What makes a leader? A Role Analysis of Latent Diffusion Networks

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Abstract

Is being a policy leader an intrinsic characteristic of a state, or is policy leadership depend on the context and policy at hand? Since Walker's initial study of policy adoptions in the states, scholars have used a variety of methods to understand what makes a state a policy leader or follower. We use role analysis to identify what states play similar roles in the latent diffusion network, and categorize states as leaders and laggards. We then use a variety of external and internal state characteristics and find that policy leadership is stable over time, with states being much more likely to remain leaders once they become one. Additionally, leadership appears to be wide spread across a variety of topic areas rather than states building expertise in one area at the cost of others. We find little evidence that policy demands predict leadership. These findings suggest policy leadership is a stable trait and once patterns of diffusion emerge, they are likely to persist.

Keywords: state politics; state policy; policy diffusion; innovativeness; structural equivalence methods; role analysis

Word Count: TBD

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1 Introduction

As social, political, and technological contexts change over time, one might expect patterns of policy diffusion to also shift. Over the past century, states have undergone tremendous economic, demographic, and political shifts. Mallinson (2021*a*) and Mallinson and Hannah (2020) show that there is heterogeneity in the relative importance of diffusion determinants across not only policies and time, but also during the course of a policy's spread (hence, prompting a life course approach to diffusion study). However, despite changes in social, political, and technological contexts and shifts in diffusion patterns and mechanisms, the overall hierarchies of which states adopt policies first may have less variability. Research has shown that innovativeness tends to be a relatively stable trait of states (Boehmke and Skinner 2012; Savage 1978; Walker 1969). At the same time, research has also shown that unlikely states that are not often among the first to adopt new policies may, in fact, take the lead for certain policy areas, such as health (Carter and LaPlant 1997).

Since Walker (1969), researchers have stratified states as ”leaders” and ”laggards” (or followers). Leader states are the most innovative, the most likely to adopt a new policy. Laggard, or follower, states are the least innovative. They rarely adopt a completely original policy, and tend to wait several years after the first set of states have adopted a policy before they are willing to give it a try themselves. Boehmke and Skinner (2012) show that the lists of the most innovative states has seen some changes, but states such as California have remained perennially as one of the most innovative despite large political changes. Related, Boushey (2012) shows that policies are spreading faster over time. These changes over time could be attributable to changes in state policy agendas and changes in how relatively active a given policy area is, or they could be attributable to more fundamental changes about the state.

Recent advancements in methods and data availability have created opportunities to better take advantage of network analysis to understand the networks that inherently underlie any policy diffusion study. Many studies of innovativeness have been of single policies or large-N studies, but we invoke Desmarais, Harden, and Boehmke's (2015) inferred latent network approach, which allows us to capitalizes on “persistent pathways” that surface in the State Policy Innovativeness diffusion data (Boehmke et al. 2020). This means we only identify ties between states that consistently borrow from or spread policy to each other. This allows us to uncover broader patterns and assess policy leadership as a quality of states (or not). Specifically, we use role analysis to explore which states arise as policy leaders and how this changes over time from 2000 to 2014.

We first use a state's position in the latent diffusion network to identify those that are leaders versus those who are laggards across a variety of policy topic areas. After assigning roles, we then use logistic regressions to estimate the predictors of being a policy leader. We find that leadership is a stable trait, with states that were previously policy leaders in an area being much more likely to continue to be a policy leader. Furthermore, we find that leadership is generally broad based, meaning when a state is a leader in one area, it is more likely to be a leader in other areas at all. We do not find consistent patterns of internal state characteristics being related to higher or lower probabilities of being a leader, and find limited evidence that policy demands coming from state economic conditions result in states being more likely to lead (or lag) in that topic area. Taken together, these results indicate that leadership is not due to states gaining expertise in specific policy areas, but is instead an enduring characteristic.

After modeling leadership, we then extend the analysis to dyadic logistic regressions to predict two states playing the same role in the diffusion network. We again find stability in network role, with two states being much more likely to belong to the same block in the latent network if they did in the previous year. We do not find evidence that states with similar characteristics are more likely to belong to the same block in diffusion networks, nor do we find that states with shared borders are more likely to belong to the same block. These results highlight the stability of the diffusion network and that once a state becomes a leader, it is much more likely to remain a leader. We find evidence that being a policy leader is an enduring trait across policy areas and that once a state becomes a leader, it tends to remain a leader regardless of changing economic, demographic, and political characteristics.

