Networks and Interest Group Influence in the Diffusion of Regulation

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Abstract

For years, scholars of state politics have suggested that interest groups affect the diffusion of policy innovations across states. Interest groups help create a network of information between the states that aids in the spread of policy ideas and actual legislative language. However, the unique role that interest groups play in policy diffusion networks is not fully understood in large part because current measures of policy adoption cannot parse out interest group influence. We address this problem by analyzing the actual text of legislation, which provides a more precise measure of policy similarity, allowing us to distinguish whether states emulate other states or interest groups. Applying this analytical framework to two diverse policies, we find that a fundamentally different picture of policy diffusion networks begins to emerge—one where interest groups play a central role in the process of policy diffusion.
Introduction

The American states have often been described as “laboratories of democracy” because of their experiments with new policies. Building on this perception, scholars of state politics have spent years studying how policy innovations are formulated, implemented, and spread across the states. As such, the literature has primarily focused on state behavior and characteristics as driving diffusion. Recently, 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 suggests a prominent role of non–state actors. Furthermore, policy-making based on pre–written legislation by narrow interests contradicts our notions of lawmaking in a representative democracy and the role of states as “laboratories of democracy.”

Some studies of policy diffusion do focus on the role of professional organizations, policy entrepreneurs, and interest groups in the spread of policies across the states (Balla 2001; Haider–Markel 2001; Kile 2005). While prior work has recognized that national groups play an important role in diffusion networks, none tests whether interest groups or states drive the diffusion process. The extant literature relies on a blunt measure of adoption—dichotomous adoption or not—to model the time ordering of state adoptions using event history analysis. We distinguish interest group influence and the influence of early–adopting states through the use of text and social network analysis. Our analytical framework is applied to two cases, laying a groundwork for future studies of the influence of interest groups in the diffusion of innovations.

Building on the assumption that national actors affect policy diffusion by encouraging the flow of information between states in a network, we argue that interest groups directly provide information to state legislators in the form of model legislation. These groups have an incentive to help state legislators with policies that advance their own agenda, and state legislators have reason to seek out policymaking assistance from groups that share their political positions. For this reason, we expect interest groups to play a central role in diffusion networks.

In order to test this theory, we compare the text of federal abortion mandate opt–out and justifiable use of force regulations passed in different states to the text of model legislation proposed by prominent interest groups. We use a common plagiarism detection technique called cosine similarity to measure the degree of similarity between model and state legislation. We then use these similarity scores in
a social network analysis to map out the path of policy diffusion between states and interest groups. This method allows us to assess interest groups’ unique influence on the diffusion process. Based on this analysis, we find that interest groups, rather than influential states, play the most central role in the policy diffusion networks.

**Background**

Since the late 1960s and early 1970s, scholars of state politics have attempted to trace and 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. Building on this work, Gray (1973) showed, 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, Berry and Berry (1990) tracked the spread of state lotteries using event history analysis, which remains the standard methodological approach used to study policy diffusion to this day.

These early works laid the foundation for scholars to focus their analysis on the state–level actors and characteristics that might influence policy adoption and innovation. Most of the literature has relied on internal state dynamics and the external influence of other states to explain why policies spread. The internal dynamics approach is relatively straightforward: scholars examine the various political, social, and economic factors within states that might sway them to adopt policies. This model helps clarify why states with certain ideological, demographic, or financial characteristics are more likely to develop specific fiscal or social policies. It does not, however, address the process by which states learn about or copy innovations in other states.

External activity theories, in contrast, focus on actors and effects outside of a state that influence the spread of policies. Two different models have come to define this approach: one focuses on economic competition (e.g., Baybeck, Berry and Seigel 2011; Berry and Berry 1990; Volden 2002) and the other on social learning that takes place between states (e.g., Grossback, Nicholson-Crotty, and Peterson 2004; 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 geo-
graphic 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 (Berry and Berry 1990, 1992; Berry and Baybeck 2005; Boehmke and Witmer 2004; 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 like social policies.

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; Volden Ting, and Carpenter 2008), 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 a national actor to address policy concerns rather than borrowing other states’ ideas.

