

The Role of Policy Attributes in the Diffusion of Innovations

Todd Makse*
Craig Volden
The Ohio State University

July 2009

Abstract

Studies of policy diffusion have given insufficient attention to the role that characteristics of the policies themselves play in determining the speed of policy diffusion and the mechanisms through which diffusion occurs. We adopt Everett Rogers' (1983, 2004) attribute typology from the diffusion of innovations literature and apply it to a sample of twenty-seven policy innovations from the sphere of criminal justice policy in the U.S. states between 1973 and 2002. We find that policy attributes, ranging from the relative advantage of the policy over its predecessors to its complexity to its compatibility with past practices, affect the likelihood of adoption. Furthermore, policy attributes shape the extent to which spatial adoption patterns and learning mechanisms are relevant to the policy's diffusion.

* The authors thank David Knapp for valuable research assistance; and Tom Nelson, Dick Winters, Alan Wiseman, and conference participants at 2006 Southern Political Science Association Meetings for helpful comments and suggestions. Please send questions or comments to: Craig Volden, 2147 Derby Hall, 154 N. Oval Mall, Columbus, OH 43210-1373, or email volden.2@osu.edu.

The Role of Policy Attributes in the Diffusion of Innovations

“When one peruses the diffusion research literature, one may be impressed with how much effort has been expended in studying ‘people’ differences in innovativeness (that is, in determining the characteristics of the different adopter categories) and how little effort has been devoted to analyzing ‘innovation’ differences (that is, in investigating how the properties of an innovation affect its rate of adoption).”

– Everett M. Rogers, “The Diffusion of Innovations” (1983)

The political science literature on policy diffusion suffers from exactly the malaise that Rogers described a quarter century ago, despite the fact that his work has been highly influential in guiding research in this field. We know that, among other things, the rate and manner of policy diffusion can be influenced by geography (Berry and Berry 1990), contextual similarity (Case, Hines, and Rosen 1993), ideology (Grossback, Nicholson-Crotty, and Peterson 2004), interest group presence and expert knowledge (Skocpol et al. 1993; Mintrom 1997; Balla 2001), policies of other levels of governments (Allen, Pettus, and Haider-Markel 2004; Shipan and Volden 2006), state policymaking institutions (Boehmke 2005; Kousser 2005), and many other factors. This list of findings, while impressive, all falls on the “people differences” side of the ledger.

Our knowledge regarding the importance “innovation differences” is comparatively scant. While initial studies of policy diffusion explored dozens of policies at once (Walker 1969, Gray 1973), they failed to account for the internal determinants that explained statewide adoptions (Berry and Berry 1990). More recent studies have examined individual policies separately, offering little in the way of comparisons across findings for different types of policies. Even where multiple policy decisions are examined, the focus has been on one specific contextual factor, such as national government influence (Allen, Pettus, and Haider-Markel

2004), local laws (Shipan and Volden 2006), or ideological similarity (Grossback, Nicholson-Crotty, and Peterson 2004), rather than on the nature of the policies themselves.

Helping to fill this void, Mooney and Lee (1995, 2000) suggest a basis for classifying public policies to aid in uncovering variance in the patterns of diffusion. Although they ultimately find results to the contrary, they explore the possibility that “morality” policies diffuse differently from economic policies; and, as a broader theoretical underpinning, they point to Lowi’s (1964) classification of public policies. As a basis for theorizing about policy diffusion, this typology has the attractive feature of being explicitly political. On the other hand, this approach fails to capture other key qualities of public policies. For example, at the time of their consideration, both the death penalty and “three strikes” laws were policies whose purpose and ideological bent could be described as very similar. Almost any political typology of these laws would group them together. Yet, they were different in a number of important respects: for three strikes laws, policymakers could not reasonably predict their deterrent power, their impact on the judicial and corrections systems, costs to the state, or the public’s reaction. That is, policymakers who considered the implementation of three strikes laws faced a highly complex and uncertain information environment, relative to death penalty, with which many states had previous experience.

In the broader literature on the diffusion of innovations, discipline-specific formulations such as the Lowi typology are not the norm. Rather, Rogers’ typology of innovation attributes, which has been applied to diffusion studies across many other disciplines, has been consistently successful as a predictor of patterns of diffusion. Although the specific definitions associated with this typology require customization to apply to the discipline in question, the general

features of this paradigm are universal. Unfortunately, this theory of diffusion has been, to date, neglected in political science.¹

In this paper, we examine the five attributes suggested by Rogers: relative advantage, compatibility, complexity, observability, and trialability. Using an original data set of twenty-seven policy adoptions from the sphere of criminal justice policy and an expert survey of criminal justice policymakers, academics, and practitioners, we find that these attributes are influential in determining the rates of policy adoption. Moreover, we find that classifying policies according to these categories allows us to better understand when and how policies spread geographically and when learning is the primary mechanism underlying policy diffusion.

We argue that such a focus on policy attributes is important in interpreting the results of the hundreds of policy diffusion books and articles published to date in all subfields of political science.² For instance, we find that complex policies that are not compatible with past practices and whose effects are not easily observed are unlikely to diffuse broadly. Thus a study in comparative politics on policy transfer is going to find little evidence of one country's influence on another for such a policy; a study of this type of policy in international relations will likewise show little coercive ability of major powers and international organizations; and a study of a complex, incompatible, low advantage policy in American state politics may find little evidence of learning-based policy diffusion. Yet the lesson to be drawn in all such cases is not about the nature of policy transfer, coercion, and learning, but about the nature of the policy itself. Utterly different findings could emerge from instead examining a compatible, observable, and not too complex policy with a significant relative advantage over past practices.

¹ One partial exception is the work of Nicholson-Crotty (2009), who finds that a policy's salience increases its speed of diffusion, conditional on the policy area not being too complex.

² See Karch (2007) and Stone (1999) for helpful reviews of these vast literatures.

If political scientists remain unaware of the role of policy attributes in diffusion studies, we will continue to be at a serious disadvantage in understanding the results of these studies, and in comparing one study's results to another. We seek to help in the interpretation of past, current, and future policy diffusion scholarship by developing, operationalizing, and testing general hypotheses about the role of attributes in policy adoption and policy diffusion.

In the following section, we describe past research on criminal justice policymaking in the U.S. states. We next discuss theoretical reasons why policy attributes are likely to affect policy diffusion in this area, and in policymaking more generally. We then turn to a description of data collection and analyses. We finally report the results of our analyses before offering concluding comments and suggestions for future research.

Criminal Justice Policy

Within the policy diffusion paradigm, criminal justice policies have received their fair share of attention. To name just two, both the death penalty and hate crimes legislation have been the subject of numerous single-issue policy diffusion studies. In examining the death penalty, Mooney and Lee (2000) find that closely divided public opinion constrains policy options, but that unified public opinion allows policymakers to follow their own ideological preferences regarding the timing and extent of the publicly preferred policy change. Langer and Brace (2005) find that the passage of death penalty policies was influenced by the likelihood of court intervention. Regarding hate crimes laws, Grattet, Jenness, and Curry (1998) find strong effects for both internal determinants and geographic diffusion, while Allen, Pettus, and Haider-Markel (2004) find evidence only in favor of internal determinants. Soule and Earl (2001) do

not find a geographic pattern of diffusion, but find that emulation is related to the repeal of sodomy laws in other states.

Of course, these studies do not allow us to make any strong generalizations about the way criminal justice policies diffuse. First of all, there is no reason to believe these two policies are representative of all state laws, or even of all criminal justice laws. Death penalty adoptions may differ from other diffusion processes in that recent actions followed a period of court-ordered abolition. Hate crimes laws, on the other hand, do indeed have a criminal justice component, but are also strongly tied to debates over the protection of gays and other minorities. If we are to find evidence that states perform a role as “policy laboratories” within the criminal justice system, we must focus on a much broader array of policies that are not subject to these single-issue idiosyncrasies.

However, the broader literature on criminal justice policy may lead us to doubt that states engage in social learning and policy diffusion at all. One of the dominant viewpoints in the criminal justice literature is that criminal justice policies are driven instead by some combination of partisan politics, ideology, the media, public opinion, and racial animus. For example, several decades of presidential campaigns, seen especially in those of Nixon and George H. Bush, are associated with a Republican strategy of being “tough on crime,” leading Democrats to gradually shift their positions to compete for the crime-conscious electorate (Merlo and Benekos 2000). The success of crime as a political wedge issue stems in part from its symbolic racial content (Rosch 1985), and, as such, is likely part of the racial “issue evolution” that has come to structure party politics (Carmines and Stimson 1989). An additional source of this trend, however, lies in the media, where portrayals of crime and poverty heavily feature images of minorities (Kellstedt 2003; Beckett and Sasson 2000). Adherents to a race-based view (or any other “internal

determinants” view of policymaking) would not, however, expect other states’ actions to be a major determinant of policy adoption decisions.