2 What makes a leader?

First, it is important to discuss how we define a ”policy leader.” We want to acknowledge the debate between the relatedness of policy leadership and innovativeness. These are closely related concepts. Policy leaders are more likely to be innovators in a given policy area, but for the sake of this paper, we keep our focus on being a policy leader rather than innovativeness more broadly. Is a state a leader only if they are among, say the first 5, to adopt a policy? Or does the shape of the policy leader hierarchy matter for determining leadership, e.g. what if MA will only adopt a policy after NY passes it, but once MA passes it VT, NH, ME, MD, VA, and PA all follow. In that case, who is the leader, MA or NY? We see two possibilities when it comes to policy leadership: 1) Policy leadership is an intrinsic characteristic of a state, or 2) policy leadership is a function of state expertise, policy area, and context.

For example, if Massachusetts is a leader for health policy but not with respect to other policies, then they may appear on the list of most innovative states only in years when there is a lot of activity in the health policy area. In this case, the variation Boehmke and Skinner (2012) find may not be due to Massachusetts's innovativeness ebbing and flowing but due to their expertise being more relevant some years than it is others. such as major budget cuts or change in political control. If the over time variation is due to more fundamental changes at the state level, then we would expect to see less variation in leadership by policy area, and we should be able to pinpoint the major change that precipitates the increase/decrease in innovativeness (e.g. budget cut, population increase, or political party transition).

2.1 Innovativeness as an intrinsic characteristic?

Rogers's (1962) original work on the diffusion of innovations proposes five categories of adopters: 1) innovators, 2) early adopters, 3) early majority, 4) late majority, and 5) laggards. Other research often dichotomizes leaders and laggards (Wang 2012; Liefferink et al. 2009). Building on recent efforts using aggregate adoption data to test theories about generalizable patterns of diffusion, this research seeks to do just that for state policy leadership. We test whether Roger's original five categories of adopters fits or if a simple dichotomy better describes policy adoption hierarchies. We test this over time and across policy area and predict we may reach different conclusions for different policy areas, but we find that the leader and laggard dichotomy produces the best fitting models. If policy leadership is an intrinsic characteristic, then we would expect states to consistently be among the first to adopt policies regardless of the policy area. While we may see some shifts in state policy leadership over time, we would not expect any significant changes in which states are leaders by policy area. This leads to our first hypothesis:

H1: Broad Leadership Hypothesis: Leadership in one policy area will predict leadership in other policy areas.

If policy leadership is an intrinsic quality, then policy expertise and the policy needs of the state (such as, agricultural policy if agriculture is the state's main industry) should not affect the likelihood that a state arises as a leader. In this case, leadership may ebb and flow over time and a state may stop being a policy leader with changes in the political party in power, for example, but we would also expect that there are a set of relatively stable state characteristics that predict leadership. This leads to our second hypothesis:

H2: Policy Leader/Follower Hypothesis: The closer two states are in terms of structural equivalence, the more similar they are in terms of state characteristics.

2.2 Or is innovativeness a function of expertise and context?

Since Walker's (1969) (1969), the literature has largely moved from thinking of innovativeness as a general trait to the study of innovativeness with respect to a specific policy (Boehmke and Skinner 2012). However, there has not actually been a study to test whether this is the case. As such, we think it likely that innovativeness may not be an intrinsic trait, but rather a function of expertise and context. Policies have known ideological locations, and policymakers have known preferences for policies' based on these locations. Regardless of whether a policy-maker's motivation is re-election, reappointment, or something else, they pursue strategic policy. Therefore, we predict that depending on factors, including the dominant industries in a state, state leaders' political goals, and the opinions of the states' citizens, states may "specialize." This leads to our third hypothesis:

H3: Leadership Specialization/Policy Expertise Hypothesis: Becoming a leader in one area decreases probability of leadership in another area.

3 Methods

3.1 Latent Network Estimation

To estimate latent networks we use policy adoption data from the SPID dataset (Boehmke et al. 2020). This large dataset includes policy adoption data on hundreds of state policies and thousands of state policy adoptions. Policies were also coded by topic area using the Comparative Agendas Project topic codings. In order to evaluate differences in network structure, we use any topic area with at least 1,000 policy adoptions. This ensured that the inferred networks were sufficiently large for analysis, and gave us more confidence in the inferred ties. The chosen topic areas are civil rights (2409 adoptions), health (1853 adoptions), labor (885 adoptions), education (1396 adoptions), transportation (1312 adoptions), law and crime (4592 adoptions), and macroeconomics (1704 adoptions). The chosen topic areas provide a diverse set of policies areas. We also estimate latent network for the pooled data in order to compare leadership across all policies to specific topic areas.

