6-1-2021

The Ties that Bind Us: The Influence of Perceived State Similarity on Policy Diffusion

Christine Bricker
Warren Wilson College

Scott LaCombe
University of Iowa, slacombe@smith.edu

Article

The Ties that Bind Us: The Influence of Perceived State Similarity on Policy Diffusion

Political Research Quarterly
2021, Vol. 74(2) 377–387

DOI: 10.1177/1065912920906611
journals.sagepub.com/home/prq
SAGE

Christine Bricker[1] **and Scott LaCombe**[2]

Abstract

In this paper, we propose a new measure to understand policy connections between the states. For decades, diffusion scholars have relied on the largely untested assumption that contiguous states are more similar than noncontiguous states, despite evidence that similarity is more complex than geographic proximity. We use a unique survey of citizens' perceptions of other states to construct a national network of similarity ties between the states. We apply this new measure with a data set of state policy adoptions in a dyadic and monadic event history analysis and find that similar state adoptions are a reliable predictor of policy innovation. We argue that perceived state similarity is a more complete measure of how states look to each other than contiguity.

Keywords

diffusion, similarity, policy, state politics, event history

Since Walker's (1969) article on policy diffusion, research focusing on how policies spread across the United States has often relied on a key assumption—geographic contiguity drives diffusion. Early diffusion literature argues that policies spread more readily from state to state when the states border each other or are in the same region (Berry and Baybeck 2005; Gray 1973; Walker 1969). Meta-analyses of the literature show that contiguity is almost always included in diffusion models and is often a predictor of policy adoption (Maggetti and Gilardi 2016).

Yet, there are plenty of examples of how contiguity does not explain how policies travel across U.S. states. The legalization of same-sex marriage is one example. Massachusetts and Connecticut were the first two states to legalize same-sex marriage in 2003 and 2008. Iowa, however, halfway across the country, was the third adopter in 2009. This is one of many examples of noncontiguous policy adoption. Clearly, there is more at play in how policies diffuse than just geographic proximity.

Recent research has challenged contiguity as a measure of diffusion and proposed alternative understandings of policy adoption and innovation. Scholars are using more sophisticated measures and methods to understand diffusion beyond the role of contiguity (Desmarais, Harden, and Boehmke 2015; Nicholson-Crotty and Carley 2018; Pacheco 2012; Shipan and Volden 2012). This more methodologically rigorous research has shown that, while contiguity is relevant to understanding policy diffusion, it is only a "good starting point" but is "overly limiting" and "sometimes misleading (or even wrong)" (Gilardi 2016). Despite this, scholars continue to include contiguity as a one-size-fits-all variable in model specification.

We propose using a new measure, *perceived state similarity*, as a more sophisticated and versatile alternative to contiguity. In this study, we generate and use a continuous measure of citizen perceptions of state similarity to predict the diffusion of eighty-nine policies adopted from 2012 to 2016. We find that *perceived state similarity* is a strong predictor of dyadic policy similarity. We also find that similarity remains a strong predictor of diffusion when expanded to a larger set of policies in a pooled event history analysis (EHA) from 1990 to 2016. We suggest scholars consider moving beyond contiguity to understand relationships between states when modeling policy adoption and innovation, and use *perceived state similarity* as a way to understand interstate connections.

[1]Warren Wilson College, Swannanoa, NC, USA
[2]The University of Iowa, Iowa City, USA

Corresponding Author:
Christine Bricker, Department of History & Political Science, Warren Wilson College, 701 Warren Wilson Rd., Swannanoa, NC 28778, USA.
Email: cbricker@warren-wilson.edu; christine-bricker.com

State Similarity, Contiguity, and Diffusion

The diffusion literature has grown considerably over the past few decades both in the number of articles published and in the sophistication of methodological tools. The introduction of EHA to diffusion research allowed researchers to include both internal and external predictors of diffusion (Berry and Berry 1990), leading to the growth of many single-policy studies that evaluated the determinants of state policy adoption. More recently, scholars have turned to large-sample analyses of dozens or even hundreds of policies (Boehmke and Skinner 2012; Boushey 2012; Kreitzer and Boehmke 2016), leading to more generalizable findings about the broader diffusion network. As the field has grown and diversified its methodological approaches, diffusion scholars have consistently found that contiguity is a reliable predictor of policy adoption. States are more likely to adopt policies previously adopted by neighboring states.

Despite the consistency of this finding, scholars have pointed out limitations of using contiguity as a measure. Researchers have struggled to determine why contiguity predicts diffusion. Rather than learning from neighboring states, some argue that states with similar characteristics are simply responding with solutions to similar policy problems (Volden, Ting, and Carpenter 2008). Others have argued that contiguity may still play a role in diffusion, but that its effect has weakened over time due to a variety of new influences (Mallinson 2019). These new factors include latent diffusion ties between the states (Desmarais, Harden, and Boehmke 2015) and the influence of interest groups on policy adoption (Garrett and Jansa 2015), among others. This more rigorous research has shown that, while contiguity is relevant to understanding policy diffusion, there are other reasons that explain how policies travel from state to state. Researchers have known that there are additional factors that influence policy diffusion, but scholars still rely on contiguity to be a catch-all variable that is used in different theoretical approaches to diffusion (Gilardi 2016). We propose a measure of state similarity as an alternate measure for researchers to include in policy diffusion models.

Our new measure *perceived state similarity* presents a more nuanced picture of how states are connected. Contiguity has been used consistently in policy diffusion research and is a binary variable that indicates whether a state shares a border with another state. A binary measure does not allow for differing strengths of connections, or levels of similarity, between states. States that border each other do not all have the same level of similarity. For example, Washington shares a border with both Oregon and Idaho, but Washington looks much more like Oregon in terms of income per capita, political ideology, partisanship, and percentage of the population that is urban.[1] Using the binary contiguity variable would give a policy adoption by Oregon or Idaho equal weight in influencing Washington's probability of adopting a policy.[2] *Perceived state similarity* is a continuous measure that is based on the strength of citizens' perceived similarity of one state to another. Our measure allows researchers to incorporate strength of ties into a model.

