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SPID: A New Database for Inferring Public Policy Innovativeness and Diffusion Networks

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Despite its rich tradition, there are key limitations to researchers' ability to make generalizable inferences about state policy innovation and diffusion. This paper introduces new data and methods to move from empirical analyses of single policies to the analysis of comprehensive populations of policies and rigorously inferred diffusion networks. We have gathered policy adoption data appropriate for estimating policy innovativeness and tracing diffusion ties in a targeted manner (e.g., by policy domain, time period, or policy type) and extended the development of methods necessary to accurately and efficiently infer those ties. Our state policy innovation and diffusion (SPID) database includes 728 different policies coded by topic area. We provide an overview of this new dataset and illustrate two key uses: (i) static and dynamic innovativeness measures and (ii) latent diffusion networks that capture common pathways of diffusion between states across policies. The scope of the data allows us to compare patterns in both across policy topic areas. We conclude that these new resources will enable researchers to empirically investigate classes of questions that were difficult or impossible to study previously, but whose roots go back to the origins of the political science policy innovation and diffusion literature.

KEY WORDS: policy diffusion, policy innovation, latent networks

虽然对州政策创新与扩散的研究已取得丰硕成果，但研究者在将其推广到一般情形时仍然受到许多关键限制。本文介绍了新的数据和方法，把对单一政策的实证分析推广为对政策群的综合分析，并严格推算出了这些政策的扩散网络。我们收集了一些有关于政策采纳的数据，这些数据适合用于估算政策的创新性并追踪扩散关系的特定方式（如通过政策领域、时间段或政策类型）；同时，我们也进一步发展出了新的方法以更加准确有效地推断这些网络关系。我们的州政策创新和扩散数据库（*SPID*）包括了按议题编码的*728*个不同政策。我们概述了这个新的数据集，并说明了其两个主要用途：（*i*）用于提供静态和动态的创新性度量；（*ii*）用于推论潜在的政策扩散网络，这些政策网络包括了政策在各州之间扩散的共同路径。这个数据集使我们得以比较不同政策议题的发展模式。对于某些源于政治学领域政策创新与扩散文献中的问题，我们过往难以或者不可能对其进行研究，然而我们在本文中的结论是，我们所提出的这些新成果可以使研究人员对这些问题进行实证上的探索。

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1. Introduction

The study of innovations in public policy and the spread of policies across jurisdictional boundaries has been an area of considerable scholarly interest over the nearly half a century since Walker's (1969) pioneering study. In the American context, lawmakers, policy practitioners, and scholars often look to state governments for solutions that can be emulated across the country. The long-established, multidisciplinary study of *public policy diffusion* is concerned with the patterns, pathways, and mechanisms underlying policy spread, and has occupied the efforts of researchers across the social sciences for decades. In this paper, we introduce new data and methods designed to improve this research. These new resources will be vital to researchers as they continue to move from individual "case study" approaches to understanding which states innovate and how policies spread to large-scale computational and data-intensive study of policy diffusion.

Indeed, despite its rich tradition, there are key limitations to researchers' ability to make generalizable inferences about state policy diffusion. The study of diffusion is typically limited to individual policy areas in which scholars examine determinants of diffusion for a single policy or a group of related policies (Boushey, 2010; Grossback, Nicholson-Crotty, & Peterson, 2004). While these studies have illuminated important dynamics that shape diffusions in areas such as health care, interstate compacts, smoking, and education, they have also provided a disparate picture of the diffusion landscape in general. Moreover, these studies must rely on implicit theoretical comparisons to tie determinants of diffusion in one area to determinants in another (e.g., Shipan & Volden, 2012).[1] From a large-scale survey of the policy diffusion literature, Graham, Shipan, and Volden (2013) call for increased efforts toward both cross-subfield attention and better aggregation to uncover larger patterns in the forces that influence diffusion.

A survey of the recent literature, however, suggests scholars have made little headway in this effort; recent studies focus on increasingly specific topics, more finely tuned predictive indicators, or the development of novel methods to demonstrate diffusion mechanisms. A cursory analysis of diffusion studies published since 2010 finds that these studies cover approximately 50 separate policy areas and almost none aggregates policies across topics (but see Boushey, 2012). Some of the areas of focus are geared toward topics of substantive or political importance such as immigration, criminal justice, or voting laws (e.g., Biggers & Hanmer, 2015; Boushey, 2016; Creek & Yoder, 2012; Makse & Volden, 2011; Ybarra, Sanchez, & Sanchez, 2016). Other areas include policies regarding government operations such as public–private partnerships and interstate compacts or less visible topic areas such as tax and building code (Geddes & Wagner, 2013; Go, 2016; Hageman & Robb, 2011; Nicholson-Crotty, Woods, Bowman, & Karch, 2014). But unifying explanations for diffusion are scarce in the recent literature as theories geared toward more universal explanations of adoption increasingly rely on alternative sources of data such as surveys and text (Hinkle, 2015). While there are many possible explanations for this trend toward greater "diffusion" of diffusion topic areas, it is unclear whether scholars have made much progress in connecting separate areas of research and thus explicitly uncovering common mechanisms.

In introducing our data and methods, we propose a major change in the trajectory of this work: from empirical analyses limited to single policies or small samples and *implied* diffusion relationships to the analysis of comprehensive populations of policies and rigorously inferred diffusion networks. Research in the past decade has started to evaluate larger samples of policies to make more generalizable claims about diffusion trends (Boushey, 2010; Caughey & Warshaw, 2016; Kreitzer, 2015), the largest of which include over one hundred policies (Boehmke & Skinner, 2012b). This project continues this trend of increasingly large sample analyses, by a factor of four. The volume and scope of the policy adoption data we have collected allow researchers the necessary information to trace adoptions, innovativeness, and diffusion ties in a targeted manner (e.g., by policy domain, time period, or policy type). Additionally, we have developed—and implemented in user-friendly software—methods necessary to accurately and efficiently estimate those quantities. Taken together, these developments will enable researchers to empirically investigate classes of questions that were difficult or impossible to study previously, but whose roots go back to origins of the political science policy innovation and diffusion literature (Walker, 1969).

One of the key barriers to systematic studies of the determinants of policy diffusion across a range of related or unrelated topic areas has been the lack of comprehensive data. Scholars are typically left to compile data themselves at significant cost in terms of time and resources. These costs multiply if scholars wish to collect data across different policy areas, especially if they lack theoretical guidance as to which policy areas may be related. Our dataset, which brings together myriad policy topics and substantive areas, is an effort to give researchers one tool to bridge policy areas or test unifying theories and predictors of policy adoption. Researchers can easily test hypotheses in several related policy areas or analyze one important contextual factor across a range of unrelated policies. By aggregating hundreds of individual policy areas across dozens of areas, scholars will be able to move from implicit theoretical comparisons to explicit empirical measurement. These empirical meta-analyses may illuminate undiscovered connections between seemingly unrelated policy areas or provided wide-ranging tests of established diffusion mechanisms.

Key issues that our resources can help scholars understand include states' positions in policy diffusion networks, the relationships between diffusion ties and policymaking across states, and the dynamics of the system comprised by the complete network of diffusion ties, with more certainty in inferred ties due to our much larger sample size. For example, what factors contribute to the formation and/or dissolution of states' diffusion ties? When migration to a state increases, do states increase their ties to each other? How do innovativeness and policy leadership vary across substantive policy areas? At the system level, researchers could use measures of the efficiency of a diffusion network to evaluate the "states as policy laboratories" concept by assessing whether the state diffusion network efficiency—a measure of the latent innovativeness of the entire system—predicts policy innovation at the federal level. Important questions such as these require comprehensive data on policy adoption and the implementation of sophisticated new methods for mapping and analyzing diffusion pathways.

Our data will also facilitate improvements to the study of policy diffusion mechanisms. With a large sample of policies, researchers can analyze subsets of the data to gain better empirical leverage over which processes—such as learning, imitation, and/or economic competition—drive states' adoption decisions (Berry & Baybeck, 2005; Mooney, 2001). This strategy could also be used to assess diffusion processes of policies with other common attributes of interest or regional versus national diffusion dynamics (Mooney, 2001). By providing a broad empirical picture of state policy adoption, this dataset gives researchers the opportunity to further understand both general and specific patterns in the process of policy diffusion.

This project, therefore, offers multiple, distinct contributions. First, our new State Policy Innovation and Diffusion (SPID) database (Boehmke et al., 2018) includes data on the adoption of 728 policies in the American states, greatly increasing the size of the largest database currently available (i.e., Boehmke & Skinner, 2012a) and yielding a sample of policies that is more representative of the universe of policies for which states make laws. Second, we leverage these new data to develop new estimates of static and dynamic policy innovativeness for the 50 states. We examine the variation in our estimates of innovativeness across different data sources to explore variation from the set of policies used to generate the scores. This includes a comparison to existing scores from Boehmke and Skinner (2012a), and the sample is large enough to compare how innovation varies by source and policy area. Additionally, the data indicate periods of high innovation, and others with low innovation. Researchers could use these data to explore system-wide factors that create more/less innovation. Are states responding to events like the Great Depression? Do periods of activity lead or lag public opinion, particularly on salient issues? Do states tend to focus more on certain policy areas before the federal government, or after?

Third, we have coded these policies by substantive topic according to the Policy Agendas Project's guidelines. Scholars can easily subsample policies by policy area while still taking a large sample approach to identify policy area leaders and laggards. Fourth, we map and analyze pathways according to which policies diffuse using the `NetInf` (Network Inference) method discussed in Desmarais, Harden, and Boehmke (2015). `NetInf` allows analysts to identify the underlying networks along which policies persistently diffuse. Fifth, we improve upon the current implementation of `NetInf` by making it more suitable for policy diffusion research (as well as social science in general). This improvement includes an implementation and extension of the method in a user-friendly package in the `R` statistical environment. Sixth, we have released a Stata program, `stpolinn`, to facilitate creation of the static and dynamic innovation scores we present here by other researchers. Finally, to maximize the potential user base of these data and methods, we have created a Dataverse for the SPID data and related products at https://dataverse.harvard.edu/dataverse/spid.

2. Policy Diffusion Episode Data

In this section, we describe how we build upon prior policy diffusion episode datasets.[2] First, we outline how we identified and collected data from other large-scale policy databases—such as those used in Boehmke and Skinner (2012a), Boushey (2016), and Caughey and Warshaw (2016)—and supplemented those data with data gathered from websites and published research. Second, we discuss how we combined the data and cleaned it for consistency. We have divided the data into four major sources, which we discuss in turn.

