Chapter 20: Learning and Diffusion Models

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1 Policy Diffusion

In this chapter, we overview different methodological approaches used to study diffusion and learning. In Political Science, studies of diffusion seek to capture interdependence across units in the spread of an idea or action, such as the adoption of a policy by a state or country, the signing of compacts or treaties, the adoption of a norm of behavior, or the occurrence of political conflict. A variety of methods has been developed to understand how such items spread, each with its own advantages and disadvantages. We will highlight the theoretical foundations of diffusion research as well as the corresponding methodologies to understand how phenomena spread.

In American politics, diffusion research often focuses on the spread of policies across states and cities. U.S. states make an ideal unit of analysis for diffusion studies because they all operate at the same level in the same federal system. Policy adoptions also represent easily observable, discrete events that are conducive to large-N quantitative analysis. Research in U.S. state policy diffusion typically asks a variety of questions: why do some policies spread widely across states, countries, or cities, and others do not? what makes a government innovative? are some governments innovative in certain policy areas but not others? how do states make decisions about what states to use as a model for policy ideas? Since Walker's (1969) foundational work on policy diffusion, political scientists have become increasingly focused on understanding how policies spread from one governing body to another. Diffusion scholars want to know what makes some policies spread widely and not others (Boushey 2010; Nicholson-Crotty 2009). In American politics, some states, such as California and Massachusetts, are historically innovative (Boehmke and Skinner 2012), while others, Wyoming and West Virginia, usually wait for others to go first before adopting a policy. Studies of American politics have helped scholars understand what makes policies more likely to spread and states or cities more likely to innovate .

International relations and comparative politics research also consider diffusion (Zhukov and Stewart 2013). As with researchers in American politics, scholars of cross-national diffusion recognize the role of international interdependence in the spread of political phenomena (Gilardi 2012): the actions of one country often influence the decisions of other actors in the international system make. Countries often use a combination of carrots and sticks to explicitly influence other countries to adopt their preferred policies, trade practices, or engage in a variety of other interstate behavior (Simmons, Dobbin and Garrett 2006). Research ranges from the diffusion of macro-economic policies cross-nationally (Simmons and Elkins 2004) to the diffusion of democratic governments (Starr 1991), government spending levels (Lee and Strang 2006), and conflict (Gleditsch 2009).

The prior examples illustrate many phenomena influence by diffusion. But why does diffusion occur? Researchers seeking to understand the causes of diffusion rely on four widely agreed upon mechanisms: coercion, imitation, competition, and learning (Simmons, Dobbin and Garrett 2006; Shipan and Volden 2008; Jensen and Lindstädt 2012). In this chapter, we will focus on learning. Diffusion via learning occurs when a government or other actor uses information resulting from the policy or other choices made by other actors. If those choices prove beneficial, then other governments will tend to make similar choices (Butler et al. 2017). Learning requires that policy makers are aware of both what policies other actors are adopting and the outcomes produced by those adoptions.

The primary empirical method for studying diffusion has long been event history analysis (EHA). In recent years, however, a wide variety of alternatives have emerged that can incorporate the diffusion of multiple policies and more explicitly model and account for interdependence among observations. We will overview the following methodological approaches that have been used to study diffusion in political science: Event History Analysis, Dyadic Event History Analysis, Pooled Event History Analysis, Network Analysis, Latent Networks, and Spatial Regression.

2 Theoretical Background

This section focuses on the four mechanisms of diffusion described above and briefly traces through the evolution of the literature on policy diffusion, with examples from related areas (e.g., conflict, monetary policy). We recap many of the original ideas on the diffusion of innovations, starting with Rogers in 1939, and briefly trace through their development in the Political Science literature (Weyland 2005; Graham, Shipan and Volden 2013; Karch 2007; Meseguer and Gilardi

2009; Berry and Berry 2007).

Despite increased attention to understand how innovations spread from state to state, researchers have struggled to develop tests to isolate the four theorized mechanisms of diffusion. When they do test mechanisms, researchers rarely agreement on appropriate indicators to distinguish between them. A recent survey of the literature found that the "same mechanisms are operationalized using different indicators, and different mechanisms are operationalized using the same indicators" (Maggetti and Gilardi 2016, p. 3). Given this, researchers have effectively focused on predicting state innovativeness rather than on specific mechanisms that may cause states to adopt policies sooner (Gilardi 2016). Four primary theoretical mechanisms have been identified: imitation, learning, coercion, and competition (Simmons, Dobbin and Garrett 2006; Shipan and Volden 2008).

The most clearly identifiable mechanism is coercion. Coercion occurs when an actor compels another to adopt a policy (Simmons, Dobbin and Garrett 2006; Berry and Berry 2007). In international relations, more powerful countries could pressure less powerful ones into implementing certain reforms or taking a desired action (Henisz, Zelner and Guillén 2005). In the American context this occurs when the federal government pushes states to adopt policies, either by using a combination of carrots and sticks (often in the form of federal funds) or via Supreme Court rulings. Diffusion through coercion, unlike other mechanisms, is a vertical relationship in the U.S. context[1], which makes it easier to observe. The federal government has a clear position above the states when coercion is used. States are horizontal actors operating at the same level within the government, so none has the authority to legally force another state to take an action. A similar dynamic has been studied in which U.S. states coerce cities to adopt preferred policies, or refrain from adoption a policy the state opposes (Shipan and Volden 2006).

The other three mechanisms mostly focus on the horizontal spread of policies across political actors, meaning that adoptions spread from actor to actor at the same level of government. Within a country this could mean spreading from state to state or city to city; in international relations it means country to country diffusion. Learning occurs when a state observes the policy outcome(s)

[1] While horizontal coercion is common in international politics (countries using their economic or military clout to force others to comply), the constitutional context of the U.S. makes horizontal coercion rare.

in another state, and uses that information to make a decision on policy adoption. If that policy produced an outcome that a state desires (reduced crime, for example), then it learns from the policies and choices of other states that have achieved that outcome and adopts the relevant components. This mechanism often occurs when a state is faced with a new problem, and is looking for potential policy solutions (Walker 1969). Learning can also incorporate more than just policy outcomes by providing information about a policy's political effects (Graham, Shipan and Volden 2013; Gilardi 2010). Butler et al. (2017) use an experimental approach to demonstrate that even when given information on a policy's success, municipal policymakers are less likely to support policies that they ideologically oppose. Policymakers have additional considerations when deciding to adopt a policy. Is the policy politically viable? Does it produce spillover effects or negative externalities?

