The Mechanisms of Policy Diffusion

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Local policy adoptions provide an excellent opportunity to test among potential mechanisms of policy diffusion. By examining three types of antismoking policy choices by the 675 largest U.S. cities between 1975 and 2000, we uncover robust patterns of policy diffusion, yielding three key findings. First, we distinguish among and find evidence for four mechanisms of policy diffusion: learning *from earlier adopters,* economic competition *among proximate cities,* imitation *of larger cities, and* coercion *by state governments. Second, we find a* temporal *component to these effects, with imitation being a more short-lived diffusion process than the others. Third, we show that these mechanisms are* conditional, *with larger cities being better able to learn from others, less fearful of economic spillovers, and less likely to rely on imitation.*

The promise of state and local policymaking in a federal system is that these subnational governments may serve as laboratories of democracy, where they experiment with different policies and learn from one another. The peril is that each government may advance its own interests at the expense of others, leading to the possibility of destructive competition and coercion. Scholars of federalism and intergovernmental relations often recognize these competing pressures, but rarely separate one from the next. For example, in the sizable literature on policy diffusion, authors frequently take note of the multiple mechanisms that lurk behind the spread of policies across governments. However, because learning, competition, imitation, coercion, and other mechanisms typically all point to an increased likelihood of policy adoption when neighbors adopt the policy, scholars often simply assess whether such a neighbor effect exists, without concern for which mechanism is driving the result.

Yet, from a normative perspective, uncovering the various mechanisms of policy diffusion is crucial to understanding when the devolution of policy control to states and localities is desirable. Policy adoption based on *learning* about effective policies elsewhere leads to good outcomes, whereas the negative externalities arising from *competition* can produce bad outcomes. *Imitating* other governments by simply copying their policies may result in inappropriate policy choices. And policy choices based on *coercion* by other governments are unlikely to be optimal. Thus, exploring the conditions under which each of these mechanisms drives policy diffusion is normatively important, and, from a social scientific perspective, is essential for a better understanding of the political incentives behind policy decisions.

In this article we demonstrate how scholars can disentangle these four mechanisms of policy diffusion. In particular, we establish that each of these diffusion mechanisms affected the spread of antismoking laws across the 675 largest U.S. cities between 1975 and 2000. We then demonstrate the temporal and conditional nature of these diffusion mechanisms, illustrating the fleeting nature of imitation and the varying susceptibility of cities of different sizes to these various mechanisms. Ultimately,

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we find that smaller governments face a relative disadvantage in policy formulation in the American federal system. They appear to be less capable of learning from the policy choices of others, more susceptible to economic competition, more likely to engage in simple imitation, and strongly at risk of coercion from their state government.

To establish these findings, we proceed as follows. First, we briefly survey the literature on policy diffusion, in order to place this study in context and to motivate our main theoretical arguments and testable hypotheses. We then discuss the literature on the adoption of antismoking laws, introduce our data, and detail how we test our hypotheses. Finally, we highlight our results and their importance.

Local Policy Adoption and the Mechanisms of Diffusion

Policy innovation occurs whenever a government—a national legislature, a state agency, a city—adopts a new policy (Mintrom 1997a; Walker 1969). The impetus for this policy innovation can come from within the polity, such as when interest groups within a state push for the adoption of a new policy, or when electoral and institutional forces within a legislature affect the likelihood of adoption. Pressure for policy innovation also can come from outside the polity, with the spread of innovations from one government to another, a process known as *policy diffusion*.

The literature on policy diffusion is vast and expanding rapidly. Building on a series of classic early studies (e.g., Crain 1966; Gray 1973; Walker 1969), as well as more recent significant theoretical and methodological advances (e.g., Berry and Berry 1990; Berry and Baybeck 2005), scholars have conducted a number of studies of diffusion during the past decade. These studies have focused on the diffusion of a range of policies, including same-sex marriage bans (Haider-Markel 2001), education reform (Mintrom 1997a), abortion (Mooney and Lee 1995), the death penalty (Mooney and Lee 1999), and HMO reforms (Balla 2001), among many others. In addition, these and other studies have shed light on the processes by which diffusion takes place, focusing on factors that enable or hinder diffusion, including the policy's success (Volden 2006), policy entrepreneurs (Balla 2001; Mintrom 1997a, 1997b), and the initiative process (Boehmke 2005).[1]

Although these works have uncovered a great deal of evidence that policies do diffuse, much less is understood about the specific *mechanisms* that cause a policy to spread from one government to another. That is, if a second government adopts a policy because a first government has already done so, what explains that second government's action? Here we focus on four mechanisms of diffusion: *learning*, *economic competition*, *imitation*, and *coercion*. While these mechanisms are also relevant to diffusion across states and countries (e.g., Simmons, Dobbin, and Garrett 2006), our focus on city-to-city diffusion allows us to examine each mechanism individually as well as in conjunction with one another. Previous scholarship has often referred to multiple mechanisms of diffusion, but with few exceptions (e.g., Berry and Baybeck 2005; Boehmke and Witmer 2004; Weyland 2005, 2007) these studies have not tested one explanation against another.

Throughout this discussion, for the purpose of simplicity, we often write of the "city" taking action—learning or competing, for example. In reality, individual decision makers—mayors, managers, council members, bureaucrats, and others—are the critical actors in these cities. Because of this large number of individuals and forms of government, we rely on the shorthand of referring to cities as actors. As is common in the diffusion literature, we believe the individual decision makers within these cities are interested in adopting beneficial policies, either as a means to reelection or reappointment or as an end in themselves. Such motivations are at work across all four mechanisms explored here.

The first mechanism of diffusion that we explore—learning—is the process that leads states to be called laboratories of democracy (Brandeis 1932). By observing the politics of policy adoption and the impact of those policies, policymakers can learn from the experiences of other governments. We follow most previous studies in adopting a general definition of learning: as Berry and Baybeck note, for example, "[w]hen confronted with a problem, decision makers simplify the task of finding a solution by choosing an alternative that has proven successful elsewhere" (2005, 505). Most generally, then, learning involves a determination of whether a policy adopted

[1]Previous studies of diffusion in American politics have focused overwhelmingly on state-to-state diffusion. Evidence of city-to-city diffusion does exist, of course, as demonstrated by Crain's (1966) study of fluoridation, Knoke's (1982) analysis of the adoption of municipal reforms, Godwin and Schroedel's (2000) investigation of local gun control ordinances in California, and Martin's (2001) examination of living wage laws. These studies, however, face a number of limitations, such as conducting tests only within one state (e.g., Godwin and Schroedel 2000), relying on bivariate rather than multivariate analysis (e.g., Crain 1966), focusing solely on internal determinants (e.g., Martin 2001), or looking at structural innovations rather than public policies (e.g., Knoke 1982). Ours is thus the first large-N, multistate, quantitative study of the diffusion of city-level policy adoptions.

elsewhere has been successful. If the policy is deemed to be successful, then a city is more likely to adopt it.