We estimate latent networks using the package `NetInf` based on Desmarais, Harden, and Boehmke's (2015) research. After converting the data to cascade form, we estimate latent networks for each policy area from 2000 to 2014. A p-value cutoff of .05 is used to determine the number of edges in each network. The decay parameter is set to 4.75 and the window to 100 years, which matches the optimized parameters from Boehmke et al. (2020). The mean number of ties per year by topic area were as follows: civil rights (230), health (159), labor (106) education (134), transportation (138), law and crime (400), and macro-economics (142). In comparison, the pooled network of all policy areas had an average of 965 ties per year.

3.2 Role Analysis

In network analysis, role analysis identifies actors in a network that occupy similar roles. For example, a simple application of role analysis could be to study an organization with three levels of employees: high-level management, mid-level management, and workers. Given data, similar to SPID, about how often the employees (of all levels) interact with each other, `NetInf` could detect the ”persistent pathways” of communication or interaction between employees. Then, role analysis would detect who the high-level managers are, who the mid-level managers are, and which workers are supervised by each of the managers based on these patterns of communication. We can apply a similar logic to policy diffusion networks to identify which states are the first to adopt policies (i.e. which are the leader states) and how policies ”cascade,” to use Desmarais, Harden, and Boehmke’s (2015) terminology, and are adopted by other follower states subsequently. As such, role analysis is an ideal method for assessing whether a state consistently performs like a leader in a policy diffusion network.

After estimating latent ties for each topic area, we converted the edgelists to networks and use blockmodeling to determine the position of states in the latent diffusion network. Blockmodeling is a common approach used in the social sciences to discover clusters or the structure of a network (Borgatti and Everett 1992). We first use Euclidean distance to measure the dissimilarity between nodes and identify the number of clusters that exist in the network. Figure 1 is a dendogram of clustering for civil rights policies in 2005. States connected at lower points on the graph have a smaller euclidean distance, while those with higher connections are farther apart. As shown by the boxes in the figure, the network can be subdivided into two groupings of states. There is a small group of states (Minnesota, California, Illinois, and Delaware) in one cluster, and all other states in the other cluster.

After using the dendogram to determine the number of clusters in the network, we then estimate a block model with the number of clusters set to two to identify nodes that have equivalent classes in the network. Figure 2 collapses the nodes into single blocks to visualize the relationships

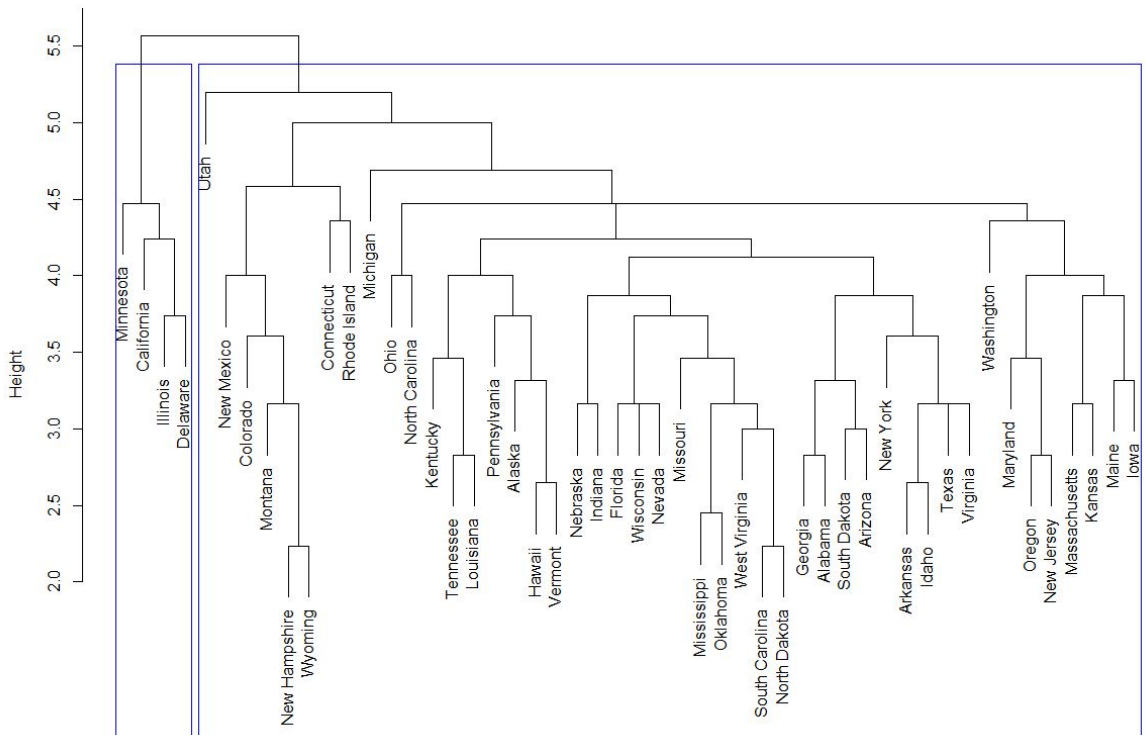

Figure 1: Network Clustering for Civil Rights Policies in 2005 by Structural Equivalence