The inclusion of *perceived state similarity* in a model also necessitates researchers to theorize *why* diffusion is happening. Past research argues that contiguity is responsible for different reasons for policies to diffuse. Some point to contiguity as a measure for learning (Gray 1973; Volden 2006), others show that contiguity leads to competition (Berry, Fording, and Hanson 2003), and others argue that contiguity causes a social contagion effect (Pacheco 2012). Some even say that using contiguity as a predictor does not allow for modeling why diffusion happens (Baybeck, Berry, and Siegel 2011). This confusion surrounding what contiguity measures has stymied progress identifying why policies diffuse (Gilardi 2016). At best, measures of contiguity are imprecise and cannot easily distinguish between diffusion processes, while at worst they may lead to wrong conclusions about what is causing policy adoption (Shipan and Volden 2012). Using *perceived state similarity*, a measure based on people's perceptions of states that are similar, requires researchers to be explicit that they are using similarity to predict diffusion, whereas a measure of contiguity is often included without an explicit rationale. A measure of perceived state similarity is a more nuanced measure of connections between the states and offers more theoretical clarity to why a policy is diffusing.

Data and Method

To measure people's perceptions of state similarity, we placed a question on the Cooperative Congressional Election Study (CCES) that asked residents of each of the fifty states to name states that are similar to their home state. The CCES is a

> 50,000+ person national stratified sample survey administered by YouGov. Half of the questionnaire consists of Common Content asked of all 50,000+ people, and half of the questionnaire consists of Team Content designed by each individual participating team and asked of a subset of 1,000 people.

We placed our question on the Team Content section in 2012, 2014, and 2016. This method of measuring perceptions rests on a longstanding tradition in network analysis of using survey respondents to generate measures of perceived networks (Huckfeldt 1979, 1983; Huckfeldt and

Sprague 1988, 1991, 1995; Klofstad, McClurg, and Rolfe 2009; McClurg, Klofstad, and Sokhey 2017; Sprague 1976). To figure out how these groups are connected, researchers ask respondents to name the individuals in their immediate social environment through a "name generator" procedure. This process uses a "descriptive stimulus" that allows the researcher to identify the type of network they are trying to measure (Klofstad, McClurg, and Rolfe 2009). In our case, we asked residents of each state to answer "What states are similar to your own state?" to understand the perceived state similarity network of the United States.

The three combined surveys yield approximately 2,300 respondents from across the United States. Respondents, or "egos" in the social network literature, could list as many or as few states, or "alters," as they preferred. In total, 6,800 similar state dyads were identified. On average, respondents listed 3.5 states as similar to their home state. Only 44 percent of responses were contiguous states. To create our independent variable of interest, *perceived state similarity*, we generate a series of dyads among the alters from each ego network. More specifically, the network consists of states that each respondent indicated were similar to their home state. Our state similarity scores use the entire sample of responses to show Americans' collective understanding of which states are similar.

Calculating State Similarity Scores

Perceived state similarity is an "alter network" of dyads of states that each respondent listed as similar to their home state. We assume that states that are similar are more likely to form ties as a result of having similar characteristics (Friedkin 2006; Lazarsfeld and Merton 1954; Skvoretz 1985, 1990; Skvoretz, Fararo, and Agneessens 2004). We argue that, if a respondent believes two states are similar to his or her home state, there is an underlying similarity between those two states they listed. For example, if a respondent listed California, Washington, and Oregon as similar to their own state, we created a series of dyads among California, Washington, and Oregon.[3] Our measure identifies a latent similarity between states listed as similar to a respondent's home state. When we aggregate this measurement strategy across thousands of survey responses, we create a measure that uses latent similarity between states to create a national network of perceived similarity ties.

Once these dyads were generated for each response, we calculated *perceived state similarity* by dividing the number of times any two states were listed together by the number of times one of the states was listed in the entire sample.[4] *Perceived state similarity* is directed because the strength of similarity is different within state dyads. For example, California is a highly populated state with a big city that is often in the news. It is possible that people think that many lesser known states are similar to California, whereas they would not think that California is similar to a lesser known state. In network terms, this would mean that California has more in-degree ties than out-degree ties. To reflect the differences in how often respondents list states as similar to their own, we create a directed state similarity score.[5]

Differences in the number of similarity connections are reflected in the descriptive data from the survey. There is a wide variation in the number of times respondents list a state as similar to their own state. For example, respondents list New York, Georgia, and Ohio more than 230 times as similar to their home state, whereas fewer than fifty list Alaska and Hawaii as similar. The Oregon and California example illustrates this well. Remember if five people listed both California and Oregon as similar to their home state and fifty respondents overall listed California as similar to their home state, then California's *perceived state similarity* score to Oregon would be 0.1. However, if twenty respondents listed Oregon as similar to their home state, California's *perceived state similarity* score to Oregon would be 0.25 (see Figure 1B). If the scores were undirected, the *perceived state similarity* score would be the same for each state (0.07; see Figure 1C). A directed score can recognize that Oregon's connection to California plays a more prominent role in its similarity connections compared with California's similarity connection to Oregon.

The *perceived state similarity* scores range from a low of 0 to a high of 0.417. A total of 2,182 of 2,450 (89%) potential dyads are listed as similar. The mean similarity score is 0.06, and 11 percent of observations have a score of 0. The high score is Mississippi's similarity to Alabama, followed by South Dakota's similarity to North Dakota at 0.386. Every contiguous state has a similarity connection, as do 88 percent of noncontiguous state dyads. This means that contiguity only measures a small proportion of the dyads that are perceived as similar. Figure 2 shows the network of directed similarity connections for the 488 dyads with a similarity score of 0.1 or higher.[6] The network further demonstrates that contiguity plays an incomplete role in understanding similarity between the states. In total, 65 percent of the strongest similarity connections are between noncontiguous states. For example, among the strongest 500 connections in the similarity network, New York is perceived as similar to California, Oregon, Washington, and Illinois, all noncontiguous states. Contiguous states are perceived as more similar on average, but the network is also strongly influenced by noncontiguous states.