If geographic proximity is not driving diffusion, this raises questions about traditional theories that focus on the economic competition and social learning that occurs between states. 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 (2013) demonstrate that states rely on information from “source” states that are politically similar—rather than geographically
proximate—in their adoption decisions. As Karch (2006, 2007a) points out, 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 in a complex information network were present at the advent of the study of policy diffusion although it was not fully explored. Walker alluded 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” (1969, 898). Ten years later, Walker (1981) claimed 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). Most 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 national actors in the diffusion of innovations begins with the theory that policy entrepreneurs, professional organizations, and interest groups shape policy diffu-
sion 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 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 in order to consider adopting a policy, and interest groups facilitate communication about these details. Years before, Mintrom and Vergari (1998) applied a similar argument about information exchange to explain the role of policy entrepreneurs in the diffusion of education policies.

Current studies have proposed several more specific mechanisms by which national forces might influence the spread of information that impacts policy diffusion. Several 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, online databases, and model bills produced by national organizations help facilitate policy diffusion (e.g., Balla 2001; Kile 2005). Yet, most of this research has not examined how these information resources connect interest groups and states.

We agree with the general premise that information flow between states affects policy consideration and adoption and that national actors foster communication between states in policy diffusion networks. Yet, we argue that current conceptions of what counts as information exchange should be modified slightly to include the direct influence of interest groups on state policies. That is to say, interest groups do more than just facilitate connections between policymakers from other states or encourage support for policies within states. Rather, we expect that interest groups actively encourage states to adopt their own policy recommendations, including model legislation. Policymakers look to interest groups for assistance in crafting policies that address issues they mutually care about. Consequently, states will sometimes 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.

Our argument rests on two points. First, we expect interest groups to 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. In order to achieve their policy objectives, these organizations have an incentive to provide resources, information, policy tools, and model legislation to state legislators who might be interested in sponsoring or supporting their bills.

Second, we expect state legislators to look to outside organizations like interest groups for help with policymaking because they face resource and time constraints and because they have other goals besides good policy to pursue. To the first point, we know that state legislators, whether from professional or citizen legislatures, struggle to do their jobs under extreme time constraints. Legislators also have limited expertise on complex policy issues. Consequently, interest groups can be valuable commodities to state legislators because of the technical, legal, and political information and resources they can provide (Hall and Miler 2008; Hansen 1991). State legislators can approach outside organizations for help legislating, and these organizations will eagerly provide them with information as a means to gain access to state lawmakers. 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. In this way, interest groups provide important support for time and resource constrained legislators.

While legislators want to pursue good public policy, their other interests 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 legislators are more likely to borrow existing policy ideas from
other political actors and then focus their energies on generating the political momentum needed to get a measure passed. This means they will look to outside organizations like interest groups that share their political vision when they need help crafting policies.

While legislators have incentives to adopt pre–existing policy innovations in their particular state, we also observe the diffusion of policies across states because of the network of information between the states bolstered by interest groups. Interest groups have technical, legal, and political information that may be difficult to find in the news media or in search engines. In particular, many non-partisan legislative service groups, such as Open States and Lexis Nexis, provide a database of bills introduced in each of the state legislatures, reports on the effectiveness of these bills, differences in the legal language between bills, and information on who introduced and co-sponsored bills. Ideological interest groups also aid in information flow between the states. The archetype group in this category is the American Legislative Exchange Council (ALEC), an association of corporations, conservative activists, and conservative legislators who meet regularly to share ideas, coordinate legislative efforts, and adopt model legislation. Legislators are not bound to their state’s borders; they are interconnected by shared interests, goals, and information which helps create the diffusion patterns that many scholars have found.

In summary, interest groups have an incentive to help state legislators with policies that advance their own agenda, and state legislators have an incentive to look to interest groups for help with policymaking. Therefore, interest groups and policymakers who hold similar political positions will work together to enact state policies, particularly when it comes to ideological issues. 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. In order to gain more empirical leverage on policy emulation between pairs of states, Kile (2005) and Volden (2006) apply dyadic event history analysis, rather than monadic models, to study the spread of policies. These studies represent a step towards network models of diffusion, despite their technical drawbacks (Boehmke 2009). More recently, Desmarais, Harden, and Boehmke (2013) advance our understanding of policy networks by estimating a latent diffusion network based on the diffusion paths of more than 8
one hundred policies. While these models are helpful for studying the diffusion of policies between states, they are less helpful for examining the role of interest groups in this process. Knowing which states adopted similar policies does not inform our understanding of the effect interest groups on the process of policy adoption and emulation.

On the flipside, studies that specifically examine the influence of national organizations on policy diffusion often examine proxies for a national groups 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 interest group influence from the impact of other actors. In the biggest advance, Balla (2001) examines national group influence based on which states have adopted a professional organizations’ model legislation. 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 laws passed in other states.

In order to capture both the complex interdependence between states and the influence of interest groups in diffusion networks, 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 provides one way for scholars to study the role non–state actors play in policy networks. We apply this method to study federal abortion mandate opt–out and justifiable use of force regulations, a process we discuss below.

Diffusion of Restrictions on Insurance Coverage of Abortion

To test our expectation that interest groups play 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
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, harkening back to the first laws passed in the late 1970s and 1980s.

Before ACA, at least five states restricted insurance coverage of abortion. Since ACA and as of this writing, 19 states have adopted policies restricting insurance coverage of abortion. Of those 19 states, three had previously adopted insurance restrictions but updated their laws following the federal health care law. In this way, national policymaking sparked a rapid chain of policy innovation and diffusion on a long-standing policy.

The Role of Americans United For Life

This diffusion case allows us to explore our expectation that interest groups are a critical link between states which has been overlooked in the literature on diffusion. Americans United for Life (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 drafting their own legislation in response to ACA. It also allows us to track AUL’s influence on state policy, allowing us to test our expectation that interest groups serve as conduits of information flow between states.

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 dataset 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 states adoption.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. 2 This issue is also sufficiently broad to allow rigorous testing of the hypothesis. 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.

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1AUL’s 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 to interested state legislators well 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 others states in passing legislation banning health care funding of abortion a month later.

2Our dataset consists of one entry per state. For states that adopted a law pre- and post-ACA, 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. While some states patterned their legislation after North Dakota or Kentucky’s early legislation, these states did not pass post-ACA laws. Post-2010, all states either adopted versions of North Dakota’s, Kentucky’s, AUL’s, or other states’ post-ACA legislation. Consequently, we only include post-ACA legislation if a state adopted bills pre- and post-ACA.
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 to study the diffusion of any policy by other scholars.

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.3 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.4 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 whitespace, 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 to the text of every other law. Our method of comparison is cosine similarity. Cosine similarity is a bag of works approach used to measure similarity that is often used to detect plagiarism. It creates a vector of words and how many times each of those words was used in one text. It then compares that vector to the vector of another text and takes the cosine of the difference between them. The result is a score that can range from negative one to one, with a score of one being exactly similar and negative one being completely different.5 For our data, the scores ranged from 0.31 to 0.89 (see Table 1 for descriptive statistics). The scores can also be thought of in angular terms, since they are based on taking the cosine of the difference of two vectors. For our data, 0.31 represents a text that is moving near a 90 degree angle to the text it is being compared to (or not very similar), while the cosine similarity score of 0.89 is closer to a zero degree

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3Preambles outline the motivation and purpose of the bill and do not have the force of law and, therefore, were omitted from the analysis. One could analyze bills with their preambles, or just look at preambles, in order to study how policy frames diffuse. We have no theoretical justification to include such analysis in this study.

4The state legislative code that corresponds with a signed bill is an exact version of the body of the bill that was signed into law.

5Cosine similarity is calculated \( \cos(\theta) = \frac{(A \cdot B)}{|A||B|} = \frac{\sum_{i=1}^{n}(A_i \cdot B_i)}{\sqrt{\sum_{i=1}^{n}(A_i)^2} \cdot \sqrt{\sum_{i=1}^{n}(B_i)^2}} \) where \( A \) and \( B \) are vectors of \( i \) attributes.
angle (or very similar). Cosine similarity is commonly used in freely-available automated plagiarism
detection programs online.\footnote{While more advanced text similarity methods can be used, this method was the most straightforward and easy to implement. We also measured similarity using Levenshtein distance, which is a string metric that reflects the difference between two sequences, or minimum number of single-character edits—i.e., insertions, deletions, or substitutions—that are required to change one bill text into another. Comparing rank ordering of scores, the two measures generated the same results.}

