Innovation Choices and Diffusion Patterns

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Abstract: How and when do political actors make policy choices in a complex world? More specifically, when do state political actors decide their status quo is fails to meet their needs and then reformulate their policy? When is this change linked to what other states have done and which states provide valuable information? ? The purpose of this paper is to compare and contrast mimicry and learning and then assess the usefulness of one existing model of innovation choices based upon learning for deriving empirically testable hypotheses about state policy innovation and diffusion patterns. The empirical implications of the formal model and limitations are also considered.

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How and when do political actors make policy choices in a complex world? More specifically, when do state political actors decide their status quo is fails to meet their needs and then reformulate their policy? When is this change linked to what other states have done and which states provide valuable information? Policy diffusion scholars have a rich and nuanced set of theories and empirical findings that point to the importance of the internal characteristics of a state and external factors buffeting a state (including geo-spatial ties between states) as well as aspects of the policy itself in determining whether and when a policy change occurs. Internal state traits include political majorities in the upper and lower chambers of a state legislator, whether these majorities are similar to the governor's party or not, a state's culture or mood, and the presence and power of interested groups and individuals. External factors include federal grant programs or changing national economic or industrial trends and geo-spatial links between states refers both to the fact that (1) what a state's neighbor (or multiple neighbors) chooses as policy may affect the value of the state's current policy, because there is competition for mobile resources such as taxpayers or industry (Tiebout 1956), or (2) because bordering states are close to each other and information gathering is easier (Walker 1969). This spatial dependence is often thought of as contiguous borders, but can also refer to close links between policy entrepreneurs in a network or peer states that share similar, relevant features. Policy-specific factors thought to effect whether a state chooses to maintain its status quo solution to a problem or make a change include its salience and technical complexity as well as the cost and success or actual benefit of the policy solution (Mooney and Lee 1999l, Volden 2006, Karch 2007, Nicholson-Crotty 2009, Boushey 2010, Gilardi 2010).

Despite this extensive knowledge, policy diffusion scholars often point to a lack of understanding of the micro-foundations related to the mechanisms by which policy ideas spread across connected states. More specifically, numerous mechanisms exist such as learning, mimicking, adaptation or competition, and coercion (Shipan and Volden 2008), but adjudicating between them can be problematic at the hypothesis development stage and in empirical analyses.[1] Recent work has begun to focus on competition (such as Baybeck, Berry and Siegel 2011) and consider differences between economic competition and learning (Boehmke and Witmer 2004), learning via competition and pure learning (Ward and John 2013), and differences in emotional reasoning versus trial-and-error learning (Boushey 2010), but the observable differences between many of these mechanisms remains elusive. For example, if a state gathers information about a policy in another state and decides to copy the policy for their own jurisdiction, is this an instance of mimicry or learning? If states learn quickly about the political benefits of a policy, will the pattern of adoptions resemble emotional reasoning? Does the degree of learning depend upon the amount or type of information collected, the update in beliefs about how policy choices map into policy outcomes in the state, or the final policy choice? The purpose of this paper is to compare and contrast mimicry and learning and then assess the usefulness of one existing model of innovation choices based upon learning for deriving empirically testable hypotheses about state policy innovation and diffusion patterns. To do so I begin first with a consideration of individual level choices over policy change and continue by assessing why a state may or may not look beyond its own experiences and borders for innovative new solutions they can use to change the status quo. Finally, I consider the empirical implications of one formal model of innovation and learning for a study of the spread of policy ideas across states.

State Policy Choices

A state revisits its current policy choice and considers changing it when: 1) the current political leaders notice a need or perceive a possible net benefit of changing policy that are large enough for legislators to spend resources on formulating a policy, herding it through the legislative and executive process, and living with the results as implementation occurs and 2) current political leaders have the capacity to

[1] Braun and Gilardi (2007) also point to cooperative interdependence, common norms, and taken-for-grantedness and Elkins and Simmons categorize clustered decision making into similar responses to similar conditions, diffusion (based on adaptation or learning), and coordinated action (cooperation or coercion) (2005).