2.1. Data Sources

We set out to create a large dataset to maximize the number of policies available for scholars studying state policy innovativeness and diffusion. We started with the policies from Boehmke and Skinner's (2012b) dataset of state policy adoption, which was built from Walker's (1969) original data by adding nearly 100 new policies. To this we added other large collections of policy diffusion data and conducted additional searches of published articles and websites. Our second source of data comes from the Uniform Law Commission's website, which provides information on 191 policies adopted from 1921 to 2017. The policies from this dataset were crafted to engender standardization across the states, and the Commission markets itself as focusing on nonpartisan legislation.

Research by Caughey and Warshaw (2016) provided information on 107 policies adopted from 1842 to 2014, which forms our third major source of data. This research focused on estimating state policy liberalism and included numerous policies relating to certification requirements for professions. The data were downloaded from the Harvard Dataverse (Warshaw & Caughey, 2017). The original data started in 1935 even if policies started diffusing in a previous year, so for such policies we identified the actual years of adoption.

Our fourth category includes a wide variety of policies assembled mostly one at a time from a wide variety of sources. We group these under the moniker "Miscellaneous." We began by searching JSTOR for publications using the key terms "policy diffusion," "policy innovation," "policy contagion," "policy adoption," and "Walker." All papers that cited Walker (1969) were also investigated for information. This search went far beyond journals in Walker's field of political science. It included fields such as public health, sociology, and environmental research. There was a particular emphasis on finding sources published after 2010 to incorporate new policies that the Boehmke–Skinner dataset may not include. As needed we contacted scholars studying public policy and policy diffusion to request their data when not available from their papers or replication materials. To supplement these efforts, we also solicited data contributions from scholars via the state politics listserv. Finally, we added data from smaller collections and websites. In total the miscellaneous category compiles data from 35 different sources. The sources range from public health data such as SHEPRD (Silver & James, 2013) and abortion policy (Kreitzer, 2015) to voting laws (Biggers & Hanmer, 2015) and crime policy (Boushey, 2016). The number of policies by source in this category range from a low of 1 to a high of 52. In total, this category includes 267 policies.

Overall, our new dataset covers 728 policy diffusion episodes. Of these, 667 policies began diffusing after 1911. This roughly quintuples the largest existing database on policy diffusion episodes and provides information on roughly 18,000 state policy adoptions from across all 50 states corresponding to over half a million state-policy-year adoption opportunities.

2.2. *Coding and Cleaning*

Our database constitutes two files. The first records adoption data including variables for the state's full name (*statenam*, the policy name *policy*, and the year the policy was adopted *adopt_year*). The second file includes information on each policy including the first year a policy was adopted (*first_year*), the last year a policy was adopted (*last_year*), and the total number of adoptions across all states (*adopt_count*).[3] We also include a brief description of each policy (*description*) as well as the source we collected the data from (*source*) and the policy topic area (*major_topic*). These two files can be merged together to build the risk set of states at risk of adopting a policy.[4] While we only calculate innovativeness for Alaska and Hawaii using policies that started diffusing after 1959, both adopt many policies that started before 1959. This information was kept in the master dataset but excluded from our calculations.

Because we combined many databases we did extensive checking to eliminate duplicate policies. First, the data were collapsed by policy, and variables were generated for the mean year of adoption, the last year of adoption, and the first year of adoption. We identified entries with identical values for these variables and investigated them further. Occasionally policies with a small number of adoptions appearing to be duplicates were in fact different. This approach identifies cases in which scholars started with the same data, but will miss cases where additional adoption dates are added to previously collected data. Our second approach attempts to address this issue. We identified policies that had the same first 10 adoption years. If matched policies were the same, then one with fewer recorded adoptions was removed from the data. In some cases, policies had the same first and last years of adoption, but one source had incomplete information about adoptions. To overcome this hurdle policies were also evaluated by their name and content. Policies that had identical names or otherwise indicated a duplicate were deleted.

In order to assess the issue areas included in our data, we coded them to the major topic areas developed by the Comparative Agendas Project.[5] We relied on the master codebook[6] and had three research assistants code each of the 728 policies by major topic area using the short descriptions we have for each policy area (see our posted data and codebooks).[7] At least two coders agreed on 91 percent of the topics and all three agreed on 57 percent. All codings were reviewed by the principal investigators. Disagreements were resolved by reference to rules outlined in the CAP codebook, additional research on the content and purpose of the policies, and via comparison to similar bills coded to the CAP topics in the U.S. Congress and the Pennsylvania legislature.

2.3. *Final Dataset*

Here we explore some of the basic features of the data and make some basic comparisons across our policy sources. The final general dataset includes policy adoptions ranging from 1691 to 2017. The early beginning year is driven by one policy from Walker's (1969), Anti-Miscegenation Laws, with the second oldest policy first adopted in 1804. While our convenience sample approach to collecting policies matches that used in Boehmke and Skinner (2012a) we have sufficiently more policies that we can make comparisons across major groupings to get a sense of the extent to which policy sources differ and then explore how these differences influence our estimates of innovativeness and the latent diffusion network. Here we begin with the basic features. Table 1 shows summary statistics for each of our major policy source categories, including the total number of policies, the first year with an adoption by source, the last year of adoption, and the average number of adoptions per policy. The overall average number of adoptions is 25 per policy. The Uniform Law dataset is significantly lower than this average while the data from Boehmke and Skinner (2012a) have the highest average number of adoptions.

The Uniform Law policies' lower average adoption count likely occurs because the organization tracks all proposed policies, meaning our data include policies that have been proposed but never adopted, those that have been adopted by very few states, and those that have broadly diffused. These policies may appeal to different states since pre-drafted legislation provides a resource for historically low-innovation states to more quickly adopt policies. They also provide some protection against pro-innovation bias. The final distribution of total adoptions per policy in our dataset is roughly uniform, with slightly higher concentrations of policies that narrowly or widely diffuse (see Figure 2).

Figure 1 shows the number of policies that enter into the dataset by decade. The number of policies begins a graduate buildup around 1900, with a larger increase during the Great Depression. There is a notable decrease in new policies following World War II, but then the gradual increase continues and most of the policies included begin between 1960 and 2000. After 2000 the number of new policies decreases, but this may be more function of data collection than decreased policy action in the states; enough time has not yet passed to collect data on such recent policy diffusions in the states.

Figure 1 shows a similar pattern in the number of adoptions per year. Very few adoptions occur during the 1800s, and growth begins toward the end of the nineteenth century. There are small spikes during the Progressive Era and Great Depression, and the number of adoptions increases rapidly after this until a peak of nearly five hundred adoptions in the year 2000. The constraints of time on data collection can be seen again in this figure as the year 2015 records very few adoptions.

Table 1. Summary of Policies by Source

Source	Total	First	Last	Adoptions	Rate
Boehmke–Skinner	164	1691	2009	33.01	0.05
Caughey–Warshaw	107	1842	2014	25.50	0.03
Miscellaneous	267	1845	2016	25.03	0.04
Uniform Law	190	1921	2017	16.84	0.04

Source: Authors' data.

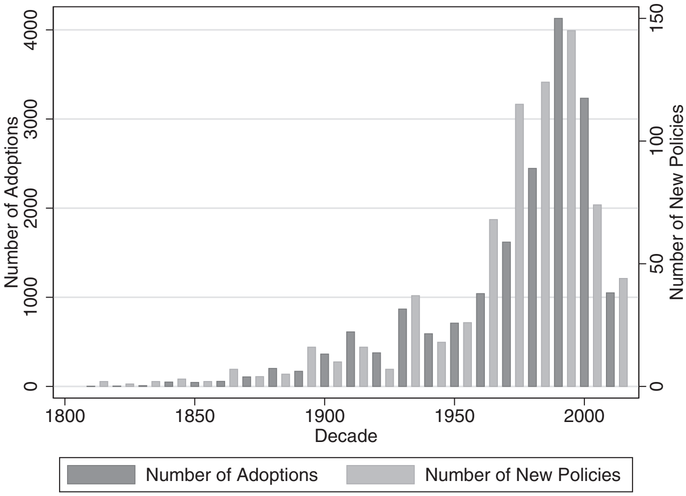

Figure 1. Number of Adoptions by Policy.

The number of adoptions tracks closely with the number of new policies. Both measures have similar spikes and dips. The 2000s decade shows the largest gap and reflects fewer policies being observed while existing ones more fully spread throughout the country.

Table 2 reports the number and proportion of policies by topic area. Law and Crime has the most policies, with just over a quarter of those coded falling into this category. Civil Rights, Health, and Domestic Commerce each constitute at least

Table 2. Distribution of Policies by Issues Areas (Policy Agendas Topics)

Item	Number	Percent
Macroeconomics	21	3
Civil Rights	112	15
Health	69	9
Agriculture	4	1
Labor	28	4
Education	57	8
Environment	17	2
Energy	17	2
Immigration	2	0
Transportation	42	6
Law and Crime	194	27
Social welfare	14	2
Housing	24	3
Domestic Commerce	81	11
Defense	3	0
Technology	2	0
Foreign trade	2	0
International Affairs	2	0
Government Operations	29	4
Public lands	7	1
Total	728	100

Source: Authors' coding based on the Policy Agendas Project major topic listings.

10 percent of all policies whereas Agriculture, Immigration, Defense, Technology, Foreign Trade, International Affairs, and Public Lands each fall under 1 percent with just one to three policies each. We have no policies in the Culture topic area. While we cannot definitively say whether these policies represent a reasonable sample of the kinds of issues that the states were dealing with over time (see below for more on this point), it appears that they focus in on a specific subset of issues, with 13 issue areas featuring nine or more policies and five featuring more than 50 policies. We, therefore, expect that our data will be of particular interest to scholars studying those more highly represented policy areas. These areas fluctuate notably over time, with Law and Crime, Civil Rights, Health, and Commerce policies comprising a greater share after 1962 (the midway point of the data after 1912) and Government Operations, Labor, Social Welfare, and Housing policies decreasing.

