s* will adopt one is positively related to the proportion of its adult population within *D* miles of *r* (and thus with access to r's lottery).

Assume instead that neither *r* nor *s* has a lottery. Now, if *s* adopts one but *r* does not, *s* would be able to poach revenue from *r* because some interested residents of *r* near *s*, not having a lottery available in *r*, would cross the border and play in *s*. Furthermore, the greater the population in *r* near the border with *s* (relative to the size of *s*'s population), the greater would be *s*'s revenue gain from adopting, and thus the greater *s*'s incentive adopt a lottery *offensively* to poach revenue from *r*.[7] This generates a second expectation regarding the impact of border population on the probability of adoption:

Offensive Competition Expectation: If *r* does not have a lottery, the probability that *s* will adopt one is positively related to the number of adults in *r* who are within *D* miles of *s* relative to the adult population of *s*.

Continue to consider the situation in which neither *r* nor *s* has a lottery, this time examining the implications of an increase in the share of *s*'s population near the border with *r*. Just as *s* would be able to poach revenue from *r* if *s* were to adopt a lottery and *r* did not, *r* would be able poach from *s* if *r* became a monopoly lottery provider. The reasoning underlying the Offensive Competition Expectation implies that as the share of *s*'s population near the border with *r* rises, *r*'s probability of an "offensive" adoption designed to poach from *s* increases. In turn, *s* anticipates *r*'s increased probability of adoption, and recognizes that it has less chance of becoming a monopoly lottery provider, leading to a decline in *s*'s probability of adoption.[8] The greater the share of *s*'s population near the border with *r*, the more this anticipatory consideration becomes important to *s*, and so the smaller *s*'s incentive to adopt a lottery. Thus, our theory generates a third expectation about the impact of border population:

Anticipatory Competition Expectation: If *r* does not have a lottery, the probability that *s* will adopt one is negatively related to the proportion of its adult population within *D* miles of *r* (i.e., the proportion of *s*'s population that would have access to a lottery in *r* if *r* were to adopt one).

Constructing Hypotheses for an Empirical Test Using the American States

To test our theory of diffusion via competition specialized to the case of lottery adoptions, we must modify the expectations about competition derived in the previous section to construct analogous hypotheses about a multi-state system while retaining the fundamental logic underlying the expectations. For example, the Defensive Competition Expectation states that if *r* has a lottery, *s*'s probability of adopting one is positively related to the proportion of *s*'s population near *r*, and thus having access to *r*'s lottery. The independent variable is designed to reflect *s*'s potential to gain revenue by adopting a lottery, thereby allowing its border residents to stay home to play rather than go across the border. An analogue to this independent variable when *s* has multiple neighboring states should measure precisely this concept, but be sensitive to all neighbors with a lottery having population near the border of *s*. In particular, we base our measure on the proportion of *s*'s population near any neighbor having a lottery, which yields a hypothesis that can be tested using data for the 48 contiguous states:

> <u>Defensive Competition Hypothesis</u>: The probability that a state will adopt a lottery is positively related to the proportion of its adult population with access to another state's lottery (i.e., the proportion of its adult population living within *D* miles of another state with a lottery).[9]

The shaded region in Figure 1a depicts the population referenced by the independent variable in this hypothesis—***Defensive Competition***—for a hypothetical state, S, with no lottery, and within *D* miles of five states, three of which have a lottery (T, U and W) and two of which do not (R and V). Note that the shaded region is obtained by forming a band of width *D* internal to the border of state S, but excluding those sections of the band that are not within *D* miles of a state with a lottery. The most extreme southeast corner of state S is in the shaded region by virtue of being within *D* miles of nearby (but nonadjacent) state W.

In similar fashion, we modify the other two competition expectations to apply to the multi-state setting, yielding:

> <u>Offensive Competition Hypothesis</u>: The probability that a state, *s*, will adopt a lottery is positively related to the number of adults in other states who (*i*) do not have access to a

lottery but (*ii*) would have access to a lottery in *s*, relative to the adult population of *s* (i.e., the number of adults in other states without lotteries who live within *D* miles of *s* but not within *D* miles of any other state with a lottery, relative to the adult population of *s*).

Anticipatory Competition Hypothesis: The probability that state *s* will adopt a lottery is negatively related to the proportion of its population that (*i*) does not have access to any state's lottery, yet (*ii*) lives close enough to another state to provide access to that state's lottery if it were to adopt (i.e., the proportion of its adult population living within *D* miles of another state without a lottery but not within *D* miles of any state with a lottery).

The shaded region in Figure 1b illustrates the population relevant to the independent variable in the Offensive Competition Hypothesis—***Offensive Competition***—for the same hypothetical state, S, examined in Figure 1a. To get the shaded region, we form a band of width *D* external to the border of state S, but we exclude those sections of the band that are within states that have lotteries or are less than *D* miles from another state with a lottery. Thus, the shaded region includes all adults from other states living near S who lack close access to a lottery.[10] The shaded area in Figure 1c depicts the population referenced by the independent variable in the Anticipatory Competition Hypothesis: ***Anticipatory Competition***. To obtain this shaded region, we form a band of width *D* internal to S's border, but we exclude those sections of the band that are less than *D* miles from another state with a lottery.

Empirical Analysis

We test the hypotheses generated by our strategic theory of competition-driven policy diffusion using a discrete-time event history analysis (EHA) model in which the observed dependent variable is whether or not a state adopts a lottery in a year (1=yes, 0=no), and each state is removed from the risk set upon its adoption. Our period of analysis is 1964 (the year the first state, New Hampshire, adopted a lottery) through 1986. This period conforms to the previous empirical analyses conducted by Berry and Berry (1990) and Berry and Baybeck (2005). It also excludes from analysis the era—beginning in 1987—in which states began to band together to create multi-state games (like Powerball), thereby complicating the dynamics of state interaction. Thus, we limit empirical analysis to a period in which it is clear that individual states are distinct actors in the diffusion process.

Our theory restricts the concept of the cost of adoption (c_s) to political factors that serve as a barrier to an initial adoption. We measure a state's *cost of adoption* with several variables used by Berry and Baybeck (2005, 516) and Berry and Berry (1990): the percentage of its population adhering to fundamentalist religions, the fiscal health of the state (both assumed to be directly related to cost), per capita income, and the proximity to gubernatorial elections (both assumed to be inversely related to cost).

Although Berry and Baybeck (2005) do not speak of a "Defensive Competition Hypothesis," their primary independent variable—"the degree of concern of a state about residents going to other states to play the lottery"—is equally valid as an indicator of *Defensive Competition*. Thus, we use Berry and Baybeck's measure without modification.[11] Because of uncertainty about the maximum number of miles someone would travel to play the lottery (D), we also emulate Berry and Baybeck's choice to estimate all models using four different values for D (100, 150, 160 and 170); for each value of D, we assume a gradual decline in the propensity of an individual to travel to another state to play the lottery as distance increases, with the rate of decline steepest at a distance of zero and declining in magnitude as distance rises. Berry and Baybeck's (2005) Figure 4 (reproduced in Part III of the on-line appendix) shows the exact assumed functional relationship between distance and propensity to travel for each value of

D, and makes evident that the four functions reflect quite different assumptions about the nature of the relationship between distance and propensity to travel.