formulate and successfully pass a new policy.[2] A perception of a net benefit of policy reform from the status quo can be the result of policy advocates bringing attention to or reframing a policy or problem in the state (Baumgartner and Jones 1993), a crisis or focusing event that highlights a need for governmental intervention (Kingdon 1984), or even the transition to a new majority party in power with different preferences over beneficial policy choices and outcomes (Eyestone 1977). In sum, a shift must occur in the attention of political leaders to the issue, which can occur following electoral cycles and can be manipulated by lobbyists, interest groups, and the media (Baumgartner and Jones 1993, Jones and Baumgartner 2005, Boushey 2010). Second to this increased attention to the issue is the ability to act on it. Political actors in the legislature must have strength in numbers to successfully pass a policy off the floor and be able to maintain support as the governor signs it into law. Prior to passage, though, state political actors must have the resources available to formulate the policy—whether based on extensive in-house policy analysis, a scan of what other states have tried, or the ability to craft a bill that addresses the issue. The knowledge and number of professional staff, activity of lobbyists and advocacy groups, as well as just sheer numbers of legislators available to specialize on an issue are attributes that build capacity of states to formulate policies (Karch 2007).

The complexity of the underlying problem the policy is meant to address can also influence the need for such resources and the technical difficulty of crafting a policy solution. Some problems are knottier than others and may be characterized by adaptive policy targets that search for loopholes in regulations or programmatic choices, possibly resulting in unintended negative consequences (Page 2008).[3] Even policy choices (including the maintenance of the status quo) in areas where the link between governmental policy choices and outcomes following implementation is straightforward may be used by political opponents in the next electoral cycle if the problem or its solution can be reframed to cast current political majorities in a negative light. These are the policy and political minefields policy

[2] Yet see Boushey (2010) regarding the implications of avenues of policy change that circumvent legislative processes on policy diffusion.
[3] These loopholes can also be manufactured during the formulation process itself as strategic interests lobby for their inclusion.

actors craft policy within; thus, the perception of net benefit of changing a policy is a comparison of the benefits and costs of the status quo today and at the next election with the benefits and costs of a new policy, a policy innovation, at the next election, given a quagmire of interests, targets, and outcomes—the "geographic, socioeconomic, and demographic complexion of [legislators'] states and districts, as well as the profile of partisan, candidate and policy preferences of various constituencies" (343, Shepsle et al. 2009).[4] States differ in the people that live there, in space and topography, natural resources, and major industries and economic factors (Gray 2012). This state complexion and political profile may be unique to each state and time period, but states may look to other states to receive clues as to how certain policy innovations may map into outcomes.

Solution Search

When state political leaders look to other states they can look for ideas for possible solutions, information about the policy outcomes that may result from different policy innovations (Glick and Hays 1991; May 1992), and knowledge about the ideological content or political repercussions of policy choices (May 1992; Grossback, Nicholson-Crotty and Peterson 2004).[5] A state can do an extensive analysis of all other states' policy choices, a quick scan of neighboring state's policies, or consider (in-depth or as a shortcut) states with a similar state complexion and political profile. A state could also engage in their own policy analysis to formulate policy solutions without having looked outwardly at what other states have done, but in-house policy analysis does not exclude the possibility that a state also looks to other states for policy ideas, implementation results, or political consequences. Bardach (2012) suggests that state-level

[4] Gray (1973) defines a policy innovation as a policy that need only be new to an adopting state. There are also concepts such as policy reinvention (Glick and Hays 1991), policy expansion (Boehmke and Witmer 2004) and contraction. In this paper I conceptualize a policy innovation as a change in a state from its status quo. This could be a return to a previous choice, a policy choice that copies another state, or a completely new innovation.

[5] States also learn competitive information about the repercussions of other states' choices on own states status quo (Ward and John 2013), yet see Mossberger (1999) where limited learning about Enterprise Zones from other jurisdictions occurred (policy entrepreneurs only made generalizations about other area's zones).

policy analysts should "look to other states" because "[it] pays to see what they have done and to assess their degree of success or failure" when designing their own policy innovations (25).

In a search for solutions, pilot or demonstration projects in a segment of the state and in-house policy simulations built upon the unique characteristics of the state at that time may provide excellent information about policy and political outcomes, but utilize extensive resources, including time, money, and analytic skill. Decisions about which programs to pilot may be based upon what other states have tried. Lacking such resources, states may use other states as their external laboratories—providing simulations and demonstrations, albeit with a less exact fit as with internal experiments. In contrast, state political leaders may have either no time or the issue is of lower priority, they just want it off their plate, and so look to other states for quick ideas (Karch 2007). Either the former extensive knowledge generation process or the latter quick scan can result in a state deciding to implement a policy solution that has been previously tried in another state, which in the aggregate could potentially result in the spread of an innovation across states.