2.4. Scope of Our Policies

These descriptives aside, we want to take a moment to reflect on the nature of our final dataset. Its clear strength lies in its size and diversity. We have information on the adoption of over seven hundred policies. These data encompass a wide variety of sources, including hundreds of academic articles focusing on single policies, a handful of articles examining larger collections of policies in one area (e.g., Boushey, 2016; Makse & Volden, 2011) or many areas (e.g., Boehmke & Skinner, 2012a; Caughey & Warshaw, 2016), organizations interested in tracking policy in general (e.g., the National Conference of State Legislators) and in specific areas (e.g., the Guttmacher Institute), academic resources (e.g, SHEPRD and the Correlates of State Policy), and organizations interested in developing model legislation (e.g., the Uniform Law Commission). Twenty-two policies have diffused completely across the states while 32 have reached just one state (see Figure 2). Fifty-two percent of policies diffuse to less than half of the states and a quarter of all policies spread to at

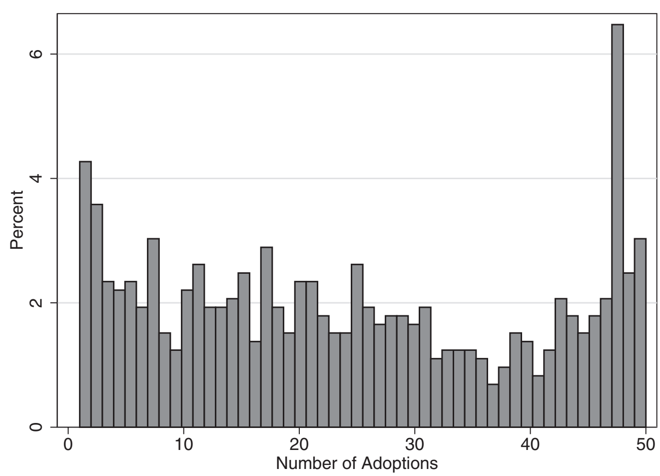

Figure 2. Adoptions and Policies by Decade.

least 40 states. Our sample therefore relatively equally covers widely and narrowly diffusing policies. With a dataset of this size, scholars can easily subset data by the number of adoptions to evaluate any systematic differences in diffusion patterns among low and highly diffusing policies, while using the pooled data to make more generalizable claims about policy diffusion.

On the other hand, our attempts to be comprehensive come at the cost of representativeness. Our sample emerges decidedly based on convenience. Some of the larger underlying components were gathered to include broad varieties of policies. In particular, both Walker (1969) and Caughey and Warshaw (2016) set out to gather information on a range of policies in different areas in order to enhance the validity of their analysis. Yet neither presumes to generate a random sample or even a representative sample of policies. The scope of data on policy diffusion makes that challenging given the long time horizon over which policies diffuse and the broad changes in the types of policies that state governments consider and adopt. Put differently, a random sample of policies from the early twentieth century might no longer be representative by the middle of the century.

In order to explore this issue, we compared the distribution of topics in our policy diffusion database to those from other projects that have used the Comparative Agendas Project to code policy activity in the United States. Specifically, we compare the distribution of topics in our data to the distribution of topics addressed in legislative bills from the Pennsylvania Policy Database Project (McLaughlin et al., 2010), which has coded all bills and resolutions from Pennsylvania from 1979 to 2014[8] and to titles from the Congressional Bills Project (Adler & Wilkerson, 2012) from 1948 to 2011. We subsampled all policies in our dataset that began diffusing during the corresponding time periods and compared the proportions across major topics.[9] Results of this comparison appear in Figure 3.

The two comparisons tell very different stories, with a correlation of 0.76 with the PA data and −0.05 with the Congressional Bills title data. Given the differences between the policy areas handled by the states and the U.S. government, this suggests our diffusion data may be fairly representative of state policy activity in terms of topics addressed but that state policies differ substantially from those addressed at the national level. Our data matches the Pennsylvania Policy Database Project with states taking much more action on law and crime, education, and domestic commerce policies relative to the federal government, and much less action on topic areas such as defense and government operations. Some key similarities and differences emerge when comparing our data to the state spending data used to generate Jacoby and Schneider's (2001) policy spending priority scores. The policy areas measured by Jacoby and Schneider (2001) make up four of our six most common policy areas, but law and crime policies are significantly overrepresented and education and welfare are underrepresented in our dataset relative to the spending data.

The negative correlation between our data and federal policies supports arguments that states dominate some domains of public policy, while the federal government dominates others. Immigration and defense are more commonly found in federal policy, while education, health, and crime are more common in the states.[10] Transportation is one area where federal and state governments appear to overlap

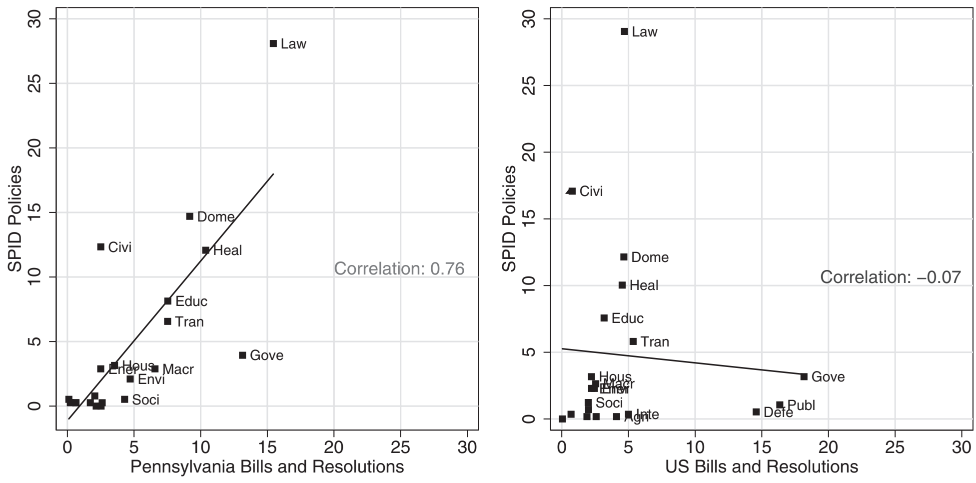

Figure 3. Distribution of Policies across Major Topic Areas Compared to PA Bills and U.S. Titles.
Note: Solid line indicates the best linear fit.

the most, with both the states and the federal government spending a considerable amounts of money (Gamkhar, 2000). It also features considerable intragovernment interaction and cooperation through federal highway grants to states. Policy scholars could examine policy areas where the federal and state government both are active to explore if they are taking complementary, redundant, or conflicting action.

The correlations between our data and both Pennsylvania and federal data indicate that our data are much more similar to state than federal policy adoptions. Of course, these similarities do not mean that the policies addressed within those topic areas are representative; indeed, at some point, someone decided they were worth singling out to document. In particular, law and crime policies and civil rights policies are notably overrepresented in our data, likely due to scholars' heightened interest in them, while government operations policies are underrepresented. Furthermore, we can only compare a subset of our data from the last few decades to the Pennsylvania data. We have considerably more uncertainty about the representativeness of our data from 50 or 100 years ago. That being said, our comparison indicates our sample covers topic areas at a similar rate to those addressed in Pennsylvania using comprehensive data. Scholars still concerned with the representativeness of diffused policies could pursue a couple of approaches. First, they could use the Pennsylvania data (or comparable data) to develop weights to emulate more representative sample.[11] More generally, researchers can weight policies based on other features such as the extent of diffusion, adoption information source, or time. Second, results can be compared across different subsets of the data. For example, as we will show shortly, important differences emerge when calculating state innovativeness on our sample of uniform and model legislation from the Uniform Law Commission or across topics. On the other hand, those looking to make claims about representativeness within policy areas would likely want to explore what's included in more detail. In particular, this would be an issue for analysis based on aggregation of the policy adoptions data whereas in the regression context many of these differences can be accounted for by including control variables, for example, for policy salience or complexity, or merely by including policy-level fixed or random effects.

On a more practical level, our data have a number of potential biases built in. First, much of our sampling strategy relies on published research on policy diffusion. We therefore include policies that diffuse but not those that fail to diffuse, which could result in pro-innovation bias (Karch, Nicholson-Crotty, Woods, & Bowman, 2016; Rogers, 1962). Surprisingly, this concern does not emerge as cleanly as one would expect in our data, with nearly the same number of policies adopted by four or fewer states as by 46 or more states. On average 25 states adopt each policy with a median of 23. The inclusion of Karch et al.'s (2016) data on interstate compacts and data from the Uniform Law Commission on adoption of their model policies likely helps with this issue because many of those policies are adopted by few, if any, states.

We explored whether different states were leaders on below average diffusing policies compared to above average diffusing policies by partitioning them at 25 total adoptions. We found a large correlation (0.75) between innovativeness between the two sets of policies with similar leaders (e.g., California, Minnesota, and Connecticut) and laggards (e.g., West Virginia and Wyoming) in both groups.[12]

Our policies also focus disproportionately on legislative policy actions. The sources we drew from do not systematically document the mode of adoption so our data do not capture this information. We do know more generally that some of our policies, such as same-sex marriage bans or medical marijuana, were adopted via the citizen initiative in some states while others were adopted through bureaucratic or executive action or state court decisions. Still, we strongly suspect that most of our data are adoptions through the legislature. This bias reflects the fact that the legislature is the primary seat of policymaking and its decisions are often studied by scholars, but it may overemphasize its importance. Different types of adoptions can have implications for how a policy diffuses or which state level and external factors influence adoption (e.g., Cann & Wilhelm, 2011). Incorporating information on the adopting venue into SPID or a similar, large database would help researchers explore important questions such as these.

3. Innovativeness in the American States

Having outlined the basic features of the data, we now explore what they tell us about policy innovativeness in the American states, how those results compare to previous findings, and explore variation across our major data sources.

3.1. Static and Dynamic Innovativeness

While a variety of scores have been used to measure state policy innovativeness, here we focus on the rate score proposed by Boehmke and Skinner (2012a), which addresses some issues with the original Walker (1969) score while producing similar results. The rate score calculates the proportion of policy adoption opportunities seized upon by a state during a fixed time period. These scores reveal California as the most innovative state followed by Minnesota and Washington, while West Virginia and Wyoming are the least innovative. The states broadly follow the same order as previous analyses (e.g., Boushey, 2010; Boehmke & Skinner, 2012a).

The rate score also facilitates the creation of dynamic innovativeness scores that show how innovativeness changes over time. The dynamic score we utilize calculates innovativeness for each biennium (because not every legislature meets every year), again by calculating the proportion of possible adoptions that occur in those two years. This results in measures of innovativeness every two years in every state. These are too extensive to display in detail, so we also calculate "national" dynamic innovativeness by pooling all adoptions and possible adoptions and calculating the grand rate score.