Consider the procedure for measuring *Defensive Competition* when applied to state S in Figure 1a. For each adult, *i*, in the shaded region, GIS is used to determine the distance, d_i, of that person from the nearest state with a lottery.[12] This distance is converted to a "propensity score" (indicating the propensity to play that state's lottery). Finally, the ultimate variable of interest is computed by adding up propensity scores over all adults in the shaded region, and dividing the sum by the adult population of S.

To measure *Offensive Competition* and *Anticipatory Competition*, we adapt Berry and Baybeck's GIS procedure to the population of concern in the hypothesis, assigning a propensity score to each adult in the population of concern based on his distance from the relevant state border. For example, for *Offensive Competition*, when observing state *s* we need to measure the number of adults in other states without lotteries who live within *D* miles of *s* but not within *D* miles of any other state with a lottery, relative to the adult population of *s*. To illustrate our measurement procedure, we consider state S in Figure 1b. For each adult, *i*, in the shaded region we use GIS to calculate the distance, d_i, of that person from S. This distance is then transformed to a propensity score (reflecting the propensity to play S's lottery). Finally, we sum propensity scores over all adults in the shaded region, and divide the sum by the number of adults in S, yielding the ultimate measure of interest.

Our theory of policy diffusion is a pure competition model in which no interstate learning occurs. Yet learning may be an alternative explanation for the diffusion of the lottery across the American states, and thus, it is important that our empirical analysis controls for the possibility of learning. We examine two types of learning hypothesized to occur in the literature on lottery diffusion. We specify regional learning—i.e., learning from neighboring states—using a variable originally used by Berry and Berry (1990) and later adopted by Berry and Baybeck (2005): the number of previously-adopting neighboring states. We specify ideologically-based learning—in which states learn from ideologically-similar states—with Grossback, Nicholson-Crotty and Peterson's (2004) measure of "ideological distance" (between a potential lottery adopter and those states that have previously adopted). We estimate models including the two learning variables—both separately and together—but we save space by reporting coefficient estimates only for the specification including just the neighbors variable.[13] Yet importantly, as we clarify below, the empirical results regarding the competition hypotheses prove robust to changes in the specific learning variables included in the model.

In sum, our empirical models include three competition variables (reflecting the Defensive Competition, Offensive Competition, and Anticipatory Competition Hypotheses), several variables assumed to measure the cost of adoption ($c_{s,t}$), and one or two variables reflecting a form of learning. We also include a time counter to allow for duration dependence. We estimate the model—assuming each of the four relationships between distance to the state border and the propensity to travel to another state to play the lottery described above—using probit and clustering by state.

Table 1 reports our results. It presents the probit maximum likelihood estimates (MLEs) for the independent variables. Not surprisingly, our findings about the effects of the cost of adopting a lottery closely mirror those reported by Berry and Berry (1990) and Berry and Baybeck (2005). There is evidence—consistent with expectations—that the probability that a state without a lottery will adopt one increases with decreases in (*i*) the fiscal health of the state, and (*ii*) the proportion of the state's population adhering to fundamentalist religions. Also, this probability of adoption is greater in gubernatorial election years—at the time a governor should derive maximum political advantage from adopting a generally popular lottery—than in other years in the electoral cycle.[14]

There is no empirical evidence that the lottery diffuses as a consequence of states learning from their neighbors. In contrast, there is consistent evidence that states learn from ideologically similar states, mirroring the findings of Grossback, Nicholson-Crotty and Peterson (2004), whose model does not specify competition among states. The coefficient for ideological distance is negative, as predicted, and statistically significant at the .05 level, whether ideological distance is included alone or along with number of previously adopting neighbors (see Part IV of the on-line appendix).

Our main focus, however, is on the results pertaining to our three hypotheses about competition among states, for which we find substantial support. Of the 12 probit MLEs for competition variables in Table 1 (each in a non-italicized font), all carry the predicted sign (positive for *Defensive Competition* and *Offensive Competition*, negative for *Anticipatory Competition*). Eight of the 12 estimates are statistically significant at the .10 level—two for *Defensive Competition*, and three each for the *Offensive* and *Anticipatory* variables.[15]

To better understand the strength of lottery competition among states, we use the probit MLEs in Table 1 to compute for each competition variable the estimated change in the probability of a lottery adoption when the variable is increased from its 5th percentile value in the sample to its 95th, and all remaining independent variables are fixed at their mean. These first differences in the probability of adoption are in bold italics in the table. Assuming the relationship between distance and propensity to travel for which D = 160 miles, when *Anticipatory Competition* is increased from its 5th to its 95th percentile, the probability that the state will adopt a lottery in a year decreases by 0.031, a value statistically significant at the .05 level. When *D* is assumed to be 100, 150 or 170, the corresponding estimated declines in the probability of an adoption are 0.006, 0.016 and 0.031, respectively. Thus, there is more than trivial variation in the magnitude of the estimated effect across the different assumed relationships between distance and the propensity to travel. Given that there is no clear theoretical or empirical justification for believing that one assumption about this relationship is more likely to be correct than the rest, we should not place a great deal of faith in interpretations of specific point estimates of the magnitude of effects. The average of the four estimated declines in the probability of adoption—which is 0.021—may more suitably reflect the coefficient for *Anticipatory Competition* than any of the four alone.

Next consider the Defensive Competition Hypothesis. Assuming the distance-propensity relationship for which *D* = 100 miles, when a state's value for *Defensive Competition* is increased from its 5th to its 95th percentile, the state's probability of adopting a lottery in a year increases by 0.012. When *D* is assumed to be 150, 160 or 170, the corresponding increases in the probability of an adoption are 0.014, 0.013 and 0.010, respectively. Although these estimates show far less sensitivity to variation in the assumed distance-propensity relationship than estimates of the coefficient for *Anticipatory Competition*, the mean of these four estimated effects—0.012—is our most reasonable estimate of the magnitude of the coefficient for *Defensive Competition*.

Finally, our results indicate that with any of the four assumed distance-propensity relationships, when a state's value for *Offensive Competition* is increased from its 5th to its 95th percentile, the probability of a lottery adoption in a year increases by either 0.005 or 0.004. Although such changes in probability may seem small, it should be noted that lottery adoptions are rare events: across the full set of state-years analyzed, the overall probability that a state without a lottery will adopt one in a year is just 0.030. Given this small overall probability, the estimated coefficient for *Offensive Competition* should not be deemed of trivial magnitude.

Conclusion

In recent years, state politics scholars have advanced the study of policy diffusion significantly by moving past the dominant empirical focus of the last two decades—"Does policy diffuse?"—to ask *why* diffusion occurs. One frequently proposed answer—advanced in a variety of policy contexts—is that polices diffuse due to interstate competition. Yet, the empirical tests of the proposition that states compete have modeled the diffusion process in ways that fail to recognize the *strategic* nature of interaction among governments, i.e., that a government's decision about whether to adopt a policy takes into account not only the current policies in other states, but also its beliefs about how these other states will respond to their own incentives. We confront this weakness of extant research by developing a spatially-explicit strategic theory of competition-driven policy diffusion. We apply the theory to analyze the diffusion of the lottery across the American states, and our empirical test of the hypotheses generated by the theory in this context offers considerable support for the theory.

