CAMBRIDGE
UNIVERSITY PRESS

SHORT ARTICLE

Learning from and Emulating Their Peers: Policy Diffusion in the Courts

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Abstract

Many studies of policy diffusion focus on what factors affect a policy's adoption. Few studies specifically test the mechanism and two of the most common explanations – learning and emulation – have not been tested outside of legislatures. While judicial scholars have applied policy diffusion to several types of laws, we know little about the motivation behind why policies spread from court to court. One unexplored area is the relationship between courts. This short article analyzes the two mechanisms most likely to affect peer institutions: learning and emulation. Using network analysis methods on an original dataset of state supreme court citations from 1960 to 2010, I provide evidence that courts are learning from and not emulating each other, but the mechanism is policy-specific.

Keywords: judicial politics; policy diffusion; state supreme courts; network analysis

Introduction

Policy diffusion scholars frequently focus on two mechanisms to explain why policies diffuse: imitation and learning. While most diffusion literature is rooted in legislatures, policy diffusion applies to all institutions. Judicial scholars have adopted policy diffusion's framework to examine how specific policies diffuse, including tort laws (Canon and Baum 1981; Lutz 1997), stand-your-ground laws (Butz, Fix, and Mitchell 2015), sexual harassment standards (Moyer and Tankersley 2012), and state and federal court precedent (Hinkle and Nelson 2016; Solberg, Emrey, and Haire 2006). These studies find mixed results about which factors contribute to a policy's likelihood to diffuse. Some find that regional geography, interstate migration, economic and political factors, reputation, and professionalism influence diffusion, while others find these have no effect. Left unexplored is how the relationship between courts contributes to the diffusion of precedent.

In this short article, I bring together policy diffusion and judicial politics literatures to analyze when and why courts rely on other courts' decisions. I ask

an important but understudied question: why do state supreme courts cite other state supreme courts? State supreme courts are autonomous institutions with significant power.[1] Despite this authority, state supreme courts rely on one another to explain why they reached their decisions. Across all policy areas, every state supreme court has been cited, and every court has cited a peer state supreme court. I argue the two diffusion mechanisms most likely to affect state supreme courts are learning and emulation. I test this with an original dataset of all published family law and judicial conduct state supreme court decisions from 1960 to 2010 and model the citations between courts using network analysis. This expands our knowledge of policy diffusion by highlighting the relational nature of peer institutions, even outside the legislature. I find courts learn from but do not imitate their peers, but the mechanisms are policy specific.

Diffusion mechanisms: learning and emulation in the courts

Courts shape their arguments by citing precedent. At the top of their judicial hierarchy, state supreme courts are not bound by any other courts on state law matters (Fix and Kassow 2020). In the absence of binding authority, state supreme courts often turn to other state supreme courts for help. Why would state supreme courts cite other courts when they are not legally bound to do so?

The theory of policy diffusion offers an explanation. Policy diffusion describes an interdependent process by which choices made by one decisionmaker influence choices made by others, who in turn are influenced by those choices (Braun *et al.* 2007). This also describes courts' decision-making process: courts make decisions based not only on their own prior cases, but also on other courts' prior cases, that is, they influence and are influenced by others. When state supreme courts cite courts outside their jurisdiction, diffusion occurs because the citing court is influenced by the cited court. Policy diffusion offers two mechanisms to explain out-of-state court citations: learning and emulation.

First, courts may seek information to learn how to resolve a case. By examining the written opinions of courts who have faced similar situations and then assessing whether to adopt that decision, a court is learning. Judges apply cognitive heuristics, simplifying the number of alternatives by turning to similarly situated states and focusing on cases and legal issues other jurisdictions have confronted (Caldeira 1985). For example, Solberg, Emrey, and Haire (2006) find that before adopting a legal rule or doctrine, federal circuit courts allow new rules or doctrines to percolate in the lower courts; the circuit courts are learning from other courts.