The last few years of the dynamic scores have substantial variation, but this again is more likely a product of limited policy adoption information rather than large swings in innovation. By 2010, scores are determined by a handful of policies, many of which are still diffusing in the states. Current trends in innovation will be more easily visible as more policies are introduced into future datasets. We also calculate smoothed innovation rate score for each state following Boehmke and Skinner (2012a); these scores approximate a three-biennium rolling average of dynamic innovation rate scores. Researchers can generate their own versions of these various scores using our Stata program, `stpolinn`.

3.2. Variation in Scores by Source

While our overall scores and state rankings line up closely with prior scores based on fewer policies, we now have sufficient data to explore how innovativeness varies across our different sources for policy diffusion data. Figure 4 plots the static rate score for all of our policies against those for the Boehmke–Skinner subset of the data and then for the Uniform Law Commission subset against all other subsets. It includes a 45-degree line indicating equal innovativeness and a dashed line for the best linear fit between the two scores. We include the Boehmke–Skinner data in the first calculation of the scores to compare how the new scores might revise our understanding of innovativeness but not the second to facilitate comparison across sources. The first comparison indicates that the new scores line up closely with the prior ones, though the average innovativeness decreases notably in the new data with most states' scores about one third lower. Only one state—North Dakota—exhibits a greater innovativeness rate in our SPID data. A look at Table 1 suggests an explanation: most of the newer policies feature fewer adoptions on average, which tends to bring down the innovation scores. In short, state rankings remain fairly similar but the absolute level of innovativeness decreases with our expanded data due to a lower adoption rate. The second comparison demonstrates that the Uniform Law Commission policies exhibit a substantially different pattern of innovativeness underscored by a small and negative correlation with the overall score. The plot

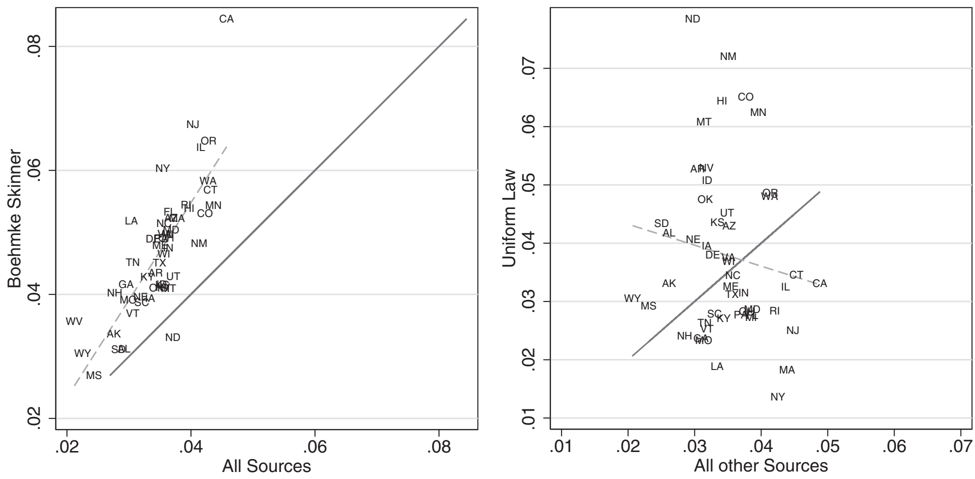

Figure 4. Comparison of Static Innovativeness Rate Scores by Source of Data.
Notes: Forty-five degree–line indicates equal innovativeness; dashed line indicates the best linear fit

makes it clear that the two are virtually unrelated. States that we estimate to be very innovative in general, such as California and New York, are in the middle of the pack and last, respectively, when adopting laws prepared by the Uniform Law Commission. States that score high on the Uniform Law policies tend to be in the middle of the pack on all other policies.

Table 3 shows the correlations between the static rate scores for all four subsets of the policy data. The Uniform Law scores correlate at low levels with the other sources and negatively correlate with Boehmke–Skinner (–0.106), Caughey–Warshaw (–0.114), and the Miscellaneous category (–0.02). The comparatively higher correlation with the overall dataset occurs because Uniform Law comprises one-fourth of the policies used in the database. The prior Boehmke–Skinner data have relatively higher levels of correlation with the other sources, which suggests that the Uniform Law data are showing distinct patterns of innovation from the other sources. As before, we suspect this difference emerges since the Uniform Law data constitute model policies for nonpartisan topics and will appeal to a different set of states as first adopters.

These results make it clear that the sample of policies used to calculate innovativeness matters quite a lot. Yet it does not necessarily undermine the idea of

Table 3. Static Rate Score Correlations by Source

Variables	Boehmke–Skinner	Caughey–Warshaw	Misc	Uniform Law	All
Boehmke–Skinner	1.000				
Caughey–Warshaw	0.621	1.000			
Misc	0.488	0.029	1.000		
Uniform Law	−0.106	−0.144	−0.024	1.000	
All	0.775	0.589	0.614	0.377	1.000

Note: Scores calculated from 1912 to 2017.

innovativeness as an inherent trait of the states: innovative states may look for solutions to their problems and work to generate new policies on their own instead of being quick to adopt model policies or policies developed by external factors such as the Uniform Law Commission. States that tend to be less innovative in general may find more value in adopting policies developed by such actors.

Our final comparison explores trends in innovativeness over time. Again, we turn to the aggregate, smoothed dynamic rates scores calculated by pooling all 50 states, but here we calculate them separately for each policy source. Figure 5 plots them over time. There are clear differences in the average rate across them, as seen earlier. Yet they often peak in similar periods: just after the Great Depression, the 1960s, and the devolution era starting under President Reagan and continuing through the Clinton presidency. Some of these peaks toward the end seem to partly arise from the data, however. Relatively few new policies enter at that time and those that do tend to be in the data because they diffused quickly. Some common drops emerge as well, such as right before the Great Depression and in the late 1970s.

Table 4 shows the correlations between dynamic scores. The Boehmke–Skinner dataset again has relatively high levels of correlation with the complete dataset compared to other sources at 0.653. The Uniform Law data is again uncorrelated with the other sources of data, but it is no longer an outlier in relation to the full dataset with a correlation of 0.465. Dynamic scores have lower levels of correlation between sources generally, as well as between each source and the aggregate set, with the exception of Uniform Law.

3.3. *Variation in Innovativeness Across Policy Areas*

Our final look at innovativeness highlights one of the strengths of our new database by comparing innovativeness across policy areas. With so many policies we are able to provide estimates of policy innovativeness in different topic areas. Scholars of policy innovativeness have from the beginning held that policy innovativeness

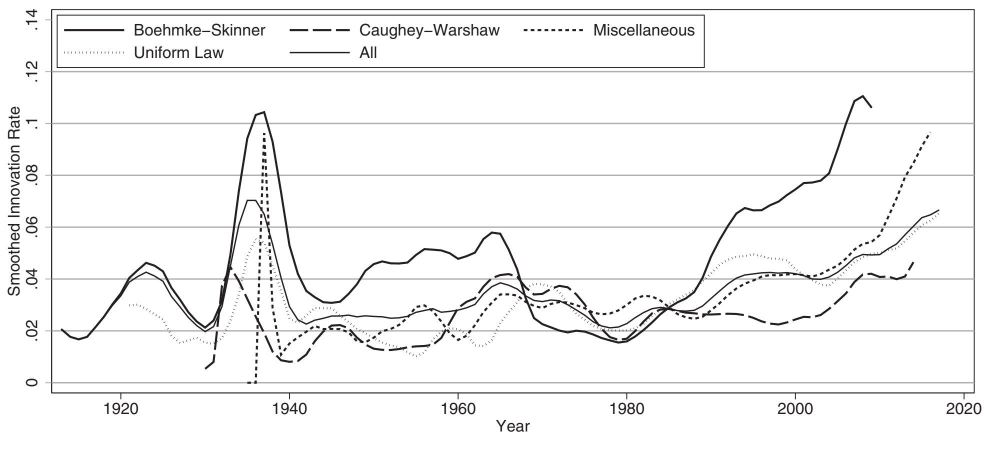

Figure 5. Smoothed Innovation Rate Scores.
Note: Dynamic rate scores for all 50 states combined, smoothed over a 3-year moving window.

varies across policy areas (Gray, 1973) and recognized that certain states specialize in specific policy areas and are looked to as leaders, for example Wisconsin in social welfare policy (Sparer, 2004). Policymakers also view specific states as leaders in general or in policy areas, for example, California in public works policies (Grupp & Richards, 1975). Here we can offer a first look at the extent to which policy leadership does, in fact, vary. We compare our static rate scores for the four largest topic areas—Civil Rights, Law and Crime, Finance and Commerce, and Transportation—in a series of scatter plots in Figure 6.

These comparisons indicate a general positive correlation in innovativeness across policy areas, but also reveal extensive variation in state innovativeness. All pairs save Commerce and Transportation have positive correlations and that exception barely falls below zero. Not surprisingly, then, states like California and New York—that lead in most other topic areas—fall near the bottom on Commerce. Colorado and North Dakota score high on Law and Crime policies but fall quite low on Transportation policy and in the middle of the pack on Civil Rights. Across the six pairings of these four topic areas, states move on average about 12–17 places in the relative ranking, with the largest move never less than 29 and at least 44 in three of the six comparisons.

Next, we turn to fluctuations in these policy areas across the states by plotting the aggregate smoothed dynamic innovativeness scores over time in Figure 7. The graphs reveal substantial variation across policies. Transportation has dramatic and regular peaks roughly every 20 years over the course of the last century. Civil rights exhibits a big peak in the 1960s that drops off by 1980 followed by a slow rise then a flattening in 2006 before a late surge. Law and Crime has a more undulating pattern, with extensive activity through the late 1930s followed by a long over the next 80 years, with small peaks every 10 years or so. Domestic commerce follows a similar pattern with activity following the Great Depression, then a slow period, followed by a bigger surge starting in 1980 through the late 1990s.