Mimicry versus Learning

To mimic, imitate, or emulate a policy choice is to copy closely what another actor has chosen as its policy. This imitative process is generally conceived of as different from learning, since it is a process whereby a state copies another state, not because it has learned about the policy or its politics, but because the state wants to look like the other state (May 1992, Shipan and Volden 2008).[6] Shipan and Volden (2008) find evidence that small cities, who are assumed to want to look like bigger cities, emulate the policies of their nearest bigger neighbor. The difference between mimicry and learning suggests the importance of understanding the concepts of learning, information, and the generation of knowledge.

Dretske (1981) defines information as a "commodity capable of yielding knowledge," which can be carried as a signal from others (86). An example of these signals, or information messages, a state may

[6] Yet see Graham, Shipan and Volden (2012) where socialization, a process to change preferences via changing the norms and rules of a community, is needed for emulation or mimicry to happen.

send is a reduction in mortality rates due to traffic collisions following passage and implementation of a helmet safety regulation or electoral defeats after passage of an abortion restriction regulation—a policy signal in the first case and a political signal in the second, two pieces of information that are important for state political leaders (Gilardi 2010). "Learning occurs when new evidence changes our beliefs…either directly from one's own experience or vicariously from experiences of others" (460, Dobbin, Simmons and Garrett 2007 also see Meseguer 2005).[7] Learning differs from what Boushey (2010) refers to as emotional reasoning, which is a quick look at salient policies and passage (often as a copy) not a consideration of the pros and cons of a policy for a state.

There are different types of learning, such as rational versus bounded learning. In rational learning evidence is used to update beliefs about the world in comparison to bounded learning where shortcuts are used instead of an updating process (Braun and Gilardi 2007). A shortcut can be using policy innovations of geographic neighbors (because they are closer), ideologically similar states (because they have similar beliefs), or relying on innovations that many states have already implemented. Braun and Gilardi (2007) note that whether via a bounded or rational learning process, states can look to other states' experiences with policy innovations (2007).

The weight of this new evidence for a state, though, depends upon that state's prior beliefs about the world, what is possible, and what is acceptable (Dretske 1981 or Gilardi 2010). As Gilardi (2010) demonstrates the same information signal about the effect of tax cuts can yield different posterior beliefs among three actors who held differing prior beliefs. Assuming ideological preferences represent prior beliefs, Gilardi (2010) analyzes unemployment benefit reforms and finds that learning about policy choices is conditioned on the preferences of political actors. Countries were more likely to copy the unemployment benefit cuts of other countries only if there were mostly controlled by left parties and unemployment trends in the country to be imitated improved and right parties would copy cuts regardless

[7] Karch (2007) argues that different political processes (agenda setting, policy formulation and debate, or voting on policies) are influenced by different factors or in different intensities. For instance, gathering information about policy effectiveness may be more important during agenda setting and solution searches versus re-election concerns during amendments and enactment phases (Karch 2007).

of the effect on unemployment. Gilardi's findings also point to a potential tradeoff between learning about political consequences and policy outcomes. He finds that right governments were "more sensitive to information on the electoral consequences of reforms, while left governments are more likely to be influence by their policy effects, especially when they are negative," information signals in his case that were in conflict with one another (660, 2010).

Volden, Ting, and Carpenter (2008) provide a different assessment of what state-to-state learning about policy choices may look like at an aggregate level in contrast to a decision theoretic choice by an only inward-looking state. The authors do so by developing both a decision and game theoretic model where states have both ideological and policy-related (effectiveness) goals. A state considers the net benefit of a policy innovation with uncertain effectiveness, which impacts the value of an additional "valence" or publically observable outcome (they use the example of budgetary impact). In the decision theoretic version of their model, a state considers the value of experimenting and makes a policy choice and in the game theoretic model a state can learn from (or free ride off of) the experimentation of other states. What Volden, Ting and Carpenter's models provide is a theoretical basis for similarities in the patterns of policy adoption that can be seen with policy ideas diffusing through learning states and state choices based solely on internal factors, which some authors refer to as policy convergence or independent adoptions based on similar circumstances (Elkins and Simmons 2005). These observational equivalents include leading and lagging states, s-shaped adoption curves, clusters of policy adoptions among geographic neighbors or similar (on ideology, industry, or other relevant attribute) states, or policy advocacy.