Yet another internal determinants argument is that criminal justice policy is influenced by a “prison-industrial complex” (Christie 2001, Davis 1998), which profits from the adoption and enforcement of tougher criminal justice policies. Additionally, criminal justice policy is often portrayed as following a cyclical pattern (Dalton 1985, Merlo and Benekos 2000), which may be unrelated to objective indicators, let alone to learning from the policy experiments of others. Finally, even to the extent that social learning does occur, the impetus for learning may not be policy success. According to one account (Teichman 2005), the criminal justice system exhibits the features of a “race to the bottom,” often associated with welfare policies (Peterson and Rom 1990, Volden 2002, Bailey and Rom 2004), in which states compete in terms of the harshness of their laws in order to rid themselves of criminals or in which politicians compete with one another for a “tough on crime” label.

Theoretical Development

As the above brief survey of criminal justice policymaking illustrates, scholars are divided on the main determinants of policy change. Some studies suggest that the diffusion of policies from one government to the next is a driving factor in the adoption of innovations, while others find no evidence of policy diffusion. This story is repeated in one policy area after another. Although political scientists have recently improved our understanding of policy diffusion by expanding beyond the focus on geographic neighbors and by exploring different mechanisms of diffusion (e.g., Berry and Baybeck 2005, Shipan and Volden 2008), there often still seems to be no rhyme or reason as to which studies find evidence of policy diffusion and

which do not. We argue that what has been missing from this literature is a direct focus on the nature of the different policies themselves. To gain such focus, we build upon work on the diffusion of innovations found in a wide variety of fields outside of political science.

Most notably, Rogers (2004) claims that five main attributes of innovations consistently predict their rates of adoption across a broad range of disciplines and contexts. These five attributes are relative advantage, compatibility, complexity, observability, and trialability. The specific meaning of these terms varies by discipline, and a debate exists over whether to measure these concepts generally, using standardized questions to maximize reliability (Moore and Bensabat 1991), or to develop an instrument specific to the types of innovation under study (Rogers 2004). We adopt the latter approach, and measure these concepts through a survey of state-level criminal justice experts, described in more detail below. The survey was designed to assess the attributes of the 27 criminal justice policies being explored here, as defined in Appendix A.

In this section, we seek to accomplish four tasks. First, we define the five innovation attributes raised by Rogers. Second, we note how those attributes could be applied to public policies. Third, we discuss the language used in our expert surveys to try to gain leverage on the attributes of state criminal justice policies. And fourth, we generate a series of general hypotheses regarding how these attributes affect the rate of policy adoption and the nature of policy diffusion from one government to the next.

Generally, “relative advantage” refers to the “degree to which an innovation is perceived as being better than the idea it supersedes...[it is] a ratio of expected benefits and costs of adoption” (Rogers 2004, p. 212). Relative advantage is certainly a concept that is relevant to public policymaking, as the comparison of the benefits and costs of policies is commonplace in

the policymaking process. In our expert survey, relative advantage is ascertained through a question regarding the “policy impact” of each policy. Specifically, we asked to what extent “the policy was perceived by policymakers as likely to improve the effectiveness of the criminal justice system in the area in question.” For exact wording of all questions, see Appendix A.

“Compatibility” is “the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters” (Rogers 2004, p. 224). This definition is multifaceted, both in general and in its applicability to public policies. Certainly, meeting policy needs and being resonant with past values and experiences will help a policy find its way through the process. And yet, this attribute in many ways conflates the characteristics of the innovation with the characteristics or needs of the potential adopter. The same policy, the death penalty for example, may be seen as compatible with existing values in one state but not in another. Therefore, we focus on the elements of “compatibility” that are most closely aligned with the policy itself, rather than dependent on the adopting government. Specifically, we asked our respondents “whether passage of this policy required statutory changes in other areas of state law.” If not, the current policy change could be perceived as being highly compatible with previous policies.

“Complexity” is “the degree to which an innovation is perceived as relatively difficult to understand and use” (Rogers 2004, p. 242). We believe that difficulty in understanding is highly relevant to policy adoption, whereas difficulty in use is more relevant to policy implementation. Therefore, we designed our instrument to ask two questions about such a difficulty in understanding the policy. The first asks about the clarity of purpose of the innovation, “whether the policy’s purpose and likely results were clear to most legislators at the time of consideration.” If not, the policy could be thought of as quite complex. The second asks about

the level of complexity involved in legislative formulation, “whether the policy idea was easy to translate into legislation.” These two questions are aggregated into an index of complexity.

“Observability” is “the degree to which results of an innovation are visible to others” (Rogers 2004, p. 244). To the extent that policy diffusion is based on awareness and learning from the experiments of others, observability is very important. Our survey therefore focused on policymaker knowledge; respondents were asked “whether the policy produced results that could be easily observed by policymakers in other states.”

Finally, “trialability” is “the degree to which an innovation may be experimented with on a limited basis” (Rogers 2004, p. 243). Once again, this attribute is relevant for public policymaking, as some policies can be tried and abandoned with lower efforts and at a lower political cost than could others. Our measure for this attribute is built from two questions: one asking “whether implementing the policy on a trial basis might have been perceived as useful to policymakers,” and a second asking “whether abandoning the policy, if it were found to be ineffective, would be problematic.”

For all five attributes, Rogers offers clear expectations about the effect that each would have on the rate of innovation adoption. We simply rely on his guidance in offering the following hypothesis.

Policy Attributes Hypothesis: *The relative advantage, compatibility, observability, and trialability of a policy innovation will be positively associated with its rate of adoption. The complexity of a policy innovation will be negatively associated with its rate of adoption.*

Finding support for the Policy Attributes Hypothesis would illustrate that the adoption of policy innovations across the American states is consistent with the diffusion of other types of innovations in numerous other settings. While important in its own right, the political science

literature has come to realize that there is a difference between the rapid adoption of a particular policy and actual policy diffusion, with the latter establishing that the policy's adoption is a function of the earlier actions of other governments. For example, Volden, Ting, and Carpenter (2008) suggest that much purported evidence of policy diffusion to date could simply have come from independent experimentation with new ideas rather than from learning from one another's experiments. And Shipan and Volden (2008) build upon earlier work by Simmons, Dobbin, and Garrett (2006) and Boehmke and Witmer (2004) in highlighting the different mechanisms through which policy diffusion might occur.

Following these recent studies, we seek to explore how policy attributes might affect not only the rate of policy adoption but also the nature of how policies spread from one state to the next. To do so, we consider the extent to which the above five policy attributes facilitate or undermine two diffusion mechanisms: the spread of policies through adoptions by neighboring states and diffusion via a learning process sparked by an accumulation of other states' experiments.³

As most commonly studied in political science, diffusion may occur through a traditional "neighbors" effect; that is, states may be more likely to adopt a given policy when one or more geographic neighbor has already adopted the policy. The mechanism behind neighbor-based diffusion is often multifaceted, including economic competition or "race to the bottom" pressures, yardstick competition among elected officials, imitation of perceived leaders, or learning through enhanced interactions among those who are nearby. As something of a catch-

³ Other diffusion mechanisms are likely to be less relevant to the spread of criminal justice policies. Simple imitation (e.g., Shipan and Volden 2008) or ideological similarity across states (e.g., Grossback, Nicholson-Crotty, and Peterson 2004) may have some relevance in this policy area, however. Therefore, in additional analyses not reported here, we examined whether the adoption of our 27 policies was a function of the ideological similarity to earlier adopters or a function of the adoptions in the nearest larger state. We found no systematic evidence of such diffusion mechanisms in general, so did not continue to explore whether such mechanisms were further affected by the policy attributes studied here.

all, neighbor-based policy diffusion is a good place to start to see whether policy attributes affect the overall diffusion process. As a baseline, therefore, we offer the following hypothesis.

Neighbor-Based Diffusion Hypothesis: *As the proportion of its neighboring states that have previously adopted a given policy increases, a state will be more likely to adopt that policy.*

Perhaps most relevant for the adoption of criminal justice policies is the mechanism of “learning,” whereby effective policies of one state are adopted at a greater rate in other states (Volden 2006). Policies designed to fight crime in its many forms are broadly discussed and analyzed, with best practices noted by numerous organizations. We are not in a position to examine the effectiveness of each of the 27 criminal justice policies in our study, and certainly not on a common scale. We therefore fall back on the “opportunity to learn” idea put forth by Shipan and Volden (2008), who argue that, as the number of early experimenters expands, the opportunity to learn about policies’ political and substantive successes is enhanced. For policies that are ultimately broadly adopted, then, the following hypothesis captures the possibility of learning.