The similarity scores are then 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 correspond with the row and column, and the diagonal of the matrix is filled with ones—reflecting where each text’s row and column align. Each non-adopter state was added to the matrix and assigned a zero for the similarity score between it and all other states. This adjacency matrix can be used to build a social network. For our study, we add the additional step of setting all but the highest similarity score for each state to zero in order to determine which state most strongly influenced the law of another state. We restrict influence to the single most similar previous adopter both for simplicity and to adopt the most conservative definition of influence.\footnote{In previous treatments, we decided to use a matrix with all text similarity scores to build our network, and then we defined influential states as first-adopters whose laws fell within the top 5% of text similarity with the legislation of states they influenced. This approach yielded similar substantive results.} While many previous-adopters could certainly be important in the process of diffusion, restricting influence to only the state with the highest similarity score allows us to identify the state that was likely the most instrumental in this process. It also allows for an examination of what characteristics make states an information source for subsequent adopting states. We also define influence as time-dependent: 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.

With the adjacency matrix of text similarities defined, we built our network using UCInet and NetDraw. The matrix is defined so that ties extend between states that are most similar in legislative language, and these ties are directed from earlier-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 and extract key statistics about the network, which can then be used in more traditional statistical analyses. Our
theoretical framework is based on the idea of centrality in social networks; states that are more central to the diffusion of an innovation are more influential. Central states are most influential in affecting how a policy spreads. 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, since 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 counter-intuitive, 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.8

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 non-adopter (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. 9

### The Influence of AUL on the Diffusion of Insurance Restrictions

8We use normalized closeness scores calculated in UCINet using the formula \( nC_c(i) = \frac{[C_c(i)]^{-1}(n - 1)}{\sum_{j=1}^{n} d_{ij}} \) and where \( d_{ij} \) = distance connecting actor \( i \) to actor \( j \).

9We include AUL as another node in the network rather than creating a two-mode network, which is the more traditional way of including two different types of nodes. 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, we are, at the core, comparing apples to apples. Second, a two-mode network requires us to assume that every state compares itself to the other mode, obscuring the fact that states are potentially looking to both states and interest groups for information, not just interest groups.
The networks for the adoption of abortion coverage restrictions are depicted in Figure 1. In network (a), the diffusion of abortion funding restrictions flows primarily from early-adopters to later-adopters, with important exceptions. North Dakota and Kentucky are the first two adopters, but they are not the most central states. Rather, Arizona is the most influential state in the network. Though 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 is innovating further. In the case of Tennessee, they adopted some of North Dakota’s language but provided much of their own language which was not adopted by those following in 2011 and 2012. 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 key 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, the central actors influencing the diffusion process change. In the network without AUL, Arizona, North Dakota, Nebraska, and Mississippi are the central actors in the network (based on their low closeness scores, which indicate that these states are closer to other states in the network). When we include AUL in the network, 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.\(^{10}\) AUL’s model legislation serves as the primary text source for the bills passed in six states, including Arizona, Nebraska, and Mississippi. In contrast, Arizona’s legislation serves as the primary text model for legislation in five other states, Nebraska’s for two, and Mississippi’s for two. The change in North Dakota and Kentucky’s influence between the two networks is even more drastic. In network (a) they were central actors, even though those tied to them are relatively weakly so. This reflects their early adoption of abortion funding opt-out policies. 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 net-

\(^{10}\) AUL’s adoption year is set as 2009, as reported by journalistic accounts
work. 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 important role in the process of policy diffusion than North Dakota or Kentucky’s early laws.

[Table 2 about here.]

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 counted as a non-adopter (network (a)). The second column of values represents the outdegree centrality scores for adopters when AUL is counted as an adopter (network (b)). 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 are statistically significantly less central from network (a) to network (b). All other states did not change in the number of other states they influenced, and therefore were not statistically significantly different between the two networks. AUL went from influencing zero states in the network where their model legislation was not considered in the diffusion process to directly influencing the legal language adopted by six states. AUL is statistically significantly more central to the diffusion process between networks. Now considering 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 or more influential nodes. When considering AUL, however, each of the top five adopters are statistically significantly less central to the diffusion network. In fact, all adopters are statistically significantly less central than previously. AUL is the only node that increases in centrality, and that increase is statistically significant. AUL’s low closeness centrality score indicates that it is the most central actor driving the diffusion of policies to restrict abortion funding in state health exchanges; 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 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.