Based on Volden, Ting and Carpenter's (2008) results, some states will be leaders versus laggards in the decision theoretic model because some states have an independent higher probability of adoption an innovation at one time period than do other states, which could be due to the presence of strong interest groups or other factors. If more than two periods exist in a decision theoretic model an s-shaped curve of independent adoptions can arise when states face similar environmental circumstances and focusing events that increase the likelihood of a policy change and clusters of adoptions could result because similar states face similar pressures, not because they have learned from one another (Volden, Ting and Carpenter 2008). The authors' model also provide hypotheses that are directly related to learning including: (1) an increased chance of adoption when policy is successful in other states, (2) ideologically moderate states (regardless of its effectiveness) are more likely to adopt a successful policy than an unsuccessful policy (compared to more ideologically extreme states), (3) states with a moderate likelihood of adoption based on internal characteristics are more likely to adopt the longer other moderate states keep a policy innovation in place, and (4) empirical evidence of policy abandonment that clusters by similarity not over time would indicate learning from others' experiences (Volden, Ting and Carpenter 2008).

In summary, state-to-state policy learning is about gathering evidence from other states' experiences (either all states or subsets of states) with policy innovations. These experiences are in the form of information about policies, politics, and outcomes—all of which could be utilized by a state to update its beliefs about which policy is expected to have the highest net benefit in their own state. Policy mimicking, on the other hand, does not entail a change in beliefs, only a preference to look like or be like the other state and then copying that state's policy. The policy choices of mimicking states are straightforward—they should look very similar, if not exactly like the state being emulated. The policy innovations of learning states in a complex world, though, require further consideration.

Policy Innovations via Learning

In a series of articles, Callendar (2008, 2011a, and 2011b) uses the path of Brownian motion as a way to model the complexity of mapping policies to outcomes.[8] Brownian motion is the description of a stochastic process where an object in space is bombarded by other particles also

[8] In these articles, Callendar considers the development of agency expertise with delegation (2008), searching for innovations in firms (2011a), and the electorate's search for good policies via elections (2011b).

moving about the space. The path can be formalized mathematically which offers an opportunity to stylize features of choices made under uncertainty.[9]

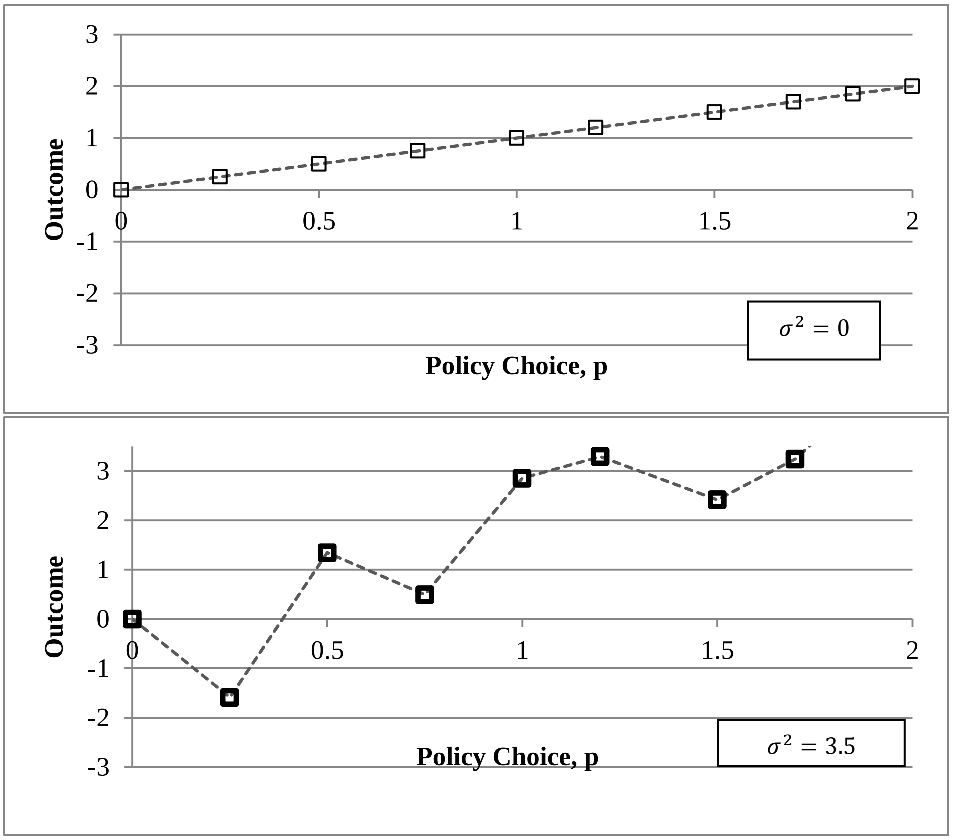
Extending this analogy to policies and implementation processes means that as the words from a policy document are translated into actions; those actions are combined with a variety of other factors. These elements include the interests, motivations, and capabilities of not just agencies and bureaucrats functioning within them, but other directly and indirectly affected parties. Those parties affected by a policy are the recipients of the policy's benefits and burdens—those who pay directly or indirectly for the program, services, or regulations, among other things and those who gain from the programs, services, regulations, etc. In sum, the interests and institutions in the trenches of the real world combine to determine what the final outcome of those policy words will be.