Learning requires that policymakers not only to be aware of what other governments are doing, but that they understand the effect of their actions. The Japanese "Economic Miracle" provided a model for other developing countries to grow their economies. Other countries, such as South Korea and Chile, successfully learned from the Japanese case by adopting similar economic liberalization policies as Japan (Simmons and Elkins 2004). Countries that successfully followed Japan's example had to identify which policies led to the desired outcome (increased growth and development).

The next mechanism, imitation, occurs when a state looks to another state for policy ideas, but without looking at the policy outcome (Shipan and Volden 2008). In this case, actors are adopting policies because of the the other state's attributes. Mississippi may adopt a gun law first passed in Alabama not because the policy was a success, but because Mississippi looks at shared conservatism (or other aspect) between the states and follows Alabama's lead, even if the policy does not have the intended effect. Similarly, urban states may look to urban states, and wealthy states to wealthy states for policy ideas. This is done irrespective of policy outcomes. Learning focuses on the policy outcome, whereas imitation uses actor characteristics to inform policy adoption decisions.

Finally, competition occurs when states look to gain an advantage, often economic, over other actors. Incentives to innovate frequently arise from negative externalities fueled by other states' previous adoptions (Baybeck, Berry and Siegel 2011). Tax rates may be lowered, business incentives increased, or welfare spending altered to prevent one state from gaining a competitive advantage over the others (Peterson and Rom 1990). While learning influences decisions to adopt policies, competition has been found to motivate post-adoption behavior. Boehmke and Witmer (2004) argue that while competition and learning often both matter for initial adoptions, future adjustments to a policy result solely due to competition. States have already adopted the policy, so they need not look to other actors for information about outcomes.

Recent work attempts to focus on developing theories and implications about learning-based diffusion. The goal is typically to offer guidance about how learning might produce specific patterns of diffusion and methodological tools that could be used to detect it. One branch of this research typically relies on conditional effects – identifying circumstances in which learning is more likely and then specifying an empirical model to test for the predicted pattern. For example, diffusion by learning might be more likely to influence those that have no experience with a given policy or behavior (Boehmke and Witmer 2004) or it might be more likely to occur among those with resources to support more careful consideration and exploration of different options (Shipan and Volden 2008).

Theoretical work has also attempted to clarify the conditions for learning and the patterns that might result from it. These typically create opportunities for learning by making the benefits or outcomes of policies uncertain and partially revealed only by experimenting with policy choices. Volden, Ting and Carpenter (2008) develop a formal model of policy adoption that demonstrates an incentive for potential adopters to free-ride on others by waiting to adopt in order to see how the policy plays out in other jurisdictions. This can lead to a delay in adoptions and specific patterns of adoption based on states' underlying predilection towards the policy. A related model from Callander and Harstad (2015) finds that the incentives for free riding can be reduced within a federal structure if states expect the national government to harmonize policy after a period of time. Within the context of a single decision maker, Callander (2011) examines optimal policy search in an environment with policy uncertainty characterized by Brownian motion. This leads to certain patterns of policy search that feature stickiness and typically end once the results seem "good enough". This model has clear applications for policy choices by multiple units. Finally, there have been some attempts to develop empirical estimators corresponding to game-theoretic models of strategic interaction and learning. Building on the development of Quantal Response Equilibrium estimators (Signorino 2003), Esarey, Mukherjee and Moore (2008) develop an estimator for incomplete information games that explicitly incorporates learning. Whang, McLean and Kuberski (2013) apply a similar estimator to determine that sanctions threats do not lead to the targets updating their beliefs about the sanctioning country's resolve but rather shape the cost-benefit calculation directly.

3 Event History Analysis

Walker's (1969) research on policy innovation was quickly met by theoretical and methodological critiques from other scholars in the field (Gray 1973). Further limiting progress in diffusion research was an inability to model both internal characteristics of states (such as legislative professionalism and demographics) and external predictors (contiguous state adopters) of policy diffusion simultaneously. Berry and Berry (1990) introduced event history analysis to the discipline and provided a framework that would allow for modeling both internal and external determinants of policy adoption into the same model.

Event history analysis typically uses a logit (or probit) estimator to model the likelihood of a state adopting a policy in a given year.[2] The logic of the analysis was taken from medical researchers that modeled medical survival data. The "event" would often be death, and the model would estimate the risk of an individual dying at different in time. In policy diffusion research, the event is the adoption of a policy, and the risk is the probability of a government adopting a policy in a given year. The risk set is the sample of units that are at risk of the event occurring to them. Once a state adopts a policy, it is no longer at risk of adopting it, and is removed from the

[2] Continuous-time duration models like the Weibull or Cox may also be employed (Jones and Branton 2005).

analysis.[3] The definition of the event can vary from state policy adoption to signing international treaties to engaging in military conflict, and is signified by a binary variable that is one in the time period the policy is adopted, and zero when it is at risk of adoption but has not done so.

Scholars must consider which units qualify to be part of the risk set, how to measure the event, and when units begin to be at risk. For diffusion scholars, the risk set typically begins once any actor in the risk set experiences the event. For example, if a scholar studied the diffusion of the ballot initiative process in U.S. states (Smith and Fridkin 2008), the risk set would initially include all fifty states. The risk would begin once the first state, South Dakota, adopts the initiative process in 1898. In 1899 the other forty-nine states are still at risk of adopting the policy, whereas South Dakota is not because it already experienced the event. Each time a state adopts the initiative, it drops out of the risk set in the subsequent year. Observations that have not adopted the policy by the time data collection ends are considered right censored – they could still adopt that policy but have not done so yet.[4]

The event does not have to be a policy adoption, and event history analysis has been used in a variety of studies. Lektzian and Souva (2001) estimate an event history model for when a country returns to pre-sanction levels of international trade after being sanctioned by the international community. A country is at risk once sanctions are put in place and the event occurs when trade reaches its pre-sanction level. After the event occurs a country drops out of the risk set. Countries that had not yet reached pre-sanction levels of trade when data collection finished would be considered right censored. Note that while the concept being measured is not binary (amount of trade), the event itself is operationalized as a discrete event that either occurs or does not occur in a discrete time period.

Event history analysis has long been the workhorse method for studies of diffusion in political science and has contributed greatly to how scholars understand policy diffusion (Berry and Berry 1990; Mintrom 1997; Balla 2001). As Gilardi (2016) summarizes, this literature has established

[3] For some policies, re-adoption of a policy is possible, but generally researchers remove an actor once the event, however defined, occurs.