4. Diffusion Networks

One of the primary motivations for collecting a dataset that covers a large set of policies across the states is the identification of latent policy diffusion networks. In latent policy diffusion networks, a tie sent from state i to state j is an indicator that state j is more likely to adopt a policy in the near future if state i has recently adopted that same policy. Desmarais et al. (2015) studied policy diffusion networks

Table 4. Dynamic Rate Score Correlations by Source

Variables	Boehmke–Skinner	Caughey–Warshaw	Misc	Uniform Law	All
Boehmke–Skinner	1.000				
Caughey–Warshaw	0.184	1.000			
Misc	0.116	0.068	1.000		
Uniform Law	0.109	0.043	0.036	1.000	
All	0.653	0.444	0.385	0.465	1.000

Note: Scores calculated from 1912 to 2017.

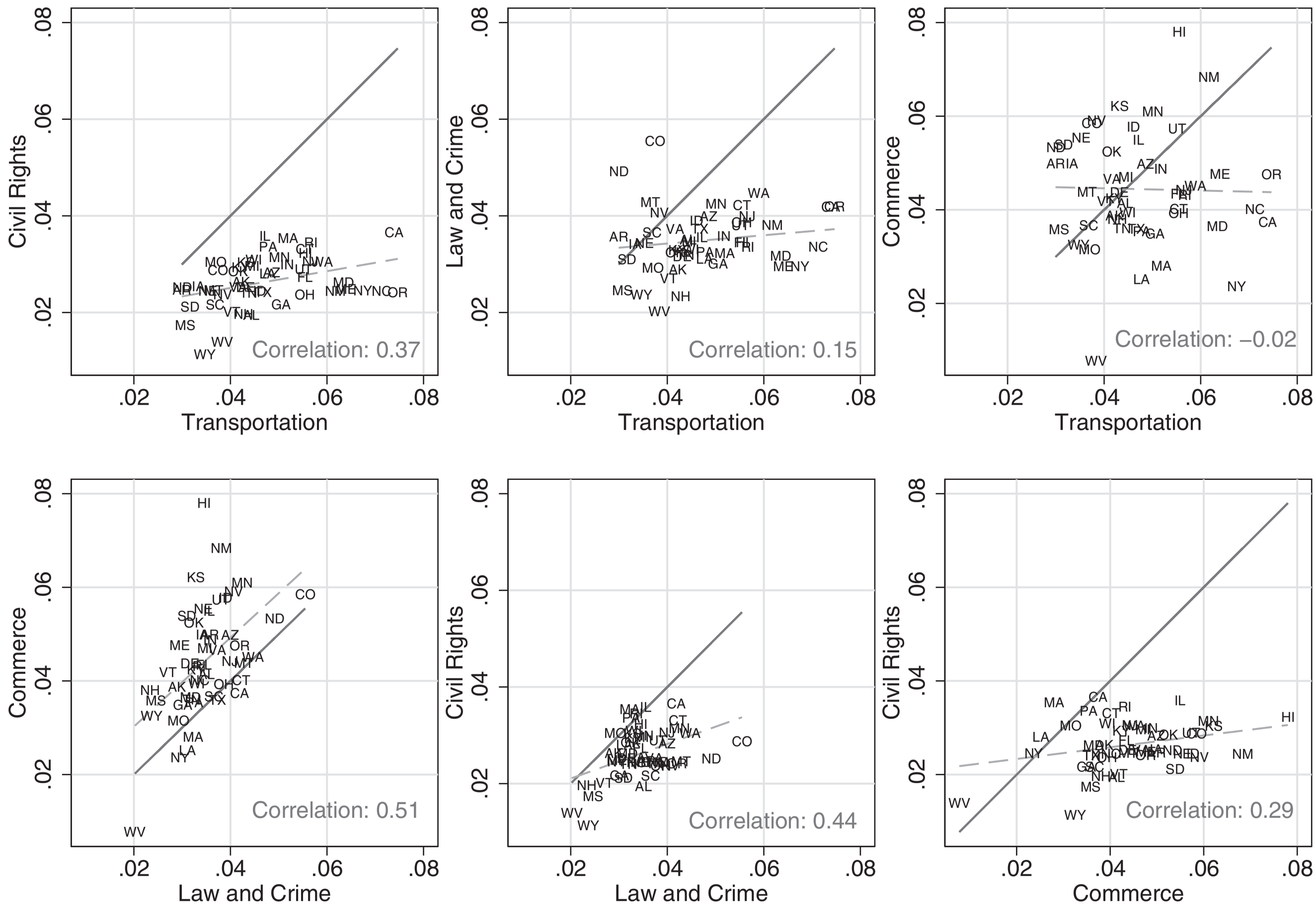

Figure 6. Comparisons of State Static Innovativeness for Select Topic Areas.
Notes: Forty-five–degree line indicates equal innovativeness; dashed line indicates the best linear fit.

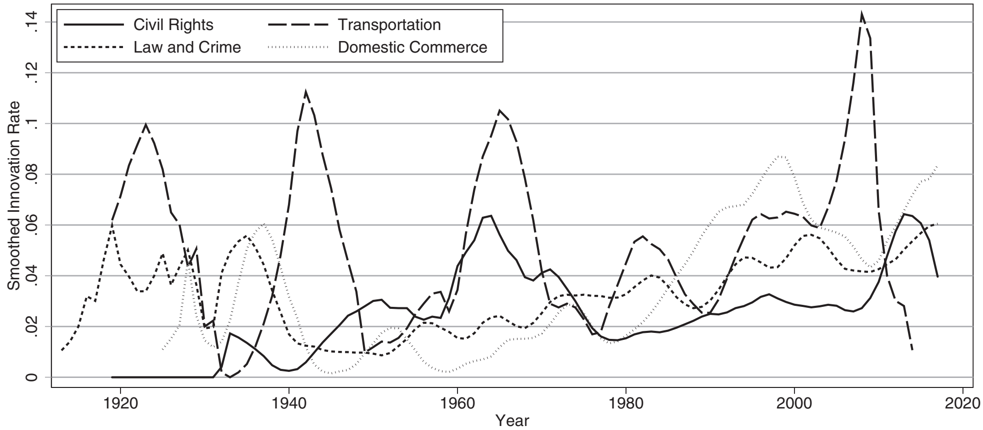

Figure 7. Smoothed Dynamic Innovation Rate Scores for Select Topic Areas.
Note: Dynamic rate scores for all 50 states combined, smoothed over a 3-year moving window.

derived through network inference and demonstrated, for example, that, contrary to conventional understanding at the time, the vast majority of policy diffusion ties are formed between states that do not share a geographic border. There is a substantial literature that aims to understand the role of policy networks in the diffusion of public policy (e.g., Arnold, Nguyen Long, & Gottlieb, 2017; Considine & Lewis, 2007; Mintrom & Vergari, 1998; True & Mintrom, 2001). The research in this area is, broadly speaking, concerned with identifying the degree to which policy networks shape the how fast, and to where, a policy innovation spreads. The policy networks that we present in this paper can be analyzed to understand the factors that predict which states (e.g., those with professional legislatures) serve as sources of diffusion for many other states, what predicts the formation of diffusion ties between states (e.g., similar political ideologies), and what factors predict the degree to which states are influenced by many others in policy diffusion networks (e.g., large/diverse population and needs). Policy diffusion networks can also be used for theoretical investigations into the way(s) in which particular policies are likely to spread throughout the states (Boehmke, Rury, Desmarais, & Harden, 2017).[13]

We use the new policy adoption data to estimate state-to-state diffusion networks, following the methodology of Desmarais et al. (2015), and compare our results to the networks inferred using their policy adoption database. By studying the differences between our network inference results and those of Desmarais et al. (2015), we highlight the information added through the new policies we have collected. The latent networks presented in this section are inferred using the `R` package `NetworkInference` (Linder & Desmarais, 2017).

4.1. Diffusion Networks: Parameter Tuning

To use the network inference algorithm, `NetInf` (Gomez-Rodriguez, Leskovec, & Krause, 2012), in the same manner as it was applied by Desmarais et al. (2015),

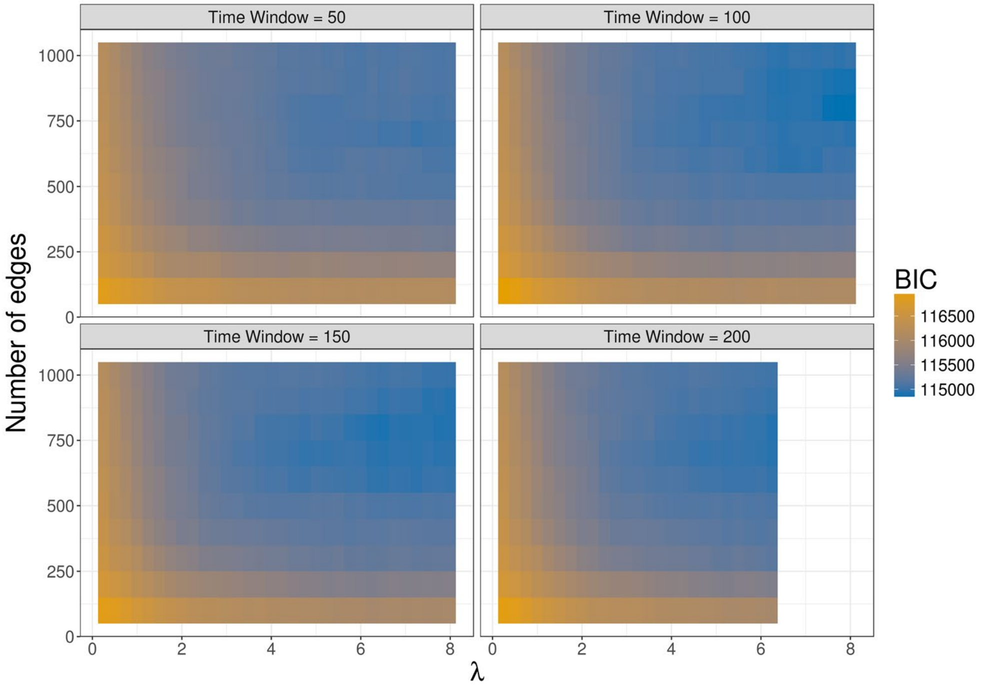

Figure 8. BIC Values Corresponding to `NetInf` Tuning Parameters.

we need to set three tuning parameters. First, we need to define the size of the time window of policy adoptions that is used to infer the diffusion network for time *t*. Second, we need to define the number of edges in the network. To maintain comparability with Desmarais et al. (2015), we infer the same number of edges in each year, though the assumption of a constant number of edges could be relaxed in future applications. Third, we need to tune a rate parameter that controls the degree to which `NetInf` penalizes diffusion episodes that span long periods of time. To compare tuning parameter combinations, we follow Desmarais et al. (2015) and compare the BICs from pooled discrete-time event-history models—pooling overall policies in our database—in which a state's adoption of a policy is modeled as a function of the number of states that adopted the policy previously, the number of a state's sources in the diffusion network that adopted a policy previously, and a policy-specific intercept.[14]

The tuning results are presented in Figure 8, in which there is a heat map of the BIC at each of the four time windows considered. The *x*-axis gives the value of λ —the inverse of the mean diffusion time, and the *y*-axis gives the number of edges in the network. Each cell in the grid is colored according to the value of the BIC for the respective grid point. The optimal tuning parameter combination includes 800 edges (out of 2,450 possible directed dyads), at a time window of 100 years, and involving a rate parameter of 4.75. Numerical results for the top 10 tuning parameter combinations are given in Table 5. These results differ considerably from those of Desmarais et al. (2015), who found that the optimal tuning parameters were 300 edges, a 35-year time span, and a rate parameter of 0.5. The new results, however, are not surprising. Adding considerably more data should lead to the discovery of more edges. The combination of the longer time span and higher diffusion lag penalty indicates that most adoptions can be explained through short diffusion episodes, but the data contains a non-trivial number of long diffusion episodes with high explanatory value.