Ideally, political and policy success would be readily observable to decision makers and researchers alike. When success is difficult to measure (as it is at the city level for antismoking policies), various shortcuts that are consistent with learning are taken. For instance, policymakers may interpret the broad adoption of a policy without subsequent abandonment over time as evidence of the success of the policy, or at least as evidence of maintained political support. Researchers, in turn, may explore the effect of the "opportunity to learn" on policy choice as a substitute for direct evidence of learning. Put simply, policymakers cannot learn about policies that have not yet been tried. They can learn more when multiple governments try the policy, and even more when such policies affect larger segments of society. The reliance of researchers on opportunity to learn is more appropriate for policies that are eventually clearly identified as successes, both politically (as evidenced by lack of repeals) and on policy grounds (as evidenced by studies of effectiveness in general). The antismoking policies studied here meet both of these criteria.[2] If they did not—for example, if evidence of success were limited or not found—then it would be more difficult to discern exactly what cities learn from the experiments of others. For our case, this "opportunity to learn" idea is expressed as follows.

> *Learning Hypothesis*: The likelihood of a city adopting a policy *increases* when the same policy is adopted broadly by other cities throughout the state.

A second mechanism—economic competition—is often raised in conjunction with learning, and these two mechanisms are viewed, at least implicitly, as the most common processes explaining policy diffusion. Two recent state politics studies have sought to disentangle these two mechanisms. Boehmke and Witmer (2004) explore state adoption of Indian gaming compacts, arguing that learning and economic competition are both important in explaining *initial* adoptions, whereas only economic competition explains *subsequent* compacts because previous experience with one's own compacts removes the need to learn from the experience of others. Berry and Baybeck (2005) argue that learning can take place across states generally, while economic competition is typically confined to individuals living near state borders. Using geographic information systems (GIS) technology, they isolate the effects of learning and of competition to explain lottery adoptions and welfare benefit levels.

Like these studies and others, we contend that economic competition can lead to the diffusion of policies with economic spillovers across jurisdictions. State welfare policy is a classic example. Fearful of becoming "welfare magnets" (Peterson and Rom 1990), states may face incentives to engage in a "race to the bottom" in welfare benefits due to competitive federalism (e.g., Bailey and Rom 2004; Volden 2002). Such competition may also take place at national or local levels of government, in policy areas ranging from education and the environment to infrastructure, minimum wages, and antismoking policies. In each instance, policymakers consider the economic effects of adoption (or lack of adoption) by other governments. If there are negative economic spillovers, where the government will be hurt if it adopts a policy that its neighbors lack, then it will be less likely to adopt the policy itself. On the other hand, if there are positive spillovers, such as are found by establishing uniformity in infrastructure, then governments will be more likely to adopt the policy of others. Consistent with both theoretical and empirical approaches to economic competition, we offer the following hypothesis.

> *Economic Competition Hypothesis*: The likelihood of a city adopting a policy *decreases* when there are negative economic spillovers from that adoption to nearby cities and *increases* with positive spillovers from nearby cities.

A third diffusion mechanism—imitation—has received much less attention in the state politics literature, but arises more frequently in comparative politics (e.g., Meseguer 2006; Simmons, Dobbin, and Garrett 2006) and has roots in social psychology and in studies of the diffusion of innovations across a multitude of fields of study (Rogers 1995). Sometimes also referred to as emulation, imitation involves copying the actions of another in order to look like that other. The nature of imitation can be understood in contrast to learning. In learning, policymakers focus on the policy itself—how was it adopted, was it effective, what were its political consequences? In contrast, imitation involves a focus on the other government—what did that government do and how can we appear to be the same? The crucial distinction is that learning focuses on the *action* (i.e., the policy being adopted by another government), while imitation

[2] This assertion is well supported by the scarcity of antismoking law repeals and by the public health literature, with numerous studies showing both that antismoking measures can have positive effects, such as reductions in the rate of smoking (e.g., Evans, Farrelly, and Montgomery 1999; Ross and Chaloupka 2004), and can avoid negative effects, such as the loss of business and restaurant income (e.g., Glantz and Charlesworth 1999).

focuses on the *actor* (i.e., the other government that is adopting the policy). Outside of the policy adoption context, a classic example of learning is avoiding touching the hot burner after observing someone doing so with bad effects, whereas imitation is jumping off the garage roof after observing your older brother doing so, without regard for the consequences. In the former case, it is the action that matters; in the latter, the actor. In the former, you learn about consequences; in the latter you simply aspire to be like the other actor.

Although imitation sometimes has been ignored or even mislabeled in the policy diffusion literature, it is wholly consistent with early studies of local and state policy adoptions. This literature focused on which states and cities were "leaders" or "laggards" (e.g., Crain 1966, Grupp and Richards 1975; Walker 1969). Innovative leaders were found to be larger, wealthier, and more cosmopolitan. Smaller communities aspire to be like these leaders, and therefore adopt the same policies as these leaders without necessarily thinking about the consequences of such adoptions. Clearly, policymakers in these smaller cities also may learn from the policy experiences of those in larger cities. And they also may worry about competition, leading them to adopt policies in an attempt to stem the flight of citizens and businesses to these larger cities. But above and beyond learning and competition, decision makers in smaller cities also may adopt policies simply because they want their communities to be as favorably viewed as the cities that are seen as leaders. They hope that such imitation will raise their profile and make them more attractive places to live, like their larger, wealthier, and more cosmopolitan neighbors. In our context, therefore, imitation may appear as smaller cities copying the policies of their larger neighbors.

> *Imitation Hypothesis*: The likelihood of a city adopting a policy *increases* when its nearest bigger neighbor adopts the same policy.

The fourth mechanism of diffusion—coercion—differs from the previous three. Like imitation, it is more commonly raised in the comparative politics literature (e.g., Simmons, Dobbin, and Garrett 2006) than in American politics. In the international setting, for example, countries can coerce one another through trade practices and economic sanctions. They can attempt to coerce others directly, or can do so through international institutions like the United Nations and the International Monetary Fund, which encourage or pressure governments to take actions that meet common expectations. Coercion was such a major concern to the founders of the U.S. Constitution that they established the commerce clause to minimize trade barriers and other coercive mechanisms across the states.

Although horizontal coercion across states or localities in the American federal system is therefore limited, vertical (or top-down) coercion is still quite possible. This should be of no surprise to scholars of policy diffusion, who have long noted that grants from the federal government to states and localities often stimulate policy adoptions (e.g., Allen, Pettus, and Haider-Markel 2004; Karch 2006; Shipan and Volden 2006; Walker 1973; Welch and Thompson 1980). For instance, the threat of lost highway funds coerced states into adopting lower speed limits and higher drinking ages. In addition to their influence through intergovernmental grants, higher levels of government can coercively influence the actions of lower levels by taking the lead in that policy area, setting their own minimum wage or antismoking restrictions, for example.[3]

Even more coercive are *preemptive* policies. Because cities are creatures of the state, with no constitutionally specified sovereignty, state governments can pass laws that disallow any city action contrary to state law. In the area of antismoking policy, for example, such state-level preemptive policies were commonplace and were an explicit strategy of the tobacco industry to fight back increasingly stringent local laws (e.g., Givel and Glantz 2001). A locality still might pass weaker laws that ensure the continuance of the policy if the state were to reverse its stance; or it could enact alternative laws in order to provoke a court challenge; but, in either case, the usefulness and hence the likelihood of passage of such laws are greatly diminished.[4]

> *Coercion Hypothesis*: The likelihood of a city adopting a policy *decreases* when the state adopts a similar policy that covers the city. This decrease is even more substantial when the state law *preempts* either future local laws on the same policy or future stronger laws.

We acknowledge that the theoretical distinctions among these four categories are starker than are the real-world empirical classifications of these diffusion mechanisms. For example, when a neighboring city restricts smoking in its restaurants, this provides an opportunity to learn, raises some economic spillover considerations, *and*

[3]See Volden (2005, 2007) for formal models of these processes and their likely policy effects.

[4]Similarly, cities could pass weaker laws if the state preemptive clause allows them to do so (e.g., the state may restrict smoking only under certain conditions, but allow cities to loosen the set of restrictions). Even in such a situation, however, far fewer cities will have the incentive to pass such laws.

may induce imitation. Separating these effects from one another is difficult. Nevertheless, we believe that raising these theoretical and archetypal mechanisms as distinct from one another provides guidance for scholars to begin to disentangle these diffusion processes. Moreover, we argue that our focus on cities provides the variance necessary to explore these distinct mechanisms. For instance, whereas learning can take place over quite a distance, economic spillovers are geographically limited. Whereas one can learn from the experiences of smaller or larger cities, imitation is focused only on the larger leader cities. And whereas larger cities may be imitated, both smaller and larger cities alike may present economic competitive concerns if sufficiently proximate. Thus, despite overlap across diffusion mechanisms, we can distinguish among them conceptually. Such conceptual distinctions guide the variable operationalizations we use to empirically test our hypotheses.

The Temporal and Conditional Nature of Policy Diffusion Mechanisms

Although a major goal of this article is to differentiate, both theoretically and empirically, among multiple mechanisms of diffusion, it is equally important to explore when each of these mechanisms takes place and why one mechanism may affect some cities more than would another mechanism. Therefore we advance two additional hypotheses.

First, we consider the *temporal* nature of each mechanism, which allows us to further distinguish among mechanisms and also to gain additional perspective on whether the operationalizations that we use are appropriate. Our starting point here is the realization that some mechanisms of diffusion should be short-lived, while others should have longer lasting effects. In the former category, we would expect to find imitation. When one city imitates another, it does so fairly quickly, as policymakers in that city imitate the actions of cities that are leaders and do so in order to look like those leaders. Because imitation involves no concern about the effects of policies, but rather only a desire to do whatever a leader city has done, the response to a policy adoption should be almost immediate. If the response does not come quickly, it becomes less likely over time, as policymakers will decide whether to imitate an action or not and then will move on to other ways to imitate the leader.

In contrast to imitation, the other two mechanisms of horizontal diffusion—learning and competition—should exhibit longer-term effects. First, consider learning. If policymakers are concerned only about how to navigate through the public policy process in order to bring about a policy adoption, then all the relevant information is revealed at the time of adoption. But if policymakers are interested in knowing the political and policy consequences of an adoption, then it may take months or years to evaluate the effectiveness of a particular policy. Regardless of what is being learned, the learning effect is unlikely to fade quickly—indeed, evidence of the effects of policies, once known, is likely to remain relevant to policymakers for a considerable period of time. Second, economic competition also should exhibit long-term effects. If governments are worried about the economic spillovers from another government's policies, that competitive pressure will remain for as long as the policy is in place.

Overall, then, we should expect to find different temporal effects for imitation than for learning and competition. For imitation, we would expect a strong initial effect that then should fade over time. For the other horizontal mechanisms, we should expect both an initial effect *and* an effect into the future (e.g., a city will continue to learn from other cities two or three years after those other cities have adopted a policy). Finally, for the coercion involved in vertical diffusion, the temporal effects are less clear. Preemptive laws may immediately influence local adoptions and those effects may persevere. Yet, localities may over time adopt laws testing whether the state restrictions still have teeth. Exploratory work below examines these alternatives, while our main temporal effects hypothesis spells out our predictions for the horizontal diffusion mechanisms.

> *Temporal Effects Hypothesis*: The effects of imitation are likely to be short-lived. Learning and economic competition, on the other hand, are likely to exhibit longer-term effects.

Second, we consider the *conditional* nature of each mechanism. Some cities are better equipped to learn from others; some are more susceptible to economic competition than are others. Some are more likely to follow leaders; and some are more likely to resist coercive actions. Although there may be many criteria that divide cities along these lines, one straightforward and broadly relevant city characteristic is simply the size of its population, which is likely to matter for each of the diffusion mechanisms we are exploring.[5] Because larger cities tend to have bigger

[5]Other city characteristics, like wealth or government structure, might likewise affect different diffusion mechanisms. However, our goal here is to demonstrate that these diffusion processes can be conditional, rather than to fully document all possible conditional relationships.

and more professional governments, they are more capable of learning from others.[6] Larger cities are less likely to be influenced by local economic spillovers, partly because of their economic diversity and partly because their smaller neighbors are less economically threatening. Because they are already the leaders that others look up to (e.g., Crain 1966), larger cities also are less likely to engage in imitative behavior than are smaller cities. Finally, larger cities are more likely than smaller cities to confront the coercive power of the state. We present these ideas in the following Conditional Diffusion Hypotheses.

> *Conditional Learning Hypothesis*: Larger cities are more likely to learn from other cities.

> *Conditional Competition Hypothesis*: Larger cities are less susceptible to economic competition.

> *Conditional Imitation Hypothesis*: Larger cities are less likely to engage in imitation.

> *Conditional Coercion Hypothesis*: Larger cities are less likely to be coerced effectively.

Antismoking Policies at the State and Local Levels

Testing these diffusion hypotheses requires, first, a policy area in which states and cities share jurisdiction, and second, data on policy adoptions at both levels of government. Antismoking policies meet both requirements. States and cities both are active policymakers in this policy area, passing a large volume of laws that regulate a wide range of activities (e.g., Schroeder 2004; Shipan and Volden 2006). In addition, we have been able to obtain comparable data on adoptions at both the city and state levels of government. Specifically, data on state-level laws come from the National Cancer Institute's State Cancer Legislative Database (SCLD), maintained by the MayaTech Corporation. For city-level laws we use the American Nonsmokers' Rights (ANR) Foundation's Local Tobacco Control Ordinance Database. Each of these comprehensive databases contains extensive information about each law passed by the state or city, including the topic of the law, the specific action taken in the law, and the adoption date. In addition, the SCLD dataset also identifies which state laws preempted future city-level laws. Thus, antismoking policies provide a useful and appropriate forum for testing our hypotheses.[7]

We focus on three types of antismoking policies in this article: restrictions on smoking in government buildings, restrictions on smoking in restaurants, and youth access restrictions. Our choice of these three policies reflects several considerations. At one extreme, we could simply look to see whether a city (or state) has adopted any antismoking law, regardless of type. This, however, would be a level of analysis that is far too aggregated and that ignores variation among types of policies. At the other extreme, we could assign each law to a category based on detailed criteria contained within the law. The problem with this approach is that the data would then be far too disaggregated. Laws that place restrictions on smoking in government buildings, for example, can contain outright prohibitions on smoking; they can restrict smoking in common areas, or provide for specific areas where smoking is allowed, such as individual offices; they can set limits on smoking near doorways, perhaps mandating a nonsmoking perimeter near the entrance; and so on. Because the list of specific modifications is nearly endless, we have chosen to strike a middle ground, neither aggregating all laws together, nor disaggregating them by their components, but rather grouping them into three fairly broad, yet distinct, categories.

Grouping laws into these three categories also has the beneficial effect of capturing variations across multiple types of laws. More specifically, two of our policy areas—government buildings and restaurants—are generally classified by public health scholars as *clean indoor air* laws, since they tend to be spurred by concerns over the health effects suffered by nonsmokers who are exposed to secondhand smoke. The other policy area—*youth access* laws—is instead designed to make it more difficult for young people, especially teenagers, to obtain cigarettes. Policies in this area include regulations regarding the location of vending machines, fines for selling cigarettes to minors, and restrictions on the sale of cigarettes out of their original packaging. To the extent that diffusion mechanisms vary across these three areas, including all three provides the greatest opportunity to uncover these distinct mechanisms.

Before turning to the data analysis, it is helpful to consider the face validity of the hypotheses suggested above in the context of antismoking policies. The public health

[6]Shipan and Volden (2006) similarly find that more professional state governments are better able to learn from local adoptions, thereby facilitating local-to-state diffusion. More generally, Huber, Shipan, and Pfahler (2001) and Huber and Shipan (2002) find that more professional governments often are better able to engage in policy control.

[7]For additional discussions of these datasets, see Shipan and Volden (2006) and Chriqui (2000).

literature has provided such an assessment through a variety of case study and single-state analyses, which suggest initial support for our main hypotheses. Skeer et al. (2004), for example, note that neighboring towns in Massachusetts, especially those with high levels of income and education, were more likely to adopt similar restaurant restrictions. Jacobson and Wasserman's (1997) case studies in seven states show a decrease in local adoption activities following the enactment of state laws.[8] And numerous studies point to the tobacco industry's state-level preemption strategy as a way to win battles that otherwise would be lost in localities (e.g., Givel and Glantz 2001; Siegel et al. 1997). Thus, public health studies provide initial evidence consistent with our expectations. We turn now to a systematic analysis of our hypotheses.

Empirical Approach

Our dependent variables of interest capture whether a city adopts a law in each of the three types of antismoking restrictions we examine. For each of our three categories of antismoking laws, we construct a dependent variable that is initially set equal to 0. In the year the city passes a law, this variable is set equal to 1; and in following years the city's observations are removed from the dataset, as the city is no longer at risk of a policy adoption. This allows us to use a standard event history analysis (EHA) to predict the probability that an event will occur given that it has not already occurred. Our analyses include all 675 cities in the United States with populations of 50,000 or greater as of the year 2000. We do not include smaller cities, for which both independent and dependent variables are less available and may be less reliable. We examine the period between 1975 and 2000. We focus on this 25-year period due to data availability and because very few city-level antismoking laws were passed prior to this time.

Because we are examining three policy choices by the same cities in the same years, these adoptions may be considered as a type of repeated event (Box-Steffensmeier and Zorn 2002). In our analyses, we therefore pool the data together, yielding one observation per city per year per policy. This pooling, which follows the approach of Shipan and Volden (2006), who in turn rely on a slight modification of the modeling approach of Wei, Lin, and Weissfeld (1989), is appropriate because any of the three policies could be adopted at any time in any order. The results are robust to either pooled or separate analyses.

In our statistical tests, we first separately examine the hypotheses regarding the individual diffusion mechanisms. Our second set of results includes all four diffusion mechanisms in the same model, illustrating the strength of each effect upon controlling for the other three. The third part of our analysis presents lagged versions of the diffusion variables, to test the Temporal Effects Hypothesis. Finally, we test the Conditional Diffusion Hypotheses by interacting the diffusion variables with city size to illustrate which types of cities are more responsive to which diffusion pressures.

Mechanism Variables

The Learning Hypothesis holds that a city will be more likely to adopt a policy if other cities in the state have already done so. To test this hypothesis, we constructed a variable, ***Proportion of State Population with Local Restriction***, which is calculated by identifying the cities that have each type of antismoking law at the beginning of the calendar year, summing up the populations of those cities, and dividing by the overall population within the state. Our expectation is that as this proportion increases, so will the likelihood that the city will adopt the same type of law. Certainly there may be other ways to formulate a variable to capture the possibility of learning.[9] And our variable may partially capture other mechanisms of diffusion beyond learning, as it includes both nearby cities (a possible source of competition) and larger cities (possible targets of imitation). Nevertheless, because learning can take place from a broad array of other cities, we rely on this broad, inclusive measure. Controlling for this learning effect will demonstrate the residual part of diffusion still captured by our competition and imitation variables, detailed below. Likewise, controlling for these other mechanisms helps uncover the residual diffusion effect due to learning.

To test for the second diffusion mechanism, as presented in the Economic Competition Hypothesis, we created a variable called ***Outflow***. This variable is designed to capture the city's concern, central to this hypothesis,

[8]On the other hand, Andersen, Begay, and Lawson (2003) illustrate the more classical pattern of positive vertical policy diffusion by highlighting how state-level funding of local tobacco control initiatives helped explain their adoption in Massachusetts. Conlisk et al. (1995) present an interesting counterpoint to this wave of research. When North Carolina attached a three-month window to their preemption law, during which time localities were allowed to adopt and grandfather their own laws, 89 new local regulations were passed, compared to a total of 16 prior to that time.

[9]Looking instead at the *number* of cities with the given law yields largely similar results. We believe that weighting by city population, however, better characterizes the opportunity to learn about policy impacts, as more buildings, restaurants, and youths are affected by policy adoptions in larger cities.

that it may lose out economically to surrounding cities if it adopts an antismoking measure—that is, benefits may flow out from the city to other cities.[10] Such fear is, of course, dependent both on whether the surrounding communities have the same kinds of antismoking laws themselves and on the relative size of those neighbors compared to the city being examined. Therefore, to construct this variable, we began by identifying all cities in our dataset that were contiguous to, or within 10 miles of, the city in question.[11] We then summed the population of those surrounding cities that did *not* have the antismoking policy—in other words, those cities to which economic benefits might flow if the city in question adopted a law—and created as our measure the ratio between the sum of these populations and the population of the city in question. For example, if a small town is next to a city that has five times as many people as the town, and neither has restaurant restrictions, *Outflow* takes a value of 5.0 for the town and 0.2 for the city, as the town is more vulnerable to the outflow of an average restaurant patron than is the big city. If there are no cities within 10 miles, or if the surrounding cities all have passed laws, *Outflow* equals zero. Because fears of economic vulnerability should diminish the likelihood of an antismoking policy adoption, we anticipate a negative coefficient on this variable.

To test the Imitation Hypothesis, we constructed a ***Nearest Bigger City*** variable by looking within the state to see whether the nearest city with a larger population than the city in question has previously adopted the policy (i.e., restrictions for government buildings, restaurants, and youth access, respectively). If it has, the variable takes on a value of 1; and if it has not, this variable is set equal to 0.[12] For example, the nearest city to Oakland that has a larger population is San Francisco; if San Francisco has adopted an antismoking law in the category of interest by the start of the year, then this variable is set equal to 1. We expect this variable to have a positive influence on the dependent variable. This focus on larger neighbors is consistent with the concept of imitation, but it creates a coding problem for the largest city in each state. Since there is no "nearest bigger city" for the largest city in a state, for these cities we look to see whether the second largest city has adopted a policy. If, alternatively, we simply drop these largest cities from our analysis, our results remain substantively unchanged. It is also important to note that we are not arguing that cities fail to learn from, or to compete with, their nearest bigger neighbors. Rather, here we are assessing whether an imitation effect exists above and beyond the learning and competition effects controlled for by our other variables.

The Coercion Hypothesis suggests that state adoption of a policy will decrease the likelihood that a city within that state will adopt a similar law and that preemptive clauses in state laws will be an even greater deterrent. To test this hypothesis, we created two variables. First, ***State Law*** is set equal to 1 in every year after the state has adopted a law and is otherwise set to 0. For example, in 1977 Iowa adopted a law restricting smoking in government buildings, so for the observations dealing with government buildings in cities in Iowa, *State Law* is equal to 0 in 1975, 1976, and 1977, and takes a value of 1 starting in 1978 and continuing through 2000. Second, ***State Preemption*** is constructed analogously to *State Law*, based on whether the state law explicitly preempted local action in a relevant category of antismoking restrictions.[13] We expect a negative coefficient on these two variables.

City, State, and Temporal Controls

Although we are mainly interested in horizontal and vertical diffusion patterns, we agree with Peterson's counsel that "[t]o ignore internal factors altogether would be as misleading as to treat urban politics and policymaking solely in terms of them" (1981, 4). Therefore, it is essential to control for city-level factors that may influence the adoption of antismoking policies. In our particular case, without such controls we would be unable to discern

[10]Economic competition is likely to affect clean indoor air adoptions more substantially than youth access restrictions, as policymakers may heed warnings about lost restaurant patrons due to restaurant restrictions and about lost business revenue due to general restrictions on public and private workplaces. Rerunning all models without including the youth access policy area affirms this expectation.

[11]A 10-mile radius seems appropriate as a limit on the distance a typical resident will travel to engage in smoking-related activities. This is consistent with numerous studies finding that the maximum distance restaurant customers are willing to travel to dine is between five and ten miles (e.g., Purlee 1995; Tanyeri 2007).

[12]To find the nearest city, we look only within state borders. Thus, the nearest bigger city for Toledo, Ohio, is Cleveland, rather than Detroit, Michigan, even though Detroit is closer. As this example indicates, our diffusion variables look within state boundaries. Future work to determine whether city-level diffusion stops at state lines would be most welcome, although it is beyond the scope of the present analysis. Initial exploratory analyses of the effects of local laws in neighboring states (e.g., by considering the proportion of the neighboring state's population that is covered by local laws) indicate that inclusion of such variables does not substantively change our results.

[13]Often these preemptive laws are more general than are the substantive state laws. For example, a state may pass a restriction on smoking in public places coupled with the preemption of local laws for all clean indoor air policies, meaning that the localities are being coerced to not act on restaurant restrictions even though the specific state law did not address restaurants at that point in time.

whether neighboring cities are adopting similar policies due to their similar political and economic conditions or due to policy diffusion (Franzese and Hays 2008). We therefore incorporate seven city-level control variables that are designed to capture separate internal influences on city-level policy adoptions. To begin with, ***City Population*** is simply the city's population (scaled in 100,000s of city residents). Larger cities have greater capabilities to pass laws and are anticipated to be early leaders, so we expect this variable to have a positive effect on the likelihood that the city will adopt a policy.

The form of government also may affect the likelihood of a policy adoption or innovation. ***Mayor-Council*** is a dummy variable that captures whether the city has a mayor-council city governance structure. As Knoke (1982) notes, many cities have adopted forms of government other than a combination of a mayor and a city council, expecting these other forms of government (e.g., commissions, council-managers) to possess more expertise and to be more effective and efficient at passing and implementing legislation. Thus, we anticipate *Mayor-Council* to have a negative influence on the probability that a city will adopt an antismoking law.[14]

Percent Health Employees captures the percentage of employed residents in the city who work in health service professions.[15] To the extent that this variable indicates the presence of health advocates or a predisposition toward more healthful policies, we would expect a positive coefficient. ***Percent High School Graduates*** captures the percent of the city population over age 25 with high school diplomas or equivalencies.[16] More educated populations are less likely to smoke, more likely to be concerned with health risks, and more liberal; thus we expect them to be more likely to favor the adoption of antismoking policies. ***Per Capita Income*** is the average income per resident in thousands of dollars.[17] We anticipate a positive coefficient on this variable. ***Percent White*** captures the non-minority presence in the city.[18] Relative to most minorities, whites are less likely to smoke, leading us to expect a positive coefficient on this variable. ***Per Capita Government Spending*** is expressed in thousands of dollars per resident and is an indicator of the liberalism or activism of the local government. We therefore anticipate a positive coefficient on this variable.[19]

We also need to account for several factors at the state level, in part to control for their overall effects within the state, and in part because good measures of these features do not exist at the urban level. ***Percent Smokers*** captures the statewide percent of adults who smoke. Ideally, this measure would be available at the city level. However, since such a measure does not exist for many cities in many years, it is necessary to control for statewide smoking rates as a proxy for local rates. ***Tobacco Production*** is a dummy variable, taking a value of 1 for cities in tobacco-producing states. We anticipate negative coefficients on both of these variables.

Other state-level measures control for governmental effects. First, we include two measures of interest group influence, ***Tobacco Lobbyists*** and ***Health Organization Lobbyists***, where the former is the ratio of tobacco lobbyists registered at the state level to the total number of lobbyists registered at the state level, and the latter is a similar ratio that uses health organization lobbyists in the numerator instead of tobacco lobbyists.[20] Our expectations here are conflicted. On the one hand, a city in a strong tobacco state will be less likely to adopt an antismoking law, while a city in a strong pro-public health state will be more likely to do so, due to interest group pressures extending to the local level. On the other hand, the inability of state officials to act may spur local action. Second, we also include a variable that measures ideology at the state level, relying on updated versions of Berry and Colleagues (1998) measure of ***State Government Ideology***, in which higher values represent more liberal views. More conservative states will be less likely to adopt antismoking laws, but this hesitancy may result in local, rather than state, adoptions.

Finally, we include dummy variables for the years in our analysis. Inclusion of these dummies allows us to

[14] Such findings would be consistent with Moon (2002), who uncovers positive effects of city size and council-manager governments in facilitating municipal website adoptions. Interestingly, Frederickson, Johnson, and Wood (2004) show how these city government types have emulated one another's features, becoming more similar and homogeneous over time.

[15] Including instead the proportion of city spending dedicated to health did not affect the diffusion relationships discussed below.

[16] Including instead other education variables, such as the current high school dropout percent or current college enrollment, showed weaker effects of education, but did not change the uncovered diffusion relationships.

[17] Similar results followed for the inclusion of household income, family income, or a variety of poverty and unemployment measures, none of which affected the uncovered diffusion relationships.

[18] Further breakdowns into other racial and ethnic categories showed some additional variation across groups, but did not change the support for the hypotheses of interest.

[19] The main findings are robust to other city-level controls, such as the population density, percent female, percent of population employed by the government, or average number of vehicles per household, most of which were not themselves significantly related to antismoking policy adoptions.

[20] These measures are based on the 1994 snapshot for each state, constructed by Goldstein and Bearman (1996).

look for patterns over time and to control for temporal dependence (Beck, Katz, and Tucker 1998). To save space in the tables, we do not report the coefficients for these year dummies, but note that they follow a general pattern: they tend to be negative in the early years of our series, positive in the middle, and negative toward the end, and are often (although not always) significant. Such a pattern is typical for S-shaped policy diffusions (Gray 1973), with a few leaders, a few laggards, and many adopters in the middle. Our results are not substantively altered if we use year and year-squared variables, rather than yearly dummies. All variables and their descriptions are summarized in the appendix.

Results

As described above, we pool our observations across the three types of antismoking policies. We test our hypotheses using logit, although the results are robust to other functional forms, such as probit or the complementary log-log function (Buckley and Westerland 2004). Other distributions of the hazard rates yield very similar results, whether based on a Weibull distribution or a Cox proportional hazards model. To account for heteroskedasticity and correlation across observations, we cluster by city-year using the cluster procedure in Stata 9.2, which allows the possibility of dependence in the three policy choices within each city in a given year and relies on Huber/White robust standard errors.[21] Year dummies help account for potential patterns of temporal dependence. The number of observations is determined by the number of cities at risk for each policy's adoption in each year.[22]

Our initial results focus on the four main diffusion hypotheses examined separately, as shown in Table 1. Although each of these models therefore faces potential omitted variable problems, this preliminary step is instructive in setting baselines against which the fully specified model can be compared. Because most previous studies have included only one mechanism or one diffusion variable, this comparison also underscores the degree to which those earlier results may be inaccurate.

Support for the Learning Hypothesis comes from our first horizontal diffusion variable, *Proportion of State Population with Local Restriction.* The coefficient on this variable in Model 1 is positive and significant, indicating that a city is more likely to adopt antismoking laws when a greater proportion of people in other cities within the state are covered by a similar law. Based on Model 1 results, a 10% increase in the state population covered by a similar antismoking restriction is associated with a 49% boost in the odds of such an adoption in the city we are focused on.

The results of Model 2 show that the second diffusion mechanism, outlined in the Economic Competition Hypothesis, is also at work here. As indicated by the negative coefficient on the *Outflow* variable, cities are hesitant to adopt antismoking laws when neighboring cities within 10 miles do not yet have such laws.[23] Because this variable is constructed based on city proximity and relative population sizes, its effect is somewhat difficult to characterize in a general sense, but examples can indicate the magnitude of the effect. For instance, compared to a city with no near neighbors, if a city has three equally sized proximate neighbors that do not have the given antismoking policy, its odds of adopting the smoking restriction on its own are 14% lower. Put another way, a one-standard-deviation increase in the *Outflow* (economic competition) variable—which indicates that a city is surrounded by more people, relative to its own population, who are not covered by the policy—is associated with a 33% drop in the odds of adoption in any given year. Cities thus are revealed to be hesitant to adopt antismoking policies until their neighbors act.

As shown in Model 3, *Nearest Bigger City* demonstrates strong support for the Imitation Hypothesis, indicating that the likelihood of a city adopting antismoking laws increases when the nearest city that is bigger has already adopted such a law. Substantively, the effect of neighboring city diffusion is quite large. Compared to a city without a previous adoption by its larger neighbor, a city whose nearest bigger neighboring city already has the same antismoking restriction in place is three times as likely to adopt its own restriction in any given year.

Finally, the results of Model 4 provide clear evidence in favor of the Coercion Hypothesis. The negative and significant coefficient on *State Law* indicates that the adoption of a state law restricting smoking decreases the odds that a city within that state will adopt a similar law. More specifically, the effect of a given state antismoking law is a 26% decline in the odds of a local adoption. Even more striking is the negative and significant coefficient for the *State Preemption* variable, indicating that the adoption of a preemptive state-level law decreases the odds of a local antismoking restriction by 94%.

[21] Similar results follow from clustering by city.

[22] Somewhat fewer observations are found in regressions including *Nearest Bigger City*, as this variable is undefined in states with only one city over 50,000.

[23] Interestingly, we found no support for an "Inflow" variable that we also constructed, a variable that sought to determine whether a city would be less likely to adopt laws if surrounding cities had already adopted such laws (i.e., where the city could hope to draw people from those other cities).

Table 1 City-Level Adoption of Antismoking Policies

	Model 1 Learning	Model 2 Competition	Model 3 Imitation	Model 4 Coercion
Horizontal Diffusion				
Learning (Proportion of State Population with Local Restriction)	3.98*** (0.365)	—	—	—
Competition (Outflow)	—	−0.0426*** (0.0148)	—	—
Imitation (Nearest Bigger City)	—	—	1.10*** (0.125)	—
Vertical Diffusion				
Coercion: State Law	—	—	—	−0.300*** (0.0980)
Coercion: State Preemption	—	—	—	−2.80*** (0.420)
City-Level Controls				
City Population (in 100,000s)	0.0453*** (0.0079)	0.0353*** (0.0078)	0.0286*** (0.0083)	0.0371*** (0.0081)
Mayor-Council	−0.118 (0.132)	−0.345*** (0.127)	−0.204* (0.128)	−0.334*** (0.126)
Percent Health Employees	0.0453*** (0.0188)	0.0288* (0.0207)	0.0340** (0.0202)	0.0247 (0.0197)
Percent High School Graduates	0.0432*** (0.0079)	0.0253*** (0.0084)	0.0284*** (0.0082)	0.0282*** (0.0081)
Per Capita Income	−0.0189 (0.0164)	0.0436*** (0.0143)	0.0213* (0.0149)	0.0208* (0.0142)
Percent White	0.00006 (0.00381)	−0.0107† (0.00362)	−0.00641 (0.00355)	−0.00762 (0.00348)
Per Capita Government Spending	0.241*** (0.0990)	0.0623 (0.107)	0.124 (0.104)	0.130 (0.106)
State-Level Controls				
Percent Smokers	−0.0405** (0.0209)	−0.0693*** (0.0185)	−0.0663*** (0.0196)	−0.0795*** (0.0200)
Tobacco Production	0.145 (0.149)	−0.310** (0.136)	−0.216* (0.136)	−0.137 (0.138)
Tobacco Lobbyists	12.6* (8.51)	10.6* (7.92)	10.2 (8.31)	6.71 (8.11)
Health Organization Lobbyists	−1.43* (0.964)	−2.68*** (0.818)	−2.34*** (0.893)	−1.90** (0.830)
State Government Ideology	−0.00453** (0.00273)	−0.00183 (0.00256)	−0.00482** (0.00262)	−0.00205 (0.00262)
Wald χ^2	528.2***	365.8***	404.1***	375.3***
N	34,415	34,415	32,810	32,903

Robust standard errors in parentheses, clustered by city-year. All models include yearly dummy variables and a constant, not shown here due to space considerations.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ (one-tailed tests).
†$p < 0.01$ (two-tailed test with coefficient taking unexpected sign).

The controls for city-level characteristics behave largely as expected. The positive and highly significant coefficient on *City Population* indicates that, as expected, larger cities took the lead in adopting antismoking restrictions.[24] Additionally, wealthier and more highly educated cities, and those with a greater presence of health professionals, were more likely to adopt antismoking policies. Consistent with a lower level of efficiency, the *Mayor-Council* variable is negative and statistically significant. Surprisingly, despite lower smoking rates among whites, predominantly white cities were actually somewhat less likely to pass antismoking measures.

At the state level, the negative coefficients for *Percent Smokers* and *Tobacco Production* are consistent with self-interested behavior. Meanwhile, the governmental state-level controls provide some intriguing results. The coefficient for *Tobacco Lobbyists* tends to be positive and statistically significant; and the negative (although not always significant) coefficients on *Health Organization Lobbyists* and *State Government Ideology* are suggestive. As we noted earlier, the expectations for these variables are unclear; and the results might seem to imply, perversely, that a strong pro-tobacco presence produces *more* antismoking restrictions, while a strong pro-health presence and a liberal state government lead to *fewer* antismoking restrictions. Another interpretation of these results, however, is also possible. Our findings, while not constituting hard proof, are nonetheless consistent with the idea that policy advocates engage in *venue shopping* (e.g., Baumgartner and Jones 1993; Boehmke, Gailmard, and Patty 2006; Pralle 2003). When the tobacco lobby is strong at the state level, for example, antismoking advocates realize that they will have little chance to succeed at the state level and thus will turn their attention to cities. Although we are hesitant to make too strong of a claim in favor of venue shopping—we would want to know, for example, that state-level strength for these advocates does not carry over to local-level strength—these results suggest that future exploration may be fruitful.

In sum, the results in Table 1 show strong patterns of policy diffusion through all four mechanisms of diffusion discussed above. We now expand on these results in two ways. First, we examine whether these mechanisms *collectively* influence diffusion—that is, do we continue to find evidence of each of these types of effects even when we control for all of the others? Second, we explore whether these mechanisms follow the systematic temporal and conditional patterns predicted by our hypotheses.

Multiple Mechanisms at Work

As noted earlier, although our main independent variables are designed to isolate key aspects of different diffusion mechanisms, they also may capture aspects of other mechanisms as well. For example, rather than just imitating the nearest larger neighbor and learning from cities throughout the state, cities may learn from their nearest larger neighbors or imitate other cities in the state. Comparing the results of Model 5 in Table 2 to the models from Table 1 demonstrates that, although all of the mechanism variables remain significant in the multivariate model, the sizes of the coefficients in Model 5 differ from those in Table 1. For instance, controlling for the other diffusion mechanisms, the coefficient on our learning variable (*Proportion of State Population with Local Restriction*) declines by about 20%, from 3.98 to 3.20. Additional analyses indicate that most of this drop is due to the inclusion of the imitation variable, indicating that about one-fifth of the learning effect detected in Model 1 was due to the policy choice of the nearest bigger city.[25]

Second, the coefficient on the competition variable (*Outflow*) likewise diminishes by one-quarter between Models 2 and 5. Again, this drop comes mainly from the inclusion of *Nearest Bigger City*, indicating that the effect of competition shown in Model 2 had been somewhat overstated by failing to control for imitation of the nearest bigger city. Third, and most dramatically, the coefficient on the imitation mechanism variable itself (*Nearest Bigger City*) is cut to less than half of its value between Models 3 and 5. This drop is mainly due to inclusion of the learning variable, indicating that a substantial portion of what previously had appeared to be imitation was due to learning from other cities, including from the nearest larger neighbor. Finally, the coercion variables maintain their sizes upon controlling for the other diffusion mechanisms, suggesting that vertical diffusion in the form of state-to-local coercion is a process wholly separate from the horizontal spread of policies from city to city.

Temporal Diffusion Patterns

The Temporal Effects Hypothesis predicted that imitation should be a relatively short-lived effect, while the effects

[24]The results in this table hold when we limit our analysis to cities with populations under 1,000,000; thus, the results are not being driven by a few large cities. In addition, similar results follow from including population squared rather than population as a control variable.

[25]Specifically, including all of the variables in Model 5 except *Nearest Bigger City* produces a coefficient on *Proportion of State Population with Local Restriction* (as well as on *Outflow*) that is very near its Table 1 value.

TABLE 2 All Diffusion Mechanisms, Temporal Lags, and Conditional Effects

	Model 5 All Mechanisms	Model 6 Lagged Effects	Model 7 Conditional Effects
Learning (Proportion of State Population with Local Restriction)	3.20*** (0.442)	2.47*** (0.474)	3.02*** (0.487)
Learning × Population	—	—	0.316** (0.190)
Competition (Outflow)	−0.0320** (0.0150)	−0.0249** (0.0125)	−0.0644*** (0.0260)
Competition × Population	—	—	0.0438*** (0.0171)
Imitation (Nearest Bigger City)	0.456*** (0.155)	0.243* (0.175)	0.486*** (0.161)
Imitation × Population	—	—	−0.0392*** (0.0123)
Coercion: State Law	−0.345*** (0.0924)	−0.422*** (0.0946)	−0.309*** (0.105)
Coercion (State Law) × Population	—	—	−0.0275 (0.0451)
Coercion: State Preemption	−2.75*** (0.428)	−2.74*** (0.508)	−2.76*** (0.470)
Coercion (Preemption) × Population	—	—	0.0376 (0.156)
Wald χ^2	562.8***	438.9***	589.6***
N	32,810	29,813	32,810

Robust standard errors in parentheses, clustered by city-year. All models include city-level controls, state-level controls, yearly dummy variables, and a constant, not shown here due to space considerations.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ (one-tailed tests).

of learning and competition should be more enduring. To test this hypothesis, we reran Model 5, replacing the diffusion variables with the same variables lagged by two years. The results are displayed in Model 6.[26] If the effect of imitation takes place immediately upon the action of the Nearest Bigger City and then fades as the imitating policymakers move on to other issues, then the coefficient on the lagged imitation variable should be substantially diminished for the lagged variable as compared to the more immediate short-term effect shown in Model 5. Conversely, if the effects of the other horizontal mechanisms are more enduring, their coefficients should remain roughly the same size as in Model 5. This is indeed what we find. While the coefficient on *Nearest Bigger City* drops nearly 50% to 0.243 and becomes statistically significant only with a very lenient $p < 0.10$ standard and a one-tailed test, the coefficients on *Proportion of State Population with Local Restriction* and *Outflow* drop by less than one-quarter and retain their substantial statistical significance.[27] Taken together, not only do our findings support the Temporal Effects Hypothesis, but they also lend additional support to our operationalization of the key variables of learning, competition, and imitation. Although there may be overlap across these variables, they exhibit temporal effects that are consistent with theoretical expectations.

The Contingent Nature of Diffusion

The models examined so far have treated the diffusion process as being fundamentally the same for all cities. Each city, for example, was found to be more likely to adopt policies found in other cities and less likely to adopt

[26]Other lags showed similar results.

[27]Interestingly, despite our lack of clear theoretical expectations, the coercion variables show temporal effects similar to those of the competition and learning variables. In addition, the effects for learning, competition, and imitation are unchanged if we simply use the unlagged versions of the coercion variables.

policies where the state government had already acted (especially with preemptive laws). There is reason to believe, however, that diffusion does not work the same way for every government. Dealing with state-level antismoking adoptions, for example, Shipan and Volden (2006) find different patterns of diffusion for states with more professional legislatures than for those with less professional legislatures. This article similarly posits that a more complete understanding of diffusion must recognize that diffusion effects—more specifically, the effects of various mechanisms—can be conditional.

The Conditional Diffusion Hypotheses suggest that larger cities are better able to learn from others, less susceptible to economic competition, less likely to engage in imitation, and less vulnerable to coercion. To test these four hypotheses, we interact *City Population (in 100,000s)* with measures for each of the four mechanisms of policy diffusion. Model 7 in Table 2 mimics Model 5, but with the inclusion of these interactive variables, and produces the following results. First, consistent with the Conditional Learning Hypothesis, the positive coefficient on the interaction between *Population* and *Proportion of State Population with Local Restriction* shows that learning is enhanced in larger cities. Because their governments are larger and more capable, these bigger cities are better able to build on the experiments of others. For example, a city of 50,000 increases its odds of adoption by 3.2% for each additional percent of the state population covered by other cities' laws. The comparable learning-based boost for a larger city of 500,000 is 4.7%.

Second, the positive coefficient on the interaction between *Outflow* and *Population* indicates that smaller cities are more concerned with economic competition than are larger cities. For example, consider two contiguous cities of the same size. If the cities are of population 50,000, the *lack* of a policy in the neighboring city diminishes the other city's odds of adoption by about 4.2%. Yet, if the cities are each of population 147,000, this economic competition effect falls to zero. This finding shows support for the Conditional Competition Hypothesis.

Third, consistent with the Conditional Imitation Hypothesis, the negative coefficient on the interaction between *Nearest Bigger City* and *Population* indicates that larger cities are indeed less likely to rely on imitation than are smaller cities—that is, the effect of *Nearest Bigger City* diminishes for larger cities. For example, a city of 50,000 has 59% greater odds of an antismoking adoption if its nearest bigger city already has the policy. Yet that boost in the likelihood of adoption due to imitation drops to 34% for a city of 500,000. Overall, the imitation effect shrinks to zero when city size reaches about 1.2 million people.

Fourth, the interactions between *Population* and the coercion variables of *State Law* and *State Preemption* are statistically indistinguishable from zero. Thus, contrary to the Conditional Coercion Hypothesis, both large and small cities alike are coerced by the governments of the states in which they are situated.[28] Vertical diffusion thus appears to be less conditional than horizontal diffusion.

Taken together, these interactions provide strong evidence in support of the Conditional Diffusion Hypotheses for the three horizontal diffusion mechanisms.[29] Put simply, the smallest cities in our dataset (with 50,000 residents) are responsive to many diffusion pressures. They imitate larger cities, learn somewhat from experiments of others, and worry about the economic consequences of their laws. The average city in our analysis (population 150,000) still imitates the biggest cities and is better able to learn from experiments elsewhere in the state, but shows little concern for economic spillovers to the (typically smaller) surrounding communities. Finally, the largest cities show no evidence of imitation and spillover concerns, seeming rather to act based on the experiences of earlier adopters throughout the state.

Discussion and Conclusion

The scholarship to date on diffusion has shown robust patterns of policies and institutions spreading from country to country and from state to state. This study finds that localities are also susceptible to horizontal and vertical diffusion pressures. More importantly, this work reveals some of the benefits of studying diffusion at the local level. In particular, we demonstrate one way to disentangle the multiple diffusion mechanisms of learning, economic competition, imitation, and coercion. We show not only that these mechanisms exist, but also that the effect of imitation fades over time while the other mechanisms' effects are more persistent. Moreover, diffusion mechanisms play different roles in large cities than in small cities. Compared to small cities, large cities are

[28] Additional analyses indicate that very small cities are somewhat more likely to be deterred by state action than are larger cities. Perhaps larger cities limit coercion by states earlier in the policy process, when city officials lobby state legislators against preemptive clauses.

[29] Interactions of the horizontal diffusion variables with *Per Capita Income* and with *Mayor-Council* suggest further conditional diffusion effects, but are excluded here due to space considerations.

equally susceptible to coercion from the state government, but are more likely to learn from others' experiments, and are less likely to simply imitate the policies of others or to be deterred in their actions by potential economic competition.

Such findings have important normative implications. First, it is altogether possible that the most appropriate policy for one government may be different from that for another government serving a different population. Evidence that small cities simply copy their larger neighbors suggests that their policies may not be as well suited for their populations as would be ideal. Second, when the control of policies is devolved to lower levels of government, one of the potential benefits is that these governments will experiment and learn from one another. Here we find such learning, even among the smallest of cities in our dataset. However, the other side of devolution is that the lower-level governments may compete with one another in ways that are not mutually beneficial, or may adopt policies with negative externalities felt by others. We find that economic competition is relevant to antismoking policy choices and has caused some (particularly small) cities to hesitate to adopt policies until their neighbors do the same. When, instead of devolution, policy centralization takes place, such as with state laws including preemptive clauses, it is unsurprising that such experimentation and competition comes to a nearly complete halt.

APPENDIX Variable Descriptions, Summary Statistics, Sources

Variable	Description	Mean	St. Dev.
Antismoking Policy Adoption[a]	Dependent variable = 1 if city adopts its first law in this area in this year. Set = 0 if no adoption to date. Observation removed if already adopted.	0.015	0.123
Proportion of Population with Local Restrictions[a,b]	Proportion of state population living in localities with restrictions in this area at start of the year.	0.112	0.163
Outflow[a,b]	Ratio of sum of populations of surrounding cities without policy to home city's population.	3.769	9.250
Nearest Bigger City[a,b]	Dummy = 1 if the nearest city that is larger than the observation city adopts its law in this area prior to the observation year.	0.211	0.408
State Law[c]	Dummy = 1 if state adopted restriction in this area prior to this year.	0.364	0.481
State Preemption[c]	Dummy = 1 if state adopted law prior to this year that prohibits or limits city-level government laws in this area.	0.144	0.351
City Population[b]	City population (in 100,000s) at the time of the nearest census.	1.482	3.834
Mayor-Council[d]	Dummy = 1 if the city has a mayor-council form of government.	0.326	0.469
Percent Health Employees[e]	Percent of employed residents working in health services professions.	9.18	2.77
Percent High School Graduates[e]	Percent of adults over age 25 with high school diplomas or equivalencies.	72.8	11.5
Per Capita Income[e]	Average income per resident ($1000s).	11.7	4.78
Percent White[e]	Percent of residents self-identified as white.	76.8	17.5

(continued)

APPENDIX Continued

Variable	Description	Mean	St. Dev.
Per Capita Government Spending[e]	Government spending in thousands of dollars per resident.	0.801	0.538
Percent Smokers[f]	Percent of adults in state who smoke.	24.5	3.51
Tobacco Production[g]	Dummy = 1 if tobacco produced in state.	0.329	0.470
Tobacco Lobbyists[h]	Proportion of lobbyists in the state working for tobacco industry, based on 1994 snapshot.	0.014	0.007
Health Organization Lobbyists[h]	Proportion of lobbyists in the state working for health organizations, based on 1994 snapshot.	0.089	0.062
State Government Ideology[i]	Ideology score for state government.	52.5	21.6

Data sources:

[a]Constructed by authors based on American Nonsmokers' Rights Foundation Local Tobacco Control Ordinance Database©.
[b]Constructed by authors based on U.S. Census data.
[c]Constructed based on National Cancer Institute, State Cancer Legislative Database Program, Bethesda, MD: SCLD.
[d]*City and County Databook*, various years.
[e]Constructed by authors based on U.S. Census data provided by the Taubman Center, Harvard University.
[f]Centers for Disease Control and Prevention website (http://apps.nccd.cdc.gov/statesystem/, choose "Detailed Report").
[g]Constructed by authors based on U.S. Department of Agriculture data.
[h]Constructed by authors based on Goldstein and Bearman (1996).
[i]Berry, Ringquist, Fording, and Hanson (1998) data on ICPSR website.

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