[4] See Box-Steffensmeier and Jones (2004) for a guide to the application and estimation of EHA.

that diffusion occurs in a wide variety of phenomena, both within and across countries. The challenge, as he see it (and we agree), is to move beyond cataloguing the presence of diffusion to understanding the mechanisms behind it. The policy diffusion literature, especially in the American states, has typically accounted for diffusion by including a count of prior adoptions by contiguous states (e.g. Berry and Berry 1990). Yet a variety of mechanisms could drive findings that find support for this effect. Given data limitations on what the relevant actors know and when, scholars have often turned to identifying conditional diffusion effects to help sort out the mechanisms. For example, Shipan and Volden (2006) find that states with greater legislative professionalism – and therefore greater capacity to learn – respond to the adoption of anti-smoking laws by cities within their borders with state-level adoptions whereas those with lower levels do not.

In addition to challenges sorting out mechanisms, EHA presents several other drawbacks. While early studies provided important theoretical contributions to the literature, single-policy studies are increasingly providing diminishing returns (Boehmke 2009*a*). Scholars hoping to produce generalizable findings about broad diffusion dynamics struggle to aggregate findings from multiple event history analyses. Finally, an EHA model only somewhat acknowledges interdependence among units by focusing on exogenous and time-lagged outcomes in other states, while diffusion scholars are explicitly arguing that actions in one unit affect actions in another. As the study of diffusion has developed and grown, a number of new methods have been used to overcome some of the shortcomings of single-policy event history analyses.

4 Pooled Event History Analysis

Pooled Event History Analysis (PEHA) was proposed as a way to apply the logic of single-policy EHA to multiple policies (or multiple components of the same policy) in a unified model (Shipan and Volden 2006; Boehmke 2009*a*). PEHA seeks to address the problem of interpreting a possibly wide range of findings from single-policy EHAs by estimating a single model. This allows it to identify systematic commonalities in the determinants of diffusion and innovation across policies and reduce the idiosyncrasies of each individual policy. Analyses with a large number of policies incorporate dramatically more information, which can offer a more accurate estimate of the average effect of a variable. The unit of analysis for PEHA shifts from unit-year as in EHA to the policy-unit-year. Each policy has a separate risk set that begins when the first unit adopts a policy, just as in single-policy EHA. The difference is that a pooled EHA stacks each policy's risk set into a single model (Makse and Volden 2011; Shipan and Volden 2006). The dependent variable, Y_{ikt} is still a binary indicator coded one if unit i adopts policy k in time period t and zero when it is at risk of adopting policy k but does not adopt.

This approach can identify common diffusion trends across policies, but makes the assumption of a fairly homogeneous diffusion pathways across policies. Single-policy analyses have demonstrated significant heterogeneity in diffusion pathways by policies. For example, morality policies may have distinct patterns of diffusion from non-morality policies (Mooney and Lee 1995) while crime and law policies may diffuse differently from education ones. Republican control of a state legislature likely positively predicts diffusion for some policies, but negatively for others. As policy databases become increasingly large (Boushey 2010; Kreitzer 2015; Makse and Volden 2011; Boehmke et al. 2018), the likelihood of heterogeneity among diffusion pathways increases. If scholars fail to account for this heterogeneity, then conclusions will simply be a function of the sample of policies chosen for analysis, which is similar to the problem posed by single-policy case studies. If the coefficients differ across policies, then both the coefficient estimates and standard errors will be incorrect.

To overcome this obstacle, Kreitzer and Boehmke (2016) propose running PEHAs as a multilevel model using random intercepts and random coefficients across policies or units to model heterogeneity in the baseline rates of adoption and heterogeneous effects of variables by policy. This form of PEHA seeks to find a middle ground between running separate single-policy EHA models and a single pooled model with all policies treated identically. Scholars must decide which variables merit random (or fixed) effects. Decisions should be guided by the nature of the data being used and the covariates included in the model. These models can be computationally intense, particularly when using a large number of random coefficients. When properly constructed, a multilevel PEHA acknowledges heterogeneity in diffusion pathways while still identifying common, generalizable trends across units and policies.

PEHA's ability to capture both common effects and heterogeneity can be of value for identifying whether mechanisms of diffusion, including learning, have consistent effects in a collection of policies or just within a subset of policies in the collection. That subset may be identified by the researcher and captured in the model via interactions with unit-level covariates (Boushey 2016; Makse and Volden 2011; Shipan and Volden 2006) or it can be left unspecified and detected via the estimated distribution of a random coefficient across policies, some values of which may indicate the presence of learning while others show no such effect.

Finally, although a PEHA can identify commonalities among diffusion pathways, it still can only partially recognize interdependence among observations. Monadic analysis assumes independence among observations, yet diffusion implies interdependence. Many researchers include variables to capture adoptions in other units, most often a lagged count of the number of contiguous units that have adopted the policy. Both the single-policy and pooled EHA can include external and internal determinants of policy adoption, but the analysis still seeks to explain policy adoption or event occurrence more generally. The methods we outline next represent attempts to directly model diffusion pathways at the level at which they occur.

5 Dyadic Event History Analysis

A critical shortcoming of the previous approaches is that they fail to capture the specific sources of learning. Theories of learning and diffusion examine how one unit learns from other units, but it does not necessarily learn from all other units equally. For example, a country can learn from the experiences of countries that have adopted a policy and from those of countries that have not adopted it. It may learn more from the adoption decisions of countries that have similar demographic and political environments or that face a similar scope of the problem the policy seeks to address. Learning therefore typically occurs from one unit to another, and often from multiple units in different ways. Single-policy and pooled EHA models struggle to capture the different sources of learning since they lump the influence of other units into a single variable or series of variables (though they may be weighted accoprding to their likely influence). They can therefore capture whether the choices of other countries influence the outcome in a single country in the aggregate, but provide little leverage on differential impacts needed to identify sources of learning and to help distinguish them from other mechanisms.

To help address this problem, diffusion scholars have often turned from monadic to dyadic structures. These have been applied extensively in the study of international conflict (Maoz and Russett 1993*b*; Leeds 2003; Danilovic and Clare 2007) but have more recently been adapted to the diffusion framework to explicitly model the spread of policies or behaviors through the development of dyadic event history analysis. Rather than a single country (or state , city, etc) being the unit of analysis, a dyadic approach evaluates dyads, or pairs of units. This approach allows for modeling sender and receiver states in order to evaluate the direction of the diffusion event flow (Volden 2006). In international relations applications, the dependent variable often measures the probability of two states going to war (Maoz and Russett 1993*a*; Leeds 2003), or signing bilateral trade agreements (Elkins, Guzman and Simmons 2006). In the case of policy diffusion, the dependent variable shifts from "policy adoption" to "dyadic policy similarity" where a receiver unit is either adopting a policy already present in the other unit in the dyad (Gilardi and Füglister 2008) or moving its policy closer in a possibly multidimensional space to that in the other unit (Volden 2006).

Importantly, dyadic EHA is directional. Each dyad consists of a sender and a receiver unit. The dyad enters into the risk set once the sender has adopted the policy (see Gilardi and Füglister (2008) for information on how to format the data). This method allows direct modeling of diffusion pathways (Boehmke 2009*b*), meaning scholars using this approach are modeling diffusion itself rather than diffusion as a part of a broader policy adoption or innovation process. Hinkle (2015) uses a dyadic logit to identify signals of policy success or failure (in this case, being ruled unconstitutional in the courts) which states consider when learning about policy solutions. If scholars can identify cases of successful policy outcomes, a dyadic approach can allow for modeling the extent to which actors are learning from previous adoptions.

While dyadic analysis offers several advantages, scholars have found theoretical and methodological issues with this approach (e.g., Erikson, Pinto and Rader 2014). As noted above, the dependent variable shifts from being the occurrence of the event of interest to the convergence of one unit's outcome with another unit's existing choices. Thus information on why some units tend to experience the event earlier than others is lost in favor of explaining the choices of later adopters vis-à-vis the choices of previous adopters. This may be helpful when the focus is explicitly on learning or other mechanisms but researchers need to be cognizant of the change in interpretation. For example, (Boehmke 2009*b*) demonstrates the need to remove observations that already have the outcome in question since they are not at risk of learning in many applications of dyadic EHA. Including them risks conflating factors that influence adoption of the underlying policy with those that influence convergence between two units.

Dyadic EHA has not yet been addressed the more challenging limitation that while it can capture policy convergence between pairs of states it can not differentiate from among a host of potential sources. That is, the dependent variable captures whether a state moves towards a set of states but its movement towards all units with the same current policy is coded the same way. Conceptually, researchers must rely on richer measures of convergence or the inclusion of lots of data to try to tease out which of the units to which a state converges matter and which may be coincidences, for example since they may all be converging to a single leader state at different points in time. Statistically, this creates problems since it induces correlation between the error terms since a state must be treated as converging to all states with similar outcomes even if it is only converging to a subset of them. The dyadic approach therefore explicitly models some interdependence among observations, but misses and can even create other forms. Compared to a monadic analysis, dyadic models may misidentify independent observations as interdependent, and thus underestimate the effect of internal characteristics on policy adoption and overstate the role of external characteristics. Finally, researchers should also address why dyads are the proper unit of analysis, and not triads, or, as we discuss in the next section, even a full network.

The dyadic approach's ability to include characteristics of both units in a pair means that it can account for features of states seeking to learn, those they might learn from, as well as relative features of the two (such as similarity). While this helpful for studying all mechanisms of diffusion, it proves particularly valuable for studying learning since it offers an opportunity to account for the performance of a policy in units that already have it. The dyadic approach therefore offers great leverage for establishing that learning occurs when such measures are available. For example, Volden (2006) analyzes convergence in U.S. states' Children's Health Insurance Programs over six dimensions and finds that states were considerably more likely to revise their policy to more closer mirror those in states that had successfully reduced their uninsured rate among poor children. In contrast to this evidence of policy learning, Gilardi (2010) finds evidence of political learning in his study of unemployment benefits in OECD countries: right wing governments are more likely to move their policies towards those of countries in which reforms have produced electoral benefits.

6 Diffusion Networks

Another way for scholars to incorporate interdependence among observations is to use network analysis to model event pathways. This approach allows for a more comprehensive incorporation of interdependence than a dyadic approach by incorporating higher ordered network processes such as transitivity (Valente 1995). Public Policy research has used network analysis for decades to understand how policies spread (Coleman and Perl 1999; Klijn 1996; Koppenjan and Klijn 2004; Thatcher 1998), and International Relations research has used networks to explain topics ranging from the structure of alliance networks (Cranmer, Desmarais and Menninga 2012) to international trade flows (Hafner-Burton, Kahler and Montgomery 2009). The basic assumption behind a network approach is that the behavior of an actor, e.g., the adoption of a policy, affects the behavior of other actors in the group. Network scholars argue that events flow through a network of actors. Countries make decisions to ratify a treaty or go to war based on their own characteristics and in response to other countries. Network analysis better approximates the theoretical flow of policies (Lubell et al. 2012). When the United States makes a decision to sign an international treaty, it is likely influenced by whether allies (or competitors) have signed the treaty, and its decision to sign (or not sign) likely influences other nations.

The shift to networks now means that the focus of analysis is how an event spreads, not whether individual actors or dyads behave in a particular way. In the context of policy diffusion, a tie forms between two nodes when they adopt the same policy. So in a network of U.S. states, after the first state adopts a policy the network would have no ties because the policy has not spread. As the policy spreads to another state, a directed tie forms from the first adopter to the second, and the network continues to build as policies go from receiver to sender states. However, scholars may struggle to identify the source of policy ties. If Florida adopts a policy previously adopted by Indiana and Wyoming, should Florida receive a tie from Indiana, Wyoming, or both states? Garrett and Jansa (2015) use bill text to identify the source of a policy and where it spreads. Their analysis reveals that interest groups can act as a policy resource. Researchers must decide what a tie means in the network, and how to determine the source of diffusing policies. A network of directed ties better mirrors the diffusion theories that policies spread from one unit to another, but there may be cases where an undirected network is the appropriate choice. Mutual defense treaties or free trade agreements imply a reciprocal relationship. Those using networks must decide how to define a tie in the network and whether it should be directed or undirected.

Network analysis presents other advantages beyond better mirroring the structure of diffusion theories. Networks have been used to identify where policies originate and how they spread through the network (Garrett and Jansa 2015). A variety of network statistics can be used to evaluate which units are the most or least central to a unit. For example, when two countries share a similar network position (measured by structural equivalence), they are likely to compete with each other (Cao 2010). Unless these two units were directly connected, a non-network approach would be unable to observe this higher-order relationship between actors. For example, during the Cold War the USSR and U.S. were the two poles of the international alliance network. They responded to each other throughout the Cold War, but did not have direct alliance ties to each other. With a network approach, unlike monadic or dyadic analyses, scholars can model how the U.S. deciding to join an alliance affects the alliance network for the USSR (Chyzh and Kaiser (n.d.). Network processes and statistics can provide insights to diffusion pathways that would otherwise go unobserved in a monadic analysis (Robins, Lewis and Wang 2012).

Beyond network statistics, estimators such as QAP or ERGMs can be used to determine the correlates of ties between the states (Cranmer and Desmarais 2010). These models can be very powerful for understanding policy diffusion because they use a combination of network structure and edge-level attributes (such as population differences or trade between units) to model diffusion (Robins, Lewis and Wang 2012). This approach directly mirrors theories of diffusion that argue that both external and internal characteristics contribute to diffusion and policy adoption. Notably, ERGMs include the dyadic logit as a special case in which there are no network-level effects. This analysis takes a similar approach of a dyadic logit but adds network dynamics to the model of nodal, edge, and system level variables. These network effects can potentially be used to distinguish between learning, emulation, and competition (Maggetti and Gilardi 2016).

ERGMs allow researchers to include features of the network structure as part of the explanatory model. For example, Thurner and Binder (2009) use an ERGM to understand how the structure of the European Union affects the network connections between high ranking bureaucrats in member states. They test if the institutionalization of the European Union replaced existing networks of communication between nation states. The ERGM they estimate includes both network statistics (reciprocity) and edge-level covariates (economic interdependence) to predict communication ties between policy makers. They find that the structural components of the network and the edge-level covariates have a significant relationship with the existence of communication ties between policy-makers. ERGMs allow researchers to leverage both network structure variables and edge covariates to understand how actor characteristics and the structure they are nested in affect diffusion pathways.

Diffusion can also be viewed as occurring within an existing network structure. Examples of this abound for exogenous networks such as contiguity, ideological similarity, or trade. In monadic models, researchers often include the network-weighted sum of policies or behaviors in other states to explain occurrence in the current state. In dyadic models such pairwise features may be included as dyadic covariates. But in some cases one might worry about coevolution of the behavior of interest and the transmission network. For example, (Chyzh 2016) argues that states' human rights policies depend on their position in the international trade network, but also contends that position in the network depends on human rights policies since states often forego trade with countries whose protections they deem insufficient. To address this, (Chyzh 2016) employs a coevolutionary actor-oriented longitudinal-network model (see, e.g., Steglich, Snijders and Pearson 2010). This estimator, referred to as RSiena, models the network connections simultaneously with a behavioral outcome, such as human rights policies, at the nodal level within that network. Both equations can include features of the network. The results indicate that states that rely more on indirect trade links (trading through mutual partners rather then directly) tend to score lower on human rights and that states that score lower on human rights have few direct trade connections to other states. Thus the network shapes policy, but policy also shapes the network.

While network models have been used to study diffusion generally, to our knowledge no published research has used an ERGM to identify learning in a policy diffusion network. However, researchers could take a few approaches to identify learning in the network. Many of these will mirror the options for a dyadic logit since they share the same underlying structure of modeling links between units, but an ERGM allows researchers to study additional features related to network structure. Researchers could evaluate how signals of success or failure alter the diffusion network, e.g., do states with successful policy outcomes take a more central role in a diffusion network? do we see greater level of transitivity when the policy is deemed a success? are isolates (states that do not have diffusion ties to any state) less common when a policy's success is clear? Additionally, different diffusion mechanisms imply different network connections. Competition suggests reciprocity between nodes as they act and react to the other's behavior. Learning, on the other hand, should mostly be a uni-directional relationship because actors are responding the the policy success of a previous adoption. Researchers can include network statistics to identify these types of connections between actors. We believe a network approach could be a fruitful avenue for identifying learning in diffusion.

One of the drawbacks of the network approach in general centers on how to pool results. Almost every policy will have a unique adoption network when considering both how and when policies spread. Different policy areas may also have different policy leaders. This presents a similar dilemma of the single-policy event history analyses discussed in an earlier section. Different networks will likely result in different conclusions. Without a systematic way to aggregate findings, scholars must assume that the chosen diffusion network is representative of general trends in the diffusion network if they wish to make generalizable claims about diffusion networks.

7 Latent Networks

More recently, network scholars have begun to use latent network analysis to examine diffusion pathways. Rather then study observed diffusion networks this approach utilizes data from a large number of such networks to estimate a single, underlying latent network that contains the ties that best explain the observed diffusion patterns. A latent network approach operates in a similar way to latent factor analysis by using observed policy cascades to infer an optimized network of ties between units (Gomez-Rodriguez, Leskovec and Krause 2010). The network is constructed using an algorithm that infers diffusion ties based on the number of cascades in which state i adopts before state j, the length of time between these adoptions,and how well state i adoption predicts state j's adoption as opposed to by other states that tend to adopt before j. Latent networks are not directly observed, but represent the most likely network of diffusion ties given the policy adoption networks used to infer the network. Rather than predicting the adoption of a single policy, researchers estimate latent diffusion ties, which can then be analyzed using appropriate models, such as dyadic logit, QAP logit, or an ERGM.

Desmarais, Harden and Boehmke (2015) apply this algorithm to a sample of more than one hundred policy adoption cascades in the American states to recover a latent diffusion network. The ties represent the most likely diffusion connections between states. Their results reveal a network that evolves over time based on a forty-year rolling window of adoption data. With one hundred years worth of data, this produces 60 estimated networks. This means that scholars can estimate and then model how diffusion networks evolve over time. To study this evolution (Desmarais, Harden and Boehmke 2015) employ a QAP logit model to find that directed ties in the latent state policy diffusion network depend on theoretically-relevant dyadic features including as geographic distance, ideological similarity, and political similarity. They also find that more populous states send out more ties and also receive more ties.

Because the networks cannot be directly observed, scholars must carefully consider how they infer a network, including what observed diffusion events to use, how quickly the influence of an adoption should decay over time, how dense the network should be, and what the appropriate universe of cases is when deciding nodes in the network. Each of these decisions will determine what the network looks like. The network will be less dense if sparse policy adoption networks are used to construct the latent network. Additionally, the longer the window of time for previous policy adoptions to influence the current diffusion network, the denser the network. When constructed appropriately, latent networks are representative of the general diffusion network in a given era. Even though there is still only a single network produced for a given time period, scholars can feel more comfortable that the network is generalizable. Additionally, latent networks represent more than just observed adoption, but the flow of information and other factors that predict diffusion between units.

