Interest Group Influence in Policy Diffusion Networks

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Abstract
Scholars have suggested that interest groups affect the diffusion of innovations across states by creating a network of information between the states that aids in the spread of policy ideas. Still, the unique role that interest groups play in policy diffusion networks is not fully understood, in large part because the current methodology for studying diffusion cannot parse out interest group influence. We address this problem by analyzing the actual text of legislation, moving away from binary adoption to a more nuanced measure of policy similarity. This allows us to distinguish whether states emulate other states or interest group model legislation. We use text similarity scores in a social network analysis to explore whether early-adopter states or interest groups are more central to the network. We apply this analytical framework to two policies—abortion insurance coverage restrictions and self-defense statutes. Based on this analysis, we find that a fundamentally different picture of policy diffusion networks begins to emerge—one where interest group model legislation plays a central role in the diffusion of innovations.

Keywords
model legislation, interest groups, policy diffusion, text analysis, network analysis

Introduction
The American states have often been described as “laboratories of democracy” because of their ability to experiment with new policies. Building on this perception, scholars of state politics have studied how policy innovations are formulated, implemented, and spread across the states. Up to this point, the literature has primarily focused on ways that state characteristics and behavior drive diffusion. Recently, however,
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journalists have documented the rise of model legislation in policy making, suggesting that interest groups exert considerable influence over policy adoption and emulation (e.g., Greenblatt 2011). This development challenges the idea that policy diffusion is driven by the states and, instead, indicates a prominent role for interest groups. In particular, it points to a specific mechanism by which interest groups affect the spread of policies—by providing model legislation that can be easily adapted for introduction across the states. Normatively, such policy making based on prewritten legislation challenges Madison’s (1787) claim in Federalist #10 that factional influence can be limited in a large and diverse federal republic. If policy is actually copied and pasted from interest group models into state law, we have to question whether states are fulfilling their roles as “laboratories of democracy.”

The extant literature suggests that interest groups affect policy diffusion by encouraging the flow of information between states (Walker 1969; 1981; see also Balla 2001; Haider-Markel 2001; Kile 2005). We build on this literature by arguing that interest groups influence the diffusion process by directly providing information to state legislators in the form of model legislation. Legislators rely on outside groups to formulate policy, including the specific language of bills, while they focus their attention on the politics of getting bills through the legislative process. In contrast, special interests rely on legislators to introduce policies and lobby colleagues in support of certain bills, while they produce and promote new policy ideas using their own expertise. As a consequence, the text of model legislation spreads as interest groups work with allied legislators across the states.

To test this theory, we adopt a new methodological approach that combines network and text analysis. Existing methods for studying policy diffusion are insufficient for studying the diffusion of model legislation. In particular, binary indicators are unable to parse out how similar a bill is to policies promoted by interest groups versus laws previously adopted in other states. Our method moves beyond binary measures of adoption, providing a framework for analyzing the centrality of interest group model legislation in the policy diffusion network. First, we measure the degree of text similarity between model bills and state laws. We then use these similarity scores in a social network analysis to map the path of diffusion between states and interest groups. This method allows us to assess the centrality of interest groups and states in the diffusion process. We apply this method to two cases—state restrictions on insurance coverage for abortion and self-defense regulations—comparing the text of laws in adopting states to one another with the text of model legislation provided by an interest group active on the issue. Based on this analysis, we find that interest groups, rather than innovative and early-adopting states, play the most central role in the policy diffusion networks. Our analytical framework lays the groundwork not only for future studies on outside group influence but also for scholarship examining multiple aspects of the diffusion of innovations.

States, Interest Groups, and Policy Diffusion

Since the late 1960s, scholars of state politics have attempted to explain the process of policy diffusion in the American states. Walker’s (1969) groundbreaking study of the
diffusion of 88 state programs suggested that policy diffusion is a function of both state characteristics and the external influences of neighboring or regional states. Gray (1973) shows, however, that policy emulation is not always restricted to neighboring states. Rather, the diffusion process is both issue and time specific and can be influenced by national forces like the federal government. In another seminal study, F. S. Berry and Berry (1990) track the spread of state lotteries using event history analysis (EHA), which remains the standard methodological approach used to study policy diffusion.

These early works focus their analysis on state actors and influence. Most of the literature, in turn, has relied on shared internal state characteristics and external dynamics between states to explain why policies spread. Two different models have come to define this approach: economic competition (e.g., Baybeck, Berry, and Seigel 2011; F. S. Berry and Berry 1990; Volden 2002) and social learning (e.g., Grossback, Nicholson-Crotty, and Peterson 2004; M. A. Peterson 1993; Walker 1969). Both approaches have typically treated geographic proximity as a driving force in the process of policy diffusion.

Economic competition theory suggests that states compete with other states, particularly geographic neighbors, where the flight of citizens and businesses from one state to another is a viable threat. According to this theory, states will adopt policies that help their bottom line, often emulating the policies of other states that they perceive as providing a competitive advantage. Scholars applying this model have shown that lotteries, tax policies, and welfare policies are adopted by states in response to economic competition (W. D. Berry and Baybeck 2005; F. S. Berry and Berry 1990; 1992; Boehmke and Witmer 2004; P. E. Peterson and Rom 1990; Volden 2002). Most recently, Baybeck, Berry, and Seigel (2011) use a spatially explicit strategic model to show that states adopt lotteries based on strategic considerations of their neighbors’ gambling policies and their own economic interests. Despite these advances, the economic competition approach has primarily been applied to study gaming, welfare, tax, and budgetary policies. The model offers little leverage to explain the diffusion of broader legislation such as social policy.

Recognizing this limitation, scholars have adopted a social learning approach to help explain a broader range of policy diffusion. According to this theory, state officials who want to solve the policy problems facing their state look to and learn from other states that have experimented with policy solutions to similar problems. Social learning often occurs between geographic neighbors (Case, Hines, and Rosen 1993; Pacheco 2012; Walker 1969), states with similar ideologies (Grossback, Nicholson-Crotty, and Peterson 2004), and states with similar economies (Volden 2006).

While the social learning model has been widely and successfully applied to study the diffusion of multiple policies, this approach has also faced criticism. For example, Volden, Ting, and Carpenter (2008) question whether social learning is really going on, suggesting instead that the diffusion of innovations is often little more than the simultaneous adoption of policies by similar states who face similar policy problems and political conditions. The fact is, states might be working independently or in conjunction with an interest group or policy entrepreneur to address policy concerns, rather than borrowing other states’ ideas.
Some scholars have started to move away from traditional explanations of diffusion, instead focusing on the information spread between the network of states. Desmarais, Harden, and Boehmke (2015), for example, demonstrate that states rely on information from “source” states that are politically similar, rather than geographically proximate, in their adoption decisions. Karch (2006; 2007) similarly points out that national political forces that operate outside of and in multiple states influence how and why policies spread across the states.

In fact, kernels of the idea that states interact with each other and with other political actors in a complex information network were present at the advent of the study of policy diffusion, although the idea itself was not fully explored. Walker (1969, 898) alludes to a nationwide network of information, ideas, and policy cues that influence state decisions, and he predicted that scholars would eventually construct “an elaborate theory of the interactions among professional associations, federal officials, private interest groups, and political leaders in setting the agenda of politics within a state.” Ten years later, Walker (1981) claims that the exchange of information through policy communities is necessary for policy innovations to spread. Other early studies (e.g., Gray 1994; Grupp and Richards 1975; Savage 1985) have argued that networks of interstate professional organizations play a pivotal role in the diffusion of policy innovations.