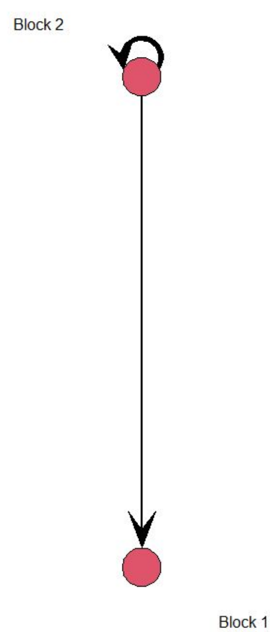

Figure 2: Blocks in 2005 Latent Network- Civil Rights

between clusters. We use structural equivalence as our definition of equivalence, and and we use euclidean distance calculate the distance between nodes. Block two is sending ties to block one and itself, meaning that states in block two are a source for policies (across all areas) for both themselves and in block two. Therefore, we label states belonging to block two as policy leaders, which represents the smaller cluster of states in figure 1. We repeat this process for all topic areas and years to identify the number of clusters and estimate block models to identify which states belong to policy leader blocks, and which belong to policy follower ones. Blocks with the highest out-degrees are coded as policy leaders, while all others are coded as policy followers. If the tie between blocks is reciprocal, then we code the block with a self-loop as the leader.

The distribution of leaders versus followers is relatively small across topic area with between 2.8% and 6% of states being coded as leaders on average. In order, the proportion of states coded as a leader by topic area are civil rights (6%), education (5.8%), economics (5.3%), law and crime (4.9%), labor (4.5%), health (3.8%) and transportation (2.8%). These numbers show that the number of leader states is relatively small, which is consistent with an s-shaped diffusion pattern with very few early adopting states. However, the similar averages mask significant temporal variation within topic area. Figure 3 shows the proportion of states categorized as policy leaders. For example, the proportion of states that are leaders in Civil Rights ranges from a low of .02 to a high of .3. Other policy areas, such as law or labor, see much more stable temporal patterns.

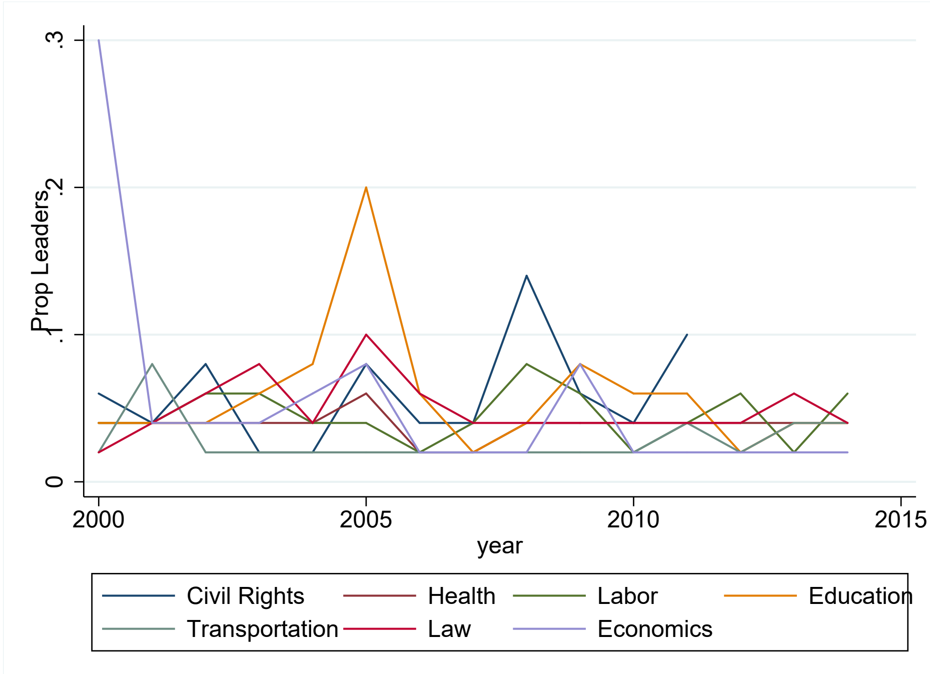

Figure 3: Proportion of States Categorized as Leaders by Topic Area over time

3.3 Predicting what makes a leader?

After we categorize states into leaders or laggards across each topic area, we then estimate the probability of being a leader. Our dependent variable is a binary indicator for whether a state is a policy leader, and we generate categories from 2000-2014 across each topic area. We use a logistic regression to model the probability of a state being a leader in a given year for each topic area, and cluster standard errors by state. We estimate separate models for each topic area and the unit of analysis is state-year.