Latent networks allow for a variety of diffusion studies. Network descriptives can be used to identify the leader and follower states, as well as the most central actors in a diffusion network. The network can be the dependent variable, where scholars analyze the determinants of ties between units in a network. This approach allows for examining the competing roles of state characteristics and network forces such as triadic closure or in-degree in the same model. Alternatively, these networks can be utilized in event history analyses as a measure of the external diffusion influences on policy adoption. In much the same way that adoptions by contiguous neighbors or ideologically similar states increase the chance of adoption in a given state – whether in a monadic, dyadic, or network analysis — past adoptions by latent sources likewise predicts adoption (Boehmke et al. 2017). Once the network has been produced, scholars can proceed using the same types of network analysis that they would use for other types of diffusion networks, including ERGM's, QAP, and other model specifications where the latent network is used as either an independent or dependent variable to understand the structure of ties between states. Notably, in contrast to the dyadic EHA models discussed earlier, the latent network approach facilitates analysis of specific links since it leverages the spread of many policies to determine the presence of a diffusion tie between all pairs of states.

Political scientists have just begun to explore the ability to estimate latent networks for studying policy diffusion. An important next step will be using the estimated networks to help study the mechanisms of diffusion, including learning. While they require a considerable amount of data and optimization, they also offer some advantages. Most importantly, they offer a direct estimate of a tendency for diffusion to occur between all pairs of units, and possibly varying over time. Rather than relying on the information contained in the adoption of a single or small number of policies researchers can obtain direct estimates of the item of interest: policy ties between units across a large number. These ties can then be modeled with variables intended to more directly capture the mechanisms of diffusion.

8 Spatial Econometric Models

Spatial econometrics offers a potential middle ground between dyadic analysis of ties in the diffusion network and monadic analysis of the choices by individual units. It allows the researcher to capture a variety of dependencies between units, both endogenous and exogenous. It does so by requiring the researcher to specify a spatial dependency matrix indicating how each unit connects to all other units. This matrix is essentially a representation of a continuous-valued network. In fact, most existing diffusion studies already use a version of spatial econometrics via the inclusion of a lagged count of adoptions in contiguous units or related measures. The lagged count comes from the multiplication of the contiguity matrix for all units by a vector capturing the presence of the policy in every unit. Since the presence of the policy variable is usually lagged, this is just a case of spatial regression with an exogenous lag.

Spatial econometric methods offer much than this, however. They can accommodate any matrix of connections between units, whether geographic-based or not. This feature proves critical for studying diffusion mechanisms since many of them are not based on notions of geography: fashion may diffuse through friend networks or via social media ties, policies may diffuse via ideological or problem similarity, or conflict may spread through terrorist networks or ethnic groups that straddle international borders. One can include a sum or weighted average of any feature of other units as an exogenous influence by specifying the spatial weights matrix (Neumayer and Plümper 2016); more than one such feature can be included via multiple weights matrices.

Even more powerfully – and much less commonly utilized in the study of diffusion – spatial econometric models permit capturing endogenous dependencies via these spatial weights matrices. Rather than include the weighted value of an exogenous covariate, one can include the weighted value of the error terms or, even better, of the outcome variable. Conceptually, the latter means that spatial autoregressive (SAR) and spatio-temporal autoregressive (STAR) models can capture the simultaneous way in which the outcome in one unit explicitly depends on the outcomes in other units and within the same unit over time (Franzese Jr and Hays 2007). This makes them valuable for studying certain forms of diffusion, including those based on contemporaneous learning or strategic interactions.

An early application of STAR models to policy diffusion concerns the question of welfare benefits in the American states. Longstanding concerns about a race to the bottom in which states work to keep their benefits levels below those of nearby states to thereby avoid attracting too many potential recipients make this a strong candidate for spatial analysis. Rom, Peterson and Scheve Jr (1998) conduct just such an analysis with contiguity as their spatial weights matrix and find evidence of positive spatial correlation: an increase of $100 in benefits per person in a state leads to a contemporaneous increase of $27 in its neighbor (which is then compounded over time and across space). A useful comparison can be made with Volden (2002), which conducts an EHA model for a binary measure of benefit increases and accounts for changes in neighboring states via a time-lagged exogenous variable, reaching similar conclusions. In contrast to the these findings, Franzese Jr and Hays (2006) find evidence of free riding in European countries' support for labor market policy, with a negative spatial correlation that produces a drop in domestic spending when neighboring states increase their spending.

Spatial autocorrelation arises from a number of possible mechanisms (Franzese Jr and Hays

2007): interdependence, unmodeled heterogeneity (in the form of spatially correlated random shocks or omitted variables), and selection (e.g., via homophily in the connectivity matrix). Interdependence includes the common forms of diffusion such as learning, emulation, competition, and coercion. As with the other models we have discussed it is often difficult to determine which mechanism undergirds a finding of spatial correlation (though see Mitchell (2018) for a recent proposal for how to do so). As with the EHA model and its variants, scholars often turn to conditional interactive effects to identify learning. For example, Arel-Bundock and Parinandi (2018) study tax competition in the American states and find that corporate tax policy in states with better-resourced (and therefore more able to learn) legislatures more closely tracks policy in connected states.

9 Moving Forward

Each of the methodological approaches outlined in this chapter has its trade-offs for studying policy diffusion and innovation. There has been tremendous growth in the diffusion literature over the past thirty years, particularly after (Berry and Berry 1990) introduced EHA to political scientists and noted its strengths in incorporating internal and external characteristics for determining when events occur. This offered a way to test for the influence of diffusion mechanisms while accounting for unit-level differences in the probability of an event occurring. As the field has moved forward greater emphasis has been placed on understanding not just whether diffusion occurs, but in testing and identifying the role of specific mechanisms.

These demands have pushed researchers to develop and apply new empirical methods for studying diffusion. EHA was introduced nearly thirty years ago, but none of the other methods discussed here was used much, if it all, just over a decade ago. This new menu of estimators offers diffusion scholars a range of options for identifying and testing for these mechanisms. As we see it, they fall broadly into two groups. The first, including PEHA, dyadic EHA, and latent network estimation, provides opportunities to leverage information from large data sets to identify common and possibly small diffusion effects while allowing for heterogeneity across events. The second group, including ERGMs, RSiena, and spatial econometrics, provides estimators designed to explicitly capture endogenous interdependencies in diffusion networks.