The policy outcome is stylized as the object in space, which is bombarded by agents, entities, recipients, etc. The collisions of these factors with each other during implementation can cause the object (the policy outcome) to move in a path with peaks and valleys, similar to those shown in the complex mapping of Figure 1 (lower panel). An empirical example of the results of such collisions is the variation of implementation and outcomes in the states after the federal law, No Child Left Behind Act of 2001 (P.L. 107-110) was implemented (see Manna 2011). (Mathematically, general Brownian paths have two parameters: a drift (μ, the rate of change of the path or slope at a point along it) and variance (σ^2, roughly how much the path

[9] One assumption implicit in this usage of Callendar's model is that all states (or some subset of states) have similar Brownian paths, which may not be the case. Additional consideration of the implication that states may learn from all possible Brownian paths is welcomed. Here I assume that states consider the experiences and mapping of states similar enough on the features that matter to make their innovation choices. If there are no states that map onto the Brownian path of a state, that state does not learn from others and makes innovation choices based on its own experience, a possibility I return to later in the article.

varies from peaks to valleys.[10] A path with a variance of zero is linear and describes the case of a simple mapping from policies to outcomes (top panel of Figure 1).

Figure 1: Complexity of Policy to Outcome Mapping



As the variance in the path that connect a policy and its outcomes increases, so too does its complexity. In the bottom panel of Figure 1 the variance has increased to 3.5 and reveals peaks and valleys in the expected outcomes associated with various policy choices. More specifically, $\frac{\sigma^2}{|\mu|}$ combines the drift of the motion (the rate of change in policies and outcomes) with the variance in a compact measure of how complex the search for new policy solutions is.

[10] This is a two-dimensional Brownian path.

Callendar's (2011a) definition of $\alpha = \frac{\sigma^2}{2|\mu|}$ as half of the complexity of searching for a product in an industry can be applied to policy innovations; α represents half of the complexity of finding policy solutions to solve a problem in an underlying issue area.

Brownian motion provides a nuanced characterization of policy-to-outcome uncertainty for five reasons. First, using the path of Brownian motion to describe how policies link to outcomes represents actors' uncertainty over outcomes paired with certainty over policy choices. Second, when a state observes other states' policies-with-outcomes the state receives some, but not full knowledge of the mapping of policies to outcomes and what might happen to them should they choose different policies. Third, the accuracy of states' beliefs about policy-to-outcome linkages decreases as the distance between what states have tried and what they have not tried increases. In other words, less is certain about how completely different policies will map into outcomes as opposed to the fact that more is known about how incremental changes would map into an outcome.

Fourth, using the path of Brownian motion as a device to mathematically describe policies and outcomes incorporates the possibility of unintended consequences of policy choices. This can be demonstrated by considering a policy choice in Figure 2 represented by the arrow on the horizontal axis at 0.25 (perhaps this represents investing $2.5 million dollars in a housing-first program and the outcome is the number of housed but previously homeless individuals or even the vote share of Democrats in the last election). Based on existing knowledge about how policy choices translate into outcomes, the expectation for a state trying a policy at that arrow's location would be for an outcome along the line between the two known outcomes in the space (represented by two solid diamonds) as indicated by the arrow in the middle of the graph. The actual mapping of that particular policy choice to an outcome, though, could be much lower or higher than expected from that line as shown by the solid dot below both sets of lines. Finally, using Brownian motion offers an opportunity to mathematically consider the complexity of searching for policy innovations in an uncertain environment.[11]

The state has beliefs over how untried policies will map into outcomes because a state is not sure if it has hit the sweet spot of policy choices, given the implementation environment (e.g., the agents, recipients, interests, institutional milieu) of the policy issue, and if they move to the left or right (in a small or large increment) with a new policy choice whether it would yield a much less versus more desired outcome (as shown from the solid dot in Figure 1). A state can learn from other states' policies and outcomes, allowing it to update its beliefs over how the implementation process may yield outcomes given different policy choices.