Consistent with findings in much previous research on the lottery, this theory implies that a state has a *defensive* motivation to adopt a lottery to prevent a loss of revenue occurring when residents play the lottery in nearby states. This motivation leads to a state having a high probability of adoption when a large proportion of its residents have close access to other states' lotteries. The theory, too, predicts that a state has an *offensive* motivation to adopt—largely ignored in extant research—to try to lure residents of other states across the border to play. This motivation gives a state a high probability of adoption when there are a large number of other states' residents without access to a lottery near its border. Finally, our theory implies that the probability that a state will adopt a lottery decreases with the extent to which it *anticipates* that nearby states are likely to adopt. One manifestation of this is that a state's probability of adoption declines as the share of its total population that is near another state without a lottery increases, because this large border population encourages an offensively-motivated adoption by neighboring states. Our results show that American states compete against one another in a more sophisticated fashion than previous scholars have recognized. When choosing whether to adopt a lottery, states appear to behave as strategic rational actors, balancing the expected revenue from a lottery—from both residents of their own states and residents of others—against the expected cost of adoption, and acting as if they understand the linked decisions that all states face.

Although our empirical analysis is limited to the case of lottery adoptions, we believe that our strategic theory of diffusion via competition is more widely applicable, since many policy choices made by governments (national, state and local) influence "location choices" made by persons or firms, which in turn have positive or negative consequences for the governments. Thus, our theory can be specialized to a variety of policy contexts, thereby permitting additional empirical tests of the theory. For example, the theory may apply—without major modification—to choices by American states about (*i*) whether to allow casino gambling, (*ii*) the level of the gasoline tax, and (*iii*) the welfare benefit level; and choices by states or cities about whether to ban smoking in restaurants. In these policy contexts, the interested individuals are persons, and the travel distance required to acquire the target good would continue to be a reasonable proxy for the cost to interested individuals of acquiring the good.

Our theory should also be applicable to situations in which the interested individuals are firms (seeking subsidies and lax regulation), and governments (states in the U.S., as well as countries) compete to retain and attract these firms. In many such contexts, however, the theory's spatial constraints on the location choices of interested individuals would need to be relaxed. Although it would continue to make sense that firms would make location choices by weighing the costs and benefits of relocation, for firms in many industries, distance would no longer be the principal determinant of the cost of acquiring the target good. Indeed, it may be cheaper for a company to build a factory in a distant state having low construction or labor costs than to build in a nearby state with higher construction or labor costs. Accordingly, a government's neighbors—those governments competing over the same firms—would not be restricted to nearby jurisdictions.

Although we believe that the strategic theory of policy diffusion via competition we develop is a significant step in better understanding the diffusion process, far more remains to be done. Both the costs and the payoffs of adoption are likely to be subject to great uncertainty, and a more complete diffusion model would acknowledge this explicitly, taking into account incentives for learning as well as competition. We expect that strategic issues such as the value of waiting for other states to act first would become relevant in this fuller model (Carpenter 2004; Volden, Ting, and Carpenter 2008). On the empirical front, our results about lottery competition could be enhanced if better information were available about the distance individuals are willing to travel to play the lottery. We confront the lack of accurate information by assessing the robustness of our results to a variety of plausible assumptions about the relationship between distance and propensity to play the lottery, but reliable information about the true relationship—perhaps derived from consumer surveys—would clearly result in superior tests of our hypotheses.

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Notes

[1] The theory we present assumes that diffusion occurs solely due to competition. A more complex model, beyond the scope of this paper, would assume multiple mechanisms for diffusion—for example, that states both compete with, and learn from, each other.

[2] The applicability to the case of the lottery of the assumption that interested individuals' willingness to acquire the target good is a decreasing function of the travel distance required is well established (Berry and Baybeck 2005).

[3] We also developed a model in which states look forward one period. Since the empirical hypotheses derived from this model are very similar to those below, but the model is much more complex, we opt for the simpler formulation.

[4] The "1" as an argument in $\delta_i(\cdot)$, as well as in other parameters below, indicates the condition that *i*'s neighbor, *r*, has previously adopted; an argument of "0" denotes the condition that *r* has not adopted. Despite the terminology "under competition", *r*'s lottery would subject *s* to competition only if there were people in *s* or *r* living within *D* miles of their shared border.

[5] Part II of the on-line appendix presents precise formal definitions of these and other technical assumptions on competition required for the expectations introduced in the next section to hold.

[6] To be precise, the revenue of *s* declines with an increase in the share of *s*'s population near *r* *regardless of whether s adopts a lottery*. However, as we show in Part II of the on-line appendix, the resulting decline in *s*'s revenue is smaller when *s* adopts a lottery than when *s* does not. Thus, the intuition for the Defensive Competition Expectation (introduced below) holds.

[7] In Part II of the on-line appendix, we show that given certain technical assumptions, even if *r* were to adopt a lottery in the same time period as *s*, so that *s* would not be a monopoly provider and would instead need to compete with *r* for lottery sales near their shared border, *s*'s expected

revenue gain from adopting when *r* has no lottery would grow with an increase in the population on *r*'s side of the border.

[8] For this to be true, *s*'s incentive to become a monopoly lottery provider must be sufficiently strong. We provide a formal definition of "sufficiently strong" in Part II of the on-line appendix, via conditions that specify when our Offensive and Anticipatory Competition Expectations hold.

[9] (1) While we refer to "the proportion of [*s*'s] adult population living within *D* miles of another state with a lottery," our empirical analysis utilizes a more sophisticated measure of this variable (and others included to test additional competition hypotheses introduced below) that weights individuals living right at the border of a state having a lottery maximally and weights those at greater distances less—thereby recognizing the gradual decline in willingness to play a lottery as the distance required to purchase a ticket increases. (2) Note that our Defensive Competition Hypothesis is equivalent to Berry and Baybeck's (2005, 507) "lottery competition hypothesis." (3) To avoid confusion, we label predictions of our theory that are tested empirically *hypotheses*, and those that are untested *expectations*.

[10] There are some complications—with no perfect solutions—when testing our theory when states have more than one neighbor. For example, in Figure 1b, S has some incentive to adopt a lottery to attract people living slightly east of S and slightly north of the shaded region of V, since they are closer to S than to T. However, we do not count these persons when measuring the independent variable in the hypothesis since they are less "poachable" than persons in the shaded region, who do not have access to any lottery.

[11] In this paper, we summarize the measurement procedure; more detail can be found in Berry and Baybeck (2005, 507-09).

[12] Since individual-level data are unavailable, in practice, we must employ county-level data. Our procedure assumes that all persons in a county reside at its geographic center.

[13] The neighbors variable has stronger correlations with our three competition variables than does ideological distance. Thus, for the purpose of minimizing the possibility of bias in the estimation of coefficients for the competition variables, the more important learning variable to include in our model is the neighbors measure.

[14] Unlike Berry and Berry (1990), we find that state per capita income has no statistically significant effect on the probability of an adoption.