Diffusion is typically conceptualized as an elite-driven process where interest groups and legislators propose and

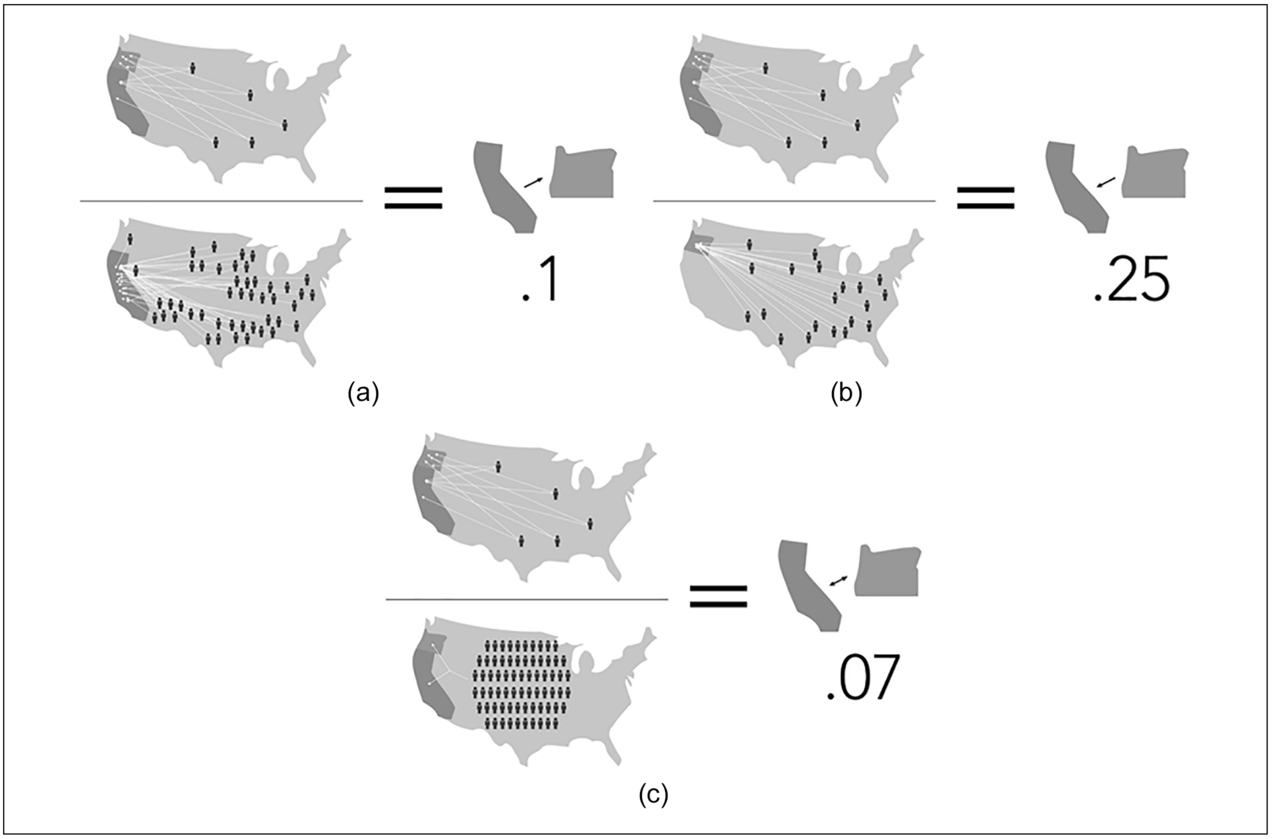

Figure 1. Example of the calculation of similarity scores: (A) California to Oregon, (B) Oregon to California, and (C) undirected calculation.

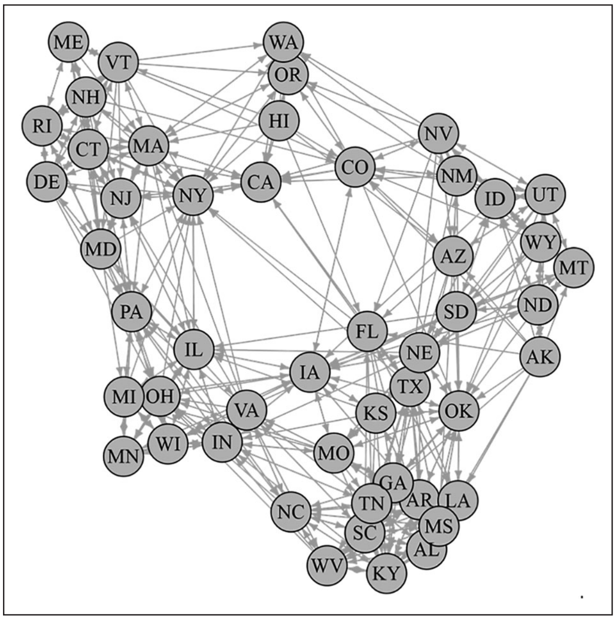

Figure 2. Network of directed similarity scores between states above 0.1.

adopt policies. Because the respondents in our survey are citizens, not elites, we create similarity networks from the survey that simulates the demographic profiles of an average state legislator. State legislators are disproportionately white, more educated, wealthier, and older than the general population (National Conference of State Legislatures 2018). We generate separate perceived similarity networks of just white respondents, respondents making at least $80,000 a year, respondents with a college degree or higher, male respondents, respondents only from the older generations in the sample (Baby Boomers [born 1946–1964] and Silent Generation [born 1945 or earlier]), and respondents with high interest in the news. The correlations between these subsampled networks and the overall similarity network are very strong. The weakest correlation is between wealthy respondents and the overall similarity score of 0.89.[7] Every correlation between the simulated elite network and the respondent network is positive, strong, and significant at the .01 level. While we cannot directly test if legislators share public perceptions of similar states, we show that respondents with similar demographics to legislators share the same

Table 1. Correlation between Subsamples and Overall Measure.

Variables	Correlation with overall score
College educated	.9210
Some college	.9160
High school	.7920
High political interest	.9650
Medium political interest	.8070
Low political interest	.6740
White respondents	.9850
Nonwhite respondents	.6900
Wealthy recipients	.8870
Older respondents	.9690
Male respondents	.9470
Female respondents	.9480
2012 respondents	.8921
2014 respondents	.8483
2016 respondents	.9114

perceptions of state similarity as the rest of the sample. Table 1 shows a full list of correlations between different subsamples of respondents.[8] Overall, perceptions of similarity appear to be very stable across subsamples of respondents and from survey to survey.

