The Seeds of Policy Change: Leveraging Diffusion to Disseminate Policy Innovations

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Abstract We conduct a series of simulations to compare how various strategies for seeding a policy in the American states affect the rate at which that policy spreads. Using empirically derived parameters of the policy diffusion process, we simulate the diffusion of a hypothetical policy after seeding the policy in just a handful of states. We compare these strategies to seeding the ten states the RWJF monitored during the states' implementation of the Affordable Care Act of 2010. We attempt to mimic the choices that policy advocates make when deciding which states to target with their resources. Our results indicate that focusing on innovative states, that is, those that tend to adopt new policies faster, offers a valuable boost in the speed of diffusion. Even better, though, is a strategy that targets policy leaders.

Keywords policy diffusion, policy advocacy, networks

Introduction

Should policy advocates spread their efforts equally across governing units, or focus on a few key jurisdictions? Faced with limited resources, advocates typically choose to pursue their case in a limited number of forums. Yet, they ultimately wish to influence policy as broadly as possible by seeding a cascade of policy adoption across jurisdictions beyond the

The authors would like to thank participants at the 2015 Robert Wood Johnson Foundation Conference on Diffusion of ACA Policies Across the American States and comments received from the anonymous referees. This research was supported in part by National Science Foundation Grants SES-1558661, SES-1619644, SES-1637089, CISE-1320219. Any opinions, findings, and conclusions or recommendations are those of the authors and do not necessarily reflect those of the sponsor.

Journal of Health Politics, Policy and Law, Vol. 42, No. 2, April 2017
DOI 10.1215/03616878-3766728

initial advocacy targets. For example, if the Robert Wood Johnson Foundation discovered an effective means to increase states' implementation of the ACA, it could target a small number of key states to maximize its implementation efforts. Wishing to understand the best way to target their resources and maximize return on their budget while maximizing policy impact, policy advocates could use this information to guide future campaigns.

Researchers have provided a body of knowledge on which to base these calculations through an extensive literature that seeks to explain the diffusion of policy innovations across countries, states, or cities. Typically, this research examines the timing of adoption for a single innovation as it spreads across a set of jurisdictions. For example, studies analyze why some states adopt antismoking bans much sooner than other states (Shipan and Volden 2006; Pacheco 2012). This literature has led to an increasingly refined theoretical understanding of the mechanisms that drive policy change, an empirical understanding of states' features that correlate with adoption, and the accumulation of substantively motivated diffusion studies of a wide variety of individual policies. While their findings may hold lessons for those supporting a new policy innovation, they do not necessarily offer immediate insight into a crucial question facing advocates: How can we best target our limited resources to maximize the chance that states adopt our policy?

And the answer matters, since advocates face this situation whether they explicitly confront it or not. Consider some examples. Advocates for bans on same-sex marriage found success in two states before taking a more comprehensive national approach targeting eleven states for ballot measures to adopt constitutional bans in 2004. Four states have approved recreational use of medical marijuana since 2012, with national groups such as the Marijuana Policy Project, NORML, and the Drug Policy Alliance playing an important role. The Marijuana Policy Project says it was targeting five more states for adoption in 2016 (Gurciullo, Mawdsley, and Campbell 2015). Similarly, after a successful campaign to ban affirmative action in California in 1996, Ward Connerly and his group followed up with attempts to do the same in Colorado, Florida, Washington, Michigan, and other states (Boehmke 2005: 39). Finally, the Robert Wood Johnson Foundation (RWJF) wished to support the implementation of the Patient Protection and Affordable Care Act (ACA) of 2010. Its program connects researchers and policy makers to monitor and track the implementation and effects of the ACA (Corlette, Lucia, and Keith 2012).

The academic literature contains important information about how to shape the course of policy diffusion. We seek to relate this evidence to the

question posed above by identifying and evaluating strategies for policy advocates. Specifically, we draw from the policy diffusion literature to extract information about which states may serve as the most effective seeds for policy change. By seeds, we mean the states on which advocates might best focus their first efforts. Given the consistent finding in the literature that adoption in one state directly influences adoption in other states, the identity of the initial policy seeds will shape the future spread of the policy across all states. Advocates can leverage these flows to identify the features that make an individual state or an ensemble of states the most effective target for their efforts.

We draw from extant findings in the policy diffusion literature on the multiple pathways through which policies spread between states. Combining these pathways with various internal features of states known to influence policy innovation allows us to identify a parsimonious set of features that explains the timing of states' adoptions of a new policy. We then estimate the parameters of an event history model using data on the diffusion of a large number of policies and use these results to explore how different combinations of seeds influence the speed of policy diffusion. We identify four strategies for choosing seed states and evaluate their effectiveness and compare them to the states with whom the RWJF collaborated.

Our results indicate that the choice of seeding strategy greatly affects the rate of diffusion. Picking the states with the most contiguous neighbors to maximize spillover effects offers little to no advantage over just picking states randomly. Choosing policy leaders, though, reduces the time to adoption by other states by up to 40 percent. The top policy leaders—identified using Desmarais, Harden, and Boehmke's (2015) measure of states most copied by other states—have a widespread and quick influence on other states, which facilitates quick diffusion. Interestingly, if we treat the states supported by the RWJF during implementation of the ACA as seeds, it performs quite well, losing out only to the strategies that include the top policy leaders.