A state makes a choice to maintain its status quo or to pass a policy innovation at each time period (over all countable time periods), based upon the data of its own experience with its status quo policy and (potentially) those of other states up to that time. The decision to innovate rests upon a consideration of the net benefit of the new policy, compared to the status quo and given the set of informative policies already in existence.[12] For a full explication of the model, equilibrium calculations, and simulations please refer to Callendar (2011a). I highlight here those results that can be extrapolated to state decisions and have implications for policy innovation and diffusion.

First, Callendar's findings include the possibility of long periods of stability followed by either quick periods of change or even a drawn out period of policy experimentation. There are

[11] Callendar (2011a) refers to this as the five key features of the Brownian motion representation of uncertainty in a product experimentation environment: (1) Expected-versus-actual outcomes, (2) Partial invertibility (some but not full knowledge), (3) Proportional invertibility (decreasing accuracy of beliefs), (4) Unintended consequences, (5) Local-not-global learning (I combine this with proportional invertibility in the case of state learning), (6) complexity of searching (as above), and (7) tractability.

[12] In Callendar's model the utility of an actor is a function of the quadratic distance from its ideal, his results hold for any weakly concave utility function and could be some combination of political outcomes, policy outcomes, or both, but is not explicitly modeled as such.

periods of stability of policy choice: when previous political leaders have not experimented with new policy solutions, wherein policy change is unlikely to occur. This finding fits well with models implying periods of stasis in policy choices that could potentially later be punctuated with periods of rapid or incremental change. These periods of stability rely on: stability in the divergence between the status quo policy's outcome and the policy decision makers' ideal outcome (or a lack of attention to the divergence), no changes in the complexity of the underlying problem-policy-outcome environment, and no new information from others states' experimenting is available.[13]

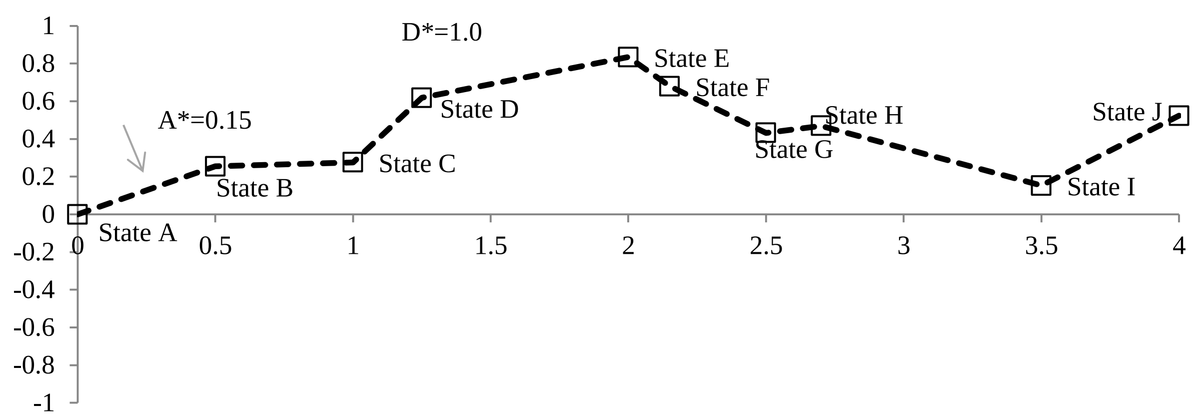
A state may lead the charge as a policy innovator, or moves from stability to experimentation, when the distance between the state's ideal outcome and its status quo is larger in size than the complexity of the policy area. Recall that complexity of searching for solutions in a policy area is a ratio of the square of the noisiness of the Brownian motion (or how much policy choices linked to policy outcomes bounces around in outcome space) and the rate of change in policies and outcomes (or the slope of the line that can be drawn linking policies and outcomes). Thus, changes in the preferences of the political leadership of just one state (i.e., new majority coalition) or a reduction in the complexity of the search (i.e., a technological advance) could move the entire system of states into an experimentation phase (with some states experimenting and others not or even most states experimenting).

Second, the model's results point to two phases of experimentation when a policy area is not stable. Callendar refers to these phases as the monotonic experimentation phase and the triangulation phase (2011a). Triangulation occurs when there are two policy-outcome pairings

[13] Additionally, a stable outcome is unlikely to be the ideal outcome of a state according to Callendar's model. Instead, a state (even learning from others) will converge to a "good enough" outcome or "get stuck" at a not great outcome that is close enough to the complexity cut-point for innovation that the state will not risk new innovations.

that straddle a state's ideal outcome. These policies paired with their outcomes provide information for the state about where to experiment with policy choices in the hopes of securing an outcome even closer to its ideal. Monotonic searches for policy solutions, in contrast, occur when all policy-outcome pairings fail to straddle the state's ideal outcome. Figure 2 demonstrates the difference between a state in the triangulation phase (State A with ideal outcome at A*) versus a state in the monotonic search phase (State D with ideal outcome at D*) which result in different choice environments, a point I return to below.

Figure 2: Information From Other States' Policies



Third, Callendar's model provides expectations regarding the size of the policy innovations (incremental versus major overhaul) since the size of the absolute value of the difference between the status quo policy and a policy innovation is increasing in the divergence of the status quo outcome from a state's ideal point and decreasing in the noisiness of the process (or σ^2). When a state's status quo is extremely out of step with the current political majority, the likelihood of a big shift in policy is increased. The state, though, must hedge its bets on an uncertain outcome as the complexity of the implementation environment increases. Relatedly, Callendar finds that the probability of unintended consequences (or movement of a policy outcome in an unexpected direction) is decreasing in ideal point to status quo divergence, increasing in complexity, and more likely when policy change is incremental. In other words, and counterintuitively, incremental change is more likely to be associated with unintended outcomes than large scale reforms.

A monotonic phase in state policy experimentation and learning can occur when all policy outcomes lie on one side of the ideal point of a state. The most likely scenario where this could happen with states is for the most conservative or most liberal states. For example, in the case of extreme conservative states, a mix of moderate and liberal policy choices linked with moderate and liberal policy outcomes could yield a set of outcomes where none of them straddle the state's ideal and very conservative preferred outcome, such as with State D in Figure 2. If an extreme state scans the environment, the most attractive of policy-to-outcome pairings will be those with outcomes closest to their conservative ideal point. The conservative state, if the net benefit of innovation is high enough, is predicted to implement a policy choice more right than the existing rightmost policy, a process repeated by all other states either in the same period or subsequent periods resulting in a one-directional change in policy choices—a parallel finding to race-to-the bottom predictions in welfare policy cuts (Peterson and Rom 1990, but see Volden 2002) or unemployment benefit cuts in right leaning countries (Gilardi 2010).[14] Once a set of at least two policy-to-outcome pairings span an extreme state's ideal point, such as with State A in Figure 2, the triangulation phase begins.

According to the construction of Callendar's model, states scan the policy-outcome environment and locate those outcomes closest to their ideal point (the two most attractive outcomes)—these form a "spanning bridge" if they straddle a state's ideal point (if not, the state

[14] The mirror expectation exists for extreme left states.

is in the monotonic phase).[15] The state then chooses a policy innovation in between the policy choices that led to those outcomes, which may result in a new (and steeper) spanning bridge.[16] The state continues to change its policy as it reviews its outcomes and other state's outcomes and may amend the policy. This amendment process results if the outcome ends up being worse than a previous policy choice was as well as if the outcome turned out better, just not at the ideal. In the first case, the state will choose a previous policy with known outcomes that is closer than the unintended most recent experiment. In the second instance, the state will choose a product between that better outcome and a second policy that has the most attractive outcome (or continue to triangulate).

Additional interesting findings in Callendar's model include the fact the size of experimentation is larger in policy areas that are less complex than those that are simple, simpler policy areas evolve more slowly than more complex ones, and that most new policy innovations are combinations of previous experiments (in the triangulating phase), exact copying of other state policies can occur not through mimicry, but through learning, and borrowing from two other state's with good (or attractive) outcomes is common (during the triangulation phase).[17]

Callendar's model differs from existing arguments in the following ways: (1) its findings diverge from incremental learning in that legislators will not look to similar policies to their status quo; instead they look to outcomes close to their ideal point; (2) the expectations differ

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[15] The extensiveness of the scan is not a feature of Callendar's model, but if a state only scans its neighbors only scans ideologically similar states, only scans demographically similar states, or any other subset, the expectation is that it will look for the most attractive single outcome (if the state has a preference for an even more extreme outcome) or the two most attractive outcomes (if the state's ideal is somewhere between them).

[16] The path of Brownian motion has fractal properties in that small distance at one scale with seemingly linear relations can be characterized by noisiness at a smaller scale (Mörters and Peres 2010).