We also examined state characteristics to understand differences between state dyads. States that are perceived as similar have smaller differences in per capita income, are more similar in population size and density, have legislatures that are more likely to be controlled by the same political party, and have more similar levels of legislative professionalism. States perceived as similar are also more likely to have similar demographics in terms of percent white and percent urban populations, and are more likely to belong to the same classification of Elazar's (1966) typology of political culture.[9] Respondents identified states that are most similar to them on a variety of demographic, economic, and cultural factors. These findings further support our argument that *perceived state similarity* is a more complete measure of similarity between states than contiguity.

Dyadic EHA

Although Berry and Berry's (1990) use of EHA has become standard practice among diffusion scholars, Volden (2006) points out two major problems with this method. Not only does EHA not take into account where a policy originated, but it also does not consider which policy is adopted. In response, Volden (2006) developed dyadic EHA. Dyadic EHA is a basic form of network analysis that is commonly used in social network research (Burt and Minor 1983; Iacobuccia, Neelameghamb, and Hopkins 1999; Knoke 1999). In the context of policy adoption, the dependent variable is the probability that state *i* in the dyad will adopt the same policy as state *j*, conditional on state *j* already adopting a policy (Boehmke 2009).

Using dyadic EHA allows us to model dyadic-level policy adoptions recognizing the role of the source state in understanding state policy adoption. Rather than looking at a single state's legislative professionalism or GDP per capita, dyadic EHA models how similar two states are to each other when predicting policy adoption. We no longer have to assume independence among our adoption observations.[10]

Dependent Variable: Dyadic Policy Adoption

We construct our dependent variable using state policies that diffuse during the five years of the survey, 2012–2016. These policies include interstate compacts, Uniform Law Commission regulatory policies, and substantive policies ranging from laws concerning the recreational use of marijuana to restricting the use of drones when hunting. We draw from both Boehmke et al.'s (2019) State Policy Innovation and Diffusion (SPID) comprehensive database of policies and additional recent policy adoptions. To identify these recent policies, we surveyed newspapers across the United States. In sum, these policies represent a wide array of substantive areas and a variety of state policy innovations.

We use a directed approach to dyadic adoption, meaning that the dependent variable is state *i* adopting a policy that state *j* has already adopted. This is because our key independent variable *perceived state similarity* is directed. When state *i* has adopted a policy that state *j* has adopted, we code our dependent variable, *dyadic adoption*, as one; otherwise, it is coded as zero. Observations are only included if state *j* has adopted a policy, because the dyad does not enter into the risk set for that given policy until state *j* adopts the policy (Boehmke 2009). If state *i* adopts a policy before state *j*, it is not included in the model. The year following the dyadic adoption, the dyad-policy observation drops out of the database as the dyad is no longer at risk of adoption. For example, Oregon is the first state to adopt a Uniform Law Commission policy regulating electronic legal material in 2014. This adoption results in dyads for Oregon with each of the forty-nine other states in 2015 and 2016. After Oregon adopts this policy, all states are at risk of dyadic adoption with Oregon (and any other adopters). As more dyadic adoptions of this policy occur, the number of at-risk dyads will shrink because adopting dyads are no longer at risk of becoming similar.

Our models include *perceived state similarity* to predict policy adoption as well as many variables typically found in models of diffusion (Lieske 1993; Pacheco 2012; Walker 1969). Contiguity is a binary indicator of whether the two states are geographically connected. Legislative professionalism is an ordinal measure from the National Conference of State Legislatures (2018). We also include measures for difference in income (standardized), the percentage of non-Hispanic white in the population (Hero 2000; Hero and Tolbert 1996), difference in the population size (logged) (Crain 1966; Lieske 1993, 2010; Sharkansky 1970; Sharkansky and Hofferbert 1969; Walker 1969) as well as percent urban to see how differences in states impact the probability of adoption (Chinni and Gimpel 2011; Crain 1966; Lieske 1993; Walker 1969). Larger values indicate greater differences between two states. Same partisan control is a binary indicator of whether the same party controls both state legislatures (including if both states have divided control), same census region indicates that states are in the same census defined area of the country (see online appendix for mapping of census regions), and same culture is a binary measure that indicates that both states in the dyad are from the same political culture region as defined by Elazar (1966). We include fixed effects for year to control for temporal dynamics, and fixed effects for policy to control for differing baseline probabilities of adoption for each policy. We also include random effects for both state *i* and state *j* to control for unmodeled differences between states (See Table 4 for summary statistics).

Monadic Application

To provide scholars with another use of *perceived state similarity* and to evaluate the robustness of our measure, we estimate a monadic pooled EHA (Kreitzer and Boehmke 2016). Pooled EHA is an extension of Berry and Berry's (1990) EHA that adds random effects by policy to account for differing baseline probability of adoptions across policies. With this approach, we can identify what increases or decreases a state's probability of innovating across a wide sample of policies while still recognizing that each policy has a unique probability of adoption. We analyze almost 5,000 adoptions of 244 policies that began diffusing between 1990 and 2016.[11]

We construct the key independent variable, the sum of *perceived state similarity*, using the same logic as the "neighbors" variable. Unlike many measures of contiguity that rely on a binary indicator, we can incorporate the strength of *perceived state similarity* into our measure.[12] For example, if two states that had previously adopted a policy have similarity scores to California of 0.25 and 0.2, respectively, the lagged sum of similarity scores for California would be 0.45. The mean sum of lagged *perceived state similarity* scores is 0.09 with a standard deviation of 0.18. We also include a lagged measure of the number of contiguous adoptions to account for the role of contiguity in policy innovation. We standardize both measures to make the coefficients more comparable.

We use fixed effects for year and include measures for duration, duration squared, and duration cubed to control for year-specific effects and the effect of the time states have been at risk of adopting a policy. We also include random effects by policy to control for differing baseline probabilities of adoption (Kreitzer and Boehmke 2016). We include controls for population, citizen ideology (Berry et al. 2010), legislative professionalism (Squire 2007), as well as a binary measure for the initiative process and a measure of the percentage requirement for the number of signatures needed to qualify an initiative on the ballot (Council of State Government 2018).

Results

The results in Table 2 compare *perceived state similarity* to contiguity. Model 1 includes state similarity and an indicator for whether the states in the dyad are contiguous, model 2 omits contiguity, and model 3 omits *perceived state similarity*. In model 1, the coefficient for perceived state similarity is positive and significant. States are more likely to adopt policies from states they perceive as similar. In the same model, contiguity does not predict policy adoption. Model 2, which omits contiguity, shows a similar result in both direction and statistical significance with similarity predicting policy adoption. Model 3 shows that when similarity is omitted contiguity is a positive and significant predictor of dyadic policy adoption.