Policy Innovations and the ACA

The ACA requires significant state effort, and states vary in the way in which they approach implementing the ACA's provisions. Passage of the ACA created an occasion to study the effects of the ACA on individuals' health. The new law also produced an opportunity to analyze the way in which states adopt the ACA's policies. Seeing a chance to pair policy practitioners and academics, the RWJF sponsored a program to examine the implementation and effects of the ACA as it spread

across the fifty states (Corlette, Lucia, and Keith 2012). The program, which began in May 2011, monitors and tracks ACA policies in ten states: Alabama, Colorado, Maryland, Michigan, Minnesota, New Mexico, New York, Oregon, Rhode Island, and Virginia.[1]

States play a prominent role in implementing the ACA. For example, the health insurance exchanges, only one aspect of the ACA, can be effected in a number of ways. States may elect to run their own exchange, they can collaborate with the federal government, or states can surrender the entire exchange to the federal government (Jones, Bradley, and Oberlander 2014). How a state goes about selecting its exchange is an area ripe for exploration. Potential barriers to enacting these reforms are also important considerations.

The ACA's provisions, although distinct, share one important commonality: states must adopt and implement the policies. We are interested in discovering what unites the ACA's policies individually, as well as policies generally, to answer the question that motivates many of us in this issue: How can we maximize the rate of policy adoption? We explore the degree to which the ensemble of starting states selected—the seeds—affects the number of eventual adoptions.

Sources of Diffusion between the American States

The study of the diffusion of innovations has been traced back to Rogers's (1962) work on the spread of hybrid corn seed, but was recast to public policies shortly thereafter with Walker's (1969) work on state policy innovativeness. Walker argued that states adopt policies to address their own internal public policy issues, but also in response to what states see happening among their peers. Legislators must make policy across a dizzying array of domains with countless alternatives for addressing each social or economic problem. The policies adopted in other states serve as shortcuts and templates in a potentially intractable information environment. A state's internal characteristics and resources for learning about new policies, as well as the actions of other states in their peer network, shape the likelihood of policy innovation.

While Walker laid the groundwork for the study of the diffusion of policy innovations, the field only really took off two decades later when Berry and Berry (1990) introduced the method of event history analysis (EHA) as a way to capture the influences of both internal and external

1. We subsequently learned that Illinois was later added as an eleventh state (Pacheco and Maltby, 2017), but our simulations use the original ten states from Corlette, Lucia, and Keith (2012).

influences on policy adoptions. EHA allows researchers to study the choice of whether to adopt the policy on a year-to-year basis while properly capturing changes in state characteristics each year. EHA also captures peer effects by incorporating information about which states have already adopted. Scholars have applied this technique in hundreds of studies to understand the spread of a wide variety of policies, including health policies such as the Children's Health Insurance Program (Volden 2006), antismoking policies (Pacheco 2012), pain management policies (Imhof and Kaskie 2008), and the ACA itself (Pacheco and Maltby 2017).

While EHA policy diffusion studies have developed and tested a wide variety of theoretical mechanisms influencing policy adoption, as well as examined the various empirical determinants of adoption for different policies, our interest lies in identifying common factors on which to build our simulation. To that end, we focus on the common distinction between internal and external determinants. For the former, we wish to identify a parsimonious set of predictors that work across a wide range of policies. This sets the baseline on which we will examine the influence of external factors that play the most interesting part in our simulation of the success of various strategies for choosing seed states.

In identifying general internal determinants of policy innovation, researchers have drawn on Walker's (1969) notion of "slack resources." These facilitate the time and ability it takes for states to identify, study, and possibly implement new policies. States with greater slack resources innovate more quickly while states deficient in them tend to lag behind, waiting to identify what works in the more innovative states. Slack resources include access to professional staff and funding sources that allow legislators the time to identify and research new policies (e.g., Shipan and Volden 2006). They also include broader characteristics of the state such as the size and diversity of its population, which tend to increase the scope of its potential public policy needs and therefore motivate innovations.

More interesting for our question of how to seed states, though, is the role of external determinants. Meaningful diffusion, rather than sequentially unrelated adoption, occurs as states react to what other states have enacted (Simmons, Dobbin, and Garrett 2006). The presence of diffusion generally means that the identity of who adopts matters since it shapes which states will follow the initial adopters.

A look to external factors, and specifically to the interstate networks through which policies diffuse, aligns our current research question with the rapidly growing body of work on maximizing marketing influence in social networks (e.g., Hartline, Mirrokni, and Sundararajan 2008; Chen, Wang, and Yang 2009; Chen et al. 2011; Van Eck, Jager, and Leeflang

2011; Bhagat, Goyal, and Lakshmanan 2012). These studies follow a similar design and research question to ours. The central question is, given a network structure connecting consumers and a set of assumptions regarding the determinants of product adoption and spread across the network, what is the set of first adopters on which the marketer should focus in order to maximize long-run adoption, subject to a marketing budget constraint? We can draw on insights from the literature on policy diffusion to formulate a model of individual states' adoption propensities, as well as the dynamics of diffusion across the states.