[17] Boushey (2010) highlights many different types of patterns of adoption over time: steep versus wide S-shapes (the steepness of the curve increases as the time over which the innovation spread across a population of states decreases), as well as step patterns or even static policies punctuated by large bursts of policy change in short periods of time (an r-shaped adoption curve) and argues that the pattern of how policies spread is related to attributes of the policy innovation, the receptivity of the state, and aspects of the agents of change (interest groups).

from geographic contiguity or neighboring state shortcuts in that states will look to the most attractive (in the current leadership's eyes) outcomes, not necessarily their neighbors; and (3) the model's predictions differ from policy process related models because as the complexity of the underlying implementation environment increases, the adoption rate is expected to increase instead of decrease. A few notable empirical hypotheses can be inferred from these results:

- Long periods of political stability are more likely to be associated with stable policies than when political majorities shift to a new majority leadership.
- States with ideal outcomes external to the existing set of outcomes tried by all states are more likely to innovate when their status quo is out of step with their own preferences conditioned on policy area complexity, regardless of what other states do. In other words, the transition to a new unified Democratic majority has a higher probability of resulting in policy innovation if it replaced unified Republican majority (and vice versa), unless complexity is too high.
- Ideologically similar states are more likely to learn from each other's policy-to-outcome linkages, thus the probability of implementing similar policies is expected to increase as similarities in leaders' preferences increases.
- Those states that implement the largest innovations are more likely to be external and ideologically extreme states (in the same direction as the innovation), not the wealthiest or largest states.
- The degree of experimentation (or number of policy reforms) is likely to increase in those states with ideal outcomes closer to existing policy-to-outcome linkages.
- Technological change increases the probability of experimentation.

The first three hypotheses have long been noted in studies of policy diffusion, the third hypothesis is similar to Gilardi's (2010) argument as well as that of Grossback, Nicholson-Crotty and Peterson's (2004) conclusion that states learn about the ideological content of policy choices, but the final three expectations are new and different from existing arguments.

Limitations

There are a number of limitations in the underlying model as well as in the extrapolation to policy innovation and diffusion. Namely, the model assumes a common Brownian path for all states, the utility function is limited to a difference between a state's ideal point and the potential outcomes, and conflicting hypotheses could be generated from the equilibrium results for one state, if aggregated across fifty states which creates a number of empirical concerns. The assumption of a common Brownian path works for Callendar's models because he is considering the action of one entrepreneur considering the benefits of innovating to a new product. If the model is extended to fifty states considering the benefits of reform policy away from their status quo, though, the likelihood that there are fifty different Brownian paths is high. In other words, states cannot learn from the policy-to-outcome linkages in other states, because the collisions of bureaucrats, budgets, policy targets, and interest groups expected to influence the final location of the policy outcome as implementation occurs is unique to each state. Perhaps states could still draw general lessons from other states' experiences, but that would be a different model of the process and may well result in different expectations.

In Callendar's (2011a) model the utility function of the entrepreneur is simply the negative squared distance of the difference between the policy outcome (or expected outcome) and the entrepreneur's ideal outcome. Although this function incorporates and future possible benefits of policy outcomes, it does not address transaction costs associated with changing policies, nor potential differences in policy versus political benefits and costs. Operationalizing outcomes in an empirical model becomes difficulty—is a state's ideal outcome its electoral margin of victory (of the current majority) at the next election, increased campaign dollars for the majority party, increased revenues for the state coffers, decreased expenditures, some policy-specific outcome, such as reductions in infant mortality, or some combination of these outcomes.[18]

A final limitation is of note: numerous and possible conflicting hypotheses. Because the extrapolation of Callendar's model aggregates a unitary decision over time to fifty decisions over time, different states can be in different phases (stable, monotonic, triangulating) at the same time and at different time periods. Thus, if half the states are in a monotonic phase and half in a triangulating phase, some states will be expected to make large leaps in policy enactments and others only incremental changes. The big innovators will use the most attractive outcome's policy as a guide and the incrementalists will use two state outcomes as their guides, which would need to be addressed in the empirical specification (if the operationalizing hurdles can be overcome). Additionally, once the big innovators hit on two outcomes that straddle their ideal point, they are expected to join the ranks of incrementalists.

Conclusion

Much elucidation of the mechanisms of learning, competition, and adaptation remains at both a theoretical and empirical level. The question of how states can incorporate what they learn from other states into their own policy choices and who makes large leaps versus incremental changes may be addressed by relying on an existing formal model. The useful of this extrapolation and possibilities for

[18] Additionally, adding terms to the utility function increase the difficulties of solving the model. Even in this stark form, Callendar relies on simulations for many of his expectations (2011a).

empirical analysis, though, remain to be seen. Future directions of this research include a consideration of the policy areas of newborn screening and abortion restrictions—policies that differ in complexity (newborn screening encountered a technological advance in the mid-1990's) and ideological preferences, but with similar emotional appeal.

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