On top of these differences in their orientation towards data and diffusion processes, each of these methods has its own strengths and weaknesses. The choice of which to use may therefore depend on the questions asked or the types of analyses needed. And as many of them are relatively recently applied to studying diffusion, work remains to be done to more fully determine their strengths and weaknesses and adapt them to diffusion applications to maximize the former while minimizing the latter. Ultimately the ability to identify the presence of a distinct mechanism of diffusion, such as learning as opposed to emulation, requires careful thinking about how theoretical concepts map into measures and which methods provide the most appropriate features for estimating them.

References

Arel-Bundock, Vincent and Srinivas Parinandi. 2018. "Conditional tax competition in American states." *Journal of Public Policy* 38(2):191–220.

Balla, Steven J. 2001. "Interstate professional associations and the diffusion of policy innovations." *American Politics Research* 29(3):221–245.

Baybeck, Brady, William D. Berry and David A. Siegel. 2011. "A Strategic Theory of Policy Diffusion Via Intergovernmental Competition." *The Journal of Politics* 73(01):232–247.

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

Berry, Frances Stokes and William D Berry. 2007. Innovation and Diffusion Models in Policy Research. In *Theories of the Policy Process*, ed. Paul A Sabatier. Second ed. Westview pp. 223–260.

Boehmke, Frederick J. 2009*a*. "Approaches to Modeling the Adoption and Modification of Policies with Multiple Components." *State Politics and Policy Quarterly* 9(2):229–252.

Boehmke, Frederick J. 2009*b*. "Policy emulation or policy convergence? Potential ambiguities in the dyadic event history approach to state policy emulation." *The Journal of Politics* 71(3):1125–1140.

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

Boehmke, Frederick J., Mark Brockway, Bruce Desmarais, Jeffrey J. Harden, Scott LaCombe, Fridolin Linder and Hanna Wallach. 2018. "State Policy Innovation and Diffusion (SPID) Database v1.0.".

Boehmke, Frederick J and Paul Skinner. 2012. "State Policy Innovativeness Revisited." *State Politics and Policy Quarterly* 12(3):303–329.

Boehmke, Frederick J and Richard Witmer. 2004. "Disentangling diffusion: The effects of social learning and economic competition on state policy innovation and expansion." *Political Research Quarterly* 57(1):39–51.

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

Boushey, Graeme. 2016. "Targeted for Diffusion? How the Use and Acceptance of Stereotypes Shape the Diffusion of Criminal Justice Policy Innovations in the American States." *American Political Science Review* 110(01):198–214.

Box-Steffensmeier, Janet M and Bradford S Jones. 2004. *Event History Modeling: A Guide for Social Scientists*. Cambridge Univ Press.

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.

Callander, Steven. 2011. "Searching for good policies." *American Political Science Review*

105(04):643–662.

Callander, Steven and Bård Harstad. 2015. "Experimentation in federal systems." *The Quarterly Journal of Economics* 130(2):951–1002.

Cao, Xun. 2010. "Networks as channels of policy diffusion: Explaining worldwide changes in capital taxation, 1998–2006." *International Studies Quarterly* 54(3):823–854.

Chyzh, Olga. 2016. "Dangerous liaisons: An endogenous model of international trade and human rights." *Journal of Peace Research* 53(3):409–423.

Chyzh, Olga V and Mark S Kaiser. (n.d.). "A Local Structure Graph Model: Modeling Formation of Network Edges as a Function of Other Edges." *Political Analysis* pp. 1–18.

Coleman, William D and Anthony Perl. 1999. "Internationalized policy environments and policy network analysis." *Political studies* 47(4):691–709.

Cranmer, Skyler J and Bruce A Desmarais. 2010. "Inferential network analysis with exponential random graph models." *Political Analysis* 19(1):66–86.

Cranmer, Skyler J, Bruce A Desmarais and Elizabeth J Menninga. 2012. "Complex dependencies in the alliance network." *Conflict Management and Peace Science* 29(3):279–313.

Danilovic, Vesna and Joe Clare. 2007. "The Kantian Liberal Peace (Revisited)." *American Journal of Political Science* 51(2):397–414.

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(02):392–406.

Elkins, Zachary, Andrew T Guzman and Beth A Simmons. 2006. "Competing for capital: The diffusion of bilateral investment treaties, 1960–2000." *International organization* 60(4):811–846.

Erikson, Robert S, Pablo M Pinto and Kelly T Rader. 2014. "Dyadic analysis in international relations: A cautionary tale." *Political Analysis* 22(4):457–463.

Esarey, Justin, Bumba Mukherjee and Will H Moore. 2008. "Strategic interaction and interstate crises: A Bayesian quantal response estimator for incomplete information games." *Political Analysis* 16(3):250–273.

Franzese Jr, Robert J and Jude C Hays. 2006. "Strategic interaction among EU governments in active labor market policy-making: Subsidiarity and policy coordination under the European employment strategy." *European Union Politics* 7(2):167–189.

Franzese Jr, Robert J and Jude C Hays. 2007. "Spatial econometric models of cross-sectional interdependence in political science panel and time-series-cross-section data." *Political Analysis* 15(2):140–164.

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. 2010. "Who learns from what in policy diffusion processes?" *American Journal of Political Science* 54(3):650–666.

Gilardi, Fabrizio. 2012. "Transnational diffusion: Norms, ideas, and policies." *Handbook of international relations* 2:453–477.

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

Gilardi, Fabrizio and Katharina Füglister. 2008. "Empirical modeling of policy diffusion in federal states: the dyadic approach." *Swiss Political Science Review* 14(3):413–450.

Gleditsch, Kristian Skrede. 2009. *All international politics is local: The diffusion of conflict, integration, and democratization*. University of Michigan Press.

Gomez-Rodriguez, Manuel, Jure Leskovec and Andreas Krause. 2010. Inferring Networks of Diffusion and Influence. In *The 16th ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD)*.

Graham, Erin R, Charles R Shipan and Craig Volden. 2013. "The diffusion of policy diffusion research in political science." *British Journal of Political Science* 43(3):673–701.

Gray, Virgina. 1973. "Innovation in the States: A Diffusion Study." *The American Political Science Review* 67(4):1174–1185.

Hafner-Burton, Emilie M, Miles Kahler and Alexander H Montgomery. 2009. "Network analysis for international relations." *International Organization* 63(3):559–592.

Henisz, Witold J, Bennet A Zelner and Mauro F Guillén. 2005. "The worldwide diffusion of market-oriented infrastructure reform, 1977–1999." *American Sociological Review* 70(6):871–897.

Hinkle, Rachael K. 2015. "Into the words: Using statutory text to explore the impact of federal courts on state policy diffusion." *American Journal of Political Science* 59(4):1002–1021.