Also to note is that in measuring average centrality among all nodes (adopters and non-adopters), there is no change in the outdegree measure of centrality which is to be expected. For closeness cen-
trality, the network is on average less central, though this change is not statistically significant. We also computed a Pearson correlation between the two networks using Quadratic Assignment Procedure (QAP). We found that network (a) is correlated .709 with network (b). This is surprising low considering they are networks of the same policy diffusion.

These results support our theoretical expectations: states that are the first to adopt a policy are not necessarily the most influential states in the process of policy diffusion. In the case of policies restricting abortion funding, if you measure policy diffusion and innovation without including interest group influence, Arizona, North Dakota, Nebraska, and Mississippi are the most influential actors. Thus, it initially appears that early adopters are the most central actors in the process of policy diffusion. When we include AUL in the network, however, we see that first adopters 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. Meanwhile, Arizona, Nebraska, and Mississippi adopt laws relatively early in the process of policy diffusion, and these states are central to the network. Their influence, however, stems in large part from both their quick policy adoption and their emulation of AUL’s model legislation. When we include AUL in the network, we can see that these states are instrumental because of their close tie to AUL, which is the central actor in the network. Ultimately, influence in the process of policy diffusion stems not only from early adoption but also from the wording used when the policy is crafted. In this case, states that adopt language that mirrors an interest group’s model legislation are more central to the process of policy diffusion. Other states might adopt the innovations made by states that adopt early, but the common language from an interest group’s packaged legislation plays the defining role in the network of policy diffusion. Furthermore, later adopters can become influential if they make meaningful and attractive innovations in their legislative language. Several secondary adopters, such as Nebraska, have several ties to later adopters, both in network (a) and after introduction of the interest group model legislation in network (b).

Consequently, when it comes to policy diffusion, it appears that interest groups reduce the amount of independent innovation that states have to do when they craft a policy. By providing ready-to-go text for states that are interested in passing a law restricting insurance funding of abortion, AUL cuts down the volume of work that states have to do to draft their own laws. For this reason, interested states are likely to turn to AUL’s model text or to other states that have already adopted modified versions of
that text. This study, therefore, offers quantitative evidence to support popular sentiments that interest groups play an important role in the process of policy diffusion and innovation.

**Justifiable Use of Force Laws and ALEC Model Legislation**

We examine another case to deepen our understanding of how interest groups influence the spread of policies across the fifty states. Here, we look at changes made to laws justifying the use of force in self-defense from 2005-2012. In general, justifiable use of force laws allow people to use force in self-defense when facing a reasonable threat. There are, however, several sub-sets of this law that justify the use of deadly force. 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 remaining four. Of these 46 states, 31 made changes to their laws in the seven year period 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 build model legislation which they would then use to promote the innovation to potential future adopters (Greenblatt 2011). This case, like that of restrictions on abortion coverage, allow for the examination of the influence of model legislation in the diffusion of innovations.

Like the abortion 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 the rigorous testing of the hypothesis. Like before, the legal text was gathered, cleaned, and compared to one another using cosine similarity. The network was built by limiting ties from the most similar early adopter to later adopters.

[Figure 2 about here.]

The network for justifiable use of force laws is depicted in Figure 2. Here we see a similar pattern...
to the abortion issue. In network (a), the early innovator, Florida, is most central. Florida influences 11 states directly with their Stand Your Ground legal language. Florida is also the most central actor 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) in network (a). 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 changes. In this case, Tennessee innovated in a way that several other states felt provided a useful model for their legislative efforts and a better model than that of Florida. Other influential innovators include Indiana and Alabama, each having multiple emulators despite themselves being directly influenced by Florida. Notable also is 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 fifteen state innovations. This is more than estimated for 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 seven 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 more that strongly emulated it 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 makes its bill a highly copied document, even though much of the language was chosen from studying Florida’s earlier innovation.

[Table 3 about here.]

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 influential in the diffusion of innovations from network (a) to network (b). ALEC, with its jump from zero ties to fifteen is statistically significantly more central. All other adopters showed no difference between networks. In examining changes in closeness centrality, we get interesting results which give us a clue to the potential power of interest groups in connecting states. Nearly all states were statistically significantly closer after the introduction of model legislation. That is, ALEC more closely ties the network of states together; information flows easier in network (b) than in network (a). This effect is also found when considering the mean closeness centrality score of all nodes in the network. Additionally, the QAP correlation between network (a) and network (b) is a surprisingly low .465. We conclude from this evidence that interest groups can act as conduits between states, actively working to spread information and ideas from one geographic location to another.