[15] When ideological distance is substituted for number of previously adopting neighbors, or when both the neighbors variable and ideological distance are included in models, seven of the 12 estimates are statistically significant at the .10 level and with the predicted sign (*Defensive Competition* when D = 100; *Offensive Competition* and *Anticipatory Competition* when D = 150, 160 or 170) (see Part IV of the on-line appendix).

The values of probit coefficients for the four measures of one of the competition variables are not comparable since the metrics for the measures are different, but it is evident that the Z-scores for the competition variables vary markedly across the four assumed relationships between the distance of an individual from the nearest state border and her propensity to travel to another state to play the lottery. This variation in Z-scores is not surprising given the substantial differences among the four assumed relationships (see Part III of the on-line appendix).

In practice, the variation in Z-scores depending on the assumed relationship between distance and the propensity to travel seems due to the presence of four observations—those for New York—in which *Anticipatory Competition* scores diverge dramatically depending on the value chosen for D. This occurs because three counties with very large populations—Queens, Kings (which contains Brooklyn), and New York (which contains Manhattan)—drop out of the shaded region for calculating *Anticipatory Competition* when *D* is greater than 150 due to relatively unique geographical circumstances. Indeed, when New York's four observations are excluded from the analysis, eleven of the twelve probit coefficients for competition variables in Table 1 (all but the one for *Defensive Competition*/*D* = 160) become statistically significant in the hypothesized direction.

FIGURE 1 Schematic Depiction of the Border Populations Referenced in the Three Competition Hypotheses

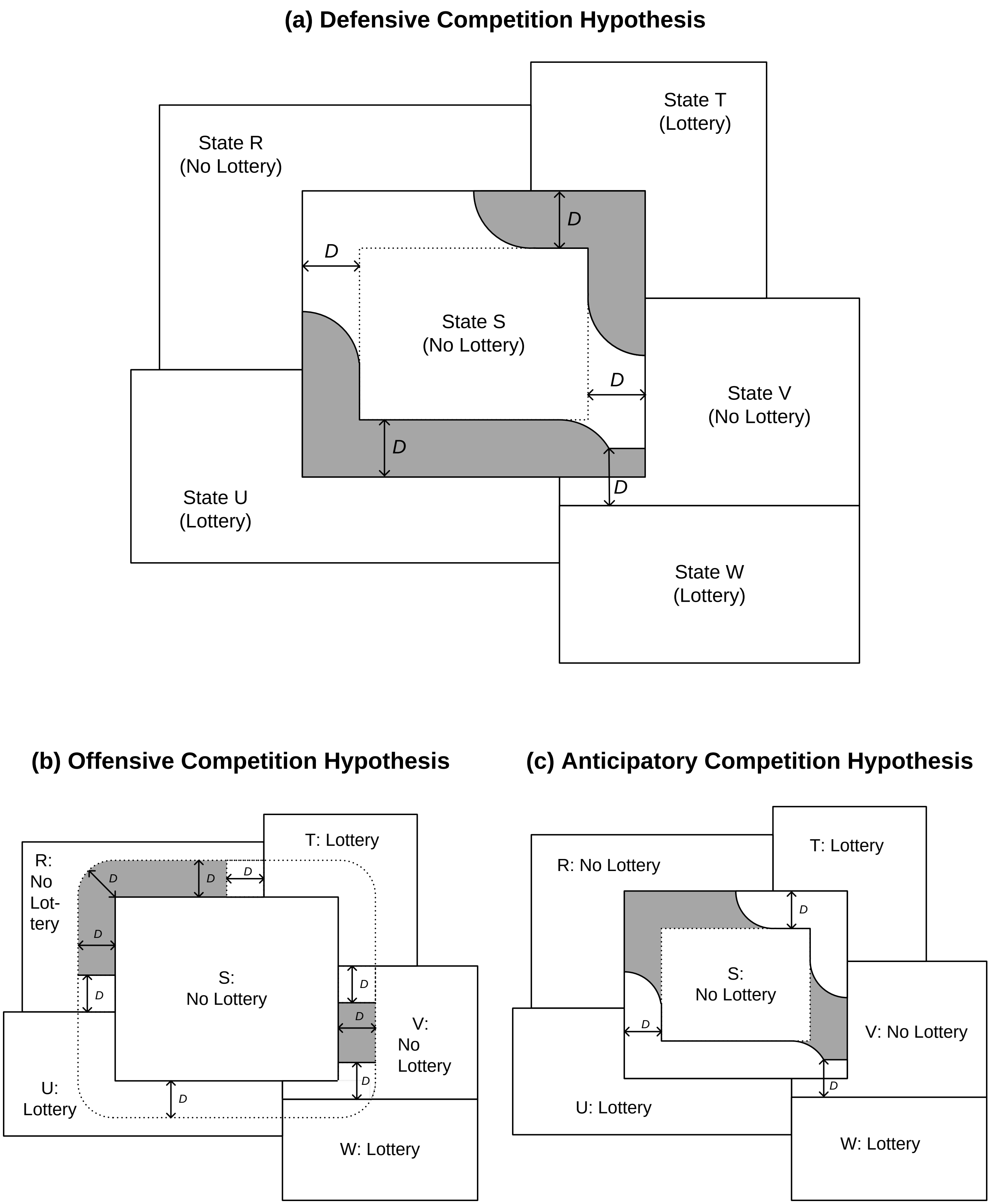

Table 1. Probit Results for Testing the Strategic Model of Lottery Adoptions

Assumed value of *D*:	100	150	160	170
Independent Variable				
Diffusion Variables				
Competition Variables				
Defensive Competition	1.61***	1.18*	0.72	0.33
	(2.56)	(1.64)	(1.01)	(0.47)
	0.012	***0.014***	***0.013***	***0.010***
	[*.001, .037*]†	**[-*.002, .059*]**	**[-*.004, .071*]**	**[-*.006, .070*]**
Offensive Competition	0.43	0.28*	0.38**	0.30**
	(0.66)	(1.37)	(2.23)	(2.01)
	0.004	***0.005***	***0.005***	***0.005***
	[-*.009, .023*]	**[-*.003, .020*]**	**[*.000, .018*]**†	**[*.000, .015*]**†
Anticipatory Competition	-1.02	-1.58*	-2.33***	-1.92***
	(-0.53)	(-1.46)	(-2.84)	(-2.57)
	-0.006	***-0.016***	***-0.031***	***-0.031***
	[-*.043, .030*]	**[-*.054, .006*]**	**[-*.087, -.005*]**†	**[-*.087, -.005*]**†
Regional Learning	-0.05	-0.14	-0.20	-0.15
	(-0.35)	(-0.83)	(-1.11)	(-0.83)
Cost Variables				
Gubernatorial election year? (1=yes, 0=no)	0.77**	0.76**	0.81**	0.80**
	(2.21)	(2.13)	(2.29)	(2.29)
Neither election year nor year after an election? (1=yes, 0=no)	0.56*	0.56*	0.60*	0.60*
	(1.57)	(1.49)	(1.63)	(1.63)
Per capita income	0.008	0.005	0.003	0.003
	(0.90)	(0.58)	(0.29)	(0.36)
Fiscal health	-2.86***	-2.67**	-2.45**	-2.48**
	(-2.39)	(-2.21)	(-1.95)	(-1.95)
Prop. of population adhering to fundamentalist religions	-0.058***	-0.057***	-0.060***	-0.062***
	(-2.48)	(-2.44)	(-2.39)	(-2.43)
Time counter	0.082***	0.088***	0.098***	0.095***
	(3.24)	(3.02)	(3.22)	(3.21)
Constant	-3.98***	-3.65***	-3.28***	-3.22***
	(-4.69)	(-4.20)	(-3.49)	(-3.32)
Observations	901	901	901	901

Notes: Values not in italics are probit parameter estimates, with *Z*-statistics based on robust standard errors (obtained using the probit procedure in Stata 9) in parentheses below. Values in bold italics are estimated changes in the probability of a lottery adoption associated with an increase in an independent variable from the 5th to the 95th percentile when all other independent variables are held at their mean [obtained using Clarify 2 (Tomz, Wittenberg and King 2003)], with 95% confidence intervals in parentheses below.

*$p < .10$, **$p < .05$, ***$p < .01$ (one tailed)

†$p < .05$ (two tailed); i.e., 95% confidence interval excludes zero.

On-Line Appendix

for

"A Strategic Theory of Policy Diffusion Via Intergovernmental Competition"

Brady Baybeck
William D. Berry
David A. Siegel

Part I

Derivation of Comparative Statics for the Lottery Competition Model and a Continuous Time Model of States' Utilities

We begin this part of the appendix by deriving comparative statics for our strategic theory of policy diffusion specialized to the case of lottery adoptions for a two-state (*r* and *s*) system. In particular, we determine the marginal effect of six parameters on the probability that one of the states, say *s*, adopts a lottery (π_s): *s*'s cost of adoption (c_s), *r*'s cost of adoption (c_r), and four variables reflecting a state's conditional revenue gain from adopting a lottery: $\delta_s(0)$ [*s*'s revenue gain as a monopoly provider], $\delta_s(1)$ [*s*'s revenue gain under competition], $\delta_r(0)$ [*r*'s revenue gain as a monopoly provider], and $\delta_r(1)$ [*r*'s revenue gain under competition]. To derive comparative statics, we begin by separating the problem into two distinct scenarios from the point of view of one of the states, say *s*. The first is that *s*'s neighbor, *r*, has previously adopted; the second is that *r* has not adopted.

Consider the first scenario, in which *r* has adopted a lottery in a previous period. Since we have assumed that *r* cannot "disadopt," the only decision belongs to *s*, and *s*'s choice is fairly simple. Given equation (3), which writes π_s as a function of Δ_s, specifying $\pi_s(1)$ requires only that we derive $\Delta_s(1)$.

When *r* has already adopted, the change in utility for adopting, $\Delta_s(1)$, takes a particularly simple form:

$$\Delta_s(1) = [b_s^A(1) - c_s] - b_s^{\sim A}(1) = b_s^A(1) - b_s^{\sim A}(1) - c_s = \delta_s(1) - c_s. \tag{A1}$$

Comparative statics are easy to compute in this case, and yield an unsurprising result. Since $\Delta_s(1) = \delta_s(1) - c_s$, *s*'s utility gain from adopting [$\Delta_s(1)$] is increasing in its revenue gain from adopting [$\delta_s(1)$] and decreasing in its cost of adoption (c_s). It follows from equation (3) that *s*'s probability of adopting is also increasing in $\delta_s(1)$ and decreasing in c_s.

The problem is more complex when *r* has not yet adopted. Now *s* must not only worry about its own gains and losses; it must anticipate *r*'s adoption decision, since the states' decisions are coupled. Formally, we can write

$$\begin{aligned}
\Delta_s(0) &= [\pi_r(0)\, b_s^A(1)] + [(1 - \pi_r(0))\, b_s^A(0)] - c_s - [\pi_r(0)\, b_s^{\sim A}(1)] - [(1 - \pi_r(0))\, b_s^{\sim A}(0)] \\
&= b_s^A(0) - b_s^{\sim A}(0) - c_s + \{\pi_r(0)[b_s^A(1) - b_s^{\sim A}(1) - (b_s^A(0) - b_s^{\sim A}(0))]\} \\
&= \delta_s(0) + \pi_r(0)[\delta_s(1) - \delta_s(0)] - c_s \\
&= [1 - \pi_r(0)]\, \delta_s(0) + \pi_r(0)\delta_s(1) - c_s
\end{aligned} \tag{A2}$$

A similar equation may be written for $\Delta_r(0)$, with *r* and *s* subscripts flipped. Due to the dependence of $\pi_s(0)$ on $\pi_r(0)$, and vice versa, when trying to discern how the probability of adoption varies with the revenue parameters (b_i^A and $b_i^{\sim A}$) it is necessary to understand not only the direct effect of parameter variation on the probability of adoption, but also the indirect effect arising from a change in the other state's probability of adoption. This reflects the strategic nature of the interaction.

Simple inspection of equation (A2) indicates that the direct effect of increasing each of $\delta_s(1)$ and $\delta_s(0)$ is to increase $\Delta_s(0)$, which in turn—by equation (3)—increases $\pi_s(0)$, while the direct effect of increasing c_s is to decrease this probability. But this does not take into account changes in the equilibrium value of $\pi_r(0)$. As $\delta_s(1) - \delta_s(0)$ is multiplied by $\pi_r(0)$ in equation (A2), there are four cases to consider: (*i*) $\delta_s(1) - \delta_s(0) > 0$, $\delta_r(1) - \delta_r(0) > 0$; (*ii*) $\delta_s(1) - \delta_s(0) < 0$, $\delta_r(1) - \delta_r(0) < 0$; (*iii*) $\delta_s(1) - \delta_s(0) > 0$, $\delta_r(1) - \delta_r(0) < 0$; and (*iv*) $\delta_s(1) - \delta_s(0) < 0$, $\delta_r(1) - \delta_r(0) > 0$.[1] We analyze each in order.

In case (*i*), an increase in $\pi_s(0)$ increases $\pi_r(0)$, which increases $\pi_s(0)$, and so on. Formally, this means that the game played by the two states has strategic complementarities, which implies that equilibrium values of $\pi_s(0)$ and $\pi_r(0)$ are both increasing in any parameter that increases either one. In fact, increasing each of $\delta_s(1)$, $\delta_s(0)$, $\delta_r(1)$, and $\delta_r(0)$, and decreasing either c_s and c_r increases both $\pi_s(0)$ and $\pi_r(0)$ in equilibrium.[2]

In case (*ii*), an increase in $\pi_s(0)$ decreases $\pi_r(0)$, which increases $\pi_s(0)$, and so on. By the same logic as in the previous case, an increase in $\delta_s(1)$ or $\delta_s(0)$, or a decrease in c_s, increases equilibrium values of $\pi_s(0)$ and decreases equilibrium values of $\pi_r(0)$. Similarly, increasing $\delta_r(1)$ or $\delta_r(0)$, or decreasing c_r, decreases equilibrium values of $\pi_s(0)$ while increasing equilibrium values of $\pi_r(0)$.

This same logic does not hold in the remaining two cases. For example, in case (*iii*), an increase in $\pi_s(0)$ decreases $\pi_r(0)$, which decreases $\pi_s(0)$, which increases $\pi_r(0)$, and so on. To derive comparative statics for these cases, we directly calculate them by differentiating the Logit Equilibrium correspondence for state *s*, making sure to keep track of the implicit dependence of the equilibrium value of $\pi_r(0)$ on $\delta_s(1)$, $\delta_s(0)$ and c_s, and the same for $\pi_s(0)$ on $\delta_r(1)$, $\delta_r(0)$ and c_r. After some algebra, this procedure yields the following set of comparative statics:

$$\frac{\partial \pi_s(0)}{\partial \delta_s(0)} = \frac{\lambda \pi_s(1-\pi_s)(1-\pi_r)}{1-\lambda^2 \pi_s(1-\pi_s)\pi_r(1-\pi_r)[\delta_s(1)-\delta_s(0)][\delta_r(1)-\delta_r(0)]},$$

$$\frac{\partial \pi_s(0)}{\partial \delta_s(1)} = \frac{\lambda \pi_s(1-\pi_s)\pi_r}{1-\lambda^2 \pi_s(1-\pi_s)\pi_r(1-\pi_r)[\delta_s(1)-\delta_s(0)][\delta_r(1)-\delta_r(0)]},$$

$$\frac{\partial \pi_s(0)}{\partial c_s} = \frac{-\lambda \pi_s(1-\pi_s)}{1-\lambda^2 \pi_s(1-\pi_s)\pi_r(1-\pi_r)[\delta_s(1)-\delta_s(0)][\delta_r(1)-\delta_r(0)]},$$

$$\frac{\partial \pi_s(0)}{\partial \delta_r(0)} = \frac{\lambda^2 \pi_s(1-\pi_s)\pi_r(1-\pi_r)[\delta_s(1)-\delta_s(0)](1-\pi_s)}{1-\lambda^2 \pi_s(1-\pi_s)\pi_r(1-\pi_r)[\delta_s(1)-\delta_s(0)][\delta_r(1)-\delta_r(0)]},$$

$$\frac{\partial \pi_s(0)}{\partial \delta_r(1)} = \frac{\lambda^2 \pi_s(1-\pi_s)\pi_r(1-\pi_r)[\delta_s(1)-\delta_s(0)]\pi_s}{1-\lambda^2 \pi_s(1-\pi_s)\pi_r(1-\pi_r)[\delta_s(1)-\delta_s(0)][\delta_r(1)-\delta_r(0)]},$$

$$\frac{\partial \pi_s(0)}{\partial c_r} = \frac{-\lambda^2 \pi_s(1-\pi_s)\pi_r(1-\pi_r)[\delta_s(1)-\delta_s(0)]}{1-\lambda^2 \pi_s(1-\pi_s)\pi_r(1-\pi_r)[\delta_s(1)-\delta_s(0)][\delta_r(1)-\delta_r(0)]}.$$

---

[1] We ignore knife-edge scenarios in which $\delta_i(1) - \delta_i(0) = 0$ for state *i*.

[2] This follows from Theorem 4 of Ashworth and Bueno de Mesquita (2006), as for each state, *i*, *i*'s Logit Equilibrium correspondence is increasing in $\delta_i(1)$, $\delta_i(0)$, $-c_i$, and $\pi_i(0)$. (Technically, we know only that the least and the greatest fixed points of the correspondence vary according to the comparative statics detailed here.)

In cases (*iii*) and (*iv*), the shared denominator of the six derivatives is always positive, implying that the sign of the numerator provides the sign of the respective comparative static. We see that in both cases $\pi_s(0)$ is increasing in $\delta_s(1)$ and $\delta_s(0)$, and decreasing in c_s. In case (*iii*), $\pi_s(0)$ is increasing in $\delta_r(1)$ and $\delta_r(0)$, and decreasing in c_r; while in case (*iv*), $\pi_s(0)$ is decreasing in $\delta_r(1)$ and $\delta_r(0)$, and increasing in c_r. This analysis yields the summary results on page 14 of the paper.

To facilitate analysis in the paper we assume adoption decisions by governments that occur in discrete intervals. However, in general, governments' decision-making processes occur in continuous time. In the remainder of this part of the appendix, we briefly specify continuous-time utilities for governments, intended to be a jumping-off point for further work.

In this continuous time model, the utility each government derives from all actions is continuously decreasing according to a factor, ρ_s. Given this notation, we can state that if s is rational, it will adopt at time t only if adopting makes its discounted expected utility looking forward from time t, $U_{s,t}$, greater than its discounted utility from not adopting, where

$$U_{s,t} = \int_t^\infty e^{-\rho_s t}\left(X^*_{s,t}[b^A_{s,t}(X^*_{L_{s,t},t}) - c_{s,t}] + (1 - X^*_{s,t})b^{\sim A}_{s,t}(X^*_{L_{s,t},t})\right)dt\,, \tag{A3}$$

starred actions indicate equilibrium values, and the dependence of $X^*_{L_{s,t},t}$ on $X^*_{s,t}$ and of the expected utility on the beliefs of s about $b^A_{s,t}$, $b^{\sim A}_{s,t}$, and $c_{s,t}$ are implicit. Together each state's expected utility, along with the paper's Assumptions 1 and 2, define a very general, spatially-explicit decision problem for a set of governments seeking to decide on policy rationally.

Reference

Ashworth, Scott, and Ethan Bueno de Mesquita. 2006. "Monotone Comparative Statics for Models of Politics." *American Journal of Political Science* 50(1):214-31.

Part II

Derivation of Spatial Expectations

This section offers a more technical version of the theoretical defense for the three expectations about competition presented in the section, "Expectations from the Lottery Competition Model."

Additional Technical Assumptions

Footnote 5 notes that additional technical assumptions are needed to derive the expectations that form the basis for an empirical test of our theory in the context of state lottery adoptions. In particular, we assume that monopoly lottery provision does not yield too high a revenue when lottery adoption is sufficiently likely. Formally, for the Offensive Competition Expectation and the Anticipatory Competition Expectation to hold, the following conditions must be met:

(B1) $1 - (v_1 + v_2)\,\pi_r(0)) > (\delta_s(0) - \delta_S(1))v_3\lambda\pi_r(0)\pi_s(0)(1 - \pi_r(0))$, and
(B2) $\mu_1 < (\delta_s(0) - \delta_S(1))\lambda(1 - \pi_r(0))(\mu_2 - (\mu_2 + \mu_3)\pi_s(0))$,

where v_1, v_2, and v_3 ($0 \leq v_i \leq 1$) represent differences in the magnitude of the shifts in parameters $\delta_s(0)$, $\delta_s(1)$ and $\delta_r(1)$, respectively, with increases in the size of *r*'s population living within *D* miles of *s* relative to the total population of *s*;[3] and the μ_1, μ_2, and μ_3 ($0 \leq \mu_i \leq 1$) represent differences in the magnitude of the shifts in parameters $\delta_s(1)$, $\delta_r(0)$ and $\delta_r(1)$, respectively, with increases in the size of *s*'s population living within *D* miles of *r* relative to the total population of *s*. (These six shifts in magnitude cannot be calculated without specifying a model of individual consumer behavior, though we can determine relative magnitudes in a few cases.) If $\pi_s(0)$ and $\pi_r(0)$ are small, as they are in the empirical case of lottery adoptions by American states, then conditions (B1) and (B2) hold as long as $\delta_s(0) - \delta_s(1)$ is positive and neither this difference nor the level of rationality, λ, is too big or too small. When the gains to monopoly lottery provision are too great or states are too strongly rational (λ very high), anticipation of the other state's preemptive adoption to prevent one's likely poaching diminishes too greatly a state's desire to poach. When states are too weakly rational (λ very low), they fail to anticipate the other state's likely adoption and adopt more often than is optimal. In this sense, a test of the Anticipatory Competition Hypothesis amounts to a test of the assumption that states consider other states' equilibrium behavior in formulating their own actions. Conditions (B1) and (B2) are also more likely to hold the larger are the shifts in the two terms reflecting revenue gains from a monopoly lottery adoption (μ_2 and v_1) relative to the shifts in the four terms reflecting revenue gains from an adoption under competition (μ_1, μ_3, v_2 and v_3).