Jensen, Nathan M and René Lindstädt. 2012. "Leaning right and learning from the left: Diffusion of corporate tax policy across borders." *Comparative Political Studies* 45(3):283–311.

Jones, Bradford S and Regina P Branton. 2005. "Beyond logit and probit: Cox duration models of single, repeating, and competing events for state policy adoption." *State Politics & Policy Quarterly* 5(4):420–443.

Karch, Andrew. 2007. "Emerging Issues and Future Directions in State Policy Diffusion Research." *State Politics and Policy Quarterly* 7(1):54.

Klijn, Erik Hans. 1996. "Analyzing and managing policy processes in complex networks: A theoretical examination of the concept policy network and its problems." *Administration & Society* 28(1):90–119.

Koppenjan, Joop and Erik-Hans Klijn. 2004. *Managing uncertainties in networks: Public private controversies*. Routledge.

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

Kreitzer, Rebecca J. and Frederick J. Boehmke. 2016. "Modeling Heterogeneity in Pooled Event History Analysis." *State Politics and Policy Quarterly* 16(1):121–141.

Lee, Chang Kil and David Strang. 2006. "The international diffusion of public-sector downsizing: Network emulation and theory-driven learning." *International organization* 60(4):883–909.

Leeds, Brett Ashley. 2003. "Do alliances deter aggression? The influence of military alliances on the initiation of militarized interstate disputes." *American Journal of Political Science* 47(3):427–439.

Lektzian, David and Mark Souva. 2001. "Institutions and international cooperation: An event history analysis of the effects of economic sanctions." *Journal of Conflict Resolution* 45(1):61–79.

Lubell, Mark, John Scholz, Ramiro Berardo and Garry Robins. 2012. "Testing policy theory with statistical models of networks." *Policy Studies Journal* 40(3):351–374.

Maggetti, Martino and Fabrizio Gilardi. 2016. "Problems (and solutions) in the measurement of policy diffusion mechanisms." *Journal of Public Policy* 36(1):87–107.

Makse, Todd and Craig Volden. 2011. "The role of policy attributes in the diffusion of innovations." *The Journal of Politics* 73(01):108–124.

Maoz, Zeev and Bruce Russett. 1993*a*. "Normative and structural causes of democratic peace, 1946–1986." *American Political Science Review* 87(3):624–638.

Maoz, Zeev and Bruce Russett. 1993*b*. "Normative and Structural Causes of Democratic Peace, 1946-1986." *The American Political Science Review* 87(3):624–638.

Meseguer, Covadonga and Fabrizio Gilardi. 2009. "What is new in the study of policy diffusion?" *Review of International Political Economy* 16(3):527–543.

Mintrom, Michael. 1997. "Policy Entrepreneurs and the Diffusion of Innovation." *American Journal of Political Science* 41(3):738–770.

Mitchell, Joshua L. 2018. "Does Policy Diffusion Need Space? Spatializing the Dynamics of Policy Diffusion." *Policy Studies Journal* 46(2):424–451.

Mooney, Christopher Z. and Mei-Hsien Lee. 1995. "Legislative Morality in the American States: The Case of Pre-Roe Abortion Regulation Reform." *American Journal of Political Science* 39(3):599–627.

Neumayer, Eric and Thomas Plümper. 2016. "W." *Political Science Research and Methods* 4(1):175193.

Nicholson-Crotty, Sean. 2009. "The Politics of Diffusion: Public Policy in the American States." *The Journal of Politics* 71(01):192–205.

Peterson, Paul E. and Mark C. Rom. 1990. *Welfare Magnets: A New Case for a National Standard*. Brookings Institute Press.

Robins, Garry, Jenny M Lewis and Peng Wang. 2012. "Statistical network analysis for analyzing policy networks." *Policy Studies Journal* 40(3):375–401.

Rom, Mark Carl, Paul E Peterson and Kenneth F Scheve Jr. 1998. "Interstate competition and welfare policy." *Publius: The Journal of Federalism* 28(3):17–37.

Shipan, Charles R. and Craig Volden. 2006. "Bottom-Up Federalism: The Diffusion of Antismoking Policies from U.S. Cities to States." *American Journal of Political Science* 50(4):825–843.

Shipan, Charles R and Craig Volden. 2008. "The Mechanisms of Policy Diffusion." *American Journal of Political Science* 52(4):840–857.

Signorino, Curtis S. 2003. "Structure and uncertainty in discrete choice models." *Political Analysis* 11(4):316–344.

Simmons, Beth A, Frank Dobbin and Geoffrey Garrett. 2006. "Introduction: The international diffusion of liberalism." *International Organization* 60(04):781–810.

Simmons, Beth A and Zachary Elkins. 2004. "The globalization of liberalization: Policy diffusion in the international political economy." *American political science review* 98(1):171–189.

Smith, Daniel A and Dustin Fridkin. 2008. "Delegating direct democracy: Interparty legislative competition and the adoption of the initiative in the American states." *American Political Science Review* 102(3):333–350.

Starr, Harvey. 1991. "Democratic dominoes: Diffusion approaches to the spread of democracy in the international system." *Journal of Conflict Resolution* 35(2):356–381.

Steglich, Christian, Tom AB Snijders and Michael Pearson. 2010. "Dynamic Networks and Behavior: Separating Selection from Influence." *Sociological methodology* 40(1):329–393.

Thatcher, Mark. 1998. "The development of policy network analyses: From modest origins to overarching frameworks." *Journal of theoretical politics* 10(4):389–416.

Thurner, Paul W and Martin Binder. 2009. "European Union transgovernmental networks: The emergence of a new political space beyond the nation-state?" *European Journal of Political Research* 48(1):80–106.

Valente, Thomas W. 1995. "Network models of the diffusion of innovations.".

Volden, Craig. 2002. "The Politics of Competitive Federalism: A Race to the Bottom in Welfare Benefits?" *American Journal of Political Science* 46(2):352–363.

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(03):319–332.

Walker, Jack L. 1969. "The Diffusion of Innovations Among the American States." *American Political Science Review* 63(3):880–899.

Weyland, Kurt. 2005. "Theories of policy diffusion lessons from Latin American pension reform." *World politics* 57(2):262–295.

Whang, Taehee, Elena V McLean and Douglas W Kuberski. 2013. "Coercion, information, and the success of sanction threats." *American Journal of Political Science* 57(1):65–81.

Zhukov, Yuri M and Brandon M Stewart. 2013. "Choosing your neighbors: Networks of diffusion in international relations." *International Studies Quarterly* 57(2):271–287.