Policy Diffusion and Polarization across U.S. States*

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Abstract

Economists have studied the impact of numerous state laws, from welfare rules to voting ID requirements. Yet for all this policy evaluation, what do we know about policy diffusion—how these policies are introduced and spread from state to state? We present a series of facts based on a data set of 602 U.S. state policies spanning the past 7 decades. First, proxies of state capacity do not predict a higher likelihood of innovating new policies, but the political leaning of the state does predict a higher likelihood of introducing partisan laws since 1990. Second, the diffusion of policies from 1950 to 2000 is best predicted by proximity—a state is more likely to adopt a policy if nearby states have already done so—as well as similarity in voter policy preferences. Third, since 2000, party alignment has become the strongest predictor of diffusion, and the speed of adoption has increased. Models of learning and correlated preferences can account for the earlier patterns, but the findings for the last two decades indicate a sharply increasing role of party control. We conclude that party polarization has emerged as a key factor recently for policy adoption, plausibly leading to a worse match between state policies and voter preferences.

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1 Introduction

In a federal system like the United States, the states have significant independence in designing state-level institutions and rules. As such, states are free to experiment, with other states potentially following suit depending on the results for early adopters. In this optimistic view, states are *laboratories of democracy*, as famously proposed by Justice Brandeis in 1932.[1] But what do we know about the actual innovation and diffusion of state policies? Have the key patterns of innovation and diffusion changed over the last half century?

Surprisingly, economists have paid limited attention to the diffusion of policy innovations, with the notable exceptions of studies on tax competition across U.S. states (Case, Rosen, and Hines Jr., 1993; Besley and Case, 1995; de Paula, Rasul, and Souza, forthcoming) and the theoretical literature on states as laboratories of democracy (Callander and Harstad, 2015). This limited attention is surprising given that numerous studies across nearly each subfield of economics have examined the impact of policy innovations, including recently the impact of Medicaid adoption on health (Goodman-Bacon, 2021), of voter ID laws on turnout (Cantoni and Pons, 2021), and of minimum-wage laws on worker earnings (Cengiz et al., 2019). Understanding the diffusion of such policies is not just of interest in its own right, but could also inform our understanding of studies such as these.

In this paper, we study key features of the innovation and diffusion of policies at the U.S. state level, and how it has changed since the 1950s. Our study builds on the efforts of political scientists who have studied this topic since at least Walker (1969), as reviewed by Graham, Shipan, and Volden (2012) and Mallinson (2020). We return below to comparing our results to those in the political science literature, but we emphasize our focus on quantifying the magnitudes across different channels and determinants.

We analyze the patterns of innovation and diffusion for a large sample of 602 state laws enacted from the 1950s until 2020. The first main source of data is the State Policy Innovation and Diffusion (SPID) Database (Boehmke et al., 2020) which includes information on over 700 state law policies adopted in the last century. For each state law—for example on "Kinship Care Program" or on "Voter Registration by Mail"—the data set reports the year of adoption by state (if ever). This recent data set, which to our knowledge has not been previously used in economics, covers a fairly representative range of state law topics, but has limited coverage of the last decade. We thus extended its coverage through the 2010s for a subset of the policies. The second source is a newly-assembled data set of state-level policies analyzed in economics working papers. Starting from 11,316 National Bureau of

[1] "A single courageous State may, if its citizens choose, serve as a laboratory; and try novel social and economic experiments without risk to the rest of the country." (New State Ice Co. v. Liebmann, 285 U.S. 262, 1932).

Economic Research (NBER) working papers from April 2012 to September 2021, we identify 170 papers with U.S. state-level policy variation. Out of this set, 91 papers meet our criteria, for a total of 53 policies (given that some policies are in multiple papers).

The combined data set has a draw-back in its black-box structure: it is not obvious what areas these policies address, and whether the composition of the policy areas has changed over time. We tackle this issue by identifying 20 of the most common categories, such as guns, education, voting, and taxes, using keywords in the policy descriptions, and keeping only laws that fall into one of these groups. Each of these categories contains at least 10 state laws and spans all decades in our sample; further, the composition of laws across categories has not changed much over the decades. The final sample includes 602 state laws adopted from the 1950s to the 2010s. Figure 1 presents three examples. The Uniform Transfer to Minors Act (Figure 1a) spread in a fairly idiosyncratic way, while the Medicaid expansion from the Affordable Care Act (ACA) (Figure 1b) followed political lines. Finally, the adoption of the initial prescription drug monitoring policy (Figure 1c) appears geographically clustered.

We consider first a case study on Medicaid. As mentioned, the ACA Medicaid expansion spread largely to Democratic states (McCarty, 2019). A possible explanation is the higher need in Democratic states, but in fact the share of population that would benefit from the policy is larger in the Republican states. Since the costs of the policy are heavily subsidized by the federal government (Gruber and Sommers, 2020), this suggests that the state-level adoption was more a function of political considerations than of match to local needs. Has this always been the case? Interestingly, the initial Medicaid introduction from 1966 at the state level was essentially orthogonal to state-level voting, as was the introduction of the food stamp program in the 1960-70s. This case study thus suggests a recent increase in the role of partisan politics in the diffusion of state-level policies, but we cannot tell whether this is a general feature, or when this change occurred. We thus turn to the full data set.

We consider three main questions. First, are some states more likely to introduce new policies? Second, what predicts the diffusion of a policy across states? Third, are there patterns that allow us to tease out different models of policy adoption?

We point out some caveats. First, the findings mostly describe the patterns of policy diffusion and do not reflect causal inferences (Manski, 1993). Second, while the data set has broad coverage, it lacks details such as the text of the law or the likely medium of diffusion. Third, we do not observe the effectiveness of all the policies, and thus cannot evaluate the general role of effectiveness in the diffusion process. Nonetheless, this descriptive evidence is valuable to cast light on different models and for predictive purposes, for instance, predicting which states are likely to adopt a particular policy in a difference-in-differences study.

Which states originate new laws? One theory is that states with more resources and capacity innovate more (Walker, 1969; Besley and Persson, 2009). If innovative policies require a fixed cost, then larger and richer states should be more likely to generate new policies (Mulligan and Shleifer, 2005). Another possibility is that political preferences in the state or political control of the legislature predict this measure of innovation. We do not find evidence of an impact for proxies of state-level resources, but we do find a partisan impact since 1990: states with higher Republican vote-share are more likely to introduce laws that are ex-post classified as Republican-leaning, and vice versa for Democratic-voting states.

How do policies diffuse? The diffusion may depend on competition, for example, states raising expenditures when neighboring states do (Case, Rosen, and Hines Jr., 1993; de Paula, Rasul, and Souza, forthcoming), learning (Wang and Yang, forthcoming), common preferences across states, and ideological alignment (Volden, Ting, and Carpenter, 2008). We measure this both "statically" and "dynamically". For the static measure, we take the states that have adopted the policy at a particular cross-section (say, after the first 10 adoptions), and assess their degree of similarity in a dimension (e.g., geographic similarity) using the Geary's C measure. For dynamic patterns, we use a logit hazard model outlining the dimensions along which policies tend to diffuse, given the adoption up to that period. The dimensions of diffusion are informative about the underlying models. For example, diffusion along politically similar states would suggest the importance of ideological alignment.