We use both internal and external factors to predict policy leadership. *Lagged Leadership* is a binary indicator for whether a state a leader in a given topic area in the previous year. This measure allows us to test if previous leadership leads to more leadership. The variable *Sum of Area Leadership* is a count of the number of policy areas that a state was a leader in the previous year, and tests whether leadership in one are leads to broad leadership across a variety of topic areas, or if states tend to build expertise in particular areas, making them less likely to lead in others. The mean is .33, the standard deviation .59, and the maximum number of areas a state is a leader in is 4 in any given year. 72% of state-year observations had 0 areas a state was coded as a leader, which suggests leadership is rare, and very few states are leaders in multiple areas (only 4% of observations). *Sum of Contiguous Leadership* measures the sum of states that share a border to a state that were leaders in the previous year. Neighboring leader states is also rare, with the mean ranging from .14 to .23 across policy areas.[1] Collectively, these three variables measure the ways leadership may have geographic, temporal, or cross-policy area effects on the probability of being a policy leader.

We also include variables frequently used in studies to predict policy innovations and diffusion. We include a measure of policy liberalism (Caughey and Warshaw 2016), income per capita (standardized), population (standardized) (Grossmann, Jordan, and McCrain 2021), and two dimensions of legislative professionalism as measured by Bowen and Greene (2014). Lastly, we include separate variables for each policy area to evaluate the role potential policy "demands" that could lead to a state becoming a policy leader. For example, are states with higher violent crime rates more likely to be policy leaders in law and crime? We use data from the Bureau of Labor Statistics' (BLS) Occupational Employment Statistics (OES) Survey to measure the percentage of the workforce that is in health care, transportation, education, and manufacturing to measure demand for policies in health, transportation, education, and labor respectively (Statistics 2017). To measure demand for law and crime policies, we use a measure of violent crime per 100,000 people, and we use the unemployment rate to measure demand for macro-economic policies (Grossmann, Jordan, and McCrain 2021). As an additional measure of demand for labor policies, we use a measure for the percentage of a state's workforce that is in a private or public sector union (Hirsch, Macpherson, and Vroman 2001).

4 Results

Table 1 shows the results predicting policy leadership. Across every topic area except health, lagged leadership strongly predicts being a policy leader the following year in the same topic area. This suggests that once a state becomes a policy leader in a given area, it is likely to remain a leader.

[1]See supplemental materials for summary statistics.

We find no evidence that neighboring states being leaders has any relationship with being a policy leader. This is consistent with a growing body of research that finds the declining role of geography in the spread of policies (Mallinson 2021*a*). Additionally, there were not contiguous leaders in health and law and crime, leading to the variable being omitted from both models. The results begin to diverge more by policy area starting with the sum of area leadership. For civil rights, health, education, law and crime, and macroeconomics, leadership in more areas is associated with a higher probability of being a leader in another area. These results suggest that policy leadership is driven less by specific expertise in a limited number of areas, but rather that once a state is a policy leader in any area, it becomes more likely to lead in others. This provides support for the broad leadership hypothesis. At the same time, for labor policy, states that are leaders in other areas are *less* likely to be labor policy leaders, and there is no significant association for transportation policy. Taken together, the results show strong evidence of leadership being an enduring trait over time, no evidence of leadership being dependent on geography, and evidence that leadership is broad-based across policy areas (although the evidence is somewhat more mixed).[2]

We next move on to evaluating internal characteristics of states. States with more liberal policies are more likely to be leaders in health and transportation, but there is no significant association in other policy areas. Larger populations only predicts leadership for education and transportation, and income per capita negatively predicts leadership in labor policy, and has no relationship with leadership for all other policy areas. Legislative professionalism only predicts leadership in law and crime and is a negative predictor of leadership for transportation policy along both dimensions. Taken together, these results suggest that there is considerable heterogeneity in what state characteristics lead to policy leadership. Perhaps most striking, variables measuring the resource capacity of states (legislative professionalism and wealth) are largely unrelated to leadership, and in some cases have a negative association with being a policy leader.

[2]As a robustness check we estimated the models without a lagged dependent variable. The results were unchanged in both direction and significance with the exception that the sum of area leadership predicts leadership across all policy areas.