Learning-Based Diffusion Hypothesis: *As the number of states that have previously adopted a given policy increases, other states will be more likely to adopt that policy.*

These general hypotheses are fairly common in the growing literature on policy diffusion. What has not been examined, however, is the degree to which these diffusion processes depend on the nature of the diffusing policies themselves. We argue that not only are the above policy attributes important in understanding the speed of adoption but they are also relevant in assessing the degree to which those adoptions are based on the earlier actions of other governments. Single-policy studies of diffusion have found everything from large to small to nonexistent

neighbor and learning effects, and we offer policy attributes as one potential cause of variance at the meta-analytic level.

Three of our five attributes should be associated with an enhanced diffusion process through these mechanisms: relative advantage, compatibility, and observability. In the case of relative advantage, policies that possess this attribute to a greater degree will create larger gaps between the criminal justice capacity of states that have adopted the new policy and those that have not. As such, lawmakers in states that have not yet adopted the policy will face more pressure, either implicitly from competitive forces, or more explicitly, from interest groups or the media. These gaps will be magnified and of a higher profile when neighboring states have adopted the policy, or when a large number of states nationwide have adopted it. And policies that possess a high degree of relative advantage will be more easily perceived as successful based on early experimentation elsewhere, thus enhancing the learning process.

High levels of compatibility will also encourage the diffusion of policies through neighboring states and learning mechanisms. When policies are highly compatible with existing law or practice, the lag time between learning of a policy innovation's existence or effectiveness and enacting that policy idea into law should be greatly reduced. Thus, whether the state is emulating its neighbors or learning from previous policy adoptions in general, compatibility will support this mechanism of policy diffusion.

Finally, high levels of observability will also encourage diffusion through both neighbor-based and learning mechanisms. In many ways, observability is a necessary condition for policy diffusion. Without awareness of what others are doing (and, to some extent, with what effects) it is not even possible to engage in emulation or learning. As policies and their effects become

more observable, the diffusion process is enhanced. Neighbors can adopt one another's policies with greater transparency, and the learning process can be accelerated.

The above logic regarding relative advantage, compatibility, and observability can be summarized in the following two hypotheses:

Enhanced Spatial Diffusion Hypothesis: *The spread of policies across neighboring states will be enhanced for policies with high relative advantage, high compatibility, and high observability.*

Enhanced Learning Hypothesis: *The role of learning in the diffusion process will be enhanced for policies with high relative advantage, high compatibility, and high observability.*

In contrast, our remaining two attributes, complexity and trialability, might be seen as lessening the effects of these two diffusion mechanisms. Policy complexity serves to make the effects of policies less obvious. State policymakers may not even be in a position to easily understand what others are doing in complex policy arenas. And, even once such understanding is achieved, policy complexity slows down the ability of a government to formulate and adopt a policy that fits with its prior policies and expresses the sense of policymakers regarding how to proceed in a difficult policy area. In all of these ways, complex policies should slow down or hinder the spread of policies across neighboring states or from early adopters to those who learn from them.

Trialability should have a pronounced effect in depressing the impact of diffusion mechanisms. Governments that can try a policy internally with little downside will be less likely to rely on the experiences of others. Instead of waiting to see what neighbors do or to learn of the policy's effects in a jurisdiction that may differ from their own, policymakers will make independent decisions about highly trialable policies. Interestingly, this is the only attribute for which the speed of adoption and the nature of policy diffusion run in opposite directions. For

relative advantage, compatibility, and observability, the speed of adoption is enhanced, as is the likelihood of policy diffusion. For complexity, the opposite is true both for adoption and diffusion. For trialability, however, adoption is more likely, but at the expense of external learning and emulation, which is deemed no longer necessary by the nature of the trialable policy.

The predictions associated with the final two attributes are summarized in the following hypotheses:

***Diminished Spatial Diffusion Hypothesis:** The spread of policies across neighboring states will be diminished for policies with high levels of complexity and with high trialability.*

***Diminished Learning Hypothesis:** The role of learning in the diffusion process will be diminished for policies with high levels of complexity and with high trialability.*

While the policy attributes, their measurement, and their expected role in policy adoption and policy diffusion have all been discussed here in the context of criminal justice policymaking in the U.S. states, this context is given merely for ease of explaining the relevant concepts, rather than to imply that the hypotheses are relevant only in one policy area. Rather, we suggest that the above hypotheses are applicable to studies of policy diffusion across numerous policy areas at local, regional, and national levels.

Data and Methods

Testing the above general hypotheses requires the analysis of diffusion processes across multiple policies that are comparable on many dimensions, but which differ in terms of the five relevant policy attributes. Recent criminal justice policymaking in the U.S. states offers

significant promise along these lines.⁴ The states have broad discretion in determining their own crime policies, allowing for substantial variation in their policies and in the adoption of innovations. Moreover, the state criminal justice policy landscape is constantly changing with numerous broad and innovative policies adopted across the states in any given year. And finally, state criminal justice policies are comparable on many grounds, typically adopted through legislative processes, typically encompassing regulatory policymaking, and often with a similar interest group landscape. By examining policies that are similar on many dimensions but differ in policy attributes, we hope not only to test the above hypotheses but also to overcome some of the limitations of prior work on diffusion of different types of policies. For example, the comparison of the adoption and diffusion of multiple criminal justice policies does not suffer from potential confounding elements in examining multiple different policy areas at once (e.g., Nicholson-Crotty 2009), or in studying policies that are influenced by significantly different interest group pressures and politics from one another (e.g., Mooney and Lee 1995).⁵

More specifically, we examine the role of policy attributes through a pooled event history analysis of twenty-seven criminal justice policy innovations in the U.S. states from 1973-2002. To construct the universe of criminal justice policies for inclusion in this study, we relied on three sources. The first is a report from the National Criminal Justice Commission (Donziger 1996). Although this study is often critical of the policies it identifies, it is a good accounting of the policy innovations that were developed as part of the “War on Crime” in the 1980s and early 1990s. The second source is the Suggested State Legislation series published by the Council of State Governments, which identifies policies that have been passed in at least one state and are

⁴ Other policy areas may be appropriate as well, and we encourage the replication of our study across other policy areas and other levels of government.

recommended by the CSG for passage elsewhere.⁶ The third source is the Criminal Justice section of the website of the National Conference of State Legislatures, which identifies recent policy innovations. These three sources helped us identify a broad array of criminal justice policies that were adopted across the states over recent decades. The information on which policies were adopted in which year was gathered from a variety of public sources, including Lexis-Nexis news archives and legislative archives. The full list of policies along their descriptions is given in Appendix A.

We analyze the adoption of these twenty-seven policies through event history analysis (EHA), which allows the simultaneous examination of internal state determinants and external diffusion processes (Berry and Berry 1990). Given that any of these policies can be adopted by any state in any order, we follow the approach of Shipan and Volden (2006) in adopting a modified pooled regression analysis adapted from Wei, Lin, and Weissfeld (1989). In our setting, this approach yields one observation per state per year per policy, over the period of time that each state is at risk of policy adoption (and after the first state has adopted the policy). Our dependent variable captures whether a state government adopts the given policy in the given year. A given state-policy-year is coded as a 1 if the policy is adopted, and 0 if it is not. Observations are removed from the dataset after the policy has been adopted in that state (as the state is no longer at risk for adopting the policy). Given the dichotomous nature of the dependent variable, logit analysis is appropriate, although other functional forms, such as probit or the complementary log-log function, yield similar results to those reported below. To control for the

⁵ Because these works were not designed to explore differences across the attributes that we consider, their approaches were instead tailored to the specific purposes of their studies. We are not suggesting that they have flawed research designs, but rather that their designs would not be ideal for testing the hypotheses raised here.

⁶ Policies from the Suggested State Legislation were excluded if they were omnibus bills on broad topics that could be adopted “a la carte” by individual states. For example, “alternative sentencing guidelines” were considered overly broad, while three strikes laws were sufficiently specific to be included.

possibility of dependence in the adoption of multiple policies by the same state in the same year, we cluster observations by state-year, using the cluster procedure in Stata 10. This procedure relies on Huber-White robust standard errors to also account for the possibility of heteroskedasticity.

Policy Attribute Variables

The EHA structure thus measures how the likelihood of these policy adoptions is affected by various independent variables. To test the Policy Attributes Hypothesis, we therefore need comparable measures of relative advantage, compatibility, complexity, observability, and trialability for each of the 27 policies under examination. Given the lack of consistent objective measures of these attributes across policies, across states, and over time, we rely on subjective assessments of these policy attributes. Rather than form our own judgments about these policies, we sought the opinions of policy experts.⁷ Given the nature of the subjective assessments needed, it is more important to receive the considered opinion of a small number of highly informed individuals than to seek the opinions of a large number of non-experts. However, a somewhat diverse range of individuals is also desirable as their varied perspectives may provide added insight. Therefore, we targeted three groups of individuals with knowledge of the policymaking process: state legislators who chair their chamber's committee with jurisdiction over criminal justice, criminal justice practitioners (district attorneys of major cities and state attorneys general), and professors of law with an expertise in criminal justice policy.

⁷ We believe that such an expert survey is an improvement over the limited scholarly practices previously utilized in exploring policy attributes. Nicholson-Crotty's (2009) characterization of policy complexity, for example, simply relied on personal judgments about whether the policy areas in question required "medical, scientific, accounting, or engineering expertise" (p. 198).

At least one individual in each of these categories was approached by email in each state. The 91 experts who did not decline to be surveyed (or for whom we believed that email was an insufficient mode of communication) were sent paper surveys, with 20 completed surveys returned, for a 22% response rate. Given the number of policies and the multiple attribute questions per policy (detailed in Appendix A), this response rate is on par with a typical demanding survey of experts. Because characteristics of the respondents themselves are not relevant to our survey analyses, we are merely looking to gain as accurate an impression of the attributes for the policies we are examining as possible, and the expert survey seems to have performed well along these lines.

Based on the average of these survey responses, each policy was given a score for each attribute, taking a value between 1 and 5. These scores were then dichotomized at their respective medians, leading to a classification of each policy as “high” or “low” with respect to each attribute.⁸ Dichotomizing the policies’ attributes serves two purposes. First, it limits the effects of potential survey outliers, possibly problematic given our fairly small sample of experts. Second, this high/low split allows us to cleanly conduct split sample analyses below to explore whether diffusion mechanisms vary when the attributes take high or low values. The attribute characterizations for each policy are given in Table 1.

[Insert Table 1 about here]

As can be seen from the table, the survey results are largely consistent with the intuition of those familiar with the policies being examined. For example, regarding relative advantage, policies like DNA Testing and Identity Theft Protections were seen as dramatic improvements over prior policies in these areas, while policies dealing with Hazing and Retail Theft were

viewed as having little effect beyond existing laws. Laws addressing Credit Card Theft and Imitation Controlled Substances were among the top as perceived to be compatible with prior law, while Concealed Carry and Three Strikes policies were seen as quite divergent from past practices. RICO and Insanity Defense policies are unsurprisingly characterized as quite complex, while Amber Alert and DWI Reform laws were seen as straightforward. The effects of DNA Testing and Victim Notification were seen by the experts to be highly observable, while Computer Crimes and Terrorism Funding laws scored much lower on this attribute. Finally, Hazing and Imitation Controlled Substance laws were viewed as being trialable, while Child Pornography and Victims' Rights laws were thought to be among the most difficult to reverse once put into place.

The dichotomous independent variables *Relative Advantage*, *Compatibility*, *Complexity*, *Observability*, and *Trialability* thus take values for each observation based on the policy being examined but not on the state or year of the observation. All variable descriptions, their summary statistics, and data sources are given in Appendix B.

Diffusion and Control Variables

To test the Neighbor-Based Diffusion Hypothesis and the Learning-Based Diffusion Hypothesis and to set the stage for an analysis of whether these diffusion processes vary for policies with different attributes, we construct two key diffusion variables. Geographic diffusion is measured in the traditional fashion, by a *Neighbors* variable that captures the proportion of a state's neighbors that have already adopted the policy being examined. Learning is captured by the variable *Previous Adopters*, which counts how many other states that have already adopted

⁸ Analyzing the variables in their raw forms yields largely similar results to those shown in Table 2 below. The main exception is for Trialability, which in its raw form is not statistically distinct from zero. As dichotomized, it

the policy (following the approach of Shipan and Volden 2008). Since diffusion processes are normally characterized by an “S-shape,” (e.g., Gray 1973, Rogers 2004), and since the effect of learning from the first adopters may be greater than learning from subsequent adopters, we also include *Previous Adopters Squared* to capture a nonlinear effect. We would expect positive coefficients on the Neighbors variable and on the Previous Adopters variable, with a negative coefficient on Previous Adopters Squared.

Controlling for the internal determinants of policy adoption is important in order to help ensure that the diffusion patterns revealed do not result from spurious patterns across otherwise similar states. We incorporate nine control variables in our analysis reported here, and note that our findings are robust to the inclusion of numerous additional controls.⁹ *Logged Population* controls for the potential enhanced innovativeness of larger states.¹⁰ *Logged Real Per Capita Income* accounts for the possibility of greater innovativeness among wealthier states.¹¹ *Proportion White* is included to capture the racial components of crime policy, as discussed above. *Proportion High School Educated* allows for the possibility of more innovative policymaking in more highly educated states.

Proportion Spent on Corrections captures the relative state government spending dedicated to corrections, accounting for the possibility that states more focused on criminal justice prosecution (or facing greater needs for criminal justice reforms) will be more likely to

attains statistical significance when included with the other attributes in Model 6 below.

⁹ Time trends and year dummies (as recommended by Beck, Katz, and Tucker 1998) are theoretically inappropriate for the current study because they simply capture the time periods during which more of the policies under investigation are being examined by the states, rather than capturing fundamental aspects of the diffusion processes themselves. We therefore do not include such time-based variables in the analyses reported below. Incorporation of policy-specific time variables tends to demonstrate the typical S-shaped diffusion patterns for these policies, while not altering the main findings of our study. Additionally, accounting for states with the initiative process or for states that differ on Elazar’s (1984) dimensions of political culture do not alter the main results reported here.

¹⁰ A linear form of population yields similar substantive results, although with a somewhat worse fit with the data.

¹¹ Linear per capita income yields substantively similar results, as do measures of per capita state revenues.

adopt policy changes.¹² *Proportion Democrats* accounts for the average proportion of the state House and Senate that is controlled by the state Democratic Party. Likewise, *Democratic Governor* accounts for the party of the governor. If Democrats are not as tough on crime as Republicans, we would expect negative coefficients on both of these variables. On the other hand, *State Government Ideology*, as conceptualized by Berry et al. (1998), would exhibit a negative coefficient if liberals are less likely to adopt the criminal justice reforms studied here. Finally, we also include *Real State Legislative Salary*, as we believe that states with more professional legislatures will be more likely to adopt innovative policies, all else equal.¹³

Results

We begin by considering the independent effects of our five attribute variables, controlling for both diffusion mechanisms and the internal determinants discussed above. The results of these individual attribute analyses can be found in Table 2 in Models 1-5. Four of the five attribute variables are statistically significant predictors of rates of policy adoption. Higher levels of Relative Advantage, Compatability, and Observability are all associated with greater likelihoods of adoption, while Complexity is associated with a lower likelihood of adoption.

[Insert Table 2 about here]

In Model 6 of Table 2, we combine the five policy attributes in a single model. In addition to the four attributes that previously exhibited statistically significant coefficients in the expected direction, Trialability is now also statistically significant and positive, as expected.

¹² Accounting for crime rates shows little direct effect of crime on the adoption of these 27 criminal justice policies, nor does it substantially impact our findings for the main hypotheses.

¹³ Incorporating alternative measures of legislative professionalism (e.g., Squire 1992) does not change the substantive results for the hypotheses of interest reported below. Legislative salary was chosen due to its unique values for every year in the dataset, whereas Squire's measure only exists for a few points in time and must be interpolated and extrapolated for the remaining years.

Including all five attributes in the same model accounts for the possibility that most of the policies that are highly trialable also have a low relative advantage, for example. Without controlling for relative advantage, these policies may wrongly be thought to have a lower probability of adoption. Including all attributes together allows these overall adoption rates to be considered with the other attributes' effects controlled for. The change in Model 6 from the earlier models is most pronounced for Trialability, although the coefficient size on Compatibility increases substantially in Model 6, as well.

In addition to their statistical significance, these attributes also have a major substantive impact on the likelihood of policy adoption. Since each attribute is captured in a dichotomous variable, we calculate the impact on the odds of adoption when the attribute is changed from low to high, all else equal. A policy with a high level of Relative Advantage, as judged in expert surveys, has 31 percent greater odds of being adopted by any given state in a given year than does a policy with low relative advantage. For Compatibility, Observability, and Trialability, the corresponding increases in the odds of adoption are 54%, 41%, and 29%, respectively. A high level of Complexity, on the other hand, is associated with a 41% *decrease* in the odds of adoption, relative to a policy with a low level of complexity. Put another way, a policy like Amber Alert, with its significant relative advantage, high compatibility, and high observability, but low complexity, is nearly four times more likely to be adopted by a state in any given year than is a RICO reform, which is just the opposite in these key attributes. A joint test of the significance for these five variables shows very strong support for the Policy Attributes Hypothesis ($\chi^2(5) = 104.91, p < 0.001$).

In all of the models of Table 2, we find strong evidence for the two traditional diffusion mechanisms. States with neighbors that have previously adopted a policy are significantly more

likely to adopt that policy in a given year, and the likelihood of policy adoption also increases with the number of previous adopters. The size of these effects, as captured in Model 6, can be interpreted as follows. Being completely surrounded by neighbors who have adopted the policy in question is associated with more than double the odds of adoption, compared to a state with no neighbors that have previously adopted the policy. This is strong evidence in support of the Neighbor-Based Diffusion Hypothesis. In terms of the learning mechanism, the effect of learning is strongest for the first few states adopting the policy with a smaller added value for each additional adoption. When no other states have the policy, the first adoption leads to a 5.4% increase in the odds of adoption by each other state elsewhere, while eighteenth adoption (which is the mean value in the dataset) only results in a 1.4% increase in the odds beyond the effect of seventeen states already experimenting with the policy.¹⁴ The cumulative learning effect from these eighteen experimenters, relative to no experiments, is an 85% increase in the odds of adoption in any given year by each of the remaining states. These results provide strong support for the Learning-Based Diffusion Hypothesis.

The control variables included in the models are mostly consistent with expectations. Larger states, more educated states, and states with larger minority populations have a higher likelihood of adopting criminal justice policies, although the effect of race is the least robust across models. Income and spending on criminal justice are in the predicted direction, but are not statistically significant. The findings for the political variables Proportion Democrats and State Government Ideology are consistent with expectations, but only ideology ever reaches statistical significance. Democratic Governor takes on an unexpected positive coefficient that reaches statistical significance in some models, indicating that Democratic governors may be more aggressive in promoting criminal justice reforms than are their Republican counterparts

¹⁴ After the twenty-fourth adoption, the odds cease to increase with additional adoptions.

during our time period. Finally, Real Legislative Salary takes on a surprisingly negative sign in every model.

The Conditional Effects of Policy Attributes on Diffusion

Thus far we have established that criminal justice policies spread through learning and through neighbor-based diffusion mechanisms and that the attributes of these policies affect their likelihood (or speed) of adoption. What we have yet to explore is whether these attributes also affect the nature of the diffusion pathways themselves. We now turn to such considerations, as we seek to test the four Enhanced Diffusion and Diminished Diffusion hypotheses.

One way to explore the conditional effects of policy attributes on diffusion mechanisms would be to simply interact the attribute variables with the diffusion variables. However, there may be reason to believe that the policy attributes themselves are also relevant for the effects of the control variables on the likelihood of policy adoption. We attempt to gauge the existence of such heterogeneity by first splitting the policies according to each policy attribute and then conducting separate split sample analyses.¹⁵ Specifically, we conduct the same regression analyses reported in Table 2, but first on the subset of the data dealing with low relative advantage policies and then for high relative advantage policies (and then likewise for data splits based on the other attributes). In Table 3 we show the results of these analyses for the low and high relative advantage policies.

[Insert Table 3 about here]

We can see immediately that the two diffusion mechanisms are having very different effects in these two subsets of the data: the coefficient for neighboring states is almost twice as

large for policies with high levels of relative advantage, while the effect of previous adopters is more than three times smaller. A number of the control variables also differ markedly across the two subsets. The signs of the control variables for the high relative advantage policies almost completely match those for all policies, as found in Table 2. However, in comparison, low relative advantage policies are less likely to be adopted by wealthier states, but more likely to be adopted by states with high levels of corrections spending and by states with a more substantial Democratic presence in their state legislatures.

The final column of Table 3 notes whether the differences in coefficients across these two models are statistically significant.¹⁶ For example, the coefficient on Neighbors is positive and statistically significant for *both* the low and high relative advantage subset. Nevertheless, this neighbor-based diffusion effect is greater for the high relative advantage policies, and statistically significantly so. Thus, consistent with the Enhanced Spatial Diffusion Hypothesis, it appears that a policy's relative advantage increases the effect of geographic neighbor diffusion. Substantively, for policies with high relative advantages, being completely surrounded by neighbors who have adopted the policy leads to a 156% increase in the odds of adoption, compared to 112% in the baseline model from Table 2. On the other hand, policies with low levels of relative advantage only experience a 63% increase in the odds of adoption when the proportion of neighbors who have adopted the policy increases from zero to one.

On the other hand, while a learning effect seems evident for both policy subsets (based on Previous Adopters), this effect is much greater for low relative advantage policies, thus running

¹⁵ This approach serves as an alternative to the random-coefficient-based “frailty” models, typically used when researchers have “clear expectations that some observations are more apt to experience the event than others” (Box-Steffensmeier and Jones 2004, p. 163).

¹⁶ This calculation is made by once again pooling all policies, but now also interacting each of the independent variables (and the constant, via inclusion of the non-interacted Relative Advantage variable in the regression) with the Relative Advantage dummy variable. If the coefficients on those interactions are statistically significant, such

counter to the expectations of our Enhanced Learning Hypothesis. Substantively, for policies with high relative advantage, the impact of the first adoption only leads to a 2.0% increase in the odds of adoption, and additional adoptions above sixteen cease to have a positive effect on the odds of adoption. On the other hand, for policies with low relative advantages, the initial experiment elsewhere is associated with a 7.1% increase in the odds of adoption, and the first *thirty* adoptions are associated with an increase in the odds of adoption.

For the remaining four attributes, we present the results of the split sample and interactive models in abbreviated form, reporting in Table 4 only on how the diffusion variables differ across these subsets of policies. For these remaining attributes, there are no statistically significant interactive effects between the neighbors mechanism and the attribute. Although some of the Neighbors coefficients appear noticeably different in the policy subsets, none of these differences achieve significance, even at generous standards of statistical significance. Thus, our support for the Enhanced Spatial Diffusion Hypothesis is limited to the relative advantage attribute, and there is no definitive support for the Diminished Spatial Diffusion Hypothesis, as neither complexity nor trialability has a strong effect on neighbor-to-neighbor diffusion, which was found to be robust across all subsets of the data.

[Insert Table 4 about here]

On the other hand, the impact of the learning mechanism seems to be more highly dependent on the five policy attributes. Table 4 shows that high levels of observability are associated with a greater impact of the learning mechanism; the coefficient on Previous Adopters is more than twice as large for highly observable policies as for those with low observability. Substantively, for policies with high observability, the increase in the odds associated with the

differences are noted in the final column of Table 3. Reporting the interactive coefficients from this overall model is redundant since such coefficients can be obtained from the coefficient differences between the first two columns.

first adoption is 5.8%, compared to 2.6% for policies with low observability. This finding is consistent with the Enhanced Learning Hypothesis. Weaker support may be seen for this hypothesis when it comes to compatibility. A significant difference in learning is exhibited between policies with high and low levels of compatibility, but only when the Previous Adopters Squared variable is removed from the analysis.

The results in Table 4 also show strong support for the Diminished Learning Hypothesis, as both complexity and trialability have the expected negative impact on the power of the learning mechanism. While the coefficient on Previous Adopters is halved for highly complex policies, compared to policies with low complexity, the effect is even more dramatic for trialability. Policies with high levels of trialability exhibit no learning effect whatsoever, whereas for policies with low trialability, the initial experiment alone is associated with a 7.4% increase in the odds of adoption elsewhere, and the first twenty adoptions collectively increase the odds of adoption by more than 78% in each remaining state in each year. This is consistent not only with the Diminished Learning Hypothesis, but also with the view that internal trials substitute for external learning possibilities.

Conclusion and Future Directions

Political scientists have conducted hundreds of studies of policy diffusion, across countries, states, regions, and localities. The policies examined stretch into every corner of public policymaking. And the cumulative knowledge generated to date has been quite impressive. On the other hand, as we turn toward an assessment of which findings complement one another and which seem paradoxical, it may be important to realize that not all policies are created equal. Some are more complex than others. Some have effects that can be readily

observed while others can be easily tried and abandoned. Some are quite compatible with past practices while others are substantial breaks from the past that yield significant relative improvements over previous policies.

We argue that these policy differences are fundamental to achieving a full understanding of policy adoption and policy diffusion. Consistent with studies of innovations outside of political science, the attributes of policy innovations affect their likelihood of adoption and the nature of their diffusion. In our context, we found that twenty-seven major criminal justice policies spread across the U.S. states between 1973 and 2002 in different ways based on their relative advantage over past policies, their compatibility with existing practices, their complexity, their observability across states, and their trialability. We found that these factors all affected the likelihood of policy adoptions in expected ways. Specifically, policies with high relative advantages, high compatibility, low complexity, high observability, and high trialability all spread across the states at a greater rate.

We also found that the pathways of diffusion varied substantially based on the types of policies being examined. In particular, policies with high relative advantages were more likely to spread from neighbor to neighbor (although not via a learning process beyond such limited geographic comparisons). Learning from other states was enhanced for highly observable policies, as might be expected, but was diminished when states could conduct internal trials of the policies rather than rely on external experiments and when the policies were too complex for such learning to be of much use. While these findings are interesting in their own right, they may also shed new light on differences in other scholarly studies that vary along these dimensions in the policies under investigation.

These findings also signal that much more work is needed in this area. We conclude by highlighting two such directions, exploring variance in policy attributes over time and across states. First, the impact of policy attributes should be examined in a more dynamic context that takes into account findings on reinvention, homogenization, and emulation of policy success. Our paper, like many in the literature on policy diffusion (but, see Glick and Hays 1991, Hays 1996, Volden 2006), treats an innovation as if it is perceived similarly throughout the diffusion process. But each of the policy attributes we explore can change over time. For example, the perceived relative advantage of a policy is highly dependent on a policy's success in combating crime in the first few states in which it is adopted. In other words, early adopters may respond to the *potential* policy impact, but later adopters will most likely be responding to the *actual* policy impact, as learned from other states' experiences.

Second, while we treat the attributes of policies as similar across governments, they may instead reflect choices made by policymakers and other political actors. For example, consider implications of the role of policy entrepreneurs, interest groups, and professional associations (e.g., Mintrom 1997, Balla 2001) for the study of innovation attributes. The presence of such actors may serve to make complex policies more comprehensible to legislators and to simplify legislative formulation, while the effects of largely unobservable policies may be illuminated by experts with inside knowledge of adopters' experiences. At the same time, interest groups and experts may actually help *determine* the attributes of a policy innovation. The broader literature on the diffusion of innovations emphasizes that patterns of diffusion are highly conditional on the role of so-called "change agents" (see Rogers 2004, for examples). Especially in the case of policy innovations, legislation may look the way it does because of interest group participation. While some innovations, such as laws that prohibit specific behaviors (i.e. hazing, stalking,

witness intimidation), may have “inherent characteristics,” other innovations have only a broad purpose (i.e. Megan’s law, victim’s rights amendments), and their specific content (and thus their relative advantage, complexity, and so on) is determined by early adopters. While we establish that policy attributes matter for their adoption and diffusion, how policies and their attributes are characterized in the first place and how they change over time are at the heart of the political processes inherent in public policymaking, thus meriting further study.

Appendix A: Survey Details (Policy descriptions and question wording)

The twenty-seven policies included in this study were described to respondents as follows:

Amber Alert: Provides resources and communication networking in order to locate and rescue kidnapped minors.

Boot Camp: Creates military-style boot camps as a diversion program or alternative sentence for youthful and/or first-time offenders.

Child Pornography: Outlaws creation and distribution of pornographic images of minors.

Computer Crimes: Creates a broad class of new or newly-defined crimes associated with the use of computers for criminal purposes.

Concealed Carry: Establishes “shall issue” language for permits to carry a concealed handgun.

Credit Card Theft: Establishes felonies for the theft of credit cards, the use and possession of stolen credit cards, and the forgery or use of forged credit cards.

Death Penalty: Reinstates the death penalty after *Furman v. Georgia (1972)*.

DNA Testing of Felons: Requires the collection of DNA from all convicted felons, or from a considerable subset of convicted felons.

DWI Reform: Reduces the legal limit for intoxication to .08 BAC.

Furlough Programs: Allows prisoners to work outside of prison during incarceration.

Hate Crimes: Establishes separate procedures and/or penalties for prosecution of crimes that are motivated by malice toward protected groups.

Hazing: Outlaws the endangerment of individuals’ mental and physical health during activities associated with admission into student organizations.

Identity Theft: Prohibits the taking of another person’s identifying information without their consent for an unlawful purpose or to cause loss to that person.

Imitation Controlled Substances: Outlaws the manufacture and sale of imitation substances which appear to be or are purported to be controlled substances.

Insanity Defense Reform: Reforms the procedures by which defendants can use an insanity defense, including the standard or burden of proof.

Megan’s Law: Authorizes public notification when sex offenders are released into a community.

Racial Profiling: Takes steps to address racial profiling by police, ranging from the commissioning of studies and outright prohibition of the practice.

Rape Shield Laws: Limits the use of a victim's sexual history in rape trials.

Retail Theft: Addresses various shoplifting-related problems, allows merchants to detain suspected shoplifters and/or mandates that parents pay restitution for minors' acts.

RICO: Establishes definitions of racketeering activity to facilitate prosecution of organized crime and other criminal enterprises.

Son of Sam Laws: Prohibits convicts from profiting from telling their story; establishes rules for setting up trusts for such proceeds that go to victims.

Stalking: Prohibits the persistent following or harassment of another person with an implied or express threat of harm.

Terrorism Funding: Prohibits charities from giving money to terrorists.

Three Strikes Laws: Establishes mandatory sentences upon three felony convictions.

Victim Notification: Requires victims to be notified of convict's sentence suspension, probation, parole, or furlough.

Victims' Rights Amendment: Amends the state constitution to guarantee the rights of victims of crime.

Witness Intimidation: Prohibits the use of threats to influence witness testimony.

Policy Attribute dummy variables were generated based on dichotomizing at their median values the cumulative responses to the following questions.

Relative advantage = average of survey responses to following question for given policy.

“For each of the following policies, please indicate whether the policy was perceived by policymakers as likely to improve the effectiveness of the criminal justice system in the area in question. A rating of ‘5’ indicates that the policy was perceived to have a large impact, while a rating of ‘1’ indicates that the policy was perceived as having a small impact.”

Compatibility = 5 – average of survey responses to following question for given policy.

“For each of the following policies, please indicate whether passage of this policy required statutory changes in other areas of state law. A rating of ‘5’ indicates that the policy required the repeal or change of many other laws, while a rating of ‘1’ indicates that no such changes were required.”

Complexity = (5 – average of survey responses to following question for given policy + average of survey responses to subsequent question for given policy)/2.

“For each of the following policies, please indicate whether the policy’s purpose and likely results were clear to most legislators at the time of consideration. A rating of ‘5’ indicates a high level of clarity, while a rating of ‘1’ indicates a low level of clarity.”

“For each of the following policies, please indicate whether the policy idea was easy to translate into legislation. A rating of ‘5’ indicates such translating the idea into legislation was complex, while a rating of ‘1’ indicates that translation of the idea into legislation was straightforward.”

Observability = average of survey responses to following question for given policy.

“For each of the following policies, please indicate whether the policy produced results that could be easily observed by policymakers *in other states*. A rating of ‘5’ indicates a high level of observability, while a rating of ‘1’ indicates a low level of observability.”

Trialability = (average of survey responses to following question for given policy + average of survey responses to subsequent question for given policy)/2.

“For each of the following policies, please indicate whether implementing the policy on a trial basis might have been perceived as useful to policymakers. A rating of ‘5’ indicates that a limited trial of this policy would be very useful, while a rating of ‘1’ indicates that a limited trial would be counterproductive.”

“For each of the following policies, please indicate whether abandoning the policy, if it were found to be ineffective, would be problematic. A rating of ‘5’ indicates that the policy was easily reversible, while a rating of ‘1’ indicates that reversing the policy would cause many difficulties.”

Appendix B: Variable Descriptions, Summary Statistics, Sources

Variable	Description	Mean	St. Dev.
<i>Adoption dependent variable^a</i>	Dummy = 1 for state adopting policy in this year	0.075	0.263
<i>Relative Advantage^b</i>	Dummy = 1 for policy above median in surveyed relative advantage	0.469	0.499
<i>Compatibility^b</i>	Dummy = 1 for policy above median in surveyed compatibility	0.444	0.497
<i>Complexity^b</i>	Dummy = 1 for policy above median in surveyed complexity	0.578	0.494
<i>Observability^b</i>	Dummy = 1 for policy above median in surveyed observability	0.450	0.497
<i>Trialability^b</i>	Dummy = 1 for policy above median in surveyed trialability	0.513	0.500
<i>Neighbors^a</i>	Proportion of state's geographic neighbors with policy at start of the year	0.283	0.326
<i>Previous Adopters^a</i>	Number of all other states with policy at start of the year	14.5	13.3
<i>Logged Population^c</i>	State population (logged)	15.0	0.987
<i>Logged Real Per Capita Income^d</i>	State per capita income (in thousands of year 2000 inflation adjusted dollars, logged)	3.18	0.166
<i>Proportion White^c</i>	Proportion of population recorded as White	0.850	0.096
<i>Proportion High School Educated^c</i>	Proportion of adult population with high school degree or equivalence	0.802	0.059
<i>Proportion Spent on Corrections^e</i>	Proportion of state budget spent on corrections	0.025	0.011
<i>Proportion Democrats^e</i>	Average of proportional control of House and Senate by Democrats	0.594	0.182
<i>Democratic Governor^e</i>	Dummy = 1 if governor is Democrat	0.564	0.495
<i>State Government Ideology^f</i>	Ideology score for state government	49.9	22.8
<i>Real State Legislative Salary^e</i>	Average state legislative salary (in thousands of year 2000 inflation adjusted dollars)	21.4	19.6

Data sources: ^aConstructed by authors from various sources, mainly Lexis-Nexis searches of state statutes.

^bConstructed by authors based on expert surveys.

^cU.S. Census Bureau website (landview.census.gov).

^dBureau of Economic Statistics website (www.bea.gov).

^eConstructed by authors based on *Book of the States*, various years.

^fUpdated Berry, Ringquist, Fording, and Hansen (1998) data available on ICPSR website.

References

- Allen, Mahalley D., Carrie Pettus, and Donald P. Haider-Markel. 2004. Making the National Local: Specifying the Conditions for National Government Influence on State Policymaking. *State Politics and Policy Quarterly* 4(3): 318-344.
- Bailey, Michael A., and Mark Carl Rom. 2004. A Wider Race? Interstate Competition across Health and Welfare Programs. *Journal of Politics* 66(2): 326-347.
- Balla, Steven J. 2001. Interstate Professional Associations and the Diffusion of Policy Innovations. *American Politics Research* 29(3): 221-245.
- Beck, Nathaniel, Jonathan N. Katz, and Richard Tucker. 1998. Taking Time Seriously: Time-Series-Cross-Section Analysis with a Binary Dependent Variable. *American Journal of Political Science* 42(4): 1260-1288.
- Beckett, Katherine, and Theodore Sasson. 2000. *The Politics of Injustice: Crime and Punishment in America*. Thousand Oaks, CA: Pine Forge Press.
- Berry, Frances Stokes, and William D. Berry. 1990. State Lottery Adoptions as Policy Innovations: An Event History Analysis. *American Political Science Review* 84(2): 395-415.
- Berry, William D., and Brady Baybeck. 2005. Using Geographic Information Systems to Study Interstate Competition. *American Political Science Review* 99(4): 505-519.
- Berry, William D., Evan J. Ringquist, Richard C. Fording, and Russell L. Hansen. 1998. Measuring Citizen and Government Ideology in the American States, 1960-93. *American Journal of Political Science* 42(2): 327-348.
- Boehmke, Frederick J. 2005. *The Indirect Effect of Direct Legislation: How Institutions Shape Interest Group Systems*. Columbus, OH: The Ohio State University Press.
- Boehmke, Frederick J. and Richard Witmer. 2004. Disentangling Diffusion: The Effects of Social Learning and Economic Competition on State Policy Innovation and Expansion. *Political Research Quarterly* 57(1): 39-51.
- Box-Steffensmeier, Janet M., and Bradford S. Jones. 2004. *Event History Modeling: A Guide for Social Sciences*. Cambridge, UK: Cambridge University Press.
- Carmines, Edward G., and James A. Stimson. 1989. *Issue Evolution: Race and the Transformation of American Politics*. Princeton, NJ: Princeton University Press.
- Case, Anne C., James R. Hines, Jr., and Harvey S. Rosen. 1993. Budget Spillovers and Fiscal Policy Interdependence: Evidence from the States. *Journal of Public Economics* 52: 285-307.

- Christie, Nils. 2001. *Crime Control as Industry: Toward Gulags, Western Style*. London, UK: Routledge.
- Dalton, Thomas Carlyle. 1985. *The State Politics of Judicial and Congressional Reform: Legitimizing Criminal Justice Policies*. Westport, CT: Greenwood Press.
- Davis, Angela. 1998. Race and Criminalization: Black Americans and the Punishment Industry. In *The Angela Davis Reader*. Malden, MA: Blackwell.
- Donziger, Steven R. 1996. *The Real War on Crime: The Report of the National Criminal Justice Commission*. New York, NY: Harper Perennial.
- Elazar, Daniel J. 1984. *American Federalism: A View from the States*. Third Edition. New York, NY: Harper and Row.
- Glick, Henry R., and Scott P. Hays. 1991. Innovation and Reinvention in State Policymaking: Theory and the Evolution of Living Will Laws. *The Journal of Politics* 53(3): 835-850.
- Grattet, Ryken, Valerie Jenness, and Theodore Curry. 1998. The Homogenization and Differentiation of Hate Crime Laws in the United States, 1978 to 1995: Innovation and Diffusion in the Criminalization of Bigotry. *American Sociological Review* 63(2): 286-307.
- Gray, Virginia. 1973. Innovation in the States: A Diffusion Study. *American Political Science Review* 67: 1174-1185.
- Grossback, Lawrence J., Sean Nicholson-Crotty, and David A.M. Peterson. 2004. Ideology and Learning in Policy Diffusion. *American Politics Research* 32(5): 521-545.
- Hays, Scott P. 1996. Influences of Reinvention during the Diffusion of Innovations. *Political Research Quarterly* 49(3): 631-650.
- Karch, Andrew. 2007. Emerging Issues and Future Directions in State Policy Diffusion Research. *State Politics and Policy Quarterly* 7(1): 54-80.
- Kellstedt, Paul M. 2003. *The Mass Media and the Dynamics of American Racial Attitudes*. Cambridge, UK: Cambridge University Press.
- Kousser, Thad. 2005. *Term Limits and the Dismantling of State Legislative Professionalism*. Cambridge, UK: Cambridge University Press.
- Langer, Laura, and Paul Brace. 2005. The Preemptive Power of State Supreme Courts: Adoption of Abortion and Death Penalty Legislation. *Policy Studies Journal* 33(3): 317-340.
- Lowi, Theodore. 1964. American Business, Public Policy, Case Studies, and Political Theory. *World Politics* 16(3): 677-715.

- Merlo, Alida V., and Peter J. Benekos. 2000. *What's Wrong with the Criminal Justice System: Ideology, Politics, and the Media*. Cincinnati, OH: Anderson Publishing Company.
- Mintrom, Michael. 1997. Policy Entrepreneurs and the Diffusion of Innovation. *American Journal of Political Science* 41(3): 738-770.
- Mooney, Christopher Z., and Mei-Hsien Lee. 1995. Legislative Morality in the American States: The Case of Pre-Roe Abortion Regulation Reform. *American Journal of Political Science* 39(3): 599-627.
- Mooney, Christopher Z., and Mei-Hsien Lee. 2000. The Influence of Values on Consensus and Contentious Morality Policy: U.S. Death Penalty Reform, 1956-82. *Journal of Politics* 62(1): 223-239.
- Moore, Gary C., and Izak Bensabat. 1991. Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation. *Information Systems Research* 2(3): 192-220.
- Nicholson-Crotty, Sean. 2009. The Politics of Diffusion: Public Policy in the American States. *Journal of Politics* 71(1): 192-205.
- Peterson, Paul E., and Mark Carl Rom. 1991. *Welfare Magnets: The Case for a National Standard*. Washington, DC: Brookings.
- Rogers, Everett M. 1983. *Diffusion of Innovations*. 2nd ed. New York, NY: The Free Press.
- Rogers, Everett M. 2004. *Diffusion of Innovations*. 5th ed. New York, NY: The Free Press.
- Rosch, Joel. 1985. Crime as an Issue in American Politics. In Erika S. Fairchild and Vincent J. Webb, eds., *The Politics of Crime and Criminal Justice*. Thousand Oaks, CA: Sage.
- Shipan, Charles R., and Craig Volden. 2006. Bottom-Up Federalism: The Diffusion of Antismoking Policies from U.S. Cities to States. *American Journal of Political Science* 50(4): 825-843.
- Shipan, Charles R., and Craig Volden. 2008. The Mechanisms of Policy Diffusion. *American Journal of Political Science* 52(4): 840-857.
- Simmons, Beth A., Frank Dobbin, and Geoffrey Garrett. 2006. Introduction: The Internal Diffusion of Liberalism. *International Organization* 60(4): 781-810.
- Skocpol, Theda, Marjorie Abend-Wein, Christopher Howard, and Susan Goodrich Lehmann. 1993. Women's Associations and the Enactment of Mothers' Pensions in the United States. *American Political Science Review* 87(3): 686-701.
- Soule, Sarah A., and Jennifer Earl. 2001. The Enactment of State-Level Hate Crime Law in the United States Intrastate and Interstate Factors. *Sociological Perspectives* 44(3): 281-305.

- Squire, Peverill. 1992. Legislative Professionalization and Membership Diversity in State Legislatures. *Legislative Studies Quarterly* 17(1): 69-79.
- Stone, Diane. 1999. Learning Lessons and Transferring Policy Across Time, Space, and Disciplines. *Politics* 19(1): 51-59.
- Teichman, Doron. 2005. The Market for Criminal Justice: Federalism, Crime Control and Jurisdictional Competition. *Michigan Law Review*.
- Volden, Craig. 2002. The Politics of Competitive Federalism: A Race to the Bottom in Welfare Benefits? *American Journal of Political Science* 46(2): 352-363.
- Volden, Craig. 2006. States as Policy Laboratories: Emulating Success in the Children's Health Insurance Program. *American Journal of Political Science* 50(2): 294-312.
- Volden, Craig, Michael M. Ting, and Daniel P. Carpenter. 2008. A Formal Model of Learning and Policy Diffusion. *American Political Science Review* 102(3): 319-332.
- Walker, Jack L. 1969. The Diffusion of Innovations among the American States. *American Political Science Review* 63: 880-899.
- Wei, L. J., D. Y. Lin, and L. Weissfeld. 1989. Regression Analysis of Multivariate Incomplete Failure Time Data by Modeling Marginal Distributions. *Journal of the American Statistical Association* 84(408): 1065-1073.

Table 1: Criminal Justice Policies and Their Attributes

Policy	Relative Advantage	Compatibility	Complexity	Observability	Trialability
Amber Alert	High	High	Low	High	High
Boot Camp	Low	High	High	Low	High
Child Pornography	Low	Low	Low	Low	Low
Computer Crimes	High	High	Low	Low	High
Concealed Carry	High	Low	High	Low	High
Credit Card Theft	Low	High	Low	Low	Low
Death Penalty	High	Low	Low	High	Low
DNA Testing	High	Low	Low	High	High
DWI Reform	High	Low	Low	High	Low
Furloughs	Low	High	High	High	High
Hate Crimes	Low	High	High	Low	High
Hazing	Low	High	High	Low	High
Identity Theft	High	Low	Low	High	Low
Imitation Drugs	Low	High	Low	Low	High
Insanity Defense	High	Low	High	High	Low
Megan's Law	High	Low	Low	High	Low
Racial Profiling	Low	High	Low	Low	High
Rape Shield Law	Low	Low	High	High	High
Retail Theft	Low	High	High	Low	High
RICO	Low	Low	High	Low	High
Son of Sam	Low	High	Low	High	Low
Stalking	High	High	High	Low	High
Terrorism Funding	High	Low	Low	Low	Low
Three Strikes	High	Low	High	High	Low
Victim Notification	High	Low	Low	High	Low
Victims' Rights	Low	Low	High	High	Low
Witness Intimidation	High	High	High	Low	Low

Table 2: The Effect of Policy Attributes on the Likelihood of Adoption

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
<i>Policy Attributes</i>						
Relative Advantage	.225 (.071)***	--	--	--	--	.268 (.092)***
Compatibility	--	.221 (.073)***	--	--	--	.433 (.099)***
Complexity	--	--	-.539 (.071)***	--	--	-.535 (.081)***
Observability	--	--	--	.215 (.069)***	--	.342 (.091)***
Trialability	--	--	--	--	-.061 (.070)	.258 (.105)***
<i>Diffusion Mechanisms</i>						
Neighbors	.800 (.161)***	.758 (.164)***	.771 (.164)***	.783 (.162)***	.783 (.162)***	.752 (.165)***
Previous Adopters	.036 (.011)***	.036 (.011)***	.048 (.011)***	.037 (.011)***	.035 (.011)***	.054 (.011)***
Previous Adopters Squared	-.0008 (.0002)***	-.0008 (.0002)***	-.0010 (.0002)***	-.0008 (.0002)***	-.0008 (.0002)***	-.0011 (.0002)***
<i>Internal Determinants</i>						
Logged Population	.167 (.061)***	.163 (.060)***	.163 (.061)***	.167 (.060)***	.166 (.060)***	.162 (.060)***
Logged Real PCI	.234 (.420)	.495 (.431)	.358 (.419)	.258 (.425)	.347 (.423)	.326 (.429)
Proportion White	-.917 (.628)*	-.842 (.640)*	-.839 (.632)*	-.952 (.632)*	-.924 (.633)*	-.705 (.636)
Proportion HS Educated	2.16 (1.21)**	2.12 (1.21)**	1.87 (1.21)*	2.22 (1.21)**	2.19 (1.21)**	1.73 (1.22)*
Proportion Corrections Sp.	4.38 (5.48)	5.11 (5.49)	5.79 (5.47)	5.25 (5.46)	4.91 (5.46)	6.27 (5.50)
Proportion Democrats	-.145 (.344)	-.126 (.346)	-.147 (.345)	-.165 (.344)	-.143 (.345)	-.167 (.345)
Democratic Governor	.127 (.107)	.105 (.107)	.146 (.107)*	.115 (.107)	.116 (.107)	.142 (.108)*
State Government Ideology	-.0035 (.0025)*	-.0032 (.0025)	-.0038 (.0025)*	-.0031 (.0025)	-.0032 (.0025)*	-.0038 (.0025)*
Real Legislative Salary	-.0051 (.0028)**	-.0051 (.0029)**	-.0047 (.0028)*	-.0048 (.0028)**	-.0050 (.0029)**	-.0044 (.0028)*
Constant	-7.17 (1.65)***	-7.98 (1.67)***	-7.05 (1.65)***	-7.29 (1.64)***	-7.40 (1.65)***	-7.60 (1.67)***
N	12390	12390	12390	12390	12390	12390
Wald χ^2	182.77***	181.33***	194.96***	180.01***	173.96***	224.11***

Observations clustered by state-year. Robust standard errors in parentheses.

*** p < 0.01, ** p < 0.05, * p < 0.10 (one-tailed).

Table 3: Split Sample Models, Relative Advantage

	Low Relative Advantage Policies	High Relative Advantage Policies	Significant Difference?
<i>Diffusion Mechanisms</i>			
Neighbors	.490 (.242)**	.940 (.212)***	Positive*
Previous Adopters	.070 (.015)***	.020 (.015)*	Negative***
Previous Adopters Squared	-.0011 (.0003)***	-.0006 (.0004)**	N.S.
<i>Internal Determinants</i>			
Logged Population	.206 (.091)**	.114 (.077)*	N.S.
Logged Real PCI	-1.12 (.575)**	1.32 (.557)***	Positive***
Proportion White	.960 (.914)	-2.14 (.775)***	Negative***
Proportion HS Educated	2.57 (1.57)*	1.74 (1.48)	N.S.
Proportion Corrections Sp.	20.8 (7.91)***	-7.19 (6.36)	Negative***
Proportion Democrats	.793 (.487)*	-.787 (.443)**	Negative***
Democratic Governor	-.019 (.143)	.304 (.137)**	Positive**
State Government Ideology	.001 (.003)	-.009 (.003)***	Negative**
Real Legislative Salary	.002 (.004)	-.009 (.004)**	Negative**
Constant	-6.99 (2.37)***	-7.23 (2.14)***	N.S.
N	6584	5806	
Wald χ^2	125.17***	104.40***	

Observations clustered by state-year. Robust standard errors in parentheses.

*** p < 0.01, ** p < 0.05, * p < 0.10 (one-tailed). N.S. = not statistically significant.

Table 4: Split Sample Models, Other Attributes

	Low Compatibility Policies	High Compatibility Policies	Significant Difference?
<i>Diffusion Mechanisms</i>			
Neighbors	.843 (.205)***	.496 (.259)**	N.S.
Previous Adopters	.045 (.017)***	.051 (.014)***	N.S. [†]
Previous Adopters Squared	-.0012 (.0004)***	-.0009 (.0003)***	N.S.

	Low Complexity Policies	High Complexity Policies	Significant Difference?
<i>Diffusion Mechanisms</i>			
Neighbors	.896 (.247)***	.637 (.219)***	N.S.
Previous Adopters	.077 (.014)***	.037 (.017)**	Negative**
Previous Adopters Squared	-.0017 (.0003)***	-.0007 (.0004)*	Positive**

	Low Observability Policies	High Observability Policies	Significant Difference?
<i>Diffusion Mechanisms</i>			
Neighbors	.832 (.233)***	.523 (.230)***	N.S.
Previous Adopters	.026 (.015)**	.058 (.015)***	Positive*
Previous Adopters Squared	-.0004 (.0003)	-.0014 (.0004)***	Negative**

	Low Trialability Policies	High Trialability Policies	Significant Difference?
<i>Diffusion Mechanisms</i>			
Neighbors	.625 (.231)***	.822 (.221)***	N.S.
Previous Adopters	.073 (.016)***	.002 (.014)	Negative***
Previous Adopters Squared	-.0017 (.0004)***	.0001 (.0003)	Positive***

Observations clustered by state-year. Robust standard errors in parentheses. All previously used control variables are included in the models, but are not reported in the tables due to space considerations.

*** p < 0.01, ** p < 0.05, * p < 0.10 (one-tailed). N.S. = not statistically significant.

[†] When the interaction *Compatibility* × *Previous Adopters* is included *without* including the nonlinear interaction *Compatibility* × *Previous Adopters Squared*, this coefficient is positive and significant, suggestive of a somewhat enhanced learning effect for more highly compatible policies.