The patterns of policy diffusion have changed substantially over the last seven decades. Policy adoption from the 1950s to the 1990s is best predicted by geographic proximity. States are more likely to adopt a policy if nearby states have already done so. The adoption by demographically similar or politically aligned states is a weaker predictor.

In the 2000s and 2010s, geographic and demographic proximity remain similarly predictive, but by far the strongest predictor becomes adoption by politically aligned states. Specifically, similarity in the Republican vote-share in recent elections becomes an important predictor in the last two decades, and even more predictive is the similarity in state party control. The latter factor implies a role of party influence.

We also examine the speed of adoption and document that it has increased in the last two decades. This increase is mostly for laws with up to 20 adoptions, as opposed to laws with more than 20 adoptions, a threshold that is more likely to be passed by bipartisan laws.

Next, we relate these findings to leading models of policy diffusion. A set of explanations stresses *correlated preferences and environments*, *learning*, or *competition* among states. These (distinct) explanations all capture the importance of geographic and demographic proximity in the earlier decades, whether due to similar contexts, local spread of information, or competition at the borders. The recent patterns are a less obvious fit, but it is plausible that recently information flows, the extent of competition, and the correlation in preferences may have shifted from mostly geographic to largely political. To control for preferences, we measure the similarity in policy views across states among voters surveyed in the American National Election Studies (ANES) and in the General Social Survey (GSS), as well as using other measures of voter preferences in the literature. To capture information flows and to an extent competition, we use migration across states. These variables do predict policy diffusion, and they reduce the coefficient on geography and demographics by nearly half and the coefficient on vote-share by nearly a third. However, they hardly affect the importance of state government control, which remains the most predictive variable.

As a further test of the growing importance of *party control*, we estimate an event study of switches from divided state governments to unified state governments (that is, the governor and the majority in both state houses belong to the same party). We detect no impact in the earlier decades, but in the last two decades, this transition indeed raises the probability of passing laws aligned with the governing state party, with no impact on bipartisan laws.

A final explanation is that different types of laws, for instance on controversial topics, have become more common. We take advantage of the classification of laws into the 20 keyword categories and estimate whether the process of diffusion has changed *within* a category. We find similar patterns, with a strong increase in the role of party control in the last two decades. We also present a case study on public health policies for preventing infectious diseases, showing that the party polarization that has characterized the approval of COVID-related laws during 2019-21 was not present for state vaccination laws passed since 1980.

Our findings indicate an important change in the match of state policy to voter preferences. The patterns for the earlier years are consistent with the findings of Erikson, Wright, and McIver (1989), that state policy used to be largely driven by voter preferences, not state party control. A contribution of our diffusion model is that we do not need to assign a partisan value to each law, as we use the *similarity* in voter preferences and in state party control to predict the diffusion; this approach allows us to use a larger sample of laws. Our findings for the last two decades, documenting a sharp uptick in polarization at the state level since the 2000s, add to the literature on polarization (Poole and Rosenthal, 1985; Fiorina and Abrams, 2008; Caughey, Warshaw, and Xu, 2017; McCarty, 2019; Canen, Kendall, and Trebbi, 2020; Boxell, Gentzkow, and Shapiro, 2024) that finds a similar trend for politicians in Congress, which had been already rising since the 1950s. These findings imply likely a worse match of policies to local voter preferences (e.g., Strumpf and Oberholzer-Gee, 2002).

The paper is related to the literature on policy experimentation (e.g., Callander and Harstad, 2015, Hjort et al., 2021, and Wang and Yang, forthcoming). While we do not observe the policy effectiveness for most policies, in the NBER sample we categorize policies as either ineffective or effective using the estimates from the papers, and find a growing role of party politics for the diffusion of both types of policies.

The paper is related to the literature on policy diffusion. Relative to the small number of papers in economics, we examine a wide range of policies, complementing the detailed evidence on specific policies, for example, taxation in the pioneering contribution of Besley and Case (1995), state-level fair employment laws (Collins, 2003), and welfare reform (Bernecker, Boyer, and Gathmann, 2021). In political science, in line with our findings, Caughey, Warshaw, and Xu (2017), Grumbach (2018), and Mallinson (2021) also detect evidence of widening polarization in the adoption of state laws. Relative to these papers, summarized in Table A.1, our unique contribution is that we compare quantitatively the determinants of diffusion, allowing us to evaluate the role of different models. We also document that the recent polarization is at least as strong for the high-profile policies studied by economists.

2 Case Study: Medicaid and Food Stamp Program

Before we present the full analysis, we consider a case study. An important component of the Affordable Care Act was the expansion of the Medicaid health insurance to cover adults earning up to 138% of the Federal Poverty Line. The expansion comes at nearly no cost to the states, as the federal government pays 100% for newly eligible enrollees until 2016, and 90% thereafter (Gruber and Sommers, 2020). Despite this generous subsidy, the adoption at the state level has followed partisan lines, as Figure 1b shows. Indeed, Figure 2a shows that the Republican vote-share of the state predicts very accurately the year of adoption.

This suggests a large partisan impact on policy adoption, but it could be that the political preferences align with the underlying demand for the policy: the Republican states that delay adoption may have fewer people who would benefit from it. In fact, the opposite is the case: the states with higher Republican vote-share—the non-adopters—have a higher share of population that would benefit from the expansion (Figure 2b). The political preference thus appears to come at the expense of the match quality between the policy and the state.

A possible explanation is that major benefit expansions have always had this partisan structure. We thus revisit the initial Medicare roll-out enacted in July 1965. Voluntarily participating states received federal funds from January 1966, with an initial match of 50-83% across states, though the states had to cover certain groups and provide required benefits. This subsidy structure is thus not too dissimilar from the one for the ACA Medicaid expansion (though not as generous). Overall, 26 states enacted the Medicaid program within the first year, 37 within two, and nearly all within four years. Strikingly, the political leaning of the state does not predict the timing of adoption, as Figure 2c shows.

Another major public benefit expansion in the 1960s is the food stamp program. After county-level food stamp programs piloted in 1961, the Food Stamp Act was passed in 1964 and counties set up their own food stamp programs, with the federal government paying for the benefits and the states setting their own eligibility criteria. As the bin scatter in Figure 2d shows, the county voting patterns have no predictive power for the timing of approval. Demographics are predictive for the timing of adoption (i.e., counties with more vulnerable population) as Hoynes and Schanzenbach (2009) show, but not politics.

These case studies suggest that polarization may be playing a role in the current adoption of state laws in a way that was not the case in earlier years. Is this a general lesson? We address this question and others in the next sections.