Aside from finding more edges using more data, our updated networks also contain different edges. Figure 9 presents the relationship between the number of years (out of 50, 1960–2009) in which a tie was inferred in a directed dyad of states in the Desmarais et al. application (i.e., Old), and in our application. We see here that there is, in general, a positive association between the number of edge-years found using the old data and the expanded database. However, there are many examples in which there were no edge-years found in the old data, but 50 or close to 50 found using the new data, and many examples in which there were 41–50 edge-years found in the old data, but fewer than 10 found using the new data. Tables 6 and 7 present the top 15 diffusion sources by 5-year period, using the expanded database, and the data from Desmarais et al. (2015), respectively. We see that many states are at or near the top in both tables, including New York, California, and Minnesota. However, there are several states that are prominent in only one of the tables, including Illinois, Oregon, and Colorado, which are near the top in the analyses using the expanded database; and Florida and New Jersey, which are much closer to the top in the analyses using the more limited database. Overall, through applying `NetInf` to the new/expanded database, we find both more and considerably different diffusion ties than those found by Desmarais et al. (2015).

4.2. Diffusion Networks: Policy Areas

Using the new topic codings, we additionally inferred diffusion networks for each policy area separately. As described above, we use the procedure proposed in Desmarais et al. (2015) to find optimal tuning parameters for the `netinf` algorithm and estimated one network per topic area using the respective optimal parameters.

Table 5. 10 Parameter Combinations With Lowest BIC Value in the Event History Model

Lambda	# Edges	Time Window	BIC	Beta	*p*-Value	Relative Beta
7.75	800.00	100.00	114,876.20	0.03	0.00	–1.94
8.00	800.00	100.00	114,877.82	0.03	0.00	–1.82
7.50	800.00	100.00	114,882.61	0.03	0.00	–2.08
8.00	900.00	100.00	114,897.54	0.03	0.00	–1.57
7.75	900.00	100.00	114,899.29	0.03	0.00	–1.67
6.50	800.00	150.00	114,909.06	0.04	0.00	–2.81
7.50	900.00	100.00	114,910.76	0.03	0.00	–1.79
6.50	800.00	200.00	114,915.37	0.04	0.00	–2.81
6.25	800.00	150.00	114,919.06	0.04	0.00	–3.08
7.75	800.00	150.00	114,920.45	0.03	0.00	–1.93

Notes: Beta corresponds to the coefficient of neighbor adoptions in the event history model. p value is the corresponding p value. Relative beta is beta normalized by the coefficient for previous adoptions.

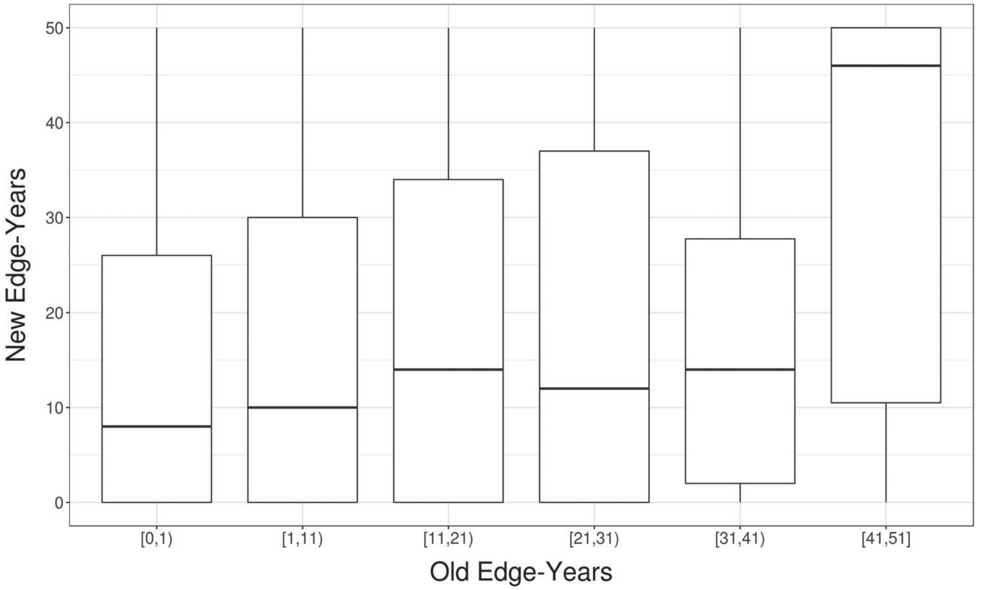

Figure 9. Each Boxplot Gives the Distribution of the Number of Years in Which a Diffusion Tie Is Identified with Network Inference.
Notes: The unit of analysis is a directed dyad (i.e., potential diffusion tie) between states. Directed dyads are binned based on the number of years in which they were found to be tied by Desmarais et al. (2015) (i.e., Old Edge-Years).

Table 8 displays the optimal parameter combinations for each topic. Table 9 displays the top five states for each year and each topic. The ranking of states, again, is based on the total number of outgoing diffusion ties from each state in each year's network.

Though many of the states that are leaders in the overall diffusion network, such as New York, Kentucky, and California, are also leaders in a few of the policy-specific

Table 6. Top 15 States Based on the Total Number of Diffusion Ties Sent to Other States within 5-Year Periods

Rank	60–64	65–69	70–74	75–79	80–84	85–89	90–94	95–99	00–04	05–09
1	KY	NY	NY	NY	KY	KY	NY	CA	CA	CA
2	LA	KY	KY	IL	NY	CA	KY	MN	CT	KY
3	OH	IL	IL	KY	LA	MN	CA	KY	KY	CT
4	NY	LA	MD	MD	IL	LA	MN	OR	MN	IL
5	VA	OH	LA	LA	MD	NY	OR	CO	IL	FL
6	MD	MD	OH	CO	MN	OR	MI	CT	LA	MN
7	IL	VA	NJ	NJ	NJ	IL	LA	LA	FL	WA
8	VT	NJ	MI	OR	CA	RI	IL	IL	MD	MI
9	NJ	CA	CA	RI	CO	MI	RI	NJ	VA	MD
10	OR	MI	VA	WI	OR	CO	CO	MI	NJ	VA
11	CA	VT	RI	CA	RI	NJ	FL	WI	MI	LA
12	MS	MS	VT	MN	FL	MD	NJ	NY	WA	OR
13	PA	PA	CO	OH	WI	CT	CT	VA	OR	NJ
14	GA	NE	WI	VA	MA	VA	WI	WA	WI	NY
15	MI	CO	OR	VT	MI	FL	VA	FL	RI	NM

Table 7. Top 15 States Based on the Total Number of Diffusion Ties Sent to Other States within 5-Year Periods.

Rank	60–64	65–69	70–74	75–79	80–84	85–89	90–94	95–99	00–04	05–09
1	NY	NY	NY	NY	NY	FL	FL	CA	CA	CA
2	KY	KY	FL	FL	FL	NY	NY	CT	CT	CT
3	CA	SC	CO	NJ	NJ	CA	CA	NJ	FL	NJ
4	MN	AL	RI	MN	MN	MN	CT	FL	WA	FL
5	AL	CO	CT	OR	RI	OR	OR	NY	NJ	WA
6	SC	NM	MN	IL	OR	NJ	MN	MN	IL	IL
7	RI	MN	MI	CO	CO	RI	NJ	OR	MN	MN
8	MI	OH	NJ	AK	CA	CT	CO	WA	AZ	AZ
9	VT	NJ	NE	NH	AK	AK	OH	LA	IA	LA
10	NJ	WA	PA	RI	IL	IL	RI	CO	NC	IA
11	IL	MI	LA	AR	LA	CO	IL	IA	OR	OH
12	WA	RI	AL	CT	MI	ID	AK	AZ	CO	NC
13	MD	MD	OR	MI	CT	MI	LA	NC	HI	CO
14	OH	PA	MD	DE	ID	OH	MI	OH	LA	WI
15	MS	VT	AR	MS	PA	KS	ID	ID	OH	UT

Source: Data from Desmarais et al. (2015).

networks, it is clear that there is considerable variation by policy area. To provide a more complete look at the similarity across time and policy domain, we ran an analysis in which we assigned a one-dimensional latent variable value to each policy area network in each year. To construct this latent variable we first calculated the similarity between each pair of issue-year networks by taking the Pearson's correlation between the off-diagonal elements of the two networks' adjacency matrices.[15] In the second step, we used classic multidimensional scaling to place each issue-year in a one-dimensional space that best explained the similarity between networks. It is not possible to directly interpret the absolute positions of issue-years in this space, but the similarity between these networks is approximately proportional to the graph correlation between them.

The positions derived from the scaling of networks are visualized in Figure 10. From this analysis we see three distinct groupings of policy areas over time. First, education policy is in its own cluster—a bit of an outlier in terms of network structure. Second, we see that health and domestic commerce form their own cluster. Third, Civil Rights and Law and Crime are located in the middle of the latent variable space, along with the network "Pooled," which is inferred using all policies. In terms of over-time trend, we see that the structures of these networks appear to be

Table 8. Parameter Combinations with Lowest BIC Value in the Event History Model for Each Topic.