Theories of diffusion in the American states typically rely on one of three mechanisms: emulation, learning, and competition (Gilardi 2016). Emulation occurs when states somewhat blindly follow other states' lead and adopt a policy because others have done so merely to avoid being left behind. Learning happens when states see the benefit of a policy for other states and realize that they, too, could benefit (Volden 2006; Volden, Ting, and Carpenter 2008; Gilardi 2010). Competition occurs when the policy creates spillover effects, such as with tax rates or environmental protection legislation, that lead to positive or negative feedback cycles (Boehmke and Witmer 2004; Berry and Baybeck 2005).

While none of the mechanisms points directly to a specific set of peer states to consider, scholars have focused on geographic contiguity. This captures many important forms of economic competition since residents in one state can evade or acquire taxes or goods by driving across a nearby border (Berry and Berry 1990; Berry and Baybeck 2005). Contiguous states also do a reasonable job of capturing states' peer networks, which may be regional in nature given the tendency for neighboring states to be similar. Thus, the number or proportion of neighboring states sharing a border often predicts policy adoption in other states (Berry and Berry 1990; Mooney 2001).

Limiting diffusion to occur only between contiguous neighbors rules out the vast majority of possible pathways. Yet, considering all possible pairs of states also creates challenges. Scholars have tackled this problem in two different ways. Some have modeled the path of diffusion between all pairs of states within a single policy area using observed variables (Volden 2006). Thus, if states adopt a policy shortly after similar states have adopted it, this suggests learning and emulation as possible mechanisms. Others have taken a less structured approach by identifying patterns of the timing of adoption across more than one hundred policies (Desmarais, Harden, and Boehmke 2015). If state A repeatedly adopts policies just a few years after state B, and is less likely to adopt a policy that state B has not previously adopted, then state A likely views state B as one of its peers.

Methods for Simulating Policy Diffusion

In the following two subsections, we outline the steps that we took to identify the influence that the identity of initial adopters has on policy diffusion. In short, we identified the parameters of a "typical" policy diffusion episode by examining the pattern across nearly one hundred different policies. We then used these parameters to simulate the diffusion of a new policy, varying the characteristics of the first adopters to see how subsequent diffusion pattern varies. Those interested in the results can skip straight to the next section, "Simulation Results."

Estimating the Parameters of the Diffusion Model

In this subsection we draw from the extant literature on policy diffusion to construct an EHA model to provide reasonable parameter estimates for a policy diffusion episode. Our task deviates from the standard approach in a couple of ways that inform our model. These both follow from our goal of identifying "typical" parameter values for our simulation that relate internal and external characteristics to the probability of adoption; we do not want our simulation to be tailored too specifically to the parameters of an EHA for a single policy.

First, we utilize a large number of polices that diffused across the American states in order to identify "typical" parameter values since they will form the basis for our simulation. By estimating the influence of internal and external factors across many policies, we avoid having our results be sensitive to the parameters from a single policy. To obtain these estimates we apply a relatively new technique to jointly estimate a single event history model for multiple policies. Known as Pooled Event History Analysis (PEHA), this approach stacks the data from multiple EHA models for a collection of policies and then estimates them in a single model (Boehmke 2009; Kreitzer and Boehmke 2016). This framework permits a wide variety of flexibility when viewed as a multilevel, or mixed, model with the policies or states viewed as the levels.

Our collection of policies comes from Boehmke and Skinner's (2012b) database of 137 policies that diffused across the American states (see also Boehmke and Skinner 2012a). The included policies draw from a variety of policy areas, such as health, corrections, taxes, welfare, etc. The policies began diffusing as early as 1912 and as late as 2007, with the last observed adoption occurring in 2009. In order to include all fifty states and to produce results more relevant for the current era, we only consider policies that

began diffusing in or after 1960, which results in eighty-seven policies. While we include all policies to obtain the most general estimates, our results do not change much if we use only the twenty-one remaining health policies, suggesting that health policy diffusion does not differ much from the spread of other policies.

Our second deviation involves estimating a parsimonious model of policy diffusion. In a typical single policy EHA, scholars will include the kinds of internal and external influences we described above, but they will also add a selection of variables to assist in explaining adoption of the specific policy. Because we use nearly one hundred policies, collecting such information for all of them would prove difficult and, just as importantly, would compromise the generalizability of our simulation. We therefore include a handful of independent variables commonly used in the policy diffusion literature to explain innovation. Motivated by Walker's (1969) notion of slack resources, we include total state population and real personal income from the Bureau of Labor Statistics, and a measure of state legislative professionalism (Squire 2007). Further, we account for citizen ideology with a continuous measure of citizen opinion liberalism (Berry et al. 1998) and partisan control of state government (Klarner 2003), via separate indicators of unified Democratic and Republican government control. Finally, to control for other differences across the states, we include fixed effects for each state.

To capture external diffusion forces, we utilize two different networks of interdependence. First, we start with the ubiquitous contiguity network that has been the focal point of most of the work on interstate policy diffusion (e.g., Mooney 2001). A variety of studies finds that policies diffuse between neighboring states due to economic competition (Berry and Berry 1990; Boehmke and Witmer 2004; Berry and Baybeck 2005) or learning (Mooney 2001; Volden 2006; Volden, Ting, and Carpenter 2008; Pacheco 2012). We therefore include a count of the number of states that share a land border and that have adopted the policy before the current year.