Acknowledging the importance of national communication networks in the process of diffusion, several scholars have attempted to examine the role of policy entrepreneurs, professional organizations, and interest groups in the adoption and emulation of policies. Mintrom (1997; 2000) and Mintrom and Vergari (1998) show that policy entrepreneurs work within interstate and intrastate policy networks to influence consideration and adoption of education policies across the states. Several studies also examine the influence of national professional organizations on policy diffusion. Clark and Little (2002) suggest that state legislators rely on professional associations for information when making policy decisions. McNeal et al. (2003) find that state officials’ leadership positions with national nonpartisan organizations facilitate policy innovation and diffusion. Similarly, Balla (2001) reports that policymakers’ membership in professional organizations influences states to adopt the organizations’ legislation. Interest groups also seek to advance their cause by convincing states to adopt their preferred policies, with studies showing that interest group campaigns played a role in the spread of urban wage laws (Martin 2001) and same-sex marriage bans (Haider-Markel 2001). More recently, Kile (2005) finds that policy assistance and stakeholder interest groups influence the diffusion of medication benefit programs by fostering communication about policy information.

**Theoretical Framework and Expectation**

Most extant research on the role of nonstate actors in the diffusion of innovations begins with the theory that policy entrepreneurs, professional organizations, and interest groups shape policy diffusion by influencing the flow of information between states (e.g., Balla 2001; Clark and Little 2002; Kile 2005; Mintrom and Vergari 1998).
Kile (2005), for example, builds on M. A. Peterson’s (1993) “two streams of social learning” model, suggesting that interest groups influence the spread of state policies by encouraging the exchange of substantive and procedural information between states. He argues that policymakers need to know specific details about both the substantive content of a policy and the procedural viability of translating an idea into law when they consider adopting a policy, and interest groups facilitate communication about these details. Mintrom and Vergari (1998) apply a similar argument about information exchange to explain the role of policy entrepreneurs in the diffusion of education policies.

Current studies have proposed several mechanisms by which interest groups might influence the spread of information that impacts policy diffusion. Some scholars have focused on the ways that national organizations facilitate communication between state officials (e.g., Balla 2001; Kile 2005; McNeal et al. 2003; Mintrom 1997). These studies suggest that officials who participate together in a national organization are more likely to share policy ideas and experiences and, thus, to adopt similar policies. Examining another angle, Kile (2005) reports that interest groups’ in-state presence—defined as the number of group members in a state—and the strength of connection between the groups’ national and state-level outfits influence the exchange of information and spread of prescription drug policies. Finally, several studies suggest that the legislative tool kits, policy briefs, and online databases produced by national organizations help facilitate policy diffusion (e.g., Balla 2001; Kile 2005). Most of this research has not, however, examined how and to what extent interest groups and states connect in policy diffusion networks.

We agree with the established premise that information flow between states affects policy consideration and adoption and that interest groups foster communication between states in policy diffusion networks. Yet, we argue that current conceptions of what counts as information exchange should be modified to include the direct influence of interest groups on state policies. More than just facilitating connections between policymakers from other states or encouraging support for policies within states, we expect that interest groups affect the network of information between states by actively encouraging states to adopt their policy recommendations in the form of model legislation. Meanwhile, we also expect that policymakers look to interest groups for assistance in crafting policies that address issues they mutually care about. Consequently, states will often emulate model legislation from interest groups rather than policies that have been enacted in other states. Laws that are patterned after model legislation will then influence policies in other states. This leads to our hypothesis that interest groups play a central role in policy diffusion networks by encouraging the spread of model legislation.

Our argument rests on two points. First, interest groups actively work to advance their policy agendas at the state level. Based on a survey of group activists working for and against same-sex marriage bans, Haider-Markel (2001, 7) shows that some advocacy coalitions try to “push” their policy ideas into states, particularly when it comes to polarizing issues like morality policies. Unlike professional organizations or non-partisan policy experts who work to promote best practices across the United States,
ideological interest groups advocate for their own broad partisan goals or issue-specific agendas. To achieve their policy objectives, these organizations have an incentive to provide resources, information, and policy tools to state legislators who might be interested in sponsoring or supporting their bills. One of the primary strategic resources that interest groups provide policymakers to help advance their agenda is the text of model legislation.

Second, state legislators look to outside organizations for help with policy making because they face resource and time constraints and because they have other goals besides good policy to pursue. To the former point, state legislators have limited expertise on complex policy issues, and they struggle to do their jobs in limited windows of time. Consequently, interest groups can be valuable commodities to state legislators because of the technical, legal, and political resources they can provide (e.g., Hall and Miler 2008; Hansen 1991). Particularly when it comes to ideological interest groups, legislators who are sympathetic to a group’s political position can use the group as an information resource for legislating, even borrowing language from any model bills the group might have. And outside organizations will eagerly provide state legislators with information and tools to help in policy making as a means to gain access to state lawmakers. In this way, interest group model legislation can be a valuable commodity for time and resource constrained legislators.

State legislators also look to outside interests for help because, while they want to pursue good public policy, they have other goals that make it difficult for them to invest time in writing legislation. As a result, new policies are more likely to be formulated by experts and activists who devote their careers to bettering policy in their given field. Think tanks, interest groups, and policy entrepreneurs spend considerable resources contriving and promoting policy ideas. In contrast, legislators split their resources between elections, influence, and shaping policy (Fenno 1973). Consequently, state policymakers are more likely to borrow existing policy ideas from other political actors, allowing them to focus their energies on generating the political momentum needed to get measures passed. This means they will look to readymade text from interest groups that share their political vision, if they have the option, rather than crafting laws themselves.

In summary, there is a network of information between the states, meaning that state legislators are not bound to their state’s borders. Rather, they are interconnected by shared interests, goals, and information, which help create the diffusion patterns that many scholars have found. Interest groups bolster the network by providing technical, legal, and political information. One type of information interest groups provide that affects the network of information between states is model legislation. Interest groups use their model legislation as a means of communicating to legislators the policies that advance their agenda, and state legislators have an incentive to look to interest group model legislation for help with policy making as it lowers the costs associated with legislating. Therefore, interest groups and policymakers across the states who hold similar political positions will work together to enact model legislation. This leads to our expectation that interest group model legislation will play a central role in policy diffusion networks.
Testing the Theory

Building on the theoretical premise that communication networks influence the spread of policies between states, several scholars have attempted to model the diffusion process as a network. To gain more empirical leverage on policy emulation between pairs of states, Kile (2005) and Volden (2006) apply dyadic EHA, rather than monadic models, to study the spread of policies. These studies represent a step toward network models of diffusion, despite their technical drawbacks (Boehmke 2009). More recently, Desmarais, Harden, and Boehmke (2015) advance our understanding of policy networks by estimating a latent diffusion network based on the diffusion paths of more than 100 policies. Although these models are helpful for studying the diffusion of policies between states, they are less conducive to examining the role of interest group model legislation in this process. Knowing which states adopted similar policies does not inform our understanding of interest groups’ impact on policy adoption and emulation.