Consistent with existing research, the control variables in our models support the idea that states that are more similar tend to adopt similar policies (Boehmke 2009; Volden 2006). Our models show that states that are controlled by the same party are more likely to adopt the same policies, as are states that are in the same census region. Large differences in legislative professionalism are associated with states being less likely to adopt the same policies, as are differences in population and percent urban. Shared political culture and differences in percent non-Hispanic white are not significant predictors of policy adoption. There are no changes in direction or significance of any control variables across the three models.

Figure 3 shows the predicted probability of policy adoption from model 1 of Table 2 at varying levels of *perceived state similarity*. There is almost a 10 percent increase in the probability of adoption of a similar policy for states viewed as more similar while controlling for other factors. The baseline probability of dyadic adoption

Table 2. Pooled Dyadic Event History Analysis Predicting Similar Policy Adoption.

	(1)	(2)	(3)
Perceived state similarity	0.7229*	0.7546*	
	(0.2180)	(0.2035)	
Contiguity	0.0186		0.0731*
	(0.0458)		(0.0428)
Diff. professionalism	−0.0826*	−0.0827*	−0.0872*
	(0.0153)	(0.0153)	(0.0153)
Same partisan control	0.1518*	0.1512*	0.1646*
	(0.0243)	(0.0242)	(0.0240)
Diff. percent white	0.0009	0.0009	0.0007
	(0.0010)	(0.0010)	(0.0010)
Diff. std. income	−0.0000*	−0.0000*	−0.0000*
	(0.0000)	(0.0000)	(0.0000)
Log diff. population	−0.0206*	−0.0206*	−0.0243*
	(0.0100)	(0.0100)	(0.0099)
Diff. percent urban	−0.0041*	−0.0041*	−0.0046*
	(0.0011)	(0.0011)	(0.0011)
Same census region	0.0923*	0.0943*	0.1346*
	(0.0313)	(0.0309)	(0.0286)
Same culture	−0.0246	−0.0244	−0.0131
	(0.0253)	(0.0253)	(0.0250)
Constant	−1.3464*	−1.3473*	−1.2217*
	(0.4618)	(0.4618)	(0.4602)
Constant (state *i*)	0.4351*	0.4353*	0.4313*
	(0.0890)	(0.0891)	(0.0882)
Constant (state *j*)	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)
No. of observations	60,182	60,182	60,182
AIC	51,795.814	51,793.978	51,804.797
BIC	52,624.285	52,613.445	52,624.263

Analysis includes eighty-nine policies and fixed effects for year and policy. AIC = Akaike information criterion; BIC = Bayesian information criterion.
*$p < .05$.

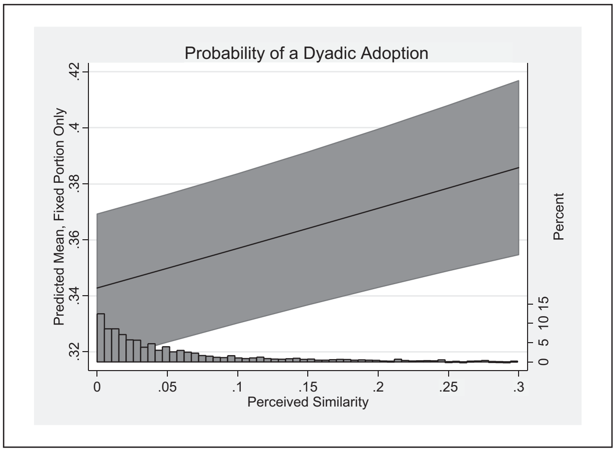

Figure 3. Dyads perceived as more similar more likely to adopt the same policies.
Probabilities shown are population-averaged probabilities with 95 percent confidence intervals for probability estimates.

in a given year goes from .34 for states with a similarity score of 0 to greater than .38 for states with similarity scores above 0.25. *Perceived state similarity* is a strong predictor of dyadic policy adoption.

Monadic Analysis

Table 3 shows the results from the pooled monadic EHA. The first model omits a lagged measure of contiguity, the second omits the lagged sum of *perceived state similarity* scores, and the third includes both measures. In model 1, *perceived state similarity* is a positive and significant predictor of policy adoption. States are more likely to adopt a policy when the sum of similarity scores is higher.[13] Model 2 shows that contiguous state adoptions increase the probability of policy adoption, when controlling for other factors. Both similarity and contiguity predict policy adoption when included in the same specification (model 3).

Figure 4 shows the predicted probability of policy adoption from model 1 of Table 3 at varying levels of the sum of *perceived state similarity*. The probability of adoption increases from just below 5 percent to just below 6 percent. This effect is substantively large considering the low baseline probability of adoption (5%) for any given state in a given year. In every model, *perceived state similarity* is a positive, significant, and powerful predictor of policy adoption.

In all three models, wealthier states, states with the initiative process, and states with larger populations are all more likely to adopt policies. These results are consistent with the existing literature on innovative states. We also find across our models that states with more professionalized legislatures are somewhat less likely to adopt a policy than states with citizen legislatures. This result is unexpected, but matches other recent research that has found legislative professionalism is not associated with higher probabilities of adoption in pooled models of diffusion (Mallinson 2019). Ideology only significantly predicts policy adoption in models that control for contiguity.

Discussion and Conclusion

Perceived state similarity is a more sophisticated measure of state similarity than contiguity. Policy diffusion research has relied on the binary variable of contiguity to account for state similarity under the assumption that states that are geographically closer together are more similar. This binary measure of geographic contiguity has limitations in its ability to represent similarity. We suggest researchers use our measure of *perceived state similarity* for a number of reasons. Unlike a binary indicator of contiguity, our measure is continuous and directed. It

Table 3. Pooled Monadic Event History Analysis Predicting Similar Policy Adoption (1990–2016).