3 Data and Summary Statistics

SPID Data Set. The main source of data is the State Policy Innovation and Diffusion (SPID) Database (Boehmke et al., 2020). The data set includes information on over 700 state law policies adopted in the last century and combines existing data sets on state-level adoptions with the purpose of providing a representative sample of state policy topics. The main datasets aggregated in the SPID data set are (i) Boehmke and Skinner (2012) with 79 policies, itself building on the pioneering work of Walker (1969); (ii) Caughey and Warshaw (2016) with 104 policies mostly related to certification requirements for professions; (iii) the Uniform Law Commission (which focuses on nonpartisan legislation) with 187 policies, (iv) the National Center for Interstate Compacts with 52 policies, and (v) other smaller sources. Figure A.1a shows the number of policies from the main sources over time, and Table A.2a presents 40 randomly sampled examples of these laws.

For each state law—for example on “Kinship Care Program” or on “Voter Registration by Mail”—the data set reports a one-line description of the law, the source, the policy area, and the year of adoption in each state (if ever). The data set does not record if a law is rescinded, since such events are rare. Furthermore, the data set records only binary adoption, and not continuous variables such as the level of the minimum wage across states. We validated the adoption dates for a sample of laws with rare corrections.[2]

A significant limitation of the data set is the limited coverage of the most recent decade. We thus extended its coverage especially from 2015 to 2020 for a subset of the policies using publicly available data sources, as detailed in Online Appendix Section A.

NBER Data Set. While the SPID data set is extensive, there is no guarantee that it covers high-profile state laws of interest to economists. We thus collected a similar, though

[2] The data set does not report information on the state-level process of law proposal, enactment, or discussion. Useful references in this regard are Boehmke et al. (2020) and Gamm and Kousser (2010).

smaller, sample from economics papers. From the 11,316 NBER working papers from April 2012 to September 2021, we manually checked and identified 170 papers with U.S. state-level policy variation, covering especially labor, public, and health economics (Column 2 in Table A.2c). We then apply our sample restrictions, including the restriction to binary policy adoption, yielding 91 papers (Column 3). For 80 out of these 91 papers we can extract the timing of state-level policy adoption, typically from a table in the paper, covering 53 policies (given that, for example, multiple papers analyze the same policy of Medicaid expansion). Health economics is the most common field, followed by public and labor economics, and the share of published papers, 45 percent, is similar to the overall share for NBER papers of 48 percent (Column 1), and similarly for the share published in "Tier A" journals (following the categorization in Heckman and Moktan, 2020). The full list of papers is in Table A.2b.

Sample. We apply a set of restrictions to the pooled SPID and NBER data. First, we keep policies with the last adoption after 1950 since we do not have enough coverage of historical patterns. Second, we consider only adoption in the contiguous 48 states, since coverage of Alaska, Hawaii, and Washington DC is spotty.

Third, we keep only laws categorized into one of 20 common areas of state legislation. To categorize laws, we take advantage of the one-line summary for the laws in the SPID data, and a similar brief description taken from the papers for the NBER sample. Starting from a word cloud of common words in the laws (Figure A.1b), we create a list of keywords associated with each category, with the goals of identifying areas that (i) are specific, (ii) contain at least 10 laws each, and (iii) span the whole sample period. Table 1a displays the 20 categories in decreasing order of number of laws, with education, abortion, health, crime, and intoxication being the leading areas. We exclude the laws that do not belong to any of the 20 areas, excluding about 15 percent of the sample per decade (Figure A.1c).

The final data set includes 549 policies from the SPID data set and 53 policies from the NBER data set (Table 1b). The coverage of the data set peaks around 2000 (Figure 3); over time, the composition of policies across keyword categories has not changed much.

Outcome Variables. For 18 policies in the NBER sample, we reconstruct the dependent variable studied in the papers, either through the replication files or public data sources. The 10 state-level outcome variables (given that there are repetitions across the papers), such as the private insurance coverage rate and BMI, are summarized in Table A.3a. We supplement these variables with 18 other state-level variables typically used in policy evaluations from the Correlates of State Policy Project (CSPP), such as the state-level poverty rate or per capita welfare expenditure. We use these variables in Section 5.1.

COVID and Vaccination Samples. We collect 76 state policies enacted from October 2019 to August 2021 to deal with the COVID pandemic, such as the requirement to wear masks or school closures, from the COVID-19 U.S. State Policy database (CUSP) (Table A.3b). We record the policy adoption at the weekly level. We also collect information on the introduction of 28 state policies regarding vaccination mandates enacted since 1980 from sources such as the CDC and the Immunization Action Coalition (Table A.3c).

4 Evidence on Innovation and Diffusion

4.1 Innovation

We first consider whether some states are more likely to be early adopters. One theory is that states with more resources, capacity, or "legislative professionalism" tend to innovate policies (Walker, 1969; Besley and Persson, 2009). If there is a substantial fixed cost, larger and richer states should be more likely to generate new policies (Mulligan and Shleifer, 2005). Another possibility is that unified political control of the state legislature facilitates policy innovation, or that policy innovation is related to political preferences in the state.

We define states that adopt a policy in its first year to be innovators, and sum the number of innovations by state. In Figure 4a-b we present a color-coded map of the U.S. displaying how often a state was an innovator in 1950-89 (Figure 4a) and in 1990-2020 (Figure 4b).[3] The map does not show an obvious pattern. California, the largest U.S. state by population, tops the list of innovators, but other large states such as Florida and Texas are in the middle of the pack, and a smaller state such as Connecticut is among the top innovators.

In Table 2 we regress at the state-year level the number of laws innovated on demographic, economic, and political features of the state for the earlier decades (Columns 1-4) and the most recent decades (Columns 5-8). We include year fixed effects and cluster the standard errors at the state level. We find no evidence that states with larger population or higher income are more likely to innovate. The only demographic predictor is the share of urban population.[4] For the political variables, a higher Republican vote-share is associated with a lower rate of innovation in the earlier decades, though the pattern if anything reverses more recently.

In Columns 2–4 and 6-8 we examine separately laws that ex-post appear to be partisan Democratic, Republican, or non-partisan as a function of the vote-share of the states that ultimately adopt a law.[5] For partisan policies, we do not find any robust pattern in the

[3] Figures A.2a-d show similar color-coded maps for all policies across time periods (A.2a), policies with ≥ 24 adopters (A.2b), Right-leaning policies (A.2c), and Left-leaning policies (A.2d).

[4] In Table A.4 we include a measure of legislative professionalism, with limited coverage of years from 1973-2014.

[5] We use the average demeaned two-party Republican vote-share (measured in the year of adoption) among all the states that ultimately adopt the policy (excluding the innovator states). We also exclude the

earlier period. Since 1990, however, the vote-share in the state predicts partisan innovation: states with a higher Republican vote-share are more likely to introduce laws that are ex-post classified as Right-leaning, and less likely to introduce laws that are ex-post Left-leaning. We do not find instead a clear impact of unified Republican or Democratic state government.

Overall, innovation appears to be idiosyncratic on most state characteristics except the share of urban population, but more recently, political orientation has become a factor in the production of partisan laws.