Spatial Expectations

Given conditions (B1) and (B2), we turn to an examination of two regions of interest: the portion of *s* that is within *D* miles of *r* (to be called *s*'s *border region*), and the portion of *r* that is within *D* miles of *s* (to be called *r*'s *border region*). Increasing the proportion of *s*'s population in its own border region has two effects on revenue. First, it should decrease $b_s^{\sim A}(1)$ since more

[3] Recall that *D* is the maximum distance someone would be willing to travel to play the lottery.

interested individuals of *s* should play *r*'s lottery, decreasing *s*'s revenue. Second, it should decrease $b_s^A(1)$ by increasing the importance of *s*'s border region to the overall revenue of *s*, thereby leading *s* to increase its competitive effort. At the extreme, if no one lived in *s*'s border region, s could behave as a monopoly lottery producer, earning maximal revenues. In contrast, the proportion of *s*'s population in its own border region has no effect on either $b_s^{\sim A}(0)$ or $b_s^A(0)$, because, absent *r*'s adoption, the locations of the interested individuals in *s* are irrelevant to their consumption choices within s.

We claim that $\delta_s(1)$ [$=b_s^A(1) - b_s^{\sim A}(1)$], *s*'s revenue gain from a lottery adoption under competition, is increasing in the proportion of *s*'s population in its own border region, as in no equilibrium would the decrease in $b_s^A(1)$ arising from an increase in the proportion of residents in this border region exceed the decrease in $b_s^{\sim A}(1)$. To see this, consider the effect on the equilibrium level of competition of moving one interested individual in *s* from the center of the state to its border region when *r* has a lottery. There are two possibilities: either the person is moved to *s*'s side of the cutline, or to *r*'s side.[4]

If the person is moved to *r*'s side of the cutline, then there is no incentive for *r* to increase its level of competition unless *s* would. But consider *s*'s choice. If *s* were not to adopt, the expected value of $b_s^{\sim A}(1)$ would decrease by the potential loss of revenue derived from this individual. The marginal increase in competition arising from this person's movement cannot decrease total revenue from the lottery more than this revenue loss absent the lottery, as *s* could have chosen not to increase competition at all and simply have seen its revenue decrease due to the resident's movement. This implies that the decrease in $b_s^A(1)$ resulting from the population shift must be less than that in $b_s^{\sim A}(1)$.

If the person is moved to *s*'s side of cutline, then the incentive to shift the cutline is *r*'s. If the cutline is in *s*, then the same argument may be made for *r*'s choice of a competitive level: *r* would never choose a level of competition that would cause a decrease in revenues more than would be gained from the addition of one lottery player. Since *r*'s gain is a loss to *s*, and since we have assumed it is cheaper for *s* to compete for an individual in *s* than it is for *r* to compete for that individual, we again have that the decrease in $b_s^A(1)$ resulting from the individual's being moved must be less than the decrease in $b_s^{\sim A}(1)$ resulting from the same shift of the individual. Finally, if the cutline is in *r*, then moving one interested individual in *s* can have no marginal effect on *r*'s desire to compete in equilibrium, since *r* has already deemed it not to be beneficial to compete for individuals in *s* in this case. Thus, we have that $\delta_s(1)$—*s*'s revenue gain from a lottery adoption under competition—is increasing in the proportion of *s*'s population in its own border region. This leads to our first spatial expectation:

> <u>Defensive Competition Expectation</u>: If *r* has a lottery, the probability that *s* will adopt one is positively related to the proportion of its adult population within *D* miles of *r* (and thus with access to *r*'s lottery).

[4] The cutline—which separates individuals that play the lottery in *s* from those that play in *r*—is defined on pp. 15-16 of the paper.

Now consider the impact of an increase in the population in r's border region relative to the population of s. If s has no lottery, this increase has no effect on s's revenue, regardless of whether r has a lottery; i.e., the increase has no effect on $b_s^{\sim A}(0)$ or $b_s^{\sim A}(1)$. In contrast, an increase in the population in r's border region relative to the population of s clearly increases $b_s^A(0)$, as more residents of r would play s's monopoly lottery. However, an increase in the population in r's border region relative to the population of s has an uncertain effect on $b_s^A(1)$. On the one hand, there are more potential players of s's lottery; on the other hand, there are more individuals over whom s and r may compete, lessening overall revenue due to competitive losses. Assume that the decrease in $b_s^A(1)$ due to competition is greater than the increase in $b_s^A(1)$ due to additional players, perhaps because it is cheaper for r to compete for individuals living in the two states' border regions than it is for s. (Our conclusions hold more strongly if this assumption is not true, so the assumption is unimportant.) The only time there is an incentive for either state to increase competition in this case is when the cutline is in r. But by the same argument introduced earlier regarding the proportion of s's population in its own border region, the decrease in $b_s^A(1)$ can never be more than the increase in $b_s^A(0)$, regardless of where the extra individual is located. Since $\delta_s(0) = b_s^A(0) - b_s^{\sim A}(0)$ and $\delta_s(1) = b_s^A(1) - b_s^{\sim A}(1)$, and since an increase in the population in r's border region relative to the population of s has no effect on $b_s^{\sim A}(0)$ or $b_s^{\sim A}(1)$, the increase in $\delta_s(0)$ can never be less than the decrease in $\delta_s(1)$. For fixed populations of s and r, however, increasing the population in r's border region relative to the population of s also increases the proportion of r's total population in its own border region. Thus, we cannot fully understand the effect on s of the population in r's border region relative to the population of s until we understand the effect of the size of this population relative to r's total population on r.

Earlier we saw that increasing the proportion of s's population in its own border region decreases both $b_s^A(1)$ and $b_s^{\sim A}(1)$ and has no impact on both $b_s^A(0)$ and $b_s^{\sim A}(0)$, leading to an increase in $\delta_s(1)$ and no change in $\delta_s(0)$. However, for fixed populations of s and r, increasing the proportion of s's population in its own border region also increases the population in s's border region relative to the population of r.