	(1)	(2)	(3)
Similarity	0.1915*		0.1693*
	(0.0115)		(0.012)
Contiguous adoption		0.1631*	0.1021
		(0.015)	(0.0157)
Initiative process	0.2158*	0.1634*	0.1799*
	(0.0747)	(0.0741)	(0.0746)
Signatures—average	−0.0098	−0.0041	−0.0058
	(0.0084)	(0.0084)	(0.0084)
Population	0.0758*	0.0702*	0.0764*
	(0.0201)	(0.0203)	(0.0203)
Citizen ideology	0.019	0.0451*	0.0395*
	(0.0221)	(0.0223)	(0.0224)
Unified control	−0.0329	−0.0299	−0.03
	(0.0331)	(0.033)	(0.0331)
Std. income	0.0660*	0.0687*	0.0713*
	(0.0268)	(0.0268)	(0.0268)
Legislative professionalism	−0.0656*	−0.0731*	−0.0702*
	(0.0268)	(0.0268)	(0.0269)
Duration	0.0226	0.0538*	−0.0104
	(0.0262)	(0.0261)	(0.0264)
Duration squared	−0.0001	−0.0082*	0.0016
	(0.0036)	(0.0034)	(0.0036)
Duration cubed	0.0001	0.0004*	0.0000
	(–0.0001)	(–0.0001)	(–0.0001)
Constant	−4.1033*	−4.2143*	−3.9899*
	(0.2007)	(0.2042)	(0.1978)
Constant (policy)	1.1793*	1.2599*	1.0798*
	(0.1209)	(0.1283)	(0.1126)
No. of observations	85,878	85,878	85,878
AIC	32,433.0328	32,587.0286	32,393.5399
BIC	32,770.0174	32,924.0132	32,739.8852

Analysis includes fixed effects for year. AIC = Akaike information criterion; BIC = Bayesian information criterion.
$^*p < .05$.

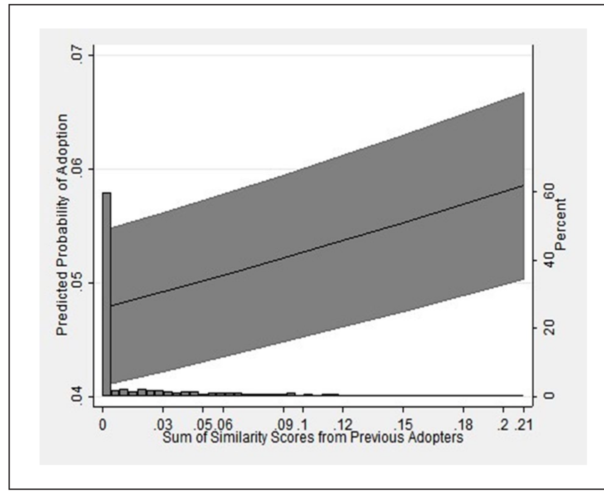

Figure 4. Adoption by states perceived as similar makes states more likely to adopt policies.

accounts for differences in the strength of similarity ties between the states and accounts for differences in the prominence of a similarity connection in a state's similarity ties. The states with the strongest similarity scores have more in common demographically, economically, and politically than the states that are perceived as less similar. Our network of similarity ties reveals that not only are many contiguous states viewed as weakly similar, but states also have strong connections to noncontiguous states. Maryland has much stronger similarity ties to Pennsylvania than to West Virginia, and Ohio has much stronger similarity ties to nonneighboring states like Illinois and Wisconsin than neighboring Kentucky.

We also demonstrate the ability of *perceived state similarity* to predict policy diffusion in dyadic and monadic EHAs. In the dyadic model, we find that *perceived state similarity* is a strong predictor of policy adoption and that contiguity no longer predicts policy adoption after accounting for similarity. In the monadic analyses, we find that similarity is a predictor of policy adoption across a larger sample of policies from 1990 to 2016. *Perceived state similarity* is a reliable predictor of policy diffusion in U.S. states. The two research designs allow us to test different aspects of the role of *perceived state similarity* in policy diffusion and innovation. The dyadic approach allows us to test how the similarity connection from a single state affects the probability of another state adopting the policy, while the monadic approach allows us to test how similarity connections from multiple states affect policy adoptions. The two models tell us that individual perceived similarity connections play a role in diffusion, but that there is also a cumulative effect as the number of adopting states that are perceived as similar increases. These effects hold when we extend the analysis to a larger number of policies and a longer time period, although more research is needed to understand the extent to which perceived similarity connections are dynamic or static.[14]

Finally, *perceived state similarity* pushes diffusion scholars to be more explicit about what they are trying to measure, including in models that explore the role of the diffusion mechanisms described by Shipan and Volden (2008). For example, our measure could be combined with a measure of policy success to evaluate if states learn more from states perceived as similar to their own. Policymakers may be less likely to learn from actors perceived as different, as indicated by Butler et al. (2017), so similarity may moderate the effect of policy success on a state's probability of innovating. In regards to competition, states may view states perceived as similar to them

Table 4. Summary Statistics.

Variable	*M*	*SD*	Minimum	Maximum
Policy adoption	0.3504192	0.4771051	0	1
Similarity score	0.0600461	0.0698523	0	0.4166667
Strong similarity	0.0530872	0.0742655	0	0.4166667
Contiguous dyads	0.087122	0.282016	0	1
Diff. in professionalism	1.036748	0.9363541	0	4
Same party control	0.4024957	0.4904048	0	1
Diff. percent white	17.48374	13.58839	0	71.7
Diff. per capita income	7,940.565	6,142.766	9	33,827
Log diff. population	15.02471	1.330655	6.169611	17.47043
Diff. percent urban	16.52629	12.07572	0.0599976	56.29
Same census region	0.2459059	0.4306266	0	1
Same Elazar region	0.3205162	0.4666788	0	1
Logged distance	1.2366009	0.89061989	0.04092589	5.1198148

as their chief competitors. Scholars could look to see if *perceived state similarity* is a stronger predictor of policies associated with economic competition (welfare policies, taxation rates, etc.) than on other policies. In addition, states with stronger similarity connections may be more likely to imitate on another as similar states may face similar problems with similar policy solutions. More research needs to be done to understand how *perceived state similarity* relates to the diffusion mechanisms. We argue that this measure will provide a more fruitful path forward than using contiguity to parse out diffusion mechanisms because the concept is an explicit measure of similarity, whereas contiguity measures some combination of geographic proximity, similarity, and contagion effect, and often the rationale for including contiguity is not mentioned at all beyond it typically being included in diffusion models.