Second, we draw on Desmarais, Harden, and Boehmke's (2015) estimates of the latent policy diffusion network. This study uses recent developments in latent network inference (Gomez-Rodriguez, Leskovec, and Krause 2010), combined with Boehmke and Skinner's (2012a) data on policy adoptions to estimate a dynamic, latent diffusion network from 1960 to 2009. Unlike contiguity networks, this approach allows for connections between all pairs of states and uses the data to identify which states influence a state's decision to adopt a new policy. The procedure uses three quantities to determine whether there is a policy diffusion tie from state

A to state B. First, how frequently does state B adopt a policy shortly after state A? Second, how frequently does state B adopt a policy that state A has not previously adopted? Third, how many other states regularly adopt in the interim between the adoptions of states A and B that could be used to explain the adoptions of state B? If these quantities are, respectively, high, low, and low, then state A is likely to be deemed a *source* for state B—a state emulated by state B. Analysis of these source states shows that they differ greatly from the network of contiguous states, reflect patterns of leadership and homophily, and that controlling for the count of adoptions in source states in an event history analysis explains adoption just as well as adoptions in contiguous states (Desmarais, Harden, and Boehmke 2015).

We make one modification to the previous calculation of this variable. The original study accounts for the role of this latent network by including the count of a state's sources that have adopted each policy prior to the current year (Desmarais, Harden, and Boehmke 2015). The latent network estimation strategy, however, assumes that the effect of adoptions by source states decays over time. Specifically, they include an exponential decay to capture the probability that a prior adoption by state A influences adoption today in state B if the latter counts the former among its sources. Using their identified value of 0.5 for the decay parameter, which constitutes an average time of two years for a policy to diffuse, we calculate the contribution in the current year from state i's source states in year t, $S_i(t)$, based on the source states' years of adoption, t_j, as

$$Sources_{it} = \sum_{j \in S_i(t)} 0.5 \exp\left(\frac{-(t-t_j)}{0.5}\right). \tag{1}$$

This means, for example, that a source state that adopts in the prior year has seven times as great an effect as a source state that adopted two years ago. The effect therefore decays quite quickly and effectively vanishes just four years after adoption.

With these variables in place, we now move to estimating our PEHA of state policy innovations in our sample of eighty-seven policies. As described above, we stack the data for each of the separate policies using the same value for each of the six variables measuring internal characteristics in the corresponding year. We include policies starting in the first year in which they begin to diffuse and then treat any remaining states that have yet to adopt as right censored in the last year of an observed adoption. Our dependent variable then marks whether a state adopts a policy in a given year and it excludes states once they have adopted the policy. For each

Table 1 Pooled Logit EHA of Policy Diffusion, 1960–2009

	Coefficient	Standard Error
Lagged sources adoptions	8.5267*	0.4382
Lagged neighbors adoptions	0.3928*	0.0223
Personal income	0.5738*	0.0748
Total population	0.0905*	0.0283
Legislative professionalism	–1.0890	0.6872
State citizen ideology	0.0098*	0.0035
Unified Republican control	–0.0204	0.0760
Unified Democratic control	0.0629	0.0664
Time	–0.1354*	0.0176
Time squared	0.0072*	0.0014
Time cubed	–0.0001*	0.0000
Constant	–5.4113*	0.2779

Notes: $N = 44{,}457$. Fixed effects for states included but not reported. Standard errors clustered on each combination of state and policy.

* Indicates that the associated coefficient achieves significance at the .01 level.

policy, we calculate our two external diffusion measures based on lagged adoptions by neighbors or sources. To account for within policy time trends, we include a cubic polynomial of time, measured since the year of first adoption for each policy (Carter and Signorino 2010). Finally, we include state fixed effects to capture any remaining, constant variation across states in their propensity to adopt policies quickly or slowly.[2]

Table1 reports the results of our model. Overall, our parsimonious model of policy diffusion recovers a variety of statistically and substantively notable effects. With the exception of the legislative professionalism and two unified government control variables, all of the reported coefficients are statistically different from zero at conventional levels. Larger, wealthier states adopt faster, as the slack resources interpretation would suggest. States that are more liberal also tend to adopt sooner, though this result likely depends to some extent on the mix of policies that we use. We also find strong evidence of diffusion between states, with the lagged neighbors' variable producing its typical positive and statistically significant effect. Further, the decayed sources variable also produces a positive and statistically significant effect. Note that the magnitude exceeds that for the

2. Note that we exclude fixed (or random) effects for each policy. Since we wish to obtain estimates for a generic policy, including such effects would then require us to pick one specific effect (or average across multiple specific effects) to use for our simulation. By omitting these terms, we effectively recover the average across policies.

coefficient on neighbors' adoptions since the decayed variable takes on much smaller values; substantive effects calculations show that a change from standard deviation below the mean to one above it increases the probability of adoption by about 0.075 for contiguous neighbors and just below 0.05 for decayed sources.

Simulating Diffusion

To simulate the diffusion of new policy innovation across the American states, we start with the estimates in table 1. We treat these estimates as the parameters of a logit EHA model governing the spread of a hypothetical policy across the American states.[3] We use them to generate adoption data in year t for state i according to the following formula:

$$y_{it}^{*} = X_{it}\beta + u_{it}, \tag{2}$$

where X_{it} represents the value of the observed covariates in state i at time t used in our EHA model in table 1, β represents the estimated coefficients reported in that table, and u_{it} follows a logistic distribution.[4]

We start our policy diffusion process in 1989 and let it run through 2009 since by then all fifty states had usually adopted. When y_{it}^{*} exceeds zero we code that state as adopting, $y_{it} = 1$, and treat that adoption as fixed in all future time periods. We assume no adoptions in 1989 other than those we explicitly seed and then generate data for 1990 according to Equation 2. We do this one year at a time in order to update our lagged diffusion variables each year. For each year, we record the number of states that adopt the policy that year.[5]

We repeat this process 1,000 times and then calculate the average number of states that have adopted by each year as well as corresponding confidence intervals.[6] At its baseline, of course, this process will merely

3. We recognize, of course, that our sample limits the generalizability of our estimates to the entire universe of potential policies, especially since our sample excludes policies that do not diffuse widely.

4. Alternatively, we could have simulated values of the independent variables into the future to start our simulation in some hypothetical future world, but using the recent past seemed like the most realistic approach and introduced less randomness into our model since we would have needed to generate a stream of hypothetical values of state population, income, the latent sources network, etc. (Hanmer and Ozan Kalkan 2013).

5. Note that we set our time variables to start with t=0 in 1989 since that marks the first year of our hypothetical policy's diffusion process.

6. Note that, due to its nonpartisan legislature, Nebraska has no data for the unified government measures and therefore gets omitted from our EHA model in table 1. In order to avoid its absence from interfering with our diffusion simulation, we set these two variables to zero for the simulation procedure.

summarize the information in our empirical model. By selectively seeding an initial set of adopters, however, we can begin to discern how different advocacy strategies influence the speed with which a policy spreads through the system.[7]

Strategies for Choosing Seed States

In this subsection, we describe strategies for choosing ensembles of policy seeds. We base these strategies off relatively simple heuristics since complex interdependencies in the system make it difficult to identify the optimal set of seeds ex ante. For example, do we seed innovative states or assume they will adopt quickly on their own and seed less innovative states? Do we seed states connected to lots of other states to maximize spread up front or focus on states that are more isolated since they are harder to reach through diffusion networks? We focus on identifying seeding strategies through heuristics based on theoretical concepts such as policy leadership and connectedness, though we discuss the results of a guided brute force approach in the discussion section. To draw a connection to the diffusion of the ACA, we also consider the ten states chosen for the RWJF's ACA monitoring program and proceed as if the RWJF had treated them as seed states rather than merely supporting their adoption.

We start with the two variables in our analysis that capture external influences. Previous adoptions by neighbors and decayed sources both have a clear, positive effect on adoption in connected states in our PEHA estimates, indicating that increasing the number of sources or neighbors that have adopted a policy increases the probability that a state will follow suit. Thus, we can choose seed states to influence the greatest number of other states as sources or neighbors.

Our first approach to identifying an ensemble of seed states therefore considers the states that serve as sources for the greatest number of other states. If we wish to spread a policy as quickly as possible, then it makes sense to target the most widely followed states first. For example, according to Desmarais, Harden, and Boehmke (2015), California serves as a source for anywhere between three and forty-one states between 1960 and 2009. Since 1990, at least nineteen states view it as a source in every year. New York serves as a source for an average of 24.6 states (compared to 19.4 for

7. Given its assumptions (which match those of the standard EHA model), our model implies that every state will eventually adopt the policy, so we focus on the cumulative proportion adopting each year rather than on the total number of adopters since that will ultimately always be fifty.

CA) per year between 1960 and 2009, though it has dropped from over thirty prior to 1990 to under ten since the mid-1990s. Since the first adoption by a source state increases the probability of adoption by a follower state by 3.9 percent according to our estimates, getting just one of the more frequently identified source states to adopt would have a widespread effect on the course of adoption by other states. At the other extreme, Oklahoma serves as a source for just 1.4 states per year over this five-decade period. Thus, the one-period effect of seeding a policy in New York exceeds that in Oklahoma by a factor of eighteen.

Our second approach follows the same logic by targeting states with the most contiguous neighbors. Consider the difference between seeding a policy in Maine with one neighbor (to say nothing of Alaska or Hawaii), or states with two neighbors such as Florida or Washington, and seeding it in states such as Missouri or Tennessee with eight neighbors, or Kentucky or Colorado with seven neighbors. While not as dramatic a difference as we see in the most and least frequent source states, choosing states with the most neighbors still influences three to four times as many states as choosing more geographically isolated states. And, according to our estimates, the first adoption by a neighboring state increases the probability of adoption by a follower state by 2 percent.

Our third approach moves beyond connectivity to identify innovative states based on their prior history of policy adoptions. Here we utilize Boehmke and Skinner's (2012a) measure of policy innovativeness. If policy innovativeness means adopting policies early on, then this list will identify the states that do so most often. While this third strategy does not focus on interstate diffusion specifically, it seems an intuitive and attractive approach: by getting widely viewed policy leaders to adopt early on, other states may likely follow.

Our final simulation strategy comes directly from the case of the ACA. In seeking to help states develop programs within the context of the ACA, the RWJF partnered with ten states in its ACA monitoring program: Alabama, Colorado, Maryland, Michigan, Minnesota, New Mexico, New York, Oregon, Rhode Island, and Virginia. We evaluate the hypothetical effect of seeding a policy in these states to see how the RWJF's choice fares when contrasted to the three above. The RWJF's states did not necessarily adopt all of the ACA's provisions, but rather the RWJF supported these states' efforts to adopt the ACA.