To untangle effects, we consider the net change to the parameters due to a change in the proportion of individuals in each region. First consider r's border population. As we have seen, increasing this population relative to the population in s increases $\delta_s(0)$, decreases $\delta_s(1)$ but to a lesser degree, and increases $\delta_r(1)$. One can use the comparative statics derived in Part I of this on-line appendix to determine the net effect of marginal changes in these parameters arising from an increase in the population in r's border region relative to the population of s. Given the relative rarity of lottery adoptions absent other states' prior adoptions—implying low probabilities that r and s will adopt when neither state has a lottery [i.e., low values of $\pi_s(0)$ and $\pi_r(0)$]—we believe that assumptions (B1) and (B2) are likely to hold. Accordingly, these comparative statics imply that the net effect of increasing the population in r's border region relative to the population of s will be to increase the likelihood that s will adopt. This leads to a second spatial expectation:

Offensive Competition Expectation: If r does not have a lottery, the probability that s will adopt one is positively related to the number of adults in r who are within D miles of s relative to the adult population of s.

Now reconsider s's border region. Increasing the proportion of s's population in this region increases $\delta_s(1)$ and $\delta_r(0)$, and decreases $\delta_r(1)$. Again we can compute the net effect of a marginal increase in the proportion of s's population in its own border region on the probability that it will adopt using our comparative statics. This time our assumptions imply a decrease in the probability of adoption, leading to a third spatial expectation:

Anticipatory Competition Expectation: If r does not have a lottery, the probability that s will adopt one is negatively related to the proportion of its adult population within D miles of r (i.e., the proportion of s's population that would have access to a lottery in r if r were to adopt one).

Part III

Figure 4 from Berry and Baybeck (2005)

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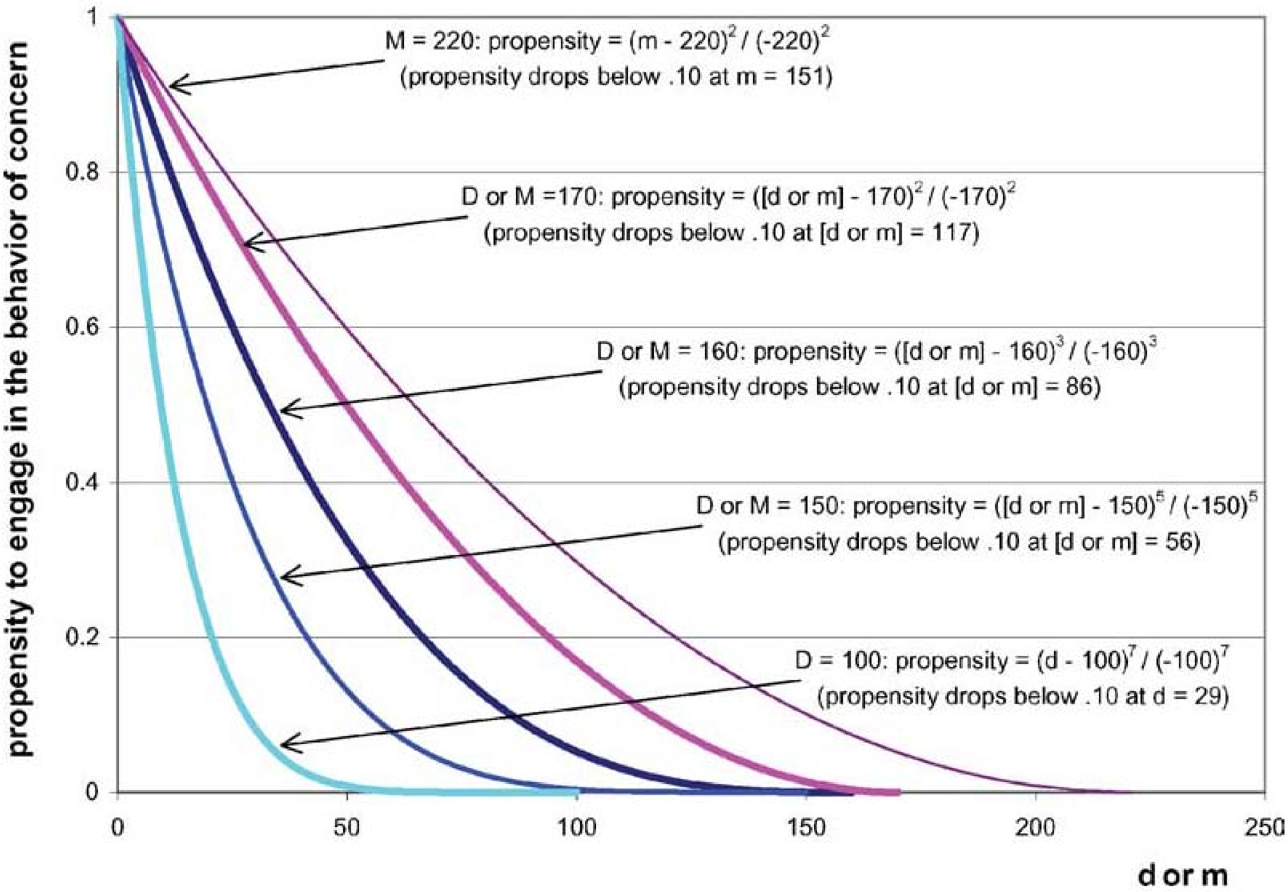
FIGURE 4. Specific Functions Mapping an Individual's Geographic Location into Propensity to Engage in the Behavior of Concern



Reference

Berry, William D., and Brady Baybeck. 2005. "Using Geographic Information Systems to Study Interstate Competition." *American Political Science Review* 99(4):505-19.

Part IV

Probit MLEs for Learning and Competition Variables in Models Specifying Ideologically-Based Learning

Assumed value of *D*:	100	150	160	170	100	150	160	170
Competition Variables								
Defensive Competition	1.14**	0.54	-0.04	-0.32	1.02*	0.66	0.19	-0.31
	(1.95)	(1.00)	(-0.08)	(-0.59)	(1.30)	(0.78)	(0.24)	(-0.43)
Offensive Competition	0.70	0.35**	0.43***	0.36**	0.68	0.36**	0.44***	0.36**
	(1.05)	(1.78)	(2.42)	(2.28)	(1.01)	(1.73)	(2.41)	(2.22)
Anticipatory Competition	-1.79	-1.97**	-2.67***	-2.42***	-1.70	-2.04**	-2.79***	-2.43***
	(-0.94)	(-1.78)	(-2.64)	(-2.52)	(-0.85)	(-1.70)	(-2.62)	(-2.47)
Learning Variables								
Ideological Distance	-0.05***	-0.05***	-0.05***	-0.05***	-0.05***	-0.05***	-0.05***	-0.05***
(Ideologically-Based Learning)	(-4.94)	(-4.93)	(-4.80)	(-4.78)	(-4.65)	(-4.69)	(-4.66)	(-4.66)
Previously Adopting Neighbors					0.03	-0.04	-0.08	-0.00
(Regional Learning)					(0.21)	(-0.19)	(-0.40)	(-0.02)

Note: All columns report coefficients from models in which one or both of our "learning variables" are added to the models estimated in Table 1 of the *JOP* article. *Z*-statistics based on robust standard errors (obtained using the probit procedure in Stata 9) are in parentheses below coefficients.

*p < .10, **p < .05, ***p < .01 (one tailed)