Lambda	# Edges	Time Window	BIC	Beta	p-Value	Relative Beta	Topic
7.25	300.00	150.00	19,968.60	0.04	0.00	–24.82	Civil Rights
1.75	200.00	100.00	12,616.14	0.30	0.00	73.31	Domestic Commerce
4.75	300.00	150.00	7,931.60	0.08	0.00	24.17	Education
3.50	200.00	100.00	11,749.53	0.16	0.00	8.11	Health
3.25	500.00	100.00	34,634.31	0.09	0.00	8.35	Law and Crime

Notes: Beta corresponds to the coefficient of neighbor adoptions in the event history model. *p* value is the corresponding *p* value. Relative beta is beta normalized by the coefficient for previous adoptions.

Table 9. Top 5 States Based on the Total Number of Diffusion Ties Sent to Other States within 5-Year Periods

Rank	60–64	65–69	70–74	75–79	80–84	85–89	90–94	95–99	00–04	05–09
Civil Rights										
1	MA	MA	MI	NJ	NJ	PA	MN	MN	UT	MN
2	CT	MI	NJ	PA	MN	MN	OH	CO	MN	UT
3	PA	CT	MA	MN	PA	NJ	PA	UT	CO	CO
4	CO	AK	PA	IL	MA	MA	NJ	NC	OH	ME
5	KS	NJ	CT	MA	IL	NY	MA	OH	CT	MO
Domestic Commerce										
1	VA	VA	VA	VA	MN	MN	MN	MN	MN	MN
2	MI	MI	MI	ID	ID	ID	KS	KS	KS	KS
3	MT	MT	NM	KS	KS	KS	ID	OR	NE	NM
4	NM	NM	FL	MT	VA	CO	OR	ID	VT	NE
5	ID	ID	ID	MD	MT	MT	CA	CA	CA	OK
Education										
1	SC	SC	NY	NY	NY	NY	CA	CA	SC	SC
2	GA	MD	SC	SC	SC	SC	NY	MA	CA	NY
3	MD	WY	MD	MD	MD	CA	MD	SC	MA	CA
4	TX	GA	WY	RI	RI	MD	FL	FL	MS	VA
5	RI	NJ	RI	WY	GA	RI	SC	MD	VA	MS
Health										
1	KY	ID	KY	IA	CA	MA	CT	CT	VT	VT
2	ID	KY	IA	SD	MA	CA	MA	MA	CA	MA
3	IA	IA	ID	ID	ID	IL	VT	VT	CT	CT
4	MA	MA	WI	KY	SD	SD	IL	WI	MA	CA
5	CT	WI	MA	WI	IA	RI	SD	ID	MD	IL
Law and Crime										
1	VA	VA	NY	NY	MN	MN	MN	CA	CA	CA
2	NY	NY	VA	MN	KY	CA	CA	MN	MN	MN
3	KY	KY	NJ	LA	CA	OR	CO	CO	CO	FL
4	IA	NJ	KY	KY	FL	KY	FL	WA	WA	CO
5	NJ	MN	LA	CA	NY	FL	KY	KY	OR	WA

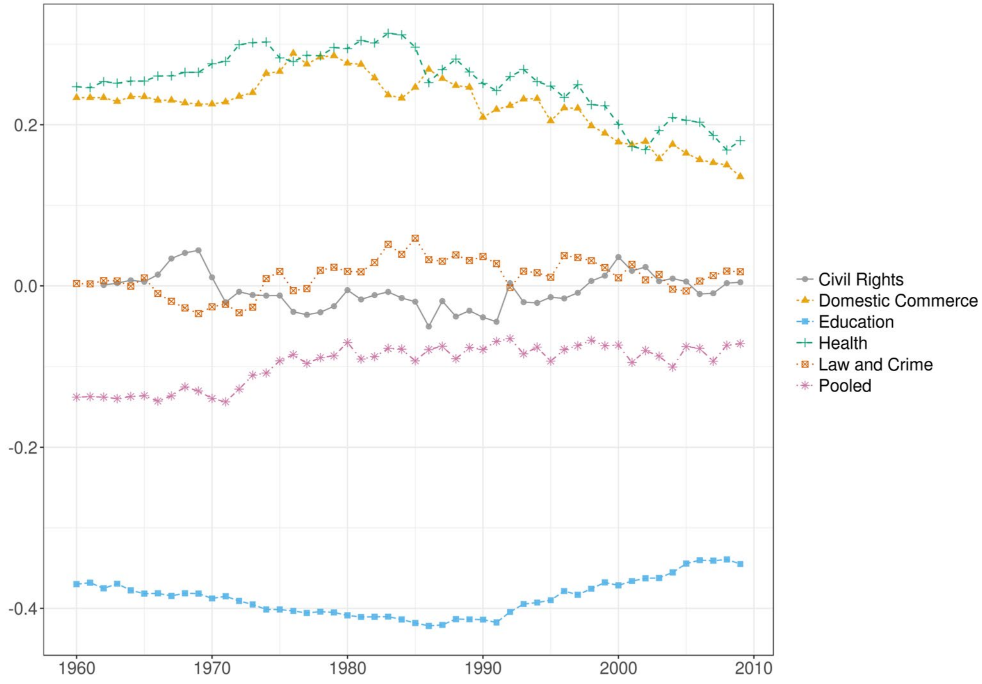

Figure 10. Similarity of Topic-Specific Diffusion Networks Over Time.
Note: Positions of each topic-year network derived via multidimensional scaling with one dimension.

converging together over time, with the clusters growing closer with time. For the sake of brevity, we refrain from further investigation of the structure of the policy-specific networks, but this represents an interesting direction for future research.

5. Discussion and Conclusion

We present and describe a new data resource for scholars interested in studying the diffusion of public policies across the American states. Our dataset includes over 700 diffusion episodes. This expands greatly the number of policies available compared to existing datasets of this type. Here we offered some basic details about these policies and compared our results to those obtained from the previous, much smaller, database (Boehmke & Skinner, 2012a). We find broadly similar results for estimates of state innovativeness across most of our clusters of policy data. The exception appears with data from the Uniform Law Commission, which produces estimates that do not correlate strongly with other clusters of policies. We speculate that this difference arises from the difference in adopting model legislation versus innovating by developing and adoption new legislation and believe the topic warrants future research.

To facilitate research on policy innovativeness and diffusion, we have released the SPID data via the Dataverse Project. We created a stand-alone Dataverse to host the SPID data and related outputs or products. The SPID database has its own dataset page with data on policies, adoptions, and documentation. Other pages in the

SPID Dataverse host our static and dynamic innovativeness scores and our latent network estimates. We plan to add additional pages with future outputs and envision other scholars adding their own related contributions or outputs of the adoption data to make SPID a crowdsourced, community resource. To aid use of the data and the related statistical techniques we will also add or link to various packages, manuals, and tutorials for estimating these quantities.

The resources made available through the SPID database can be used by both practitioners and researchers. Practitioners have access to a history of policy adoption dates for hundreds of policies. Through our innovation scores, they can also see which states adopt sooner in different topic areas. Our latent networks offer information on which states are most influential overall and to each of the 50 states individually. Learning about such patterns can provide important background for exploring new policy options or for identifying other states' related policies to explore in more detail. Researchers will have the opportunity to answer several types of research questions. First, the raw policy adoption data can be used as a source of data for conventional event history analyses exploring the factors that explain the diffusion of one, a few, dozens, or hundreds of policies across the states. Such an analysis could help identify the way in which the mechanisms of diffusion vary across policies or policy areas, for example, based on the salience and complexity of policies (Mallinson, 2016; Nicholson-Crotty, 2009) or by Rogers's (1962) full list of innovation traits as Makse and Volden (2011) did for a set of criminal justice policies. For example, in subsequent research we have found that policies with a clear partisan appeal diffuse faster than moderate or nonideological policies. Second, the state innovativeness scores can be studied to understand the causes and consequences of cutting-edge policymaking (e.g., is policy innovativeness driving and/or driven by the health of a state's economy). Third, the latent diffusion network estimates can be studied both as outcome variables, in which researchers seek to understand the formation of diffusion ties between states, and as vectors of diffusion, in which researchers seek to understand or predict the diffusion of future policies based on persistent ties identified through existing adoption data. The latter can aid in evaluating diffusion mechanisms by providing a broader alternative to the ubiquitous contiguity measure. Last, given the number of policies covered by SPID and their distribution across different policy domains, researchers can address the types of questions listed above for specific policy areas or draw comparisons across policy areas.

The data and measures we provide will be of use in several domains of scholarship. The breadth of coverage in our database enables scholars of public policy to study policy adoption and diffusion from either a very general perspective—analyzing patterns that transcend specific policies or policy areas, or to easily target specific policy interests—searching our database across relevant dimensions to find ideal cases for specific research aims (e.g., health policies that began spreading in the 1980s). Scholars who study state legislatures can use our measures of diffusion networks to help explain the success or failure of legislation based on what has been passed in states that serve as sources of diffusion, and innovativeness scores could be used as an additional dimension of outputs for researchers who study productivity and professionalism in state legislatures. Political and policy networks scholars can use our diffusion networks to study the factors and network structures that predict policy-based connectivity between states.

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Notes

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1. See Volden, Ting, and Carpenter (2008) for a formal model of policy diffusion.
2. Episodic data records a series of events that occur over defined time periods, in this case the adoption years for the U.S. states of a specific policy over time.
3. Some of the sources we drew from included information on adoptions beyond the first. Because this information is inconsistently available and we may not be able to distinguish between sources that did not consider multiple adoptions and those that did but did not find any for a given policy, we removed this information from our public database. Scholars interested in repeat adoptions should contact us directly.
4. Example code for generating this form of data is available on the SPID Dataverse page.