In order to provide a baseline against which to compare our four seed strategies, we take two approaches. In the first we seed no states, while in the second we seed five random states for each draw. The former indicates

how policies diffuse in the absence of advocacy in seed states, while the latter provides a more direct comparison to an arbitrary seed strategy in that it does not begin with a five-state deficit.

To identify the most innovative states or the top source states, we take the average for each over the last ten years' worth of data (1980–1989). We use this approach since advocates would need to work off available data at the beginning of their attempt to spread a policy. We identify the top five states for each variable—most contiguous neighbors, top sources, and most innovative—and set them as having adopted the policy in 1989. We then run the diffusion process as described above across the forty-five remaining states. To compare the effectiveness of our strategies to that taken by the RWJF in the context of the ACA, we repeat our simulations with the top and bottom ten states. We chose five states for our main results since this seems a more reasonable target for an advocacy group than seeking to get ten states to adopt in the first year.

In selecting these strategies, we hope to identify how each shapes the spread of a proposed new policy innovation. Using real-world values of state characteristics and diffusion networks complicates our ability to isolate the distinct effects of each strategy, though, since these characteristics often overlap. For example, as we show in the next section, highly innovative states tend to be sources for more states, whereas states with many contiguous neighbors are not necessarily top sources. Thus, our results must be interpreted as illustrating the empirical and real-world differences between various strategies for seeding new policies rather than isolating the theoretical contributions of different mechanisms of diffusion. We turn to these issues in more detail in the following section.

Simulation Results

In this section, we report on the performance of our four seeding strategies. As detailed in the previous section, this involves starting our hypothetical policy diffusion processes by seeding five states that adopt the policy in year one and then tracing out the rate of adoption among the other forty-five states. We consider four strategies. The first seeds policy leaders—those states whose adoptions influence the greater number of other states based on Desmarais, Harden, and Boehmke's (2015) estimates. Second, we consider states with the most contiguous geographic neighbors since that forms the other primary pathway of policy diffusion. Third, we consider a strategy that combines these two to identify the states with the largest combined effect of the two. Finally, we seed the five most innovative states as identified by Boehmke and Skinner (2012a).

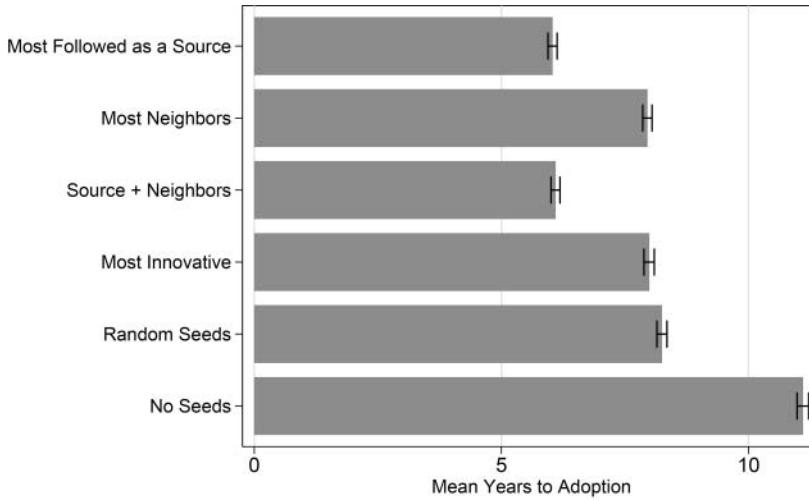

Figure 1 Expected Years to Adoption, by Seed Ensemble Type (Five Seeds)

Notes: Bars represent the average years to adoption. We calculated these by taking the average years to adoption within each draw and then averaging across draws. The black capped lines represent 95 percent confidence intervals for the average years to adoption based on the standard error of the mean across all 1,000 draws.

Each simulation produces a diffusion sequence over the fifty states consisting of the year of adoption for each state. These produce the familiar S-curve of cumulative adoptions explored in the literature, but with differences in how quickly the policy spreads across seeding strategies. Rather than present the average adoption curve along with standard errors, we focus more on succinct metrics to capture the relative speed of each seeding strategy. Our first chart presents the average years until a state adopts the policy along with a 95 percent confidence interval. To calculate this, we took the average years to adoption within each draw and then averaged and calculated the standard error of the mean across all 1,000 draws.

The bars in figure 1 show that having no seeds is, not surprisingly, the slowest strategy, with an average of just over eleven years until a state adopts. This mostly sets the stage for interpreting the efficacy of the other strategies, all of which start out with a built-in advantage from the five states that we seed in year one. Two strategies emerge as the most effective according to figure 1: seeding the top five sources or seeding the top five combinations of sources and neighbors. These both result in an

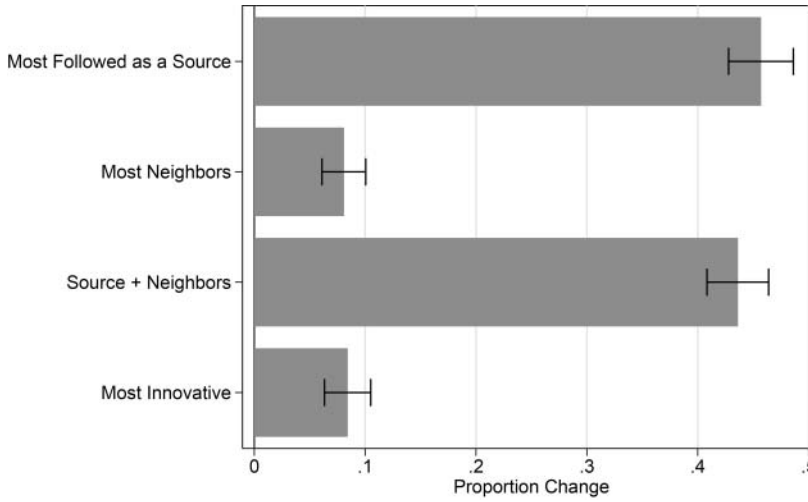

Figure 2 Proportion Increase in Probability of Adoption per Year Relative to Random Seed Strategy, by Seed Ensemble Type (Five Seeds)

Notes: Bars represent the average proportion reduction in the probability of adoption for each strategy relative to the random seed strategy. We calculated these using the average probability of adoption for each strategy within each draw and then calculating the proportion improvement relative to random seeds within each draw. We then averaged across draws. The black capped lines represent 95 percent confidence intervals for the average improvement based on the standard error of the improvement across all 1,000 draws.

average adoption time of just over six years, nearly half the time for no seeds. Perhaps a more appropriate comparison lies with seeding five randomly selected states each draw. The average time here is 8.2 years, still substantially faster than seeding no states. Relative to a random seeding strategy, the two best strategies offer a 26 percent reduction in time to adoption. Interestingly, seeding the top five states in terms of contiguous neighbors, or the five most innovative states, produces almost no gain relative to five random states.

Figure 2 offers a different perspective on the results. Rather than focus on years to adoption, it turns to the average probability of adoption per year. Further, we focus more explicitly on relative performance by comparing the reduction in the probability of adoption for each strategy to the random seeds strategy. Random seeds offers a fairer comparison than no seeds since the latter does not start out with five adoptions in year one. We estimate the improvement by calculating the average probability of adoption for each strategy and then calculating the proportion reduction of

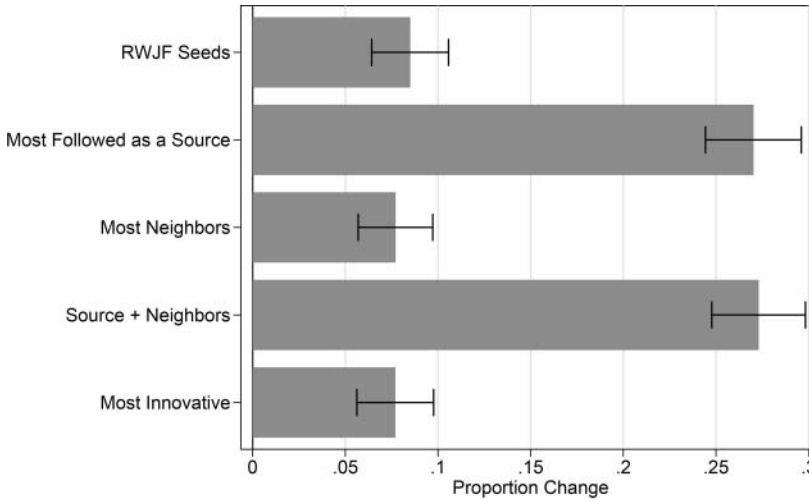

Figure 3 Comparison of RWJF Seed Ensemble to Alternatives Relative to Random Seeds (Ten Seeds)

Notes: Bars represent the average proportion reduction in the probability of adoption for each strategy relative to the random seed strategy. We calculated these using the average probability of adoption for each strategy within each draw and then calculating the proportion improvement relative to random seeds within each draw. We then averaged across draws. The black capped lines represent 95 percent confidence intervals for the average improvement based on the standard error of the improvement across all 1,000 draws.

each relative to random seeds. As before, we do this for each draw and then take the average improvement and the standard deviation of the average across draws. These results correspond to those presented in the previous figure in terms of ordering the strategies. Top sources and top sources plus neighbors offer about a 44 percent improvement over a random seeding strategy. Most innovative offers an 8.4 percent gain while most neighbors produces an 8.1 percent increase.

Finally, we repeat the simulation process to compare the effectiveness of the ten states supported by the RWJF for the adoption and implementation of the ACA. As noted earlier, for the purpose of comparison we run our simulation using the top or bottom ten states for each strategy. Figure 3 displays the results by repeating the previous plot of the proportion improvement against random seeds. The general pattern of our previous results holds. Notably, the top ten states in terms of contiguous neighbors performs worse than the random seed strategy. Of particular interest, though, is that seeding the ten RWJF states emerges as the second best

strategy with an 8.5 percent improvement relative to random seeds, which is greater than the improvement from the top innovators or the most neighbors strategies, about one-third the improvement of the top sources strategy, and puts the RWJF "seeds" as the second best strategy. Thus, it appears the RWJF chose the ten states wisely if the goal was to maximize influence on other states.