In contrast to the learning mechanism, a court may adopt the same legal rule as another court simply because another court already adopted it. Once a court has adopted a policy, subsequent courts may feel compelled to adopt the policy because it is now the norm: when this happens, this is emulation (Gilardi 2016; Lee and Strang 2006). Emulation does not evaluate policy; instead, the decision-maker assesses the actor or institution (Shipan and Volden 2008). For example, as countries appoint more women to positions on high courts, the remaining countries face regional pressure to follow suit (Escobar-Lemmon *et al.* 2021). The same is true for judges. A judge interviewed by Klein (2002, 89) described this

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[1] I use the term "state supreme court" as a synonym for a court of last resort.

phenomenon: "if (my) circuit hasn't spoken and I see seven circuits have taken a position with a pretty logical argument, I'd probably go along." This judge is not adopting a legal policy after weighing the benefits and costs, but because the other circuits had.

Scholars sometimes disagree about the mechanisms' definitions. For this article, what distinguishes the theories is how decision-makers process information to reach a decision. When courts learn, they use information from out-of-state jurisdictions to update preferences to make choices, while social pressure to conform to those around them motivates courts under the emulation mechanism. As is true in all policy diffusion, for both mechanisms the key is the courts are not relying on their own binding cases, and instead are looking to other states.

This leads me to the hypotheses about learning and emulation. For learning, I expect courts will spread citations among peers because courts are not limited to precedent from a single court. Therefore, courts exhibiting the learning mechanism will have varied citation patterns.

Learning Hypothesis: *When courts learn from other courts, the court will cite multiple other courts.*

To measure learning, I include the number of times a court cites at least two peer courts in a year, known in network analysis as out-degree centrality.

We can think of emulation in terms of popularity or leaders; courts that receive many citations are well-regarded. Walker (1969) named these states "leaders" and "laggards," where the leaders are the innovative actors whom the laggards emulate. If a court receives many citations, others may choose to cite that court due to pressure to conform or because everyone else is doing it, as the judge's quote above illustrates. For emulation, I expect leader courts to receive more citations than their peer courts.

Emulation Hypothesis: *State supreme courts will cite a state supreme court because other courts have also cited it. In other words, a state will become a leader and receive more citations than other courts.*

To measure emulation, I count the number of times a court receives at least two citations from other state supreme courts in a year, known in network analysis as in-degree centrality.

The state supreme court network is not limited to citations between two courts. A relationship between two courts may affect a third. In networks, when two actors are connected, the likelihood that the first actor is linked to a third actor increases. Figure 1 illustrates an example of this. If the Tennessee Supreme Court cites the Texas Supreme Court, the citation connects those two courts. When Texas cites the California Supreme Court, Texas's citation links the two courts. The citations do not end here; in this scenario, Tennessee and California are also connected when Tennessee cites California. Together, the three courts form a triangle, where each court connects to another. The adage, "a friend of a friend is my friend" captures this phenomenon ($A \rightarrow B$, $B \rightarrow C$ and $A \rightarrow C$), also known as transitivity.

Transitivity offers another test for learning. Transitivity occurs when Tennessee cited California because Texas cited California. Put another way, if Texas had not cited California, Tennessee might not have learned about the case and not cited California. I include a full example of transitivity in Supplementary material A1,

Figure 1. Transitivity Example.

illustrating how the citations can lead to transitivity. Since Texas's citation motivated Tennessee's decision to cite California, this reflects policy diffusion's learning mechanism; court A adopts a policy after learning about it from court B.

Transitivity Hypothesis: *A learning court will seek information from the citations of other courts. A citation from court A to court B and court B to court C, increases the probability of a citation from court A to court C.*

To measure transitivity, I include the number of times a triangle forms among courts in which the citations are transitive ($A \rightarrow B$, $B \rightarrow C$ and $A \rightarrow C$).

The directed citations can lead to other triangle formations. Continuing the example from above, if Tennessee cites Texas, and Texas cites California, California will close the triangle and cite Tennessee. This arrangement is like transitivity, except the citation from California to Tennessee is reversed so the arrow continues in the same direction ($A \rightarrow B$, $B \rightarrow C$, and $C \rightarrow A$). Together, the three states form a group. This group is the smallest subset of three states that share citations. In this cycling triangle, just as with emulation mechanism, the courts are driven by pressure of other courts' citations. Its peer group has adopted the same policy, so it, too adopts the policy.