On the flip side, studies that specifically examine the influence of national organizations on policy diffusion often examine proxies for a national group’s influence, such as the number of interest group members in a state (e.g., Kile 2005), the number of years since a federal law was passed (e.g., Haider-Markel 2001), or state legislators’ participation with national organizations (e.g., Balla 2001; McNeal et al. 2003). Some of this work also utilizes case studies (Kile 2005) or surveys (Haider-Markel 2001) to analyze interest group influence on policy adoption. Based on these methods, however, studies cannot distinguish the influence of interest group model legislation from the impact of other state and national actors. In the biggest advance, Balla (2001) examines national group influence based on which states have adopted a professional organization’s model bill. Still, this dichotomous measure of adoption does not allow us to examine whether state policies were more influenced by the national organization’s model legislation or by other states’ laws.

For this reason, we develop and test a novel method for tracing the spread of policies between interest groups and states by comparing the text of interest groups’ ready-made legislation and states’ policies. This attempt to model both state and interest group effects in the process of policy diffusion allows us to examine our hypothesis. It also provides one way for scholars to study the role nonstate actors play in policy networks. We apply this method to two cases in a process we discuss below.

Diffusion of Restrictions on Insurance Coverage of Abortion

To test our expectation that interest group model legislation plays a pivotal role in policy diffusion networks, we gathered the texts of state laws that restrict insurance coverage of abortion. State laws prohibiting insurance funding of abortion have been in effect in states since 1979, when North Dakota passed a law that made abortion coverage in insurance plans (public and private) only available as a premium rider, with the exception of emergency abortions to save the life of the mother. Recently,
many states have enacted restrictions on abortion coverage in response to the federal Affordable Care Act (ACA) of 2010. ACA requires states to operate and maintain health insurance exchanges, but it explicitly allows states to pass laws regulating the coverage of abortion in the exchanges. As a result, most of the state laws passed since 2010 have restricted abortion coverage in the state-run insurance exchanges. Many of the laws also apply to private health exchanges and insurance plans in general, harking back to the first laws passed in the late 1970s and 1980s.

Before ACA, at least 5 states restricted insurance coverage of abortion. From ACA to the end of 2013, 19 states have adopted policies restricting insurance coverage of abortion. Of those 19 states, 3 had previously adopted insurance restrictions but updated their laws following the federal health care law. In this way, national policy making sparked a rapid chain of policy innovation and diffusion on a long-standing policy.

The Role of Americans United for Life (AUL)

This diffusion case allows us to explore our expectation that interest group model legislation is a critical link between states. AUL is a pro-life interest group that focuses on drafting model legislation, legal resolutions, and opinions for use by lawmakers at the state and federal level. In the past, AUL has been active in the drafting and passage of the Hyde Amendment at the federal level and in the passage of fetal homicide protection bills in 36 states. Soon after the passage of ACA, AUL published model legislation called the “Federal Abortion Mandate Opt-Out Act,” a bill that restricts abortion coverage in state-funded health care exchanges. This model legislation provides a potential foundation from which states can begin crafting their own legislation in response to ACA.

We know from media coverage that AUL was highly active on this issue. The interest group was frequently credited or decried by news reports as the organization behind states’ rapid action to ban funding for abortion in response to federal health care legislation. In 2010, Newsweek’s “The Daily Beast” reported that AUL had already been in contact with legislators or individual citizens in 37 states who were interested in pursuing opt-out legislation (Kliff 2010). Also, AUL took public credit on their website and in news stories for abortion funding opt-out laws passed in numerous states. For example, the organization claimed involvement with an opt-out bill (LB22) passed in Nebraska in 2011, explaining that it was based on its own model bill language (AUL 2011). Furthermore, several state legislators specifically acknowledged that they crafted their bill after AUL’s “Federal Abortion Mandate Opt-Out Act” model legislation, thanking AUL for its assistance. Mississippi State Representative Andy Gipson celebrated his work with AUL to help pass the Mississippi Federal Abortion Mandate Opt-Out Act in 2010 (Gipson 2010). Also in 2010, House Minority Leader John Boehner publicly thanked the AUL legal team for crafting model legislation that “zeroed in on specific language in the new [federal] health care reform law that allows states to ‘opt-out’” of abortion funding. He further complemented AUL on helping a number of states, including Florida and Mississippi, to pass opt-out bills (Krajacic 2010).
By selecting this policy issue and interest group, we are able to test whether AUL or another state legislature was more central in influencing the policy diffusion process. Two states—North Dakota and Kentucky—are included in the data set that passed their legislation restricting insurance funding of abortion years before the federal health care law was passed, making them potential sources of language. Also, AUL offered states assistance with model legislation in early 2010 prior to any state’s adoption.\textsuperscript{1} Therefore, states adopting post-ACA had three potential sources (two states and one interest group) of detailed information on legal language, policy implementation, and success.\textsuperscript{2} This issue is also sufficiently broad to allow rigorous testing of the hypothesis.\textsuperscript{3} States do not have to adopt AUL’s model legislation or legislation from early-adopter states. They can enact broader measures that restrict coverage in private plans or they can place obstacles, rather than outright prohibitions, on abortion funding.

**Using Text Analysis to Build a Social Network**

We analyze the collection of laws by first measuring the proportion of similarity between the texts of the legislation and then using this information to construct a social network of the states. While novel, this method can be easily adapted by other scholars to study the diffusion of any policy.

The first step is to collect and prep the texts being used for analysis. In our case, we focus on laws restricting abortion coverage. These laws were found using Internet search engines, state legislative websites, and bill databases and then saved as text files in a single electronic folder. If found in bill form, we deleted the preamble and saved just the body of the bill. A few times, we could not find the laws in bill form. In these cases, we used the state legislative code to recover the legal language. Once assembled, texts need to be “scrubbed” of idiosyncrasies before examining their similarity. In the case of laws, the numbers and unique formats associated with legislative and legal code indexing is unique to each state and will artificially deflate the similarity scores between two texts. We scrubbed the laws of numbers, symbols (such as ), punctuation, and general white space, and we converted all words to lowercase letters. In this way, we attempted to remove noise that did not reflect the actual content of the legislation.

The next step of our methodology is to compare the text of each law with the text of every other law. Our method of comparison is cosine similarity. Cosine similarity is a bag of words approach to measuring text similarity, commonly used in automated plagiarism detection programs. The cosine similarity method takes a vector of word frequencies (\(A\)) in one text and compares it with a vector of word frequencies (\(B\)) as shown in equation 1:

\[
\cos(\theta) = \frac{A \times B}{||A|| \times ||B||} = \sum_{i=1}^{n} \frac{A_i \times B_i}{\left(\sum_{i=1}^{n} A_i^2\right)^{\frac{1}{2}} \times \left(\sum_{i=1}^{n} B_i^2\right)^{\frac{1}{2}}},
\]

(1)
The result is a similarity score that can range from 0 to 1. A score of 1 indicates two identical texts, and a score of 0 indicates the texts are completely different. On laws restricting insurance coverage of abortion, the scores ranged from 0.31 to 0.89 (see Table 1). The scores can also be thought of in angular terms, as they are based on taking the cosine of the difference of two vectors. Thus, the minimum score 0.31 represents a text that is moving near a 90 degree angle to the text it is being compared with (or not very similar), while the cosine similarity score of 0.89 is closer to a 0 degree angle (or very similar).