Discussion and Conclusion

It is infeasible and possibly ineffective for policy entrepreneurs to lobby directly every policy maker and/or policy-making body. Given that an advocate will have to select targets, two important questions should inform the composition of the initial target (i.e., seed) set. First, how likely are the targets to respond to the efforts of the advocate and adopt the policy? Second, how will the targets' adoptions influence the propensity for other policy makers to support the policy? We have shown that the policy diffusion literature can be used to integrate answers to both of these questions into a comprehensive data-driven strategy for policy advocacy. We show that careful selection of the seed set can increase the speed with which a policy spreads through the states by over 40 percent relative to a random strategy, and even more relative to a poorly chosen strategy.

While the combinatorics makes it impractical to check all possible combinations of states, we find that choosing the top policy sources over the last few years offers the greatest improvement in the speed of diffusion. Recall that sources are states that other states tend to follow in the adoption of new policies. So if, for example, an entrepreneur persuades New York or Florida or California to adopt a new policy, then over two dozen other states will be more likely to adopt that policy in the next year or so. And, while this may sound obvious—getting leader states to adopt will increase adoption among other states—our other results indicate it is not. Consider our finding for contiguity, the other primary source of interstate diffusion. Seeding the states with the most neighbors barely performs better than a random seeding strategy in terms of average years to adoption.

These results underscore the fact that the effectiveness of a seeding strategy depends on a fairly complex interaction of features within the system of fifty states and how they evolve over the course of a diffusion. For example, we speculate that the findings for neighbors occurs because, while states with lots of neighbors will influence many other states up front, they also have more pathways of inward influence, whereas states with few neighbors have only one or two pathways of influence. Starting with the

easy-to-reach states that maximize short-term influence does not offer much advantage over starting with the hard-to-reach states and letting them propagate outwards to the easy-to-reach states. In this light, it is not obvious that seeding the five most influential states produces the fastest diffusion across all states. A variety of characteristics of the seed ensemble matter. In addition to the geographic spread, the underlying probability of adoption of its member states also matters. For example, if California is very likely to adopt in year one or two, then targeting it may be a wasted effort compared to seeding a state that would be much less likely to adopt otherwise. Further, seeding California and Oregon may not make sense since they border each other.

While our results indicate that seeding top sources offers a very effective strategy, we have not fully explored the interdependence of states within an ensemble. We have, however, attempted to explore the issue a little bit to see if we can improve on the top sources approach. Briefly, we tried to identify likely candidate states by running fifty simulations with each state as the single seed. We identified the top ten states and then ran all 252 five-state combinations of the top ten individual states based on fastest diffusion times when they are seeded. These results largely confirmed what we found already, since the top combinations all involved states ranked very highly as sources. In fact, the top five source states emerged as the second and fifth best strategies (two states are tied for the fifth most frequent source), and the differences among these top strategies were minuscule. Similar results emerge when we identify the best state on its own, then identify the best state to pair it with, then the best third state to add, and on to the best fifth state.

Overall then, these results seem to support the notion that a strategy for seeding policies that targets the most frequent sources will fare quite well. Of course, the identity of the most frequent source states changes over time. Table 1 in Desmarais, Harden, and Boehmke (2015) shows that New York, for example, ranks as the most frequent source state for all five of the five-year intervals from 1960 through 1984, then drops to number two for the next two intervals and to number five from 1995 through 1999 before dropping out of the top fifteen after 2000. Washington, in contrast, does not make the top fifteen for 1970–1995 but then moves into the top five from 2000 through 2004 and again from 2004 through 2009. Thus, to seed the top sources, one has to know who they are at any given point in time. And, while we do not have sufficient data to know for sure, we suspect that the identity of those policy leaders varies across policy areas as well.

Policy advocates appear to follow a strategy that overlaps somewhat with our approach, though they clearly place an important premium on identifying states in which they perceive a high chance of success. While that conclusion may be premature without a more comprehensive study to evaluate advocates' choice of seed states, it appears to match the strategies chosen in many of the cases we outlined previously, though perhaps not the one selected by the RWJF in support of the ACA. The RWJF appears to have sought out more geographic and ideological diversity than the groups working on legalizing recreational marijuana, anti–affirmative action policies, or same-sex marriage bans. The Marijuana Policy Project effectively acknowledges the importance of receptivity when Rob Kampia, the group's executive director, called efforts to legalize marijuana in Michigan, Missouri, and Ohio "outlier initiatives" and "premature" due to their low chance of success (Gurciullo, Mawdsley, and Campbell 2015).

This suggests an important line of inquiry for future investigations of advocacy strategies. Our approach assumes that advocates can successfully lobby states to adopt their policy, whereas the reality clearly indicates that failure may be more common than success and that it may take years to persuade potential seeds to adopt. This likely helps explain advocates' apparent focus on early successes rather than on choosing states to maximize the future spread of their policy. Such successes help build momentum and facilitate fundraising and membership recruitment going forward. Yet, our results show that the spillover effects of securing adoption in a desirable seed state—in particular, one of the top source states—offers benefits of its own by increasing the chance of adoption in other states that might outweigh the additional up-front cost of advocacy in that state. While further simulations could explore the cost-benefit tradeoff more explicitly, the consistent emergence of the most frequent sources as the most effective targets suggests that one might rank states by expected influence by multiplying the probability of adoption by the number of states that count the target among their sources.

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