Perceived state similarity is a step forward in finding a measure that captures state similarity. Yet there is still work to be done. Our *perceived state similarity* network identifies demographic, economic, and political differences between the states. Understanding what metrics citizens use to determine similar states will give us a better understanding of how policies diffuse through imitation and learning. If ideology is the primary driver of what makes people think states are similar, then we would expect *perceived state similarity* to affect policies with ideological or partisan appeal. Alternatively, if perceptions of similarity are due to economic factors, then *perceived state similarity* may influence the diffusion of economic policies more than others. Finally, we see value in understanding how *perceived state similarity* interacts with other predictors of diffusion like interest group influence and latent diffusion connections. Incorporating *perceived state similarity* with other predictors is important for moving the diffusion literature forward so that we can develop a comprehensive understanding of what causes policies to spread across the states.

Authors' Note

Scott LaCombe is now affiliated with Smith College, Northampton, MA, USA.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

ORCID iD

Christine Bricker https://orcid.org/0000-0002-7391-7755

Notes

1. This is not to say that Washington and Idaho are completely different. Areas of Eastern Washington may look much more similar to Idaho than the population centers in the Western parts of Washington, but the state as a whole shares more demographic similarities with Oregon.
2. While some measures of contiguity are also continuous (i.e., the proportion of the state's border shared by another state), they still cannot distinguish between two borders of the same length mattering more/less in influencing a state's policy adoptions.
3. Due to the small sample size of the original surveys, we tried a number of alternative measures to evaluate the robustness of our measure. We first generated scores separately for each survey and found them to be highly correlated with the overall measure. Secondly, we constrained our score generation process to only states that were mentioned at least hundred times. These scores also predicted policy adoption in the states.

4. We visualize this calculation in Figure 1A and 1B. If five people listed both California and Oregon as similar to their home state and fifty respondents overall listed California as similar to their home state, then California's similarity score to Oregon would be 0.1 (Figure 1A). A directed approach allows us to recognize that Oregon's similarity ties to California make up a larger proportion of its overall similarity ties than those of California to Oregon. This measure incorporates both whether states have any similarity, and the relative importance of that similarity connection.
5. We replicated the analysis with an undirected measure of *perceived state similarity*. The scores were strongly correlated (.95) and the results of the dyadic EHA with this measure did not change from the directed version.
6. A value of 0.1 was chosen to give a clear representation of network for the strongest 25 percent of connections that could be visualized in a network, but should not be viewed as a substantively important value to distinguish between meaningful ties.
7. We also generated networks of voters with no college education (correlation of .79 with the overall measure), nonwhite voters (.69 correlation), and those with low political interests (.67 correlation) and found that, while some differences emerge, the correlations between every type of measure of similarity by subsample are strong or very strong.
8. We also generated similarity networks by survey to evaluate if responses were stable across surveys. The 2012, 2014, and 2016 scores all strongly correlated with the overall similarity measure.
9. See online appendix for a logistic regression modeling perceived similarity between states. The results show that respondents are more likely to indicate a state being similar if the state has similar cultural, demographic, and economic characteristics.
10. To evaluate the role of interdependence in our models, we also estimated a network regression with the dependent variable being the latent diffusion ties calculated by Desmarais, Harden, and Boehmke (2015). See online appendix for the model.
11. We also estimate the same model specifications for a smaller sample of policies closer to the time period when the surveys were conducted (policies that began diffusing on or after 2010). Similarity is again a strong predictor of diffusion. The results are available in online appendix.
12. We use the *sources* package in Stata to calculate the lagged sum of similarity scores from previous adopters, as well as a lagged count of contiguous adoptions. We also estimated a parallel analysis using the count of the number of similar states that previously adopted the policy, and the findings were similar both in direction and significance.
13. The same relationship holds when we include a measure of the count of similar state adoptions.
14. States have undergone substantial demographic, economic, and political transformations over time, so we do not expect the states perceived as similar in 2016 to be the same as those perceived as similar fifty or one hundred years ago.

Supplemental Material

Replication materials available at: christine-bricker.com and scottlacombe.weebly.com. Supplemental materials for this article are available with the manuscript on the *Political Research Quarterly* (PRQ) website.

References

Baybeck, Brady, William D. Berry, and David A. Siegel. 2011. "A Strategic Theory of Policy Diffusion via Intergovernmental Competition." *The Journal of Politics* 73 (1): 232–47.

Berry, Frances Stokes, and William D. Berry. 1990. "State Lottery Adoptions as Policy Innovations: An Event History Analysis." *American Political Science Review* 84 (2): 395–415.

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

Berry, William D., Richard C. Fording, and Russell L. Hanson. 2003. "Reassessing the 'Race to the Bottom' in State Welfare Policy." *The Journal of Politics* 65 (2): 327–49.

Berry, William D., Richard C. Fording, Evan J. Ringquist, Russell L. Hanson, and Carl E. Klarner. 2010. "Measuring citizen and government ideology in the US states: A re-appraisal." *State Politics & Policy Quarterly* 10 (2): 117–35.

Boehmke, Frederick J. 2009. "Policy Emulation or Policy Convergence? Potential Ambiguities in the Dyadic Event History Approach to State Policy Emulation." *The Journal of Politics* 71 (3): 1125–40.

Boehmke, Frederick J., Mark Brockway, Bruce Desmarais, Jeffrey J. Harden, Scott LaCombe, Fridolin Linder, and Hannah Wallach. 2019. "SPID: A New Database for Inferring Public Policy Innovativeness and Diffusion Networks." *Policy Studies Journal*. Published electronically June 11. doi:10.1111/psj.12357.

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

Boushey, Graeme. 2012. "Punctuated Equilibrium Theory and the Diffusion of Innovations." *Policy Studies Journal* 40 (1): 127–46.

Burt, Ronald S., and Michael J. Minor. 1983. *Applied Network Analysis: A Methodological Introduction*. Beverly Hills: SAGE.

Butler, Daniel M., Craig Volden, Adam M. Dynes, and Boris Shor. 2017. "Ideology, Learning, and Policy Diffusion: Experimental Evidence." *American Journal of Political Science* 61 (1): 37–49.

Chinni, Dante, and James Gimpel. 2011. *Our Patchwork Nation: The Surprising Truth about the "Real" America*. New York: Penguin Books.

Cooperative Congressional Election Study. n.d. https://cces.gov.harvard.edu/.

Council of State Government. 2018. *The Book of the States*. Lexington, KY: Council of State Government.