Cycling Hypothesis: *Based on the citations of Court A and Court B, Court C will cite Court A.*

To measure cycling, I include the number of times a triangle forms among courts in which the citations cycle ($A \rightarrow B$, $B \rightarrow C$, and $C \rightarrow A$).

Data and research design

To evaluate the learning and emulation mechanisms, I use an original dataset of state supreme court case citations. I limit my research to examining two policies across the states: family law and judicial conduct. State-specific policy areas are crucial for two reasons. First, federal courts rarely get involved in these areas, though when they do, states can and do ignore federal courts and often rely upon other states as justifications for doing so (Fix and Kassow 2020). This means there are few federal court

decisions for states to cite, and relying on state law issues reduces the chance of federal court interference (Hettinger, Lindquist, and Martinek 2004; Leonard and Ross 2016), controlling for exogenous factors. Second, many scholars find that policy area affects a court's adoption of legal rules (see, e.g., Caldarone, Canes-Wrone, and Clark 2009; Moyer and Tankersley 2012).

Family law comprises issues such as divorce, maternity and paternity proceedings, child custody and support, and adoption. I contrast family law with judicial conduct, a subset of legal ethics. Judicial conduct is a peculiar area of law often ignored by scholars, yet it has a profound influence beyond judges; it also affects attorneys and the public. States enact codes of judicial conduct to ensure the judiciary is independent, fair, and impartial. States' judicial commissions handle most cases of judicial (mis)conduct. An injured party or sanctioned judge may turn to the appellate court for relief, to challenge the commission's finding. Judicial conduct cases include abuse of power, conflict of interest, and abusive demeanor, among others. The universe of cases for each issue area at the supreme-court level is modest. Because the number of cases is relatively small, the courts may not have legal precedent of their own to guide their decision-making.

The dataset is citations between state supreme courts from 1960–2010. To create the data, I searched LexisNexis Academic to obtain a list of all state supreme court opinions involving family law and judicial conduct issues. Next, I identified each time a court cited another state supreme court. Finally, I removed instances in which a court cites itself, leaving 50 states who might cite any of the other 49 states. For each year, there are 2,450 possible directed dyads per year (50 courts x 49 potential courts to cite).

Since courts are interdependent – they cite one another – I directly model the relational dynamics between them. I apply network analysis because it can model the citations and account for dependencies within the citation network. I model the ties between courts using an exponential random graph model ("ERGM"), a method that allows scholars to formally test hypotheses. ERGMs offer an inferential approach to quantify relationships while also relaxing the strict independence assumptions required by traditional OLS and logit models. If the data generating process is truly independent, ERGMs reduce to a logit model (Cranmer, Desmarais, and Menninga 2012). ERGMs model both the actors (state supreme courts) and the interactions (citations) between them.

The ERGM I apply is a temporal exponential random graph model with bootstrapped pseudo-likelihood ("TERGM") (Desmarais and Cranmer 2010). Other network models cannot account for the lagged network connections and time, which the TERGM explicitly models.

The bootstrapped pseudo-likelihood estimation does not provide standard errors but provides confidence intervals for coefficient estimates.[2] Alternative network models pool all the data together; they also make the assumption that previous and successive networks are independent from one another. TERGMs offer a novel way to test for diffusion because traditional models, such as event history analysis, do not explicitly model relations between institutions.

Network analysis treats the network as a single observation. The unit of analysis is network-year, and the dependent variable is the network at year t. State supreme

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[2]The model is bootstrapped 1,000 times.

courts are the nodes. Citations from the citing court to the cited court are the links that connect the courts. Courts direct their citations; a citation from Court A to Court B differs from a citation from Court B to Court A. Although there could be several citations between the same courts, I dichotomize the citations: coded 1 when court A cites court B in a year, and zero otherwise.

For example, in 1991, the California Supreme Court cited the Nebraska and North Dakota supreme courts when it wrestled with interpreting a jurisdictional issue in a modification of a child support order.[3] In the same legal opinion, the California Supreme Court cites two different North Dakota cases. Although California cites North Dakota twice in the same opinion, the citation variable takes a value of one for the California-North Dakota dyad.

Control variables

I also control for the two courts' shared characteristics to test whether courts are more likely to cite a court that shares similar attributes.[4] The control variables fall into four categories: political, demographic, geographic, and court characteristics. For the continuous variables, I calculate the absolute difference to capture the effect of similarity, or homophily, on citation adoption. For indicator variables, if the two states or courts in the dyad share the feature, it is coded as a 1, zero otherwise.

To begin, I control for political similarities between the two courts and the citizens of the states in each dyad. To capture the demographic features of the two states, I include state population and gross state product. Another way to conceive of similarity is based on geography. First, I include an indicator variable for contiguous borders. Contiguous states are likely to share not only similar geographic features but also cultural and economic characteristics. The federal court system also defines courts' borders and whom they consider neighbors, so I control for shared federal circuit. I also control for legal regional reporting system, using West's Reporter regions.

Institutional rules and design of the judicial branch may influence a state's decision to cite another state. I include an indicator variable, Same Judicial Selection Method when the courts in the dyad possess the same judicial selection mechanism (retention, governor-appointed, partisan election, or non-partisan election). I also control for the court's professionalism (Squire 2008).

Because courts must wait for litigants to file a lawsuit before they can cite other courts, I control for courts that do not cite and are not cited by other state supreme courts, known as isolates. Substantively, more isolated courts mean fewer courts are available to engage in citations. I also control for the number of cases a state supreme court publishes each year. Finally, I include a linear time trend and a lagged network, which accounts for whether previous citations affect the current network.

Results

I display the TERGM results in Figure 2. Variables that are statistically significant at the .05 level are shown in red. Full model results are available in the

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[3]*Monterey County* v. *Cornejo*, 812 P.2d 586 (Cal 1991).
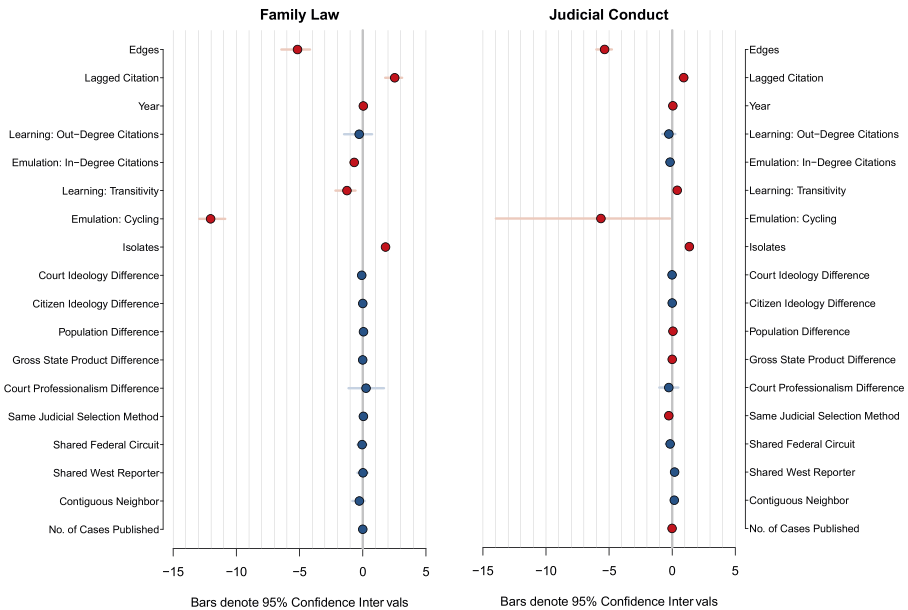[4]The Supplementary material offers a detailed description of the variables.

Figure 2. Coefficient Plots of State Supreme Court Citations.

Supplementary material. Controlling for the shared characteristics, I find evidence courts do not emulate but learn from each other.

Beginning with family law, in-degree emulation is negative and statistically significant. Under the emulation hypothesis, I expected that a state would become a leader and receive more citations than other courts. However, the negative coefficient indicates that every additional citation decreases the probability of a state supreme court citing another court. Substantively, this means that some state supreme courts do not receive more citations than others. Next, cycles, is also negative and statistically significant. The presence of a citation from A → B and B → C does not increase the probability of a citation from C → A. The courts do not form cliques, as emulation would suggest. Together, these results reveal courts do not imitate one another in family law cases.

The learning out-degree coefficient for family law is not statistically significant. This variable is measured as two or more citations to other courts, but the results suggest learning occurs at a chance rate given other model parameters. The other learning measure, transitivity, is also negative and statistically significant. Courts are not likely to seek citations from the friend of a friend. Together, these results reveal there is no learning or imitation in family law cases.

The results for judicial conduct uncover a clearer mechanism. There are statistically significant results for transitivity, and in the opposite direction as family law. A positive coefficient means there is a tendency towards transitivity in judicial conduct cases, that is, transitivity positively and significantly predicts courts' citations. Substantively, this means citations between two courts (A and B) influence the original court to cite the second court (A to C). Transitivity was included as a proxy for learning. The learning covariate, the outward measure of citation activity, did not

reach statistical significance. As with judicial conduct, learning occurs at a chance rate given other model parameters.

Judicial conduct emulation has mixed results. The statistically significant and negative cycle coefficient means there is not a tendency for cliques to form, as emulation predicts. Emulation, measured by the citations courts receive, is not statistically significant. The negative cycle and the positive transitivity coefficients together offer evidence state supreme courts learn from one another in judicial conduct cases.

In addition to the main variables of interest, I included two temporal variables: a lagged dependent variable and year. The year covariate is slightly positive and statistically significant in judicial conduct, meaning a linear time trend is present. Both models have a positive and statistically significant lagged citation. The network at time 1 affects the network at time 2. This means that the previous year's citations affect the current year's citations. For example, a state that is likely to cite Minnesota in year 1 is likely to do so in year 2.

I included the remaining covariates to control for shared features of the two states and courts. Most variables are not significant except a few in the judicial conduct model. Same judicial selection method and gross state product are negative and statistically significant in the judicial conduct model, indicating that courts cite courts that share the same judicial selection method and have similar economies. The positive population variable means courts cite courts from states with different populations. The remaining control variables do not reach statistical significance. This is likely because the TERGM models the interdependent nature of the citations. To determine how well the model fits, I tested the model's goodness of fit. The models perform reasonably well; the plots are available in the Supplementary material.

Like all models, there are limitations. The results presented examine dyadic ties, yet one court can cite another state's courts many times in a year. Reducing the citations to binary variables is a limitation of temporal longitudinal network models, at least those with polished software. Thus, the results likely underestimate the effect size.

Conclusion

State supreme courts are autonomous institutions with significant power. Despite this authority, they rely on one another to explain why and how they reached their decisions. Yet, scholars often assume – theoretically and methodologically – that the courts behave independently. Applying the policy diffusion theory and TERGM framework to courts offers a novel way to examine courts and their citations. My results demonstrate state supreme courts are interdependent: courts rely on one another to make their decisions.

I draw two additional conclusions from these results. First, the citation patterns may reveal the mechanisms. For family law cases, the courts do not emulate each other. The negative emulation variable means certain state courts do not accumulate more citations than others, which we would expect if there was a popular or leader court to whom the others turn. And the negative cycling variable signifies courts do not form cliques and follow the lead of another. The negative transitivity measure and the absence of statistically significant learning effects do not offer strong conclusions of the learning mechanism in family law cases. Judicial conduct has a stronger

mechanism. Transitivity, or the friend of a friend is my friend, was positive and significant meaning courts cite a court because they learn from one another. The negative cycling variable offers evidence that courts do not form cliques, as we would expect from emulation. Finally, the emulation and learning coefficients were not statistically significant. As before, a variable that is not significant means there is no evidence for or against the mechanism. Together, for judicial conduct cases, these results suggest state supreme courts are citing other courts because they are learning – and not imitating – one another.

The second conclusion is the motivation behind the citations is important. Learning and transitive courts look to the law first to solve their current legal issue. And cycling and emulation suggest courts are citing other courts based on pressure to do what others have done. Yet there's no reason to believe that the mechanisms must occur in isolation: multiple mechanisms can take place at the same time. Instead of making assumptions about which mechanisms occur, network analysis allows researchers to directly test the mechanisms, and test them simultaneously. While these results do not suggest they occur at the same time, other policy areas may reveal multiple mechanisms operating together, a fruitful avenue for future research.

References

Braun, Dietmar, Fabrizio Gilardi, Katharina Füglister, and Stéphane Luyet. 2007. "Ex Pluribus Unum: Integrating the Different Strands of Policy Diffusion Theory." In *Transfer, Diffusion Und Konvergenz von Politiken*, eds. Katharina Holzinger, Helge Jörgens and Christoph Knill, 39–55. Wiesbaden: VS Verlag für Sozialwissenschaften.

Butz, Adam M., Michael P. Fix, and Joshua L. Mitchell. 2015. "Policy Learning and the Diffusion of Stand-Your-Ground Laws: Policy Learning And SYG Diffusion." *Politics & Policy* 43 (3): 347–77.

Caldarone, Richard P., Brandice Canes-Wrone, and Tom S. Clark. 2009. "Partisan Labels and Democratic Accountability: An Analysis of State Supreme Court Abortion Decisions." *The Journal of Politics* 71 (2): 560–73.

Caldeira, Gregory A. 1985. "The Transmission of Legal Precedent: A Study of State Supreme Courts." *American Political Science Review* 79 (1): 178–94.

Canon, Bradley C., and Lawrence Baum. 1981. "Patterns of Adoption of Tort Law Innovations: An Application of Diffusion Theory to Judicial Doctrines." *American Political Science Review* 75 (4): 975–87.

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

Desmarais, Bruce A., and Skyler Cranmer. 2010. "Consistent Confidence Intervals for Maximum Pseudo-likelihood Estimators." In *Proceedings of the Neural Information Processing Systems 2010 Workshop on Computational Social Science and Wisdom of Crowds*.

Escobar-Lemmon, Maria C., Valerie J. Hoekstra, Alice J. Kang, and Miki Caul Kittilson. 2021. "Breaking the Judicial Glass Ceiling: The Appointment of Women to High Courts Worldwide." *The Journal of Politics* 83 (2): 662–74.

Fix, Michael P., and Benjamin J. Kassow. 2020. *US Supreme Court Doctrine in the State High Courts*. New York: Cambridge University Press.

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

Hettinger, Virginia A., Stefanie A. Lindquist, and Wendy L. Martinek. 2004. "Comparing Attitudinal and Strategic Accounts of Dissenting Behavior on the U.S. Courts of Appeals." *American Journal of Political Science* 48 (1): 123–37.

Hinkle, Rachael K., and Michael J. Nelson. 2016. "The Transmission of Legal Precedent among State Supreme Courts in the Twenty-First Century." *State Politics & Policy Quarterly* 16 (4): 391–410.

Klein, David E. 2002. *Making Law in the United States Courts of Appeals*. Cambridge, U.K.: Cambridge University Press.

Lee, Chang Kil, and David Strang. 2006. "The International Diffusion of Public-Sector Downsizing: Network Emulation and Theory-Driven Learning." *International Organization* 60 (4): 883–909.

Leonard, Meghan E., and Joseph V. Ross. 2016. "Understanding the Length of State Supreme Court Opinions." *American Politics Research* 44 (4): 710–33.

Lutz, James M. 1997. "Regional Leaders in the Diffusion of Tort Innovations among the American States." *Publius: The Journal of Federalism* 27 (1): 39–58.

Matthews, Abigail. 2023, "Replication Data for: Learning from and Emulating Their Peers: Policy Diffusion in the Courts,", UNC Dataverse, V1, UNF:6:AowCmvVh7s7ZIFyQZWocZA== [fileUNF]. doi: 10.15139/S3/JX0BF4.

Moyer, Laura P., and Holley Tankersley. 2012. "Judicial Innovation and Sexual Harassment Doctrine in the U.S. Courts of Appeals." *Political Research Quarterly* 65 (4): 784–98.

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

Solberg, Rorie Spill, Jolly A. Emrey, and Susan B. Haire. 2006. "Inter-Court Dynamics and the Development of Legal Policy: Citation Patterns in the Decisions of the U.S. Courts of Appeals." *Policy Studies Journal* 34 (2): 277–93.

Squire, Peverill. 2008. "Measuring the Professionalization of U.S. State Courts of Last Resort." *State Politics & Policy Quarterly* 8 (3): 223–38.

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

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