Lastly, models 2 through 7 include topic area specific variables that are hypothesized to measure demand for policy leadership or expertise. Contrary to expectations, the size of the healthcare industry is unrelated to policy leadership on health policy. For labor policy, the size of state's union workforce is unrelated to leadership, but states with a larger manufacturing industry are more likely to be policy leaders.[3]. Similarly, states with larger transportation work forces are more likely to be leaders in transportation policy, but education employment negatively predicts leadership. Both the unemployment rate and violent crime rate were unrelated to leadership in their respective policy areas. These results are decidedly mixed and show that policy demands have heterogeneous relationships with policy leadership.

The results from table 1 show that policy leadership is heavily based in a historical legacy of being a leader in a policy area, and that states that are leaders in one area tend to be leaders in other areas as well. We find little evidence that internal characteristics are driving policy leadership, and mixed evidence that leadership is driven by policy demands. Together these results suggest that innovativeness is more of an intrinsic characteristic than driven by state characteristics, which is consistent with research from Boehmke and Skinner (2012) among others showing that states, such as California have consistently ranked among the most innovative states over the last century despite large demographic, economic, and ideological changes.

5 Dyadic Analysis

Thus far we have focused primarily on modeling policy leadership, but we next switch to a dyadic approach to understand a state's role in the latent diffusion network. Rather than modeling leadership, we now model the predictors of states belonging to the same cluster in the network. In other words, what predicts states belong to the same block? We take this approach because it allows for investigating the determinants of being in any network position, not just a leadership role. Gaining insights about what determines a state's position in the network, and understanding how stable that role is, helps to better understand patterns of diffusion.

[3]We estimated separate models including each of the measures of labor demands individually, and the results were unchanged in both direction and significance.

Table 1: Logistic Regression Predicting Policy Leadership by Topic Area

	(1) Civil	(2) Health	(3) Labor	(4) Education	(5) Transportation	(6) Law/Crime	(7) Economics
Lagged Leader	1.255*	0.576	4.226***	2.380***	4.442***	2.202***	1.761***
	(0.494)	(0.294)	(0.561)	(0.390)	(1.088)	(0.222)	(0.491)
Sum of Contiguious Leaders	0.582		0.659	0.738	-1.516		-1.165
	(0.411)		(0.553)	(0.381)	(1.772)		(0.665)
Sum of Area Leadership	1.431***	1.236**	-0.854*	0.846**	0.634	1.237***	1.921***
	(0.298)	(0.454)	(0.377)	(0.270)	(0.533)	(0.213)	(0.498)
Policy Liberalism	0.200	2.627**	0.407	-0.374	1.427**	0.248	0.049
	(0.175)	(0.995)	(0.425)	(0.353)	(0.454)	(0.445)	(0.369)
Population	-0.101	-0.970	0.237	0.795***	1.384**	-0.076	-0.351
	(0.278)	(1.088)	(0.377)	(0.211)	(0.487)	(0.256)	(0.664)
Real Income Per Capita	-0.312	0.250	-1.502**	-0.044	-0.433	-0.347	-0.165
	(0.281)	(0.636)	(0.489)	(0.365)	(0.748)	(0.615)	(0.436)
Legislative Prof- Dim 1	-0.285	0.489	0.124	-0.297	-1.393*	0.432	-0.720
	(0.370)	(1.351)	(0.437)	(0.362)	(0.561)	(0.383)	(0.826)
Legislative Prof- Dim 2	0.421	-0.003	-0.249	-0.475	-1.432***	0.503*	0.232
	(0.347)	(0.645)	(0.242)	(0.243)	(0.315)	(0.241)	(0.424)
Percent Health		0.382					
		(0.788)					
Percent Union			0.035				
			(0.074)				
Percent Manufacturing			0.794*				
			(0.336)				
Percent Education				-0.090*			
				(0.045)			
Percent Transportation					1.549***		
					(0.265)		
Violent Crime Rate						-0.000	
						(0.002)	
Unemployment Rate							-0.402
							(0.219)
Constant	-4.083***	-10.369*	-3.724***	-4.228***	-16.443***	-4.417***	-3.022*
	(0.550)	(4.447)	(1.078)	(0.442)	(1.665)	(0.889)	(1.349)
Observations	700	700	700	700	700	700	700

Standard errors in parentheses are clustered by State
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Our dependent variable is a 0/1 indicator generated from the same block model discussed earlier to signify states are categorized in the same block. Our unit of analysis is now dyad-year, with each year having 2,450 observations from 2000-2014. We use the same independent variables, but transform them to be edge attributes between states. For continuous measures, each variable is now the absolute value between the two states in a dyad, and we use binary indicators for shared borders and the lagged dependent variable. We then estimate a logistic regression with standard errors clustered by dyads. If state characteristics and policy demands are driving policy leadership then we expect for larger differences to be negatively associated with sharing a group.