The similarity scores are arranged in an adjacency matrix where column A is identical to row A. Each cell of the matrix is filled with the cosine similarity score between the two texts that corresponds with the row and column, and the diagonal of the matrix is filled with 1’s—reflecting where each text’s row and column align. Each nonadopter state was added to the matrix and assigned a 0 for the similarity score between it and all other states. We use this adjacency matrix to build a social network in UCInet and NetDraw (Borgatti, Everett, and Freeman 2002). For our study, we add the additional step of setting all but the highest similarity score for each state to 0, restricting ties to the single most similar previous adopter. While many previous adopters could certainly be important in the process of diffusion, restricting ties to only the state with the highest similarity score allows us to identify the state that was likely the most instrumental in this process. We also draw ties with respect to time: a state can only be said to be the policy source for another state if it adopted its law prior to the other state. Date of adoption is based on the year a state enacts its legislation. Thus, the network is defined such that ties extend between states that are most similar in legislative language, and these ties are directed from early adopter to later adopter.

### Measures of Influence: Outdegree and Closeness Centrality

The social network framework helps us visualize the dynamic process of diffusion in a way that differs from previous studies. This method of modeling diffusion allows us to calculate key statistics about the network. Our theoretical framework is based on the

<table>
<thead>
<tr>
<th>Table 1. Descriptive Statistics of Similarity Scores.</th>
<th>Minimum</th>
<th>Maximum</th>
<th>M</th>
<th>No. of adopters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abortion coverage without AUL model legislation</td>
<td>0.31</td>
<td>0.89</td>
<td>0.60</td>
<td>21</td>
</tr>
<tr>
<td>Abortion coverage with AUL model legislation</td>
<td>0.31</td>
<td>0.94</td>
<td>0.61</td>
<td>22</td>
</tr>
<tr>
<td>Self-defense without ALEC model legislation</td>
<td>0.06</td>
<td>0.94</td>
<td>0.63</td>
<td>31</td>
</tr>
<tr>
<td>Self-defense with ALEC model legislation</td>
<td>0.06</td>
<td>0.94</td>
<td>0.64</td>
<td>32</td>
</tr>
</tbody>
</table>

Note. AUL = Americans United for Life; ALEC = American Legislative Exchange Council.
idea of centrality in social networks: states that are more central to the diffusion of an innovation are more influential. The network measures, outdegree centrality and closeness centrality, best capture this concept. Outdegree centrality is the number of ties a node sends to the other nodes in the network. This is the most direct measure of influence as it is simply a count of how many states a particular state influenced. Closeness centrality, however, is a more refined measure that reflects the independence of a node in a network. A node that is independent does not rely on others to relay and receive information. Rather, a close node has many ties and short pathways to other nodes, indicating its capacity to influence the network. Close nodes are those that can “easily mobilize a network” (Prell 2012, 107). In our case, because we are examining a network post hoc, close nodes are those that mobilized the network through their policy innovation. It is important to note that high closeness centrality scores actually indicate less influence. Although counterintuitive, scholars equate closeness centrality to a “farness” score (Prell 2012). The lower the closeness score, the less far a node is from others, and therefore more central.

Both outdegree and closeness centrality scores are used to determine the influence of interest groups in the diffusion process. Using the methodology described above, we build two networks: one with the interest group as a nonadopter (network (a)) and one as an adopter (network (b)). In network (a), AUL cannot influence the legislation of any state, reflecting the current state of the literature on diffusion as being a process between states only. In network (b), however, we allow AUL’s model legislation to be a possible source of information for states. Thus, each network has 51 nodes, but network (a) has 21 adopters and network (b) has 22. After constructing the networks, we extract the centrality scores for each of the networks and compare them using dependent t-tests for paired samples.

For each case, we examine network density and cohesion descriptive statistics to help inform our nodal-level analysis. In particular, we look at density, average path length, diameter, and degree centralization. Density is measured simply as the number of ties over the maximum possible number of ties. The diameter is the longest geodesic (i.e., shortest path) in the network. Degree centralization represents the percentage of ties flowing through one node in the network. Average path length is the mean number of steps between nodes in the network. We expect the introduction of interest group model legislation to result in a denser, more cohesive network between the states. Finally, we calculate the quadratic assignment procedure (QAP) correlation between the two networks to assess the degree to which the two networks are correlated, given the only change between the two is treating the interest group as an adopter. QAP correlation is simply a Pearson correlation between the two networks, calculated using QAP (see Hanneman and Riddle 2005).

The Influence of AUL on the Diffusion of Insurance Restrictions

The networks for the adoption of abortion coverage restrictions are depicted in Figure 1. In network (a), the diffusion of abortion coverage restrictions flows primarily from early adopters to later adopters, with important exceptions. North Dakota and Kentucky
Figure 1. Abortion coverage restrictions policy adoption networks.  
Note. Nodes are labeled with their state name and year of adoption. Nodes are sized by outdegree centrality; more central nodes are larger. Ties are directed from early adopters to later adopters and thicker lines indicate stronger similarity scores between the two nodes’ legislation. Nodes colored dark gray in network (b) have outdegree centrality scores that are statistically significantly different than in network (a), $p < .05$ for two-tailed test. Isolates are excluded from the picture, but included in analysis. AUL = Americans United for Life.
are the first two adopters, but they are not the most central states. Rather, Arizona is the most central state in the network. Although its legislation mirrors North Dakota’s, Arizona’s law serves as the template that six later-adopting states imitated. Furthermore, North Dakota is more weakly related to its states than Arizona; that is, the states it influenced used less of its law as a framework than did those who emulated Arizona. While Arizona is much more directly influential in the spread of legislative language than is North Dakota, all legislative activity branches off North Dakota’s initial adoption.

Often, a state adopts some of the language used by a previous state but then innovates further. In the case of Tennessee, for example, it adopted some of North Dakota’s language but then provided much of its own language, which was not adopted by any subsequent states. As a different illustration, Idaho was heavily influenced by the legislation of Louisiana (cosine similarity = 0.85), even though Louisiana was only nominally influenced by early-adopting North Dakota (cosine similarity = 0.49).

Our most important finding, however, is that interest groups appear to play a central role in the diffusion process. Simply including an interest group’s model legislation fundamentally alters the policy diffusion network. Network (b) in Figure 1 depicts AUL’s influence on the diffusion of innovations. When we add AUL as an adopter, Arizona, Nebraska, and Mississippi remain central actors (based on their low closeness scores), but they become less central than AUL. In fact, AUL becomes the single most important actor in the network. AUL’s model legislation serves as the primary text source for the bills passed in six states, including Arizona, Nebraska, and Mississippi. Arizona’s legislation serves as the primary text model for legislation in five states (down from six), Nebraska’s for two (down from three), and Mississippi’s for two (no change). The change in North Dakota’s and Kentucky’s influence between the two networks is even more drastic. In network (a), they were central actors, even though their ties to other states were relatively weak. In network (b), North Dakota only influences the adoption of Kentucky, and Kentucky is only emulated by Missouri’s 2010 law. This component is isolated from the rest of the diffusion network. All of the other states emulate AUL’s model legislation, whether they directly adopt and adjust AUL’s text or adopt and adjust text from other states that directly rely on AUL’s model. Consequently, AUL’s prepackaged legislation plays a more central role in the process of policy diffusion than North Dakota’s or Kentucky’s early laws.