**Conclusion: Model Legislation and Madison’s Mischievous Factions**

Our study finds that interest groups are central actors in policy making at the state level, facilitating the spread of information between states. When introduced into a diffusion network, interest group model legislation was found to be the most frequently emulated document; lawmakers turn to the ready-to-go, easily adaptable legislation when possible. Traditional empirical treatments of diffusion have neglected the role of interest groups in the spread and adoption of innovations. The findings of this study, however, suggest that the literature should increasingly focus on the role national policy and communication networks play in policy diffusion.

The rise of model legislation in the political world and the rise of text analysis tools in the academic world create great opportunities to learn about the dynamics of the diffusion process that remain elusive using traditional methods. News reports abound regarding states copying legislative language word-for-word from one another and from the model legislation produced by interest groups. Academics can apply text analysis and leverage these cases to help sharpen our understanding of policy making at the state level. Our study represents a start down this promising path. The combination of bill text analysis and network methods allowed us to examine the influence of non-state actors in a way that event history models would make difficult.

Despite our contributions, questions remain. What makes a state more or less likely to emulate
another state’s legal language? Are there similar political factors present among and between the states that affect the likelihood of adoption? In our cases, the interest groups are conservative and the adoption of the policies tended to be from relatively conservative states. This could be initial evidence that the states are active participants in divergent laboratories—one liberal and one conservative— which could exacerbate conflict and dampen the spread of best practices in our federal system. Exponential random graph models (ERGMs), used to estimate tie formation in social networks, is but one way diffusion scholars could study these questions.

This is an important area of research not only theoretically, but practically. What are the implications for democratic representation if prefabricated bills promoted by organized interests are often the basis of important policies rather than bills careful crafted by elected officials? Our findings suggest that on two important and fast diffusing policies, the language chosen by un-elected, singularly-interested groups provided the foundation for nearly all the states who chose to adopt. Even those who innovated beyond the interest group’s language still had much in common with the group’s initial model bill. While the expertise of groups is certainly an asset in the lawmaking process, the near plagiaristic tendencies of state lawmakers found here raises concern. Madison (1787) theorized that the mischiefs of factions would be localized in a nation as large and diverse as the United States. We instead uncover that there are organized interests that have a substantial impact on policy making across the United States without being active at the federal level.
References


Figure 1: Abortion Coverage Restrictions Policy Adoption Networks

(a) Network of States Only

(b) Network of States and AUL

Nodes are labeled with their state name and year of adoption. Nodes are sized by outdegree centrality, with more central nodes larger. Ties are directed from early adopters to later adopters and thicker lines indicate stronger similarity scores between the two nodes’ legislation. Nodes colored red 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.
Figure 2: Stand Your Ground Policy Adoption Networks

(a) Network of States Only

(b) Network of States and ALEC

Nodes are labeled with their state name and year of adoption. Nodes are sized by outdegree centrality, with more central nodes larger. Ties are directed from early adopters to later adopters and thicker lines indicate stronger similarity scores between the two nodes’ legislation. Nodes colored red 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.
Table 1: Descriptive Statistics of Similarity Scores

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Table 2: Change in Centrality from Network (a) to Network (b) for Laws Restricting Abortion Coverage

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<tr>
<th>Node</th>
<th>Network (a) Outdegree</th>
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<th>Network (a) Closeness</th>
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Mean 0.39 0.39 0.00 1555.80 2222.15 -1.94

QAP Correlation 0.709

Table displays centrality scores among states that adopted laws that restricted 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-test for paired samples and measure the statistical significance between centrality in network (a) and network (b). * denotes statistical significantly different at $p < .05$ for two-tailed test. Bold face text denotes the most influential node in the network using the corresponding metric. Non-adopters included in analysis, but not included in table.
Table 3: Change in Centrality from Network (a) to Network (b) for Self-Defense Laws

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QAP Correlation .465

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-test for paired samples and measure the statistical significance between centrality in network (a) and network (b). * denotes statistical significantly different at p < .05 for two-tailed test. Bold face text denotes the most influential node in the network using the corresponding metric. Non-adopters included in analysis, but not included in table.