5.1 Results

Table 2 shows the results from the dyadic logistic regression predicting two states sharing the same block in the network. Just as in the monadic models, the lagged dependent variable is large, positive, and significant. States that were in the same block the previous year are much more likely to be in the same block the previous year. This provides more support that the network is relatively stable over time, and being a follower or leader is an enduring trait. The variable for the difference in the number of areas two states are policy leaders in is positive for health and labor, while negative for law and crime and macro economics. Shared borders is insignificant in most cases, but positively associated with dyads belonging to the same block for labor policy, and negatively associated for transportation policy. These results highlight the stability of block categorization, but provide less clear evidence of whether leadership is due to policy expertise or broad based leadership.

Moving to dyad characteristics, we again find mixed evidence that a shared block in the network is due to similar characteristics. Differences in policy liberalism are negatively associated with shared blocks for civil rights, health, and education policy, but positively related to labor and transportation policy. Differences in population and income also present mixed results, having a positive association for some policy areas, and negative for others. For health, education, and law policy the results results generally indicate that as states become more different along a variety of measures they are less likely to share the same group. On the other hand, for labor policy shared block membership is more common between states with differing characteristics.

Policy demands also show heterogeneity in their relationship with block membership by policy area. States with larger differences in the percentage of workers in health care, manufacturing, and education are more likely to share the same block membership, while differences in the size of the transportation workforce, union membership rates, and unemployment rate are negatively associated with shared blocks. States with differences in crime rates are somewhat more likely to share block membership, while differences in unemployment predict different macro-economic blocks. Interestingly, across both sets of models only the results for transportation demands support the hypothesis for policy demands. States with a larger transportation sector are more likely to be transportation leaders, and differences in the size of the transportation sector are associated with states being less likely to belong to the same block in the transportation policy latent network.

The results from the dyadic analysis do not suggest that policy demands or state characteristics are the driving force behind policy leadership. Although the results are mixed and vary considerably by policy area, we argue that the heterogeneous result suggest that a states role in diffusion networks is an enduring trait more so than being driven by particular characteristics.

Table 2: Dyadic Logistic Regression Predicting Shared Block in Latent Network

	(1) Civil	(2) Health	(3) Labor	(4) Education	(5) Transportation	(6) Law/Crime	(7) Economics
Same Group-Lagged	2.695***	5.278***	3.332***	3.060***	4.988***	4.131***	2.856***
	(0.037)	(0.094)	(0.062)	(0.048)	(0.125)	(0.079)	(0.068)
Dif Sum Leader	-0.038	0.315***	0.257***	0.041	-0.074	-0.278***	-0.928***
	(0.033)	(0.066)	(0.041)	(0.027)	(0.052)	(0.030)	(0.054)
Shared Border	-0.115	-0.188	0.263*	0.069	-0.334*	-0.046	0.080
	(0.065)	(0.122)	(0.114)	(0.086)	(0.160)	(0.121)	(0.110)
Dif. Policy Lib	-0.296***	-0.150***	0.140***	-0.119***	0.175***	-0.007	0.056
	(0.016)	(0.031)	(0.035)	(0.026)	(0.044)	(0.034)	(0.035)
Dif Pop	-0.023	0.040	0.091**	-0.402***	0.136*	-0.157***	0.048
	(0.017)	(0.031)	(0.029)	(0.023)	(0.053)	(0.028)	(0.041)
Dif Income	-0.015	-0.459***	0.352***	-0.082*	-0.226**	0.159**	0.264***
	(0.025)	(0.041)	(0.057)	(0.038)	(0.069)	(0.053)	(0.056)
Dif Leg Prof- 1	0.078***	0.070*	-0.055	0.393***	-0.057	-0.195***	0.030
	(0.019)	(0.034)	(0.034)	(0.026)	(0.053)	(0.033)	(0.050)
Dif Leg Prof- 2	-0.018	-0.351***	-0.173***	-0.031	-0.223***	-0.048	0.256***
	(0.018)	(0.034)	(0.030)	(0.026)	(0.042)	(0.035)	(0.042)
Dif Health		0.138**					
		(0.049)					
Dif Union			-0.035***				
			(0.007)				
Dif Manu			0.852***				
			(0.108)				
Dif Educ				0.559***			
				(0.041)			
Dif Transp					-0.215***		
					(0.042)		
Dif Crime						0.001*	
						(0.000)	
Unemployment Dif							-0.089***
							(0.018)
Constant	-0.178***	-0.512***	-0.739***	0.008	-0.463*	-0.250**	0.846***
	(0.051)	(0.130)	(0.087)	(0.081)	(0.190)	(0.097)	(0.095)
Observations	34300	34300	34300	34300	34300	34300	34300

Standard errors in parentheses are clustered by dyad

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6 Discussion and Conclusion

Our work both contributes to the theoretical literature on learning and introduces a new way to take advantage of the network structure inherent to diffusion data to address questions of learning and diffusion patterns. Identifying who is a policy leader and how the categorization may change by policy area has implications for scholarly research as well as practical implications for policy advocacy groups. For scholars of diffusion and public policy, understanding who is a leader (and when) based on the persistent policy diffusion pathways we use with `NetInf` offers a new way of understanding innovativeness. Since we find that there are significant differences in the predictors of policy leadership by policy typology, but find that previous leadership strongly predicts leadership. Furthermore, leadership in on area strongly predicts leadership in other areas. Together, these results suggest that while there may be policy area specific predictors for policy leadership, once states are a source for policy solutions, they remain so, even in the face of changing internal characteristics including policy demands. For policy advocacy groups, given their policy area, if they can identify the most innovative states that other states are most likely to follow, they can target their resources and hopefully have wider adoption of their desired measure.

There are several remaining questions to explore regarding the research design and results, mostly centering on the data used. First, we only cover a relatively small time period (less than 20 years), and most state characteristics see incremental shifts over time, so this study is unable to capture the dramatic changes seen in virtually all the states over the last century. Additionally, the estimated networks come from a time of very active state policymaking. The networks are much denser post-2000 than earlier decades.[4] Extending the analysis to a larger time period could provide greater insights into the role of state characteristics. Secondly, We constrained the analysis to only two groups of states, leaders and laggards. However, this if diffusion patterns follow and S-shape curve, then estimating more blocks may provide a more nuanced understanding of what it means to be a leader versus early adopter, middle adopter, late adopter, or hold out against a policy.

[4]Although, as Karch et al. (2016) note this may be due to researcher decisions on data collection, and we do not claim these samples are representative.

Future research will explore how decisions on the number of blocks will change our understanding of what it means to be a policy leader. Lastly, while we do see heterogeneity in the predictors of policy leadership and shared block, we do not have clear explanations for *why* these differences exist. For example, why are states with larger population differences more likely to belong to the same block on labor policy, but less likely on education policy? Future research will attempt to address these questions to better understand if policy leadership is an enduring trait.

Furthermore, the diffusion literature has seen increasing critiques that patterns we have been identifying as policy diffusion, may actually just be states making similar policy decisions at similar times. The classic view of policy diffusion as geographic clustering has been declining (Mallinson 2021*b*). Although geographic proximity offers a good starting point for understanding diffusion patters, it is often overly limiting, sometimes misleading (or even wrong). Similar governments often face problems and opportunities at about the same times. Because of this, similar states tend to adopt similar policies, and because geographically neighboring states tend to have many political, economic, and demographic similarities, evidence of geographic policy clustering may have little to do with policy diffusion and may be instead independent policy choices (Volden, Ting, and Carpenter 2008). We find no evidence that geographic is driving patterns of leadership.

If there is no learning happening, and states are just making similar decision at similar times independent of one another, we would expect there to be oscillation in who the leaders are. On the other hand, if learning is occurring, then we would expect leadership to be relatively consistent holding all other variables constant (e.g. policy area, political party, state budget). If the same states are consistently policy leaders and have similar sets of states that follow them across time and across policy area, then this is evidence that the pattern reflects diffusion rather than independent action. Using a game theory approach, Volden, Ting, and Carpenter (2008) find that whether states respond to evidence of policy success depends on the preferences of policymakers involved in the learning process. As such, we include several controls for state ideology in our models to account for this. Although our approach is not a perfect test of whether adoption patterns are evidence of diffusion or similarly timed, but independent, policy adoptions, the network analysis approach uniquely allows us to account for the interdependence of policy adoptions. This approach is also easier to implement than Volden, Ting, and Carpenter's (2008) game theory approach. Further, if a certain state is consistently the leader, it seems this is evidence of diffusion whereas if it were independent decisions we would see more oscillation in leadership. We find evidence to suggest that patterns of diffusion are persistent, and the stability of leadership suggest states have identified clear leaders who they look to for policies regularly. More robustness testing (and maybe additional methods) are needed to investigate this further. This research also sets the stage for additional studies of how diffusion patterns may be different for different types of policy.

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