Whether the change in a node’s centrality between the two networks is statistically significant is reported in Table 2. The first column of values reports the outdegree centrality scores for adopters of laws restricting abortion when AUL is not included as an adopter (network (a)). The second column of values represents the outdegree centrality scores for adopters when AUL is included in the network (network (b)). The \( t \)-statistics for whether the values are statistically significantly different from one another are reported in the third column of values. What we see is that each of the three most central nodes based on outdegree centrality is statistically significantly less central from network (a) to network (b). AUL is statistically significantly more central to the diffusion process between networks.

Now considering the closeness centrality scores reported in Table 2, Arizona, North Dakota, Nebraska, Mississippi, and Oklahoma are the top five most central actors by
this metric, indicating their influence in the network’s capacity to spread information. Recall that lower scores indicate closer, more influential nodes. When considering AUL, however, each of the top five adopters is statistically significantly less central to the diffusion network. In fact, all adopters are statistically significantly less central than they previously were. AUL is the only node that increases in centrality, and this increase is statistically significant.

AUL’s low closeness centrality score indicates that it is the most central actor to the diffusion network; AUL’s model bill either directly or indirectly provides the textual template for the majority of states that have adopted abortion funding opt-out policies. Meanwhile, the closeness scores for every state increase when we add AUL to the

<table>
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<th>Node</th>
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<th>Outdegree (b)</th>
<th>t-statistic</th>
<th>Closeness (a)</th>
<th>Closeness (b)</th>
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<td>-2.73*</td>
</tr>
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</table>

Note. The table displays centrality scores among states that adopted laws restricting insurance coverage for abortion. The states are ranked based on outdegree centrality in network (a). Outdegree is measured as the number of ties sent from the node to others. Closeness is measured as the inverse sum of distances to all other nodes. T-scores are based on dependent t-tests for paired samples and measure the statistical significance between centrality in network (a) and network (b). Boldface text denotes the most influential node in the network using the corresponding metric. Nonadopters are included in the analysis but not included in the table.

*Significantly different at p < .05 for two-tailed test.
Garrett and Jansa

network, indicating that the states are less independent, leaning on AUL’s efforts to help them pass legislation in response to the 2010 federal health care law.

Looking at network-level descriptive statistics, we also find some evidence that network (b) is more cohesive than network (a). Table 3 presents density and cohesion descriptive statistics for the two networks. The density (.008) and diameter (3) for networks (a) and (b) are the same. The average path length between network (a) and network (b) decreased. That is, the nodes in network (b) are bound more closely together than in network (a); it takes fewer steps to reach other nodes in the network when AUL’s model legislation is included. We take this as an indication that interest groups draw state policy closer together with their portable model legislation. Interestingly, degree centralization is higher in network (a) than in network (b). Recall that degree centralization is a measurement of how centralized the network is through a single actor. We also computed a Pearson correlation between the two networks using QAP. We found that network (a) is correlated .709 with network (b). This is surprisingly low considering the networks are exactly the same, except for the addition of model legislation.

These results support our theoretical expectations. First, states that are the first to adopt a policy are not necessarily the most influential states in the process of policy diffusion. By using text analysis, we find that Arizona’s law served as the framework for more later adopters than early-adopting North Dakota and Kentucky. Traditional EHA models would not be able to pick up this distinction. Second, when we include AUL in the network, we see that states are not necessarily the most influential actors. North Dakota and Kentucky, the first states to adopt a policy prohibiting insurance funding for abortions, are peripheral to the process of policy diffusion, serving as a model for the legislation adopted by only one state. Arizona, Nebraska, and Mississippi adopt laws relatively early in the process but their centrality stems from their emulation of AUL’s model legislation. These states are instrumental because of their close tie to AUL, which is the central most actor in the network. Third, centrality in the policy diffusion network stems not only from early adoption but also from the wording used when the policy is crafted. Later adopters are more central if they make meaningful and attractive innovations in their legislative language. Several secondary adopters, such as Nebraska, have multiple ties to later adopters, both in network (a) and after introduction of the interest group model legislation in network (b). The case also

Table 3. Network Level Descriptive Statistics for Laws Restricting Abortion Coverage.

<table>
<thead>
<tr>
<th></th>
<th>Network (a)</th>
<th>Network (b)</th>
</tr>
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<tr>
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<td>Average path length</td>
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<td>Degree centralization</td>
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<tr>
<td>Diameter</td>
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<td>3</td>
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<tr>
<td>QAP correlation</td>
<td>.709</td>
<td></td>
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</tbody>
</table>

Note. QAP = quadratic assignment procedure.
shows that states that adopt language that mirrors an interest group’s model legislation are more central to the process of policy diffusion. While states may adopt the innovations made by other states, the common language from an interest group’s packaged legislation plays the defining role in this policy diffusion network.

Finally, model legislation is a specific mechanism by which interest groups can influence policy making. Interest group model legislation reduces the amount of independent innovation that states have to do when they craft a policy. By providing ready-to-go text for states that were interested in passing a law restricting insurance funding of abortion, AUL cut down the volume of work that states had to do to draft their own laws. Legislators in several states readily took advantage of this resource. This case offers quantitative evidence to support popular accounts that specific, interest-group-crafted language spreads across the states, making interest groups central actors in the network of policy diffusion.

Self-Defense Laws and American Legislative Exchange Council (ALEC) Model Legislation

To further our understanding of how interest groups disseminate policy language across the states, we also look at changes made to laws justifying the use of force in self-defense from 2005 to 2012. In general, these laws allow people to use force in self-defense when facing a reasonable threat. There are several subsets of this law that justify the use of deadly force, including Stand Your Ground laws. Stand Your Ground laws typically allow people to defend themselves with deadly force and without a duty to retreat inside or outside the home. Stand Your Ground is based on the more largely accepted Castle doctrine, which designates that people can use force to defend their home or other personal property. Currently, 46 of the 50 states have sections of their legal code that govern the justifiable use of force in self-defense, while it is governed by common law in the remaining 4. Of these 46 states, 31 made changes to their laws in the seven-year period we studied.

Many of these changes may have been spurred by the innovation of Florida, which adopted a new Stand Your Ground provision in 2005. However, we know from journalistic accounts that the group ALEC used Florida’s bill to help construct model legislation, which they then used to market their innovation to potential future adopters (Greenblatt 2011). This case, like that of restrictions on abortion coverage, allows us to examine the influence of model legislation in the diffusion of innovations.

Like the abortion insurance study, we include not only Stand Your Ground laws but any change made to self-defense laws in the seven-year period. States adopting in 2006 or later again have three potential sources of information in our research design—ALEC’s model legislation (adopted in late 2005 following Florida’s adoption), Florida, and South Dakota (which also changed its law in 2005). Thus, the issue is sufficiently broad and contains multiple information sources, allowing for rigorous testing of the hypothesis. Like before, the legal texts were gathered, cleaned, and compared with one another using cosine similarity. The network was built by limiting ties from the most similar early adopter to later adopters.
The network for justifiable use of force laws is depicted in Figure 2. Here we see a similar pattern to the abortion funding issue. In network (a), the early innovator, Florida, is most central. Florida directly influences 11 states with its Stand Your Ground legal language, and it is the most central actor based on the closeness metric. The next most central state is Tennessee. Tennessee adopted its measure two years after Florida and is two steps removed from Florida (with Indiana in between). Tennessee’s legal language was directly emulated by five later adopters. The tie strengths between Tennessee and its direct emulators are, in general, stronger than that of Florida and many of its direct emulators. This is evidence that while the policy idea of strengthening and updating self-defense laws may be diffusing unchanged, the way in which the law is formulated is undergoing modifications. In this case, Tennessee innovated in such a way that several other states felt it provided a useful model for their legislative efforts that was better than Florida’s policy. Other influential innovators include Indiana and Alabama, which each have multiple emulators after they initially adopted certain components of Florida’s legislation. It is also notable that South Dakota, an early 2005 adopter, is not pictured. Isolates are not included in the graphic, and South Dakota’s legislation was never most similar to any future adopter; their legislative innovation never caught on in the wake of Florida’s innovation. Traditional models of legislative diffusion would identify South Dakota as an influential first adopter by virtue of time ordering. Our analysis, however, does not.

Introducing ALEC’s model legislation in the network drastically changes who we view as the central innovator and engine of diffusion. ALEC is the most central node in network (b). ALEC’s model legislation was the direct source for 15 state innovations. This is more than Florida in network (a) and by far the most for any node in network (b). Florida falls behind Tennessee, Alabama, and Indiana in its outdegree centrality, having only directly influenced ALEC’s adoption. Looking at closeness centrality scores, ALEC is still considered the central innovator, with 7 states ranking below it but above Florida. In comparing cosine similarity scores between ALEC’s emulators in network (b) and Florida’s in network (a), ALEC has many more emulators and stronger emulators than Florida. This is compelling evidence for the role of interest group model legislation in the spread of policies. ALEC’s purposeful drafting of legislation that is portable and attractive to many states encouraged legislators to copy its document, even though much of the language was chosen from studying Florida’s earlier innovation. A separate analysis of reach centrality, a metric that measures the number of nodes reachable in a certain number of steps, confirms ALEC’s centrality over Florida; Florida ranks second in reach centrality, higher than its ranking on closeness and outdegree, but still below the top-ranked ALEC.

Table 3 present t-tests for the difference in centrality scores between network (a) and network (b). For outdegree centrality, Florida, Indiana, North Dakota, and South Carolina are statistically significantly less central in the diffusion of innovations from network (a) to network (b). ALEC, with its jump from 0 ties to 15, is statistically significantly more central. All other adopters showed no difference between networks.

When we examine changes in closeness centrality, we get interesting results that give us a clue to the potential power of interest groups in connecting states. Nearly all
Figure 2. Self-defense policy adoption networks.
Note. Nodes are labeled with their state name and year of adoption. Nodes are sized by outdegree centrality; more central nodes are larger. Ties are directed from early adopters to later adopters and thicker lines indicate stronger similarity scores between the two nodes’ legislation. Nodes colored dark gray in network (b) have outdegree centrality scores that are statistically significantly different than in network (a), $p < .05$ for two-tailed test. Isolates are excluded from the picture but included in analysis. ALEC = American Legislative Exchange Council.
states were statistically significantly closer after the introduction of model legislation. That is, ALEC more closely ties the network of states together; information flows more easily in network (b) than in network (a) (see Table 4). This is corroborated by network descriptive statistics presented in Table 5.

This is corroborated by network descriptive statistics presented in Table 5. While the average path length is longer in network (a) than in network (b), the degree centralization is much greater in network (b). This fits with what we found in our nodal analysis. ALEC took Florida’s innovation and helped spread it among the states. This increased the average path length between nodes, but the density of the network is much more reliant on the many ties of ALEC. While the density and diameter remain the same, the ties flow more through one node in network (b) than in network (a), providing evidence that interest groups help spread specific language, which plays a central role in networking states together. Furthermore, the QAP correlation between network (a) and network (b) of .465 is surprisingly low given that these networks are modeling the same policy diffusion.

Conclusion: Model Legislation and Madison’s Mischiefous Factions

The existing literature suggests that interest groups play an important role in policy diffusion by facilitating the spread of information between states. Existing methodological tools, however, are insufficient for measuring interest group centrality in comparison with the states. Using text and network analysis, we were able to compare the spread of policy proposals that interest groups produced to the laws that were passed by states. Our new methodological approach led to a key substantive finding: the promotion of model legislation is a strategic mechanism by which interest groups are able to influence state policy making. In our diffusion networks, interest group model legislation was the most frequently emulated document, suggesting that lawmakers turn to this ready-to-go, easily adaptable legislation.

The rise of model legislation in the political world and the rise of text analysis tools in the academic world afford great opportunities to learn about dynamics of the diffusion process that remain elusive using traditional methods of analysis. Multiple news reports suggest that states copy legislative language word-for-word from one another and from the model legislation produced by interest groups. Scholars can apply text and network analysis to examine these cases and help sharpen our understanding of policy making at the state level. This study represents a start down this promising path. The combination of bill text analysis and network methods allows us to examine the influence of nonstate actors in a way that event history models would not permit.

While noting this contribution, it is also important to acknowledge the limited nature of our study. We apply our method to only two cases, both of which are relatively contentious social issues and for which the adopting states lean in a conservative direction. Ideally, we would apply our method to numerous cases, but we are limited by data availability. Recent studies by Boehmke and coauthors (Boehmke and Skinner 2012; Desmarais, Harden, and Boehmke 2015) use data on the time ordering of 180
Table 4. Change in Centrality from Network (a) to Network (b) for Self-Defense Laws.

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<thead>
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<th>Node</th>
<th>Network (a) Outdegree</th>
<th>Network (b) Outdegree</th>
<th>t-statistic</th>
<th>Network (a) Closeness</th>
<th>Network (b) Closeness</th>
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<td>1,183.00</td>
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<td>2.16*</td>
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Note. The table displays centrality scores among states that adopted changes to self-defense laws. The states are ranked based on outdegree centrality in network (a). Outdegree is measured as the number of ties sent from the node to others. Closeness is measured as the inverse sum of distances to all other nodes. T-scores are based on dependent t-tests for paired samples and measure the statistical significance between centrality in network (a) and network (b). Boldface text denotes the most influential node in the network using the corresponding metric. Nonadopters are included in the analysis but not included in the table.

*Significantly different at $p < .05$ for two-tailed test.
policy adoptions to study which states consistently lead, which consistently emulate, and why. The problem for our study, however, is that we are limited to cases where we have access to the text of state bills and to interest group model legislation, and existing data for the 180 policy cascades do not fit these criteria.

Despite these limitations, we expect model legislation to tie states together on other issues as well. On economic issues, previous studies have shown that competitive pressure between states leads to the diffusion of policies (e.g., Baybeck, Berry and Seigel 2011; F. S. Berry and Berry 1990; 1992; Volden 2002). Therefore, if a group promoting model legislation to lower a particular regulation was successful in passing the law in one state, we would expect to see language from the model legislation diffuse to other states, especially as interest groups use their success in one venue to help promote the policy in other venues. On less controversial issues, we might actually see a greater reliance on model language in policy making because interest groups and lawmakers share more agreement on what should be done, and the policy conflict has not been extended to involve rival groups or garner the attention of the mass public. While our cases are not broadly representative, we maintain that they provide a good first test of our theoretical framework. Moreover, our findings suggest that there is merit in continuing to examine the influence of model legislation using different economic, social, contentious, and noncontentious policy issues.

Many theoretical and practical questions on diffusion remain. What makes a state more or less likely to emulate another state’s legal language? Are there similar political factors among and between the states that affect likelihood of adoption? Are professional legislatures more or less likely to adopt interest group model legislation? In extending our methodological framework, researchers can investigate some of these questions by introducing independent variables to a diffusion network using an exponential random graph model (ERGM), which is used to estimate tie formation in social networks. ERGMs hold advantage over traditional EHA models in that they can account for the interdependence between states that act and react to one another in the federal system, while still measuring the effect of state attributes on policy adoption. As one example, ERGMs could be used to parse out specific political influences from the tendency of states to economically compete with one another and to uniformly respond to stimuli from the federal government. Scholars could also apply autologistic actor attribute models (ALAAMs), which model a nodal attribute on the network

<table>
<thead>
<tr>
<th>Table 5. Network Level Descriptive Statistics for Self-Defense Laws.</th>
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<tr>
<td>Network (a)</td>
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<tr>
<td>---------------------------------------------------------------</td>
</tr>
<tr>
<td>Density</td>
</tr>
<tr>
<td>Average path length</td>
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<td>Degree centralization</td>
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<tr>
<td>Diameter</td>
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<td>QAP correlation</td>
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*Note. QAP = quadratic assignment procedure.*
structure and other attributes. ALAAMs could be used to predict the adoption of a policy based on ties built from previously diffused policies and state attributes (see Desmarais, Harden, and Boehmke 2015). This article has established the framework for measuring ties and building diffusion networks from similarity scores, creating a platform from which scholars can move toward testing theories of state policy making using network models.

Our results suggest that new scholarship should focus on the nationwide policy and information networks that affect policy diffusion, paying particular attention to the connecting role of model legislation. Interest groups sit at the nexus of the ties between states, helping to facilitate communication and provide policy expertise. The capacity to shape state policy making has increased with the growth in electronic communication and reduction of restrictions on money in politics. Many groups now have the financial resources to organize nationally, but they still participate at the state and local level. Using their legal, policy, and political resources, these groups are able to write model bills and quickly promote them across the states. In the cases we examine, prefabricated bills that were endorsed by organized interests served as the basis for important policies, rather than customized bills that were crafted by elected officials.

Our findings pose serious concerns for democratic representation. On two important and rapidly diffusing policies, the language chosen by unelected groups provided the foundation for many of the states who chose to adopt. Even those states that innovated beyond the interest group’s language still had much in common with the group’s initial model legislation. While the expertise of groups is certainly an asset in the lawmaking process, the near plagiaristic tendencies of state lawmakers, which we found, raise concern. Madison (1787) theorizes that the mischiefs of factions would be localized in a nation as large and diverse as the United States. Instead, we uncover that organized interests can have a substantial impact on policy making across the United States without being active at the federal level.

Appendix A

Discussion on Network Structure

Our network analysis involves imposing some structure on tie definition. The structure we define is limiting ties to only the most similar previous adopter. This structure entails the assumption that states are not influenced by the second most similar adopter. The argument can certainly be made that states are influenced by the number of proximate states previously adopting, or that they borrow from several sources. Although these claims are valid, we determined that our structural assumption was acceptable in trying to understand the diffusion of model legislation language.

In some ways, this network structure is more conservative than others we could have imposed. It is more difficult for us to conclude that interest groups are central, in that states several steps removed from the interest group model have many sources to borrow from. As the language used in new adoptions morphs through the diffusion process, state law may look more similar to other states than to the original model bill.
In our framework, the interest group would not be credited with influence despite being central to the diffusion of the policy.

The choice to impose no structure other than time ordering would also reflect certain assumptions. If no limitation of ties were imposed (meaning we included every tie to every node in the network), states would be tied to each other in cohorts, with each wave of adopters influencing each subsequent wave. Such a restriction mirrors that of traditional event history analysis (EHA) models, where earlier adopters are assumed to be more influential in the spread of a policy than later adopters. The interest group model legislation would then just become part of a wave, and we would not be able to identify which model and state bills are more influential than others. Some structure is needed to explore the research question we care about.

Another possibility is to allow similarity scores above a certain threshold to constitute a tie. This is a compromise approach in that we do not impose a strict rule, but also get rid of the time-ordering bias. To explore the efficacy of this approach, we drew a self-defense law network that included all ties above the mean similarity score and one that included all ties with a cosine similarity score greater than .85 (97th percentile). We did this for the networks with and without American Legislative Exchange Council (ALEC) as an adopter and examined the outdegree centrality of the nodes. We also drew time-ordered networks with and without ALEC as an adopter in which each policy adoption could be influenced by any previous adopter. All of these networks are pictured below for comparison.

Figure A1. Policy adoption networks with varied tie definition.
Note. Nodes are labeled with their state name and year of adoption. Nodes are sized by outdegree centrality; more central nodes are larger. Ties are directed from early adopters to later adopters. Isolates are excluded from the picture. ALEC = American Legislative Exchange Council.
The full network (without ALEC) in which the only constraint is time ordering (network (a)) consists of 416 total ties. Florida and South Dakota are the most central actors in the network, influencing each of the 30 states that followed them in adopting self-defense regulations. The states are grouped in centrality by cohort, with the 2006 adoption cohort influencing 19 other states, the 2007 cohort influencing 14 others, and so forth, until the final 2012 cohort influences no other states. In a second network (without ALEC) where ties are limited to those above the mean similarity score (network (b)), Florida remains the most central actor with 21 emulators. South Dakota, the early 2005 adopter, becomes an isolate and drops from the network. In the network (without ALEC) that shows ties with similarity scores above .85 (network (c)), Tennessee is the most central state with 4 emulators. Florida is tied with Pennsylvania, Texas, and South Carolina, with each state only influencing 1 other state. This network contrasts with models that treat states as influential based on their early adoption. The full, time-ordered network with ALEC (network (d)), like network (a), is defined by cohort. ALEC lags behind early-adopting Florida and South Dakota, but influences all other cohorts. In the ALEC network where ties are limited to those above the mean similarity score (network (e)), ALEC jumps ahead of Florida as the most central actor with 25 emulators. In the final ALEC network that shows ties with similarity scores above .85 (network (f)), ALEC is the most central node with 6 emulators. Tennessee is second with 4 emulators, and Florida sits in a four-way tie for third with 3 emulators. From this evidence, we can conclude that interest group model legislation is most central to the self-defense policy diffusion network, and this result is robust to the definition of a tie.

Appendix B

Moving toward Network Models of Diffusion

Here, we explore which variables may be useful to include in network models of diffusion, or in future explorations of the influence of model legislation on policy diffusion. There are two steps implicit in the diffusion of innovations. The first is whether or not to adopt a policy, and the second is how much of a policy/what policy details to emulate. Different variables may be at play at these two stages. We started by exploring how legislative term limits and legislative professionalism affect (1) the decision to adopt and (2) how much to borrow from interest group model legislation. In Figure B1, we show the proportion of states adopting the policy by term limits and professionalism (Figure B1a) and the cosine similarity scores among adopters by term limits and professionalism (Figure B1b). To calculate these proportions, we identified the states with legislative term limits using National Conference of State Legislatures data (2014) and found the proportion of states with and without term limits that adopted the given policy. Similarly, we used the Squire (2007) index to break the states into three groups by professionalism and found the proportion of each group that adopted the policy. We also ran a series of simple regressions, defining term limits and then legislative professionalism as the lone predictor of either policy adoption or similarity with...
model legislation to determine whether the trends we found in the descriptive data were statistically significant.

In the abortion insurance restrictions case, we find that states with term limits and low professionalism had a high proportion of states adopting. This fits with what we might expect, as legislators from those states have fewer resources and less time to invest in formulating new policies. Consequently, they are more likely to follow the innovations of other states or specialized interest groups. Analyzing the data in a simple logit regression (with no control variables), we find that term limits are a significant predictor of adoption at the .1 level. Professionalism was negatively related to adoption, but the effect is not statistically significant.

The term limit pattern also appears in the case of self-defense laws. A higher proportion of states with term limits adopted a new self-defense law than the proportion of states without term limits. A simple logit regression of term limits on adoption of self-defense laws shows that the positive relationship is statistically significant at the .1 level. The pattern for professionalism in predicting the adoption of self-defense laws is not as clear. A large proportion of states that are low in professionalism chose to adopt, but so did a substantial proportion of highly professional states. Professionalism is not a statistically significant predictor of adoption in the self-defense law case.

Turning now to similarity with model legislation among adopters (network (b)), there is no clear pattern in the cases we studied of how term limits or professionalism influence how much a state chooses to borrow language from model legislation. Opposite trends are seen in the effect of term limits when comparing the two cases. In neither case are term limits statistically significant predictors of similarity scores. The category of professionalism for states with the highest bill similarity to model legislation is low professionalism for the abortion issue and medium professionalism for the self-defense issue. However, each of the categories are very close in value to one another, so there is not a large substantive difference between them. The results of the simple regression show that professionalism is not a statistically significant predictor of model legislation similarity among adopters in either case. It appears that the variables that we may expect to matter at the adoption stage do not matter as much at the formulation stage. Rather, interest group tactics or internal political factors may determine how much language a state borrows from model legislation.

One such factor may be ideology. Desmarais, Harden, and Boehmke (2015) demonstrate that states have consistent ties with other states in diffusion, and these ties are largely determined by ideological proximity. As such, states that are more ideologically similar may act in uniform ways when adopting and formulating policy. To explore the possible effect of ideology on adoption and emulation, we took the average government ideology score (W. D. Berry et al. 1998) for adopters and the average government ideology score for nonadopters and compared the two groups. We found that adopting states were more conservative than nonadopting states. Adopters of abortion coverage restrictions had an average government ideology score of 37.35 while nonadopters had a score of 55.71. A similar pattern emerged for self-defense laws as adopters had an average score of 43.05 and nonadopters had an average score of 56.06. In a simple logistic regression, ideology was determined to be a statistically
significant predictor of the adoption of policy in both the self-defense and abortion coverage restriction cases. On both issues, more conservative states were more likely to adopt.

We ran a simple ordinary least squares (OLS) regression model looking only at the similarity to model legislation among states that chose to adopt. The coefficients in each case were near 0, in the opposite direction expected (.002 for AUL and .0005 for ALEC), and not statistically significant. It appears that, like term limits and professionalism, the effect of ideology is stronger on the decision to adopt than on the choice to emulate language.

Figure B1. Term limits, professionalism, and adoption of model legislation. Source: Data on legislative term limits from National Conference of State Legislatures; data on legislative professionalism from Squire (2007).
This very limited analysis demonstrates that scholars should be aware that there are different effects influencing the policy diffusion process, depending on the aspect of diffusion being studied. The variables researchers may expect to be correlated with the decision to adopt a policy seem to be correlated with the decision to enact legislation in the cases we examine. However, these variables do not predict how similar each state is to model legislation. One way forward for scholars is to produce two models, one that examines the decision to adopt and one that tests similarity to model legislation. Scholars could also examine the two stages as a states-only process to identify the consistent leaders and emulators at each stage. Scholars may find that states have many weakly tied partners in the decision to adopt, but a few strong and consistent ties in the emulation of policy language.

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Authors’ Note
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Notes
1. Americans United for Life’s (AUL) model legislation was not published in their book Defending Life until 2011 because their 2010 book had already been published before the federal health care law was passed. Still, it is clear from press statements by state legislators and AUL itself that AUL had already written and disseminated model legislation before the first state, Arizona, passed a law in 2010. President Obama signed the Universal Health Care law on March 23, 2010, and AUL released an announcement three days later that they had already finished drafting the “Federal Abortion Mandate Opt-Out Act” model bill (Ardelean 2010). Arizona led other states in passing legislation banning health care funding of abortion a month later.
2. Our data set consists of one entry per state. For states that adopted a law pre- and post-ACA (Affordable Care Act), we only include the later adoption. Part of this choice was practical, as it was difficult and sometimes impossible to recover the original text of the earlier law without the aid of the current state legal code. Having been amended, the legal code reflects the more recent bill, rather than the original text. When we included both pre- and post-ACA laws, for which we could obtain the original bill language, the results of our analysis did not change. No state modeled its abortion opt-out legislation after a state’s pre-ACA law if that state also had a post-ACA law. Post-2010, all states either adopted versions of North Dakota’s, Kentucky’s, AUL’s, or other states’ post-ACA legislation.

3. This case and the self-defense case examined later in the article were chosen because they were two policies that had successfully diffused across the states and that had interest group model legislation we could access. To test our research question and the new methodological approach, we needed to find policies that met both criteria. We guarded against selecting on the dependent variable by making sure the issues were broad enough to include policy adoptions that differed from the proposed model legislation. On each issue, states could pursue a range of potential policy details, and many states do not enact the model legislation. That said, we are limited in our case selection based on the availability of text for model and state legislation. Still, we point to Karch et al.’s (2013) sentiment that most studies of diffusion only look at successful policies for which data are available. Even studies that include hundreds of policy diffusions display the same problem of sample selection (e.g., Boehmke and Skinner 2012; Desmarais, Harden, and Boehmke 2015). We outline a process for broadening the scope of research in our conclusion, based on what we find in these two cases.

4. Cosine similarity scores can range from −1 to 1, but the cosine similarity of two documents will only range from 0 to 1 because term frequencies cannot be negative. The angle between two document vectors cannot be greater than 90 degrees.

5. The bag of words cosine similarity approach performs just as well as substring matching and fingerprinting techniques in detecting “copy and paste” and “disguised” plagiarism (Potthast et al. 2011). We also measured similarity using Levenshtein distance, a substring metric, which generated the same results. We opted for cosine similarity because the method was more straightforward, adaptable, and easy to implement.

6. Alternative methods of using cutoff points produce the same substantive results as our method of using only most similar scores (see Figure A1 in Appendix A for an illustration of the different cut-points we used). We focus on the more restrictive network results and figures because they most clearly and intuitively demonstrate the central role that interest groups play in the process of policy diffusion. See Appendix A for a more detailed discussion.

7. We use normalized closeness scores calculated in UCInet using the formula
\[ nC_{ci} = \frac{C_{ci}}{(n-1)} \]
where \( C_{ci} = \sum_{j=1}^{n} d_{ij} \) and where \( d_{ij} \) = distance connecting actor \( i \) to actor \( j \).

8. We include AUL as another node in the network rather than creating a two-mode network. We do this for two reasons. First, regardless of the actors involved, we are comparing the text of bills; even though they originate from different political sources, both model and state legislation influence the same network of information. So, at a basic level, we are comparing apples to apples. Second, a two-mode network requires us to assume that every state compares itself with the other mode, obscuring the fact that states are potentially looking to both states and interest groups for information, not just interest groups.

9. See Appendix B for a more detailed discussion of these questions.
References


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