Crain, Robert L. 1966. "Fluoridation: The Diffusion of an Innovation among Cities." *Social Forces* 44 (4): 467–76.

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.

Elazar, Daniel Judah. 1966. *American Federalism—A View from the States*. London: Thomas Cromwell.

Friedkin, Noah E. 2006. *A Structural Theory of Social Influence*. Vol. 13. Cambridge: Cambridge University Press.

Garrett, Kristin N., and Joshua M. Jansa. 2015. "Interest Group Influence in Policy Diffusion Networks." *State Politics & Policy Quarterly* 15 (3): 387–417.

Gilardi, Fabrizio. 2016. "Four Ways We Can Improve Policy Diffusion Research." *State Politics & Policy Quarterly* 16 (1): 8–21.

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

Hero, Rodney E. 2000. *Faces of Inequality: Social Diversity in American Politics*. New York: Oxford University Press.

Hero, Rodney E., and Caroline J. Tolbert. 1996. "A Racial/Ethnic Diversity Interpretation of Politics and Policy in the States of the U.S." *American Journal of Political Science* 40 (3): 851–71.

Huckfeldt, R. Robert. 1979. "Political Participation and the Neighborhood Social Context." *American Journal of Political Science* 23 (3): 579–92.

Huckfeldt, R. Robert. 1983. "Social Contexts, Social Networks, and Urban Neighborhoods: Environmental Constraints on Friendship Choice." *American Journal of Sociology* 89 (3): 651–69.

Huckfeldt, R. Robert, and John Sprague. 1988. "Choice, Social Structure, and Political Information: The Information Coercion of Minorities." *American Journal of Political Science* 32 (2): 467–82.

Huckfeldt, R. Robert, and John Sprague. 1991. "Discussant Effects on Vote Choice: Intimacy, Structure, and Interdependence." *The Journal of Politics* 53 (1): 122–58.

Huckfeldt, R. Robert, and John Sprague. 1995. *Citizens, Politics and Social Communication: Information and Influence in an Election Campaign*. Cambridge: Cambridge University Press.

Iacobuccia, Dawn, R. Neelameghamb, and Nigel Hopkins. 1999. "Measurement Quality Issues in Dyadic Models of Relationships." *Social Networks* 21 (3): 211–37.

Klofstad, Casey A., Scott D. McClurg, and Meredith Rolfe. 2009. "Measurement of Political Discussion Networks: A Comparison of Two "Name Generator" Procedures." *Public Opinion Quarterly* 73 (3): 462–83.

Knoke, David. 1999. *Political Networks: The Structural Perspective*. Cambridge: Cambridge University Press.

Kreitzer, Rebecca J., and Frederick J. Boehmke. 2016. "Modeling Heterogeneity in Pooled Event History Analysis." *State Politics & Policy Quarterly* 16 (1): 121–41.

Lazarsfeld, Paul F., and Robert K. Merton. 1954. "Friendship as a Social Process: A Substantive and Methodological Analysis." In *Freedom and Control in Modern Society*, edited by Morroe Berger and Theodore Abel, 18–66. New York: Van Nostrand.

Lieske, Joel. 1993. "Regional Subcultures of the United States." *The Journal of Politics* 55 (4): 888–913.

Lieske, Joel. 2010. "The Changing Regional Subcultures of the American States and the Utility of a New Cultural Measure." *Political Research Quarterly* 63 (3): 538–52.

Maggetti, Martino, and Fabrizio Gilardi. 2016. "Problems (and Solutions) in the Measurement of Policy Diffusion Mechanisms." *Journal of Public Policy* 36 (1): 87–107.

Mallinson, Daniel J. 2019. "Who Are Your Neighbors? The Role of Ideology and Decline of Geographic Proximity in the Diffusion of Policy Innovations." *Policy Studies Journal*. Published electronically June 18. doi:10.1111/psj.12351.

McClurg, Scott D., Casey A. Klofstad, and Anand Edward Sokhey. 2017. "Discussion Networks." In *The Oxford Handbook of Political Networks*, edited by Jennifer Nicoll Victor, Alexander H. Montgomery, and Mark Lubell, 525–36. Oxford: Oxford University Press.

National Conference of State Legislatures. 2018. https://aifl.org/2018-national-conference-state-legislatures-ncsl/.

Nicholson-Crotty, Sean, and Sanya Carley. 2018. "Information Exchange and Policy Adoption Decisions in the Context of U.S. State Energy Policy." *State Politics & Policy Quarterly* 18 (2): 122–47.

Pacheco, Julianna. 2012. "The Social Contagion Model: Exploring the Role of Public Opinion on the Diffusion of Antismoking Legislation across the American States." *The Journal of Politics* 74 (1): 187–202.

Sharkansky, Ira. 1970. *Regionalism in American Politics*. New York: Bobbs-Merrill.

Sharkansky, Ira, and Richard I. Hofferbert. 1969. "Dimensions of State Politics, Economics, and Public Policy." *American Political Science Review* 63 (3): 867–79.

Shipan, Charles R., and Craig Volden. 2008. "The Mechanisms of Policy Diffusion." *American Journal of Political Science* 52 (4): 840–57.

Shipan, Charles R., and Craig Volden. 2012. "Policy Diffusion: Seven Lessons for Scholars and Practitioners." *Public Administration Review* 72 (6): 788–96.

Skvoretz, John. 1985. "Random and Biased Networks: Simulations and Approximations." *Social Networks* 7 (3): 225–61.

Skvoretz, John. 1990. "Biased Net Theory: Approximations, Simulations, and Observations." *Social Networks* 12 (3): 217–38.

Skvoretz, John, Thomas J. Fararo, and Filip Agneessens. 2004. "Advances in Biased Net Theory: Definitions, Derivations, and Estimations." *Social Networks* 26 (2): 113–39.

Sprague, John. 1976. "Estimating a Boudon Type Contextual Model: Some Practical and Theoretical Problems of Measurement." *Political Methodology* 3 (3): 333–53.

Squire, Peverill. 2007. "Measuring State Legislative Professionalism: The Squire Index Revisited." *State Politics & Policy Quarterly* 7 (2): 211–27.

Volden, Craig. 2006. "States as Policy Laboratories: Emulating Success in the Children's Health Insurance Program." *American Journal of Political Science* 50 (2): 294–312.

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

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