5. The codebook we used was based on the data collected by Frank R. Baumgartner and Bryan D. Jones, with the support of National Science Foundation grant numbers SBR 9320922 and 0111611, which are distributed through the Department of Government at the University of Texas at Austin. Neither NSF nor the original collectors of the data bear any responsibility for the analysis reported here.
6. Downloaded from http://www.comparativeagendas.net/pages/master-codebook in May 2017.
7. We attempted to code to minor topics but abandoned that goal when it proved too difficult given the often limited descriptions we have for many policies and since those subcategories would have too few policies to analyze separately.
8. Pennsylvania Policy Database Project, Principal Investigator Joseph P. McLaughlin, Temple University. Data accessed May 23, 2017.
9. The PA project added one more topic area, local government and governance, which we did not use when coding our data.
10. In fact, if we omit Public Lands and Defense the correlation becomes positive at 0.07 and jumps to 0.33 if we further omit Government Operations, which as we just noted is underrepresented in our policies compared to the PA data.
11. Researchers would generate weights by dividing the percentage of policies in a topic area in the Pennsylvania data by the percentage of policies in the same topic area in the SPID data. So if 10 percent of the Pennsylvania policies are about education and our dataset had 15 percent education policies, researchers could weight our education policies by 0.666 and similarly for other topics to adjust the distribution of our data to match that in Pennsylvania.
12. To be precise, we calculated innovativeness using the static rate score, discussed elsewhere.
13. For a broader introduction to the role of network theory and analysis in the study of public policy see Lubell, Scholz, Berardo, and Robins (2012).
14. We implement one deviation from the tuning methodology of Desmarais et al. (2015) in that in the parameter evaluation event history analysis we weight prior adopting sources using the weighting function implemented in Boehmke et al. (2018), which is based on the probability density function of the exponential distribution.
15. We did this using the gcor function in the R package sna (Butts, 2008).

References

Adler, E. Scott, and John Wilkerson. 2012. "Congressional Bills Project: NSF 00880066 and 00880061." Accessed May 24, 2017.

Arnold, Gwen, Le Anh Nguyen Long, and Madeline Gottlieb. 2017. "Social Networks and Policy Entrepreneurship: How Relationships Shape Municipal Decision Making about High-Volume Hydraulic Fracturing." *Policy Studies Journal* 45 (3): 414–41.

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

Biggers, Daniel R., and Michael J. Hanmer. 2015. "Who Makes Voting Convenient? Explaining the Adoption of Early and No-Excuse Absentee Voting in the American States." *State Politics & Policy Quarterly* 15 (2): 192–210.

Boehmke, Frederick J., Abigail Matthews Rury, Bruce A. Desmarais, and Jeffrey J. Harden. 2017. "The Seeds of Policy Change: Leveraging Diffusion to Disseminate Policy Innovations." *Journal of Health Politics, Policy and Law* 42 (2): 285–307.

Boehmke, Frederic J, Mark Brockway, Bruce Desmarais, Jeffrey Harden, Scott LaCombe, Fridolin Linder, Hanna Wallach. 2018. "State Policy Innovation and Diffusion (SPID) Database v1.0" [Data File and Codebook]. Harvard Dataverse. 10.7910/DVN/CVYSR7.

Boehmke, Frederick J., and Paul Skinner. 2012a. "State Policy Innovativeness Revisited." *State Politics and Policy Quarterly* 12 (3): 303–29.

Boehmke, Frederick J., and Paul Skinner. 2012b. "State Policy Innovativeness Scores V1.1." http://hdl.handle.net/1902.1/18507. Accessed July 8, 2016.

Boushey, Graeme. 2010. *Policy Diffusion Dynamics in America*. New York: Cambridge University Press.

———. 2012. "Punctuated Equilibrium Theory and the Diffusion of Innovations." *Policy Studies Journal* 40: 127–46.

———. 2016. "Targeted for Diffusion? How the Use and Acceptance of Stereotypes Shape the Diffusion of Criminal Justice Policy Innovations in the American States." *American Political Science Review* 110 (1): 198–214.

Butts, Carter T. 2008. "Social Network Analysis with SNA." *Journal of Statistical Software* 24 (6): 1–51.

Cann, Damon, and Teena Wilhelm. 2011. "Policy Venues and Policy Change: The Case of Education Finance Reform." *Social Science Quarterly* 92 (4): 1074–95.

Caughey, Devin, and Christopher Warshaw. 2016. "The Dynamics of State Policy Liberalism, 1936–2014." *American Journal of Political Science* 60 (4): 899–913.

Considine, Mark, and Jenny M. Lewis. 2007. "Innovation and Innovators Inside Government: From Institutions to Networks." *Governance* 20 (4): 581–607.

Creek, Heather M., and Stephen Yoder. 2012. "With a Little Help from Our Feds: Understanding State Immigration Enforcement Policy Adoption in American Federalism." *Policy Studies Journal* 40: 674–97.

Desmarais, Bruce A., Jeffrey J. Harden, and Frederick J. Boehmke. 2015. "Persistent Policy Pathways: Inferring Diffusion Networks in the American States." *American Political Science Review* 109 (2): 392–406.

Gamkhar, Shama. 2000. "Is the Response of State and Local Highway Spending Symmetric to Increases and Decreases in Federal Highway Grants?" *Public Finance Review* 28 (1): 3–25.

Geddes, R. Richard, and Benjamin L. Wagner. 2013. " Why Do U.S. States Adopt Public-Private Partnership Enabling Legislation? " *Journal of Urban Economics* 78: 30 – 41.

Go, Min Hee. 2016. "Building a Safe State: Hybrid Diffusion of Building Code Adoption in American States." *American Review of Public Administration* 46: 713–33.

Gomez-Rodriguez, Manuel, Jure Leskovec, and Andreas Krause. 2012. "Inferring Networks of Diffusion and Influence." *ACM Transactions on Knowledge Discovery from Data (TKDD)* 5 (4): 21.

Graham, Erin R., Charles R. Shipan, and Craig Volden. 2013. "The Diffusion of Policy Diffusion Research in Political Science." *British Journal of Political Science* 43: 673–701.

Gray, Virgina. 1973. " Innovation in the States: A Diffusion Study." *American Political Science Review* 67 (4): 1174 – 85.

Grossback, Lawrence J., Sean Nicholson-Crotty, and David A. M. Peterson. 2004. "Ideology and Learning in Policy Diffusion." *American Politics Research* 32 (5): 521–45.

Grupp, Fred W., and Alan R. Richards. 1975. "Variations in Elite Perceptions of American States as Referents for Public Policy Making." *American Political Science Review* 69 (3): 850–58.

Hageman, Amy M., and Sean W. G. Robb. 2011. "A Regional Diffusion Theory Explanation for States' Proposal and Adoption of Anti-Passive Investment Company Laws." *Journal of Accounting and Public Policy* 30: 551–69.

Hinkle, Rachael K. 2015. "Into the Words: Using Statutory Text to Explore the Impact of Federal Courts on State Policy Diffusion." *American Journal of Political Science* 59: 1002–21.

Jacoby, William G., and Saundra K. Schneider. 2001. "Variability in State Policy Priorities: An Empirical Analysis." *The Journal of Politics* 63 (2): 544–68.

Karch, Andrew, Sean C. Nicholson-Crotty, Neal D. Woods, and Ann O'M. Bowman. 2016. "Policy Diffusion and the Pro-Innovation Bias." *Political Research Quarterly* 69 (1): 83–95.

Kreitzer, Rebecca J. 2015. "Politics and Morality in State Abortion Policy." *State Politics and Policy Quarterly* 15 (1): 41–66.

Linder, Fridolin, and Bruce A. Desmarais. 2017. "NetworkInference: Inferring Latent Diffusion Networks." https://github.com/desmarais-lab/NetworkInference.

Lubell, Mark, John Scholz, Ramiro Berardo, and Garry Robins. 2012. "Testing Policy Theory with Statistical Models of Networks." *Policy Studies Journal* 40 (3): 351–74.

Makse, Todd, and Craig Volden. 2011. “The Role of Policy Attributes in the Diffusion of Innovations.” *The Journal of Politics* 73 (1): 108–24.

Mallinson, Daniel J. 2016. “Building a Better Speed Trap: Measuring Policy Adoption Speed in the American States.” *State Politics & Policy Quarterly* 16 (1): 98–120.

McLaughlin, Joseph P., J. Paul Wolfgang, Wesley Leckrone, Justin Gollob, Jason Bossie, Jay Jennings, and Michelle J. Atherton. 2010. “The Pennsylvania Policy Database Project: A Model for Comparative Analysis.” *State Politics & Policy Quarterly* 10 (3): 320–36.

Mintrom, Michael, and Sandra Vergari. 1998. “Policy Networks and Innovation Diffusion: The Case of State Education Reforms.” *Journal of Politics* 60 (1): 126–48.

Mooney, Christopher Z. 2001. “Modeling Regional Effects on State Policy Diffusion.” *Political Research Quarterly* 54: 103–24.

Nicholson-Crotty, Sean. 2009. “The Politics of Diffusion: Public Policy in the American States.” *The Journal of Politics* 71 (1): 192–205.

Nicholson-Crotty, Sean C., Neal D. Woods, Ann O'M. Bowman, and Andrew Karch. 2014. “Policy Innovativeness and Interstate Compacts.” *Policy Studies Journal* 42: 305–24.

Rogers, Everett. 1962. *Diffusion of Innovation*. New York: Free Press.

Shipan, Charles R., and Craig Volden. 2012. “Policy Diffusion: Seven Lessons for Scholars and Practitioners.” *Public Administration Review* 72: 788–96.

Silver, Diana, and James Macinko. 2013. *State Health Policy Research Dataset (SHEPRD): 1980–2010*. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor]. http://doi.org/10.3886/ICPSR34789.v3

Sparer, Michael S. 2004. “States and the Politics of Incrementalism: Health Policy in Wisconsin during the 1990s.” *Journal of Health Politics, Policy and Law* 29 (2): 269–92.

True, Jacqui, and Michael Mintrom. 2001. “Transnational Networks and Policy Diffusion: The Case of Gender Mainstreaming.” *International Studies Quarterly* 45 (1): 27–57.

Volden, Craig, Michael M. Ting, and Daniel P. Carpenter. 2008. “A Formal Model of Learning and Policy Diffusion.” *American Political Science Review* 102 (3): 319–32.

Walker, Jack L. 1969. “The Diffusion of Innovations Among the American States.” *American Political Science Review* 63 (3): 880–99.

Warshaw, Christopher, and Devin Caughey. 2017. “Replication Data for: The Dynamics of State Policy Liberalism, 1936–2014. V1” Harvard Dataverse. Retrieved from https://doi.org/10.7910/DVN/ZXZMJB. Accessed February 20, 2017.

Ybarra, Vickie D., Lisa M. Sanchez, and Gabriel R. Sanchez. 2016. “Anti-Immigrant Anxieties in State Policy: The Great Recession and Punitive Immigration Policy in the American States, 2005–2012.” *State Politics & Policy Quarterly* 16: 313–39.