4.2 Policy Diffusion

Following innovations, we examine the dimensions of similarity across states—geographic, demographic, and political—that predict the diffusion of policies. We consider first a static analysis of the first 10 states adopting a given policy, comparing their similarity along a particular dimension, relative to a benchmark of random diffusion. This static comparison provides non-parametric evidence but it does not use all the information on the path of diffusion, and it does not lend itself to multivariate comparisons of various determinants. We thus analyze the dynamics of adoption with a logistic hazard model.

Static Evidence. For each law, we compute the proximity of the first 10 adopters (provided that this threshold of adoption was reached) with respect to the relevant dimension—for example, geography and politics. As a measure of clustering along a dimension, we use the Geary's C statistic, which is typically used to measure geographic correlation (Geary, 1954; Barrios et al., 2012). The denominator is an unweighted average of the squared differences between all pairs, and the numerator is a weighted average where the weight for each pair increases in their proximity along the specified dimension:

$$C = \frac{\frac{1}{W}\sum_{i=1}^{n}\sum_{j\neq i} w_{ij}(x_i - x_j)^2}{\frac{1}{n(n-1)}\sum_{i=1}^{n}\sum_{j\neq i}(x_i - x_j)^2}$$

where $x_i \in \{0,1\}$ is an indicator for whether state i has adopted the policy, n is the number of states in the sample, w_{ij} is the weight for the pair ij, and W is the sum of weights.[6] If the states that are closer in the dimension are similar in policy adoptions, the weighted average of the differences in the numerator should be smaller than the unweighted average in the

innovating states from the calculation of the average vote-share for demeaning. If the average demeaned vote-share is 1 percentage point (pp.) or above, the policy is categorized as a right-leaning policy; if 1 pp. or below, a left-leaning policy; and between -1 to 1 pp., a non-partisan policy. We also categorize as non-partisan the policies that are adopted by fewer than five non-innovating states and policies with more than five innovating states, as a partisan classification for these policies is likely to be quite noisy.

[6] The weight for pair ij may not equal the weight for the pair ji. For example, Michigan is in the closest third of states for Maine, but Maine is not in the closest third of states for Michigan.

denominator. Consequently, values of this measure below 1 indicate clustering, values above 1 suggest the opposite, and a value of 1 is the null hypothesis.

To gain intuition, consider 5 states on a line, A, B, C, D, E, with each state contiguous to the nearby ones, that is, A is contiguous to B, B is contiguous to A and C, and compute Geary's C with respect to contiguity. Consider first the case in which the adoption of a policy is (1,1,1,0,0), that is, A, B, and C adopted, but D and E did not. The contiguous pairs are (1,1), (1,1), (1,0), and (0,0), each repeated. We average the squared difference between these pairs, yielding a numerator of 1/4. The denominator is the average of squared differences between all pairs, 12/20=3/5. This results in a C of $\frac{1/4}{3/5} = 5/12 < 1$, indicating substantial correlation among contiguous neighbors. Consider instead the case in which adoption is (1,0,1,0,1), with the same number of adoptions, but none contiguous. The numerator is 1 given that all contiguous pairs are of the type (0,1), while the denominator is unchanged; the C is $1/(3/5) = 5/3 > 1$, indicating a negative degree of contiguous clustering.

In our case, in the numerator we assign equal weight to the third of other states most similar in the dimension of interest—geography or politics—and put zero weight on other states. We display 1-C, so higher values correspond to higher similarity, and 0 corresponds to no clustering. We compare the observed clustering after 10 adoptions to a counterfactual of adoption by 10 random states, from 1000 simulations.

In Figure 5a we display the geographic clustering of policies in the 1950s-70s (95 policies), 1980s-90s (193 policies), and 2000-10s (140 policies), indicating a degree of geographic clustering that is both substantial and persistent over time. For example, in the 1950-70s the Geary's C for the median policy corresponds to the 80th percentile of random policies.

In Figure 5b, we consider the extent of political clustering measured by the vote-share for the Republican presidential candidate, averaged over the two most recent elections. For the 1950s-70s and 1980s-90s, the median policy has a 1-C statistic close to 0, implying no measurable political clustering. In the 2000-10s, instead, we observe a clear rightward shift at all quantiles, including in the right tail. At the 90th percentile, the average $1 - C$ for the 2000-10s is 0.2, indicating substantial correlation, compared to 0.1 for the earlier decades.

Thus we detect both geographic and, increasingly, political clustering in policy diffusion. This finding is robust to measuring the clustering at the 16th adoption (a third of the contiguous states) and at the 24th adoption (a half) (Figure A.3).

A limitation of this analysis is that geography and politics are correlated, which this analysis does not separate. We thus turn to a hazard-type multivariate model.

Hazard Model of Diffusion. For all states i that have not yet adopted policy q in year t, we model the discrete-choice decision to adopt ($Y_{iqt} = 1$) with a logit specification:

$$\log\left(\frac{P(Y_{iqt}=1)}{1-P(Y_{iqt}=1)}\right)=\eta_q+\Pi X_{it}+\sum_k \beta_k p\left(A^k_{-iqt},A_{-iqt}\right)+\varepsilon_{iqt}. \qquad (1)$$

This specification, with the log odds on the left-hand side, has three right-hand-side variables. The first one, η_q, is a policy-specific baseline hazard rate for each decade, allowing for differences across policies in the overall probability of adoption. The second term, ΠX_{it} captures the overall impact of state-level features, such as state capacity, on adoption.

The third, key term, $\sum_k \beta_k p\left(A^k_{-iqt},A_{-iqt}\right)$, captures the influence of adoption by other states that are similar along a particular factor k, such as geography, demographics, or politics. We adopt a functional form that measures how likely, or unlikely, the pattern of adoption by similar states (A^k_{-iqt}) is, relative to the adoption by all states (A_{-iqt}), with respect to a particular dimension k. Considering the case of geography ($k=g$), we first compute the probability of $a^g_{-iqt}\in\{0,...,15\}$ adopters within the closest third of states, given the total number of adopters $A_{-iqt}\in\{1,...,47\}$, under the null of uniform adoption:

$$P(a^g_{-iqt}|A_{-iqt})=\begin{pmatrix} A_{-iqt} \\ a^g_{-iqt}\end{pmatrix}\frac{\left(\frac{15!}{(15-a^g_{-iqt})!}\right)\left(\frac{32!}{(32-(A_{-iqt}-a^g_{-iqt}))!}\right)}{\left(\frac{47!}{(47-A_{-iqt})!}\right)}$$

The measure is then the probability of having fewer adopters in the closest set of states minus the probability of having more adopters in the closest set of states:

$$p\left(a^g_{-iqt},A_{-iqt},\right)\equiv P(A^g_{-iqt}<a^g_{-iqt}|A_{-iqt})-P(A^g_{-iqt}>a^g_{-iqt}|A_{-iqt}) \qquad (2)$$

Consider a state i that has yet to adopt a policy that has been adopted by $A_{-iqt}=16$ states, of which $a^g_{-iqt}=5$ in the closest third geographically. Under the null, the probability of seeing fewer adoptions in the closest third of 15 states is 0.38, and the probability of more adoptions in the closest third is 0.37. Hence, $p\left(a^g_{-iqt},A_{-iqt},\right)$=$0.38-0.37=0.01$: the adoption by nearby states is in line with the overall adoption. Suppose instead that 10 of the 16 adoptions had been in the closest third of states. In this case, the probability of seeing fewer adoptions in the closest third is 0.998, and the probability of seeing more is 0.0002, and $p\left(a^g_{-iqt},A_{-iqt}\right)=0.998-0.0002=0.998$, indicating diffusion in the neighboring states.

This measure ranges from -1 (states similar to state i statistically have been unlikely to adopt a policy) to +1 (states similar to state i have proven quite likely to adopt). This functional form captures the strength of clustering along a particular dimension, with a cap; that is, if hypothetically 14 out of the 16 adoptions had been in the contiguous states, instead of 10 out of 16, the measure $p\left(a^g_{-iqt},A_{-iqt}\right)$ would have been essentially the same, as the evidence was already statistically very strong. Later, we consider alternative measures, such as the proportion of the states in the closest third that have adopted.

We build analogous measures of demographic and political similarity, except that the set of similar states is time-varying. To capture demographic (and economic) similarity, we take the average state-level log population, share of urban residents, log income per capita, the share of workers in manufacturing, and the share in farming. We standardize each variable within each year, calculate the absolute difference in each dimension, average to create the index, and then identify the closest third of states.

We create two measures of political similarity, one for voter preferences and one for party control. For voter preferences, we take the third of states with the smallest absolute difference in the average Republican vote-share from the two most recent Presidential elections. For similarity in state party, we categorize three types of state governments—unified Democratic (i.e., the governor is Democratic and both state houses have a Democratic majority), unified Republican, and divided state control (all other cases)—and define the "closest" states to be those with the same partisan control. We consider separately the case of unified control (Republican or Democratic) and the case of divided split-party governments.

Table A.5a shows for each decade pairs of states that are especially close along that dimension, and Figure A.4 displays how often a pair of states that are close along a dimension in year t are still close in that dimension in year $t+4$. The stability is of course 1 for geography, above 0.9 for demographics, between 0.6 and 0.9 for vote-share, and between 0.5 and 0.8 for party control of state government.

The four similarity parameters—β_g for geography, β_d for demographics and economics, β_v for vote-share and β_p for party control—are scaled to be comparable allowing for a quantitative comparison across determinants, which is unique in the literature (Table A.1). Hence if β_g is larger than β_d, adoption by geographically similar states is more predictive on average for future adoption by state i than adoption by demographically similar states.

We estimate specification (1) separately by decade, pooling the 1950s and 1960s given the limited coverage early on. In each year t, only states that have not yet adopted policy q are in the sample. For each policy, we include observations starting the first year of adoption and ending in the last year of adoption in the sample, and exclude policies that end with fewer than five adopters or span less than three years. We cluster the standard errors at the state level to capture autocorrelation, as well as correlations across policies. We re-weight the sample to keep the composition of areas of laws the same as the average across all years.

We stress that we do not place a causal interpretation on the estimates in (1) (Manski, 1993). For example, the adoption of a policy may be predicted by the adoption among geographic neighbors because of learning and diffusion of information (Banerjee, 1992; Bikhchandani, Hirshleifer, and Welch, 1992), or because of common demand or a common shock (e.g., a shared lobbyist). With this in mind, it is still useful to examine which dimensions predict adoption, as they inform us about the most likely nature of common shocks and circulation of ideas. Furthermore, even viewing the results as purely descriptive, they enable one to make predictions about future adoptions, which can be useful, for example, in the econometric evaluation of a difference-in-differences design. In Section 5.3, we provide estimates with a causal interpretation from an event study design for the change in state government control.

Hazard Estimates. We do not find any reliable pattern that state-level demographics X_{it}, including state income or population, predict faster adoption (see the coefficients in Table A.6). Turning to the similarity predictors β_k in Table 3, demographic and economic similarity is mildly predictive of adoption: in the 1980s we estimate a coefficient of 0.13 (s.e.=0.06), which has increased slightly (though not significantly) to the most recent decade, at 0.23 (s.e.=0.07). These estimates are consistent with some impact of similar context and preferences, but can also reflect competition and learning.

Next, we consider the impact of geographic closeness, which we expect to capture the impact of competition across neighboring states, learning about policies, and similarity in contexts and preferences. Geographic similarity is highly predictive, with a larger impact than demographic similarity, and with consistent importance over time, with a coefficient of 0.39 (s.e.=0.07) in the 1970s and of 0.43 (s.e.=0.07) in the most recent decade.

Third, we consider the role of similarity in the state-level Republican vote-share. For the first five decades, political similarity is a modest predictor, with an effect size mostly between a third to a half of that for geographic similarity: 0.11 (s.e.=0.06) in the 1970s, 0.08 (s.e.=0.06) in the 1980s, and 0.24 (s.e.=0.05) in the 1990s. In the last two decades, however, the impact jumps, to 0.45 (s.e.=0.05) in the 2000s and 0.47 (s.e.=0.08) in the 2010s.

The impact of similarity in voting could capture similarity in voter political preferences, or the impact of parties. To capture the latter component, we include party control of the state government. In the decades up to the 1990s, similarity in state party control is an inconsistent predictor. Yet in the 2000-10s period, previous adoption by governments with the same state party control becomes the strongest predictor of adoption for states under a unified state government (coef.=0.64, s.e.=0.10 for the 2010s). For states with split governments, there is no predictive power of adoption by other states with split governments, further underscoring the role of party control.

Figure 6 displays the similarity coefficients. Geographic and demographic similarity between states has consistently predicted the likelihood of passing the same laws. Similarity in the vote-share and party control, which explained little in the past, has become the most important predictors. We interpret this change as evidence of a shift in state policy-making, with party discipline taking on a key role in the 21st century.

Speed of Diffusion. Table 3 shows that the baseline probability of adopting a law in a given year has increased from 0.03 early on to 0.05 most recently, suggesting an increase in the speed of diffusion. In Figure 7a we plot the number of adoptions at t years since the introduction, for policies observed for at least 10 years. Policies are categorized into time periods based on the year of innovation (1950-70s, 1980-90s, and 2000-10s). The figure indicates an increase in the speed of adoption in the last two decades, compared to the earlier decades. Figure 7b, which shows the number of adopters by the 10th year since introduction, finds that this acceleration is due to a substantial increase in the share of laws with 11-20 adoptions by the 10th year and a corresponding decrease in the share of laws with fewer than 10 adoptions, with no change in the share of laws with 20+ adoptions. Figure A.5 shows a similar pattern for adoptions at 5 years. These patterns indicate an overall increase in the speed of adoption, consistent with faster diffusion of information or more efficiency, but not necessarily for bipartisan laws that spread to a majority of the states.

Simulated Diffusion. We present counterfactuals for the 1990s (Figure 8a) versus for the 2010s (Figure 8b). We take a hypothetical policy introduced by California in 2000 and simulate its diffusion over 20 years or until 10 adopters. For every state that has yet to adopt, we calculate its probability of adopting, and based on that probability, we randomly draw whether it adopts in that year. We assume the same political and demographic variables from the relevant years (2000 onward) across the two plots, and only vary the estimated diffusion coefficients. We color-code the states as a function of the probability that a state is among the first ten adopters across 1,000 simulations.

The policy with the estimated 1990s coefficients (Figure 8a) diffuses geographically in the West, as well as in some demographically similar states such as Florida and politically aligned states in the Northeast. With the estimated 2010s coefficients (Figure 8b), the spread of the policy becomes concentrated in the states with similar political leaning in the Northeast and along the West Coast in Oregon and Washington, while geographically close but politically distanced states such as Nevada, Utah, and Arizona become less likely to adopt.

In Figures A.6a-f, we document a similar increase in the role of political leaning following an innovation in: (i) Connecticut, a state that is reliably Democratic like California but is smaller and on the other coast (Figure A.6a-b); (ii) Texas, a large, Republican state (Figure A.6c-d); and (iii) Ohio, a Republican-leaning Midwestern state (Figure A.6e-f).

Robustness and Heterogeneity. In Table 4 and Table A.7 we present additional evidence. We run the models for the decades 1950-70s, 1980-90s and 2000-10s and report the coefficients on geographic, political, and state party similarity.

In Panel A of Table 4 we address an important concern about the measures of political similarity. Given the political realignment in the South, the lower impact of political similarity in the earlier periods may be due to inaccurate political measures of the South during this time. To address this concern, we present two specifications, one in which we exclude the Southern states altogether from the sample (and recode all similarity measures accordingly), and another in which we hold fixed the political similarity between states at the average vote-share and party control over the 2000-10s. In both specifications, the role of political diffusion increases drastically in the last two decades.

In Panel B we estimate the specification for the NBER and SPID subsamples. By definition, the NBER sample only includes policies of sufficient importance to warrant research into their impact, while the SPID sample is likely to also include laws with more limited importance. The recent increase in political polarization in the NBER sample is as large as in the SPID sample, suggesting that this shift applies also to more consequential policies.

In Panel C we examine separately economic versus non-economic laws. For both types of policies, we find an increased role of political determinants over time, and especially so for the non-economic policies, as one would expect, given the polarizing nature of social issues.

In Panel D we split the states into thirds based on their vote-share as Republican-voting and Democratic-voting. The increased importance of politics is driven by both Republican-voting states and the Democratic-voting states.

In Panel E we focus on the NBER sample and categorize the policies as effective or ineffective, using the estimated policy effects in the NBER papers (Table A.2b). Effective policies have a positive impact on desirable outcomes, whereas ineffective policies have null, negative, or mixed impacts.[7] For both ineffective and effective policies, partisanship appears to now play a significant role in determining which states enact them into law.

In Table A.7 we present an additional set of estimates: (i) a linear probability model instead of a logit; (ii) a model with an expanded set of controls;[8] (iii) an analysis without our own extensions to SPID of policy adoption data, (iv) a parsimonious specification which drops the state characteristics X_{it} (e.g., the level of urban %), which are typically not

[7]We code effectiveness mainly from the abstracts of the papers, and refer to the text in ambiguous cases. We take the position of the paper wherever possible; for example, one paper studying laws requiring parental consent for abortion among teenagers states that lower abortion rates among minors likely represents a higher rate of unintended births and adverse effects on the teens' current and future wellbeing. We exclude three policies where the outcome does not have a clear welfare interpretation, for example, the effect of right-to-work laws on Democratic vote-share (Table A.2b).

[8]The additional set of controls include the non-white percentage, the unemployment rate, indicators for unified Democratic and Republican state governments; quadratic terms for the proportion of other states adopted, Republican vote-share, log population, income per capita, urban percentage, non-white percentage, and the unemployment rate; adoption measures among the closest third of states in migration flows, non-white percentage, and the unemployment rate; a flexible policy-specific baseline hazard parametrized as a step function that varies every five years; and state fixed-effects. Table A.8a also shows the estimates for each demographic variable separately.

significant. The results are similar across these specifications.

Next, we adopt alternative measures of adoptions among similar states: (i) using the closest fifth, fourth, third, or half (Figure A.7) instead of the closest third in Equation 2; (ii) adoption by other states up to year $t-1$, instead of up to year t in row 6 of Table A.7; (iii) a weighted average of the adoption status of all other 47 states, with weights proportional to the other state's rank in similarity; for example, the most distal state carries 1/47th of the weight of the most similar state (row 7). These results are very similar to the benchmark. In rows 8-10, we present simpler parametrizations compared to Equation 2, such as the proportion of adoption among states in the closest third. These measures, which suffer from mis-specifications (Online Appendix B), all point to the increasing role of politics.

Comparison to Results in the Literature. The diffusion of policies along geographic lines is consistent with the results on tax legislation and competition across U.S. states, for example, in Besley and Case (1995) and de Paula, Rasul, and Souza (forthcoming), and with findings in the political science literature as early as Walker (1969) and in Mallinson (2020), which reviews the papers since then. More recently, Caughey, Warshaw, and Xu (2017), Grumbach (2018), and Mallinson (2021) find evidence, as we do, for the increasing importance of political alignment for policy diffusion. Relative to these papers, we compare quantitatively the impact of polarization to the impact of geographic, demographic, and economic similarity, we present results for the most recent years, and we document strong patterns for the high-profile policies studied by economists.

5 Evidence Relating to Models of Policy Diffusion

We now relate findings in the previous section to leading models of policy diffusion.

5.1 Correlated Environments, Learning, and Competition

A set of explanations stresses the *role of correlated preferences and environments*, *learning* across states, or *competition* among states. While these explanations are distinct, they share the prediction about the importance of demographic and geographic proximity for policy diffusion, whether due to similar contexts, local spread of information, or competition at the borders. The evidence for the 1950s to the 1990s thus fits neatly with these models.

These explanations are a less obvious fit for the patterns from the 2000-10s, though it could be that the diffusion of information, the extent of competition, and the correlation in preferences or environments across states have recently followed less geographic lines and more political lines. We present three pieces of evidence to assess these explanations.

Voter Policy Preferences. The first test for *correlated preferences* uses survey measures of voters' policy preferences from both the ANES and the GSS beginning in the 1960s. Specifically, we find the average response to policy preference questions (e.g., whether abortion should be legal) in each state, standardize the ordinal responses across questions, and calculate the average absolute difference across questions to measure the similarity in voter preferences between each pair of states. Since 15 states, such as Delaware, Vermont, and Wyoming, have irregular representation in these data sets (Figure A.8a), we use as the sample the remaining 33 contiguous states (with the closest third now including 10 of the other 32 states). Further, we use an index of voter policy preference measures in the literature as an alternative measure. We provide more detail in Online Appendix Section C.

Migration Flows. The second test uses cross-state migration. If unobserved interstate flow variables such as information and competition are responsible for the diffusion of policies and have recently followed more political lines, the observed interstate flow of migration likely would exhibit similar patterns and predict policy diffusion. We thus identify the top third of other states with the highest volume of inflow-outflow migration.

Estimates. In Table 5 we first replicate the result of Table 3 pooling across decades in Columns 1-3, including only the 33 states consistently represented in ANES and GSS. Then in Columns 4-6 we add controls for similarity in migration flows and in voter preferences. The measure of migration flows has modest explanatory power, while the two measures of similarity in voter preferences are strong predictors. The measure based on the ANES and GSS has coefficients of 0.22 (s.e.=0.10) in the earliest time period and 0.25 (s.e.=0.08) in the latest. The coefficients on the index of public opinion measures in the literature are also fairly constant over time ranging from 0.16 (s.e.=0.06) to 0.22 (s.e.=0.05).

What is the impact of controlling for voter preferences and migration flows? The addition of these variables reduces by half the explanatory power of geography and demographics. The predictive power of Republican vote-share in the most recent decades also falls, from 0.43 (s.e.=0.06) to 0.30 (s.e.=0.06). Strikingly, these variables leave the coefficient on the similarity in state government party control essentially unaffected, from 0.58 (s.e.=0.09) to 0.55 (s.e.=0.09). The lack of movement in the coefficient even after including measures of voter preferences suggests that the rise in recent decades likely reflects top-down partisanship rather than bottom-up demand from the voters.[9]

Evidence from Outcome Variables. As a final piece of evidence, we consider typical policy outcomes, such as the state-level opioid mortality rate, income, and poverty rate. If

[9] In Table A.8a we examine separately the impact of each policy opinion measure used in the index. In Table A.8b we use a GSS-ANES similarity variable computed separately for questions that either match or do not match the broad policy area of the law. For example, we match voter responses to ANES questions on the economy to policies in the Economics policy area. Online Appendix Section C discusses these results.

changes in local preferences or environments are driving the increased impact of politics in policy adoption, we would expect these outcomes to have become more correlated among politically similar states. If instead other factors are at play, the correlation may not have changed. We compute the Geary's C statistic using the closest third of states by vote-share for these variables for the periods 1980-85 and 2005-10, Figure A.9a provides no evidence that these variables have become more politically correlated.[10]

These findings suggest that the increased weight of political variables on policy adoption is not due to patterns of interstate correlation in voter policy preferences, information flows, or competition, but to other factors.

5.2 Evidence Within Area

A possible confound for the findings is that the composition of policies may have changed over time, for example, to include more politically controversial laws. Reassuringly, the composition of policy keyword categories has remained fairly stable (Figure A.1c), and throughout our analyses, we have re-weighted the observations to hold the composition of keyword categories fixed. Nonetheless, the strongest test would be to examine the change in policy diffusion *within* policy area.

We estimate the within-area change in policy diffusion by adding interactions for each keyword category in the hazard model. Specifically, we pool all time periods, and for each dimension of diffusion (e.g., distance and vote-share), we include an interaction term with each policy keyword category. Controlling for these time-invariant category-specific diffusion patterns, the model estimates the average diffusion along each dimension for the 1980-90s and the 2000-10s separately, with the 1950-70s as the omitted base period. We estimate the coefficients for the 1950-70s base period from a separate specification without the keyword category interaction terms, and then add the base-period coefficients to the coefficients for the subsequent time periods from the interacted regression.

In Panel F of Table 4 we present the results. Even when considering only the within-area change, the estimated patterns are very similar, with a constant weight on geographic similarity, and an increasing role of political similarity, especially in the last two decades.

As a specific case study, we focus on public health policies for preventing infectious diseases, comparing COVID-related state policies adopted since October 2019, such as masking policies and school closures, with earlier vaccination policies adopted since 1980, such as immunizations requirements for schools and hospitals. For the COVID policies, given the shorter time frame, we estimate the model (1) at the weekly level in Columns 1 and 2 of

[10] Figure A.9b documents that the outcomes have become less geographically correlated in recent times.

Table A.9. We estimate a significant impact of demographic and geographic similarity, but especially of state party control.[11] For comparison, in Columns 3 and 4 we estimate (at the yearly level) the adoption of vaccination policies beginning in earlier decades. In this sample, demographic and geographic similarity are the strongest predictors, with no impact of political similarity in vote-share or state party control.

5.3 Event Study on Party Discipline

The hazard estimates so far provide descriptive evidence on the predictors of adoption. We now use an event study to provide causal evidence on the impact of party political control. We focus on the switch to unified party control at the state level, a critical threshold according to the political science literature. We estimate the model

$$Y_{iqt} = \sum_{d=-4}^{4} 1\left\{t - e_i = d\right\} \left(\delta_d^{\text{aligned}} 1\{q \text{ is aligned}\} + \delta_d^{\text{opposing}} 1\{q \text{ is opposing}\} + \delta_d^{\text{neutral}} 1\{q \text{ is neutral}\}\right)$$
$$+ \Pi X_{it} + \boldsymbol{\alpha}_i + \gamma_{qt} + \varepsilon_{iqt}$$

where Y_{iqt} is an indicator for whether state i adopts policy q in year t, e_i is the year of switch to unified party control (with the state elections typically occurring late in the prior year), and the key parameter δ_d is allowed to depend on whether the ideology of the policy q is aligned with the incoming party in power. We categorize the ideology of policies using the vote-share of the states that have adopted the law so far.[12] We control for each state's baseline probability of adopting left-leaning, right-leaning, and neutral policies with $\boldsymbol{\alpha}_i$, for state government election years with X_{it}, and for the different levels of adoption with policy-year fixed effects γ_{qt}. We include all state-year-policy observations for states that have yet to adopt around the event window if at least one state has a switch during that window to identify the baseline parameters, such as the policy-year fixed effects γ_{qt}.

Figure 9a displays the coefficients for the period 1990-2020. A switch to a unified state

[11] Cui et al. (2021) also provides consistent evidence of partisan spread of COVID policies.

[12] We take the average two-party Republican vote-share (demeaned by year) in the latest Presidential election at the year of adoption, among the states that have adopted the policy by year $t-1$. If a policy has been adopted on average by states with a 1 percentage point or higher advantage in the Republican vote-share, we define the policy as Right-leaning, and conversely for Left-leaning policies. If the average vote-share of states adopting a policy is within -1 to 1 percentage points, we code the policy as Neutral-leaning. Policies can be classified as neutral in one year but ideologically aligned with one party in another year when new adoptions occur, but we drop a small number of policies that switch from Left- to Right-leaning or vice versa at some point. Figure A.10a shows the distribution of the average demeaned Republican vote-share among adopters over the last 30 years. Figure A.10b follows the ideological evolution of the three most Left-, Right-, and Neutral-leaning policies in 1990 until 2020. Figure A.10c displays the classification of policies for thresholds other than 1 pp.

government does not lead to any increase in the passage of neutral-leaning state laws; it does not appear that unified government reduces gridlock. Next, we consider the impact on the probability of adopting a policy that aligns ideologically with the inaugurated unified state government, compared to the adoption of policies leaning in the opposite direction. We detect a statistically significant increase of about 2 percentage points in the 4 years following the switch, compared to the year before the switch. The increase arises already in year e_i, as one would expect, and appears to be persistent. In contrast, in the earlier 1950-1989 time period (Figure 9b) we do not uncover any partisan impact of a switch in party control.[13] We find similar results using the event study estimator from Chaisemartin and D'Haultfœuille (2020) (Figure A.11c-d). Thus, this event study confirms that partisan support of laws is a recent phenomenon at the level of U.S. states (Caughey, Warshaw, and Xu, 2017).

6 Discussion and Conclusion

This paper has documented a series of facts about the diffusion of state-level policies in the U.S., and related them to models of policy diffusion. The estimated impact of similarity in geography, demographics, and voter preferences resonates with models of competition across states, learning from state to state, and underlying similarity of voter preferences. It is difficult to tell these models apart, given that they share several key predictions.

The pattern for the most recent two decades—a significant increase in the importance of political similarity, and especially of state party control—points to the increasing role of another factor: party influence. Thus, policy adoption at the state level increasingly appears to have a top-down influence, beyond a simple match to bottom-up voter preferences.

This result runs parallel with other studies on polarization. Politicians in the U.S. Congress have shown polarizing voting patterns since the 1950s, as reproduced in Figure 10 using DW-NOMINATE data. Our results indicate that the polarization of state-level policies did not start until later, in the 2000s. Still, its role is rapidly rising and it has affected even topics such as vaccinations which in previous years had not been politicized.[14]

One of the most touted advantages of the U.S. federalist system is the ability of inde-

[13] In Figure A.11a-b, we also show the event study estimates with the most plausible confound path (Freyaldenhoven et al., forthcoming). In Table A.10 we estimate the separate components of the event study: the switch to a Republican unified government on the passage of Republican-leaning policies (as per the coding above, Column 2) and of Democratic-leaning policies (Column 3), with the difference in Column 4; the impact on neutral policies (Column 5); and the same specifications, but for switches to unified Democratic state government (Columns 6-9). The findings generally follow the expected patterns, with the largest impacts from switches to Democratic state governments for Democratic-leaning policies. In Column 10 we consider switches away from unified state governments, which yield smaller impacts.

[14] This evidence is consistent with the roll-call state data patterns in Shor and McCarty (2011).

pendent states to tailor their policies to voter preferences and state-specific needs. We do find that policy adoption has become faster, but the adoption is becoming less responsive to local preferences and demands, and more determined by partisan forces. While measuring the welfare implications of such top-down policy choices is beyond the scope of the paper, we find that policy polarization has increased for both ineffective and effective policies (as estimated in the NBER papers). We note the implications for the quality of the match between policies and state voter preferences, as well as the welfare externalities (e.g., Knight, 2013). An example of welfare impact is on the take up of ACA marketplaces, leading to adverse election of enrollees in health markets with more Republicans (Bursztyn et al., 2024).

Our findings raise a number of additional questions for future work. For one, it would be meaningful to disentangle the sources behind the increasing role of political factors, whether it be lobbyists, party rules, or organizations that provide "copy-and-paste" legislation, such as the American Legislative Exchange Council (Angelucci, Ash, and Longuet Marx, 2022). It would also be useful to know whether this trend of polarization has reached even lower levels of governments, such as city policy-making, or other decisions in the public interest. In this regard, Kim (2024) shows that medical spending also has grown politically polarized in the last two decades. It would also be important to know what forces are driving the increasing role of parties in policy-making, a possible cause of which could be a less informed electorate, for example due to disappearing local media (Snyder and Stromberg, 2010).

Finally, methodologically our findings suggest that researchers can assess the extent to which any particular law diffuses more geographically or politically. As a first approximation, in Figure 11 we plot a scatter plot of our measure of clustering, $1-$ Geary's C, computed for every policy along both the geographic and the political dimension. The shaded regions show the 5th to 95th percentile of the $1-C$ statistic under the null of random diffusion. Generally, the actual policies fall into three categories. One group has a pattern of diffusion that is largely predicted by politics, such as the Medicaid expansion. A second group has diffusion that is predicted by both geography and politics, such as the ban on employers asking about a prospective employee's past salary. Finally, a third group appears to be fairly idiosyncratic, at least based on these parsimonious measures. This simple categorization can guide researchers studying a policy change to identify the diffusion process of their policy. More generally, the predictability of policy diffusion points to the importance of adjusting standard errors for spatial correlation, a topic we contribute to in DellaVigna et al. (2024).

References

Angelucci, Charles, Elliott Ash, and Nicolas Longuet Marx. 2022. "The Nationalization of American Lawmaking? Evidence from State Statutes." Working paper.

Banerjee, Abhijit V. 1992. "A Simple Model of Herd Behavior." *Quarterly Journal of Economics*, 107 (3), 797–817.

Barrios, T., Rebecca Diamond, Guido W. Imbens, and Michal Kolesar. 2012. "Clustering, Spatial Correlations, and Randomization Inference." *Journal of the American Statistical Association*, 107 (498), 578-591.

Bernecker, Andreas, Pierre C. Boyer, and Christina Gathmann. 2021. "The Role of Electoral Incentives for Policy Innovation: Evidence from the U.S. Welfare Reform." *American Economic Journal: Economic Policy*, 13 (2), 26-57.

Besley, Timothy and Anne C. Case. 1995. "Incumbent Behavior: Vote-Seeking, Tax-Setting, and Yardstick Competition." *American Economic Review*, 85 (1), 25-45.

Besley, Timothy and Torsten Persson. 2009. "The Origins of State Capacity: Property Rights, Taxation, and Politics." *American Economic Review*, 99 (4), 1218–44.

Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch. 1992. "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades." *Journal of Political Economy*, 100 (5), 992-1026.

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

Boehmke, Frederick, Mark Brockway, Bruce Desmarais, Jeffrey Harden, Scott LaCombe, Fridolin Linder, and Hanna Wallach. 2020. "SPID: A New Database for Inferring Public Policy Innovativeness and Diffusion Networks." *Policy Studies Journal*, 48 (2), 517-545.

Boxell, Levi, Matthew Gentzkow, and Jesse M. Shapiro. 2024. "Cross-country Trends in Affective Polarization." *Review of Economics and Statistics*, 106 (2).

Bursztyn, Leonardo, Jonathan Kolstad, Aakaash Rao, Pietro Tebaldi, and Noam Yuchtman. 2024. "Polarization and Public Policy: Political Adverse Selection under Obamacare." Working paper.

Callander, Steven, and Bård Harstad. 2015. "Experimentation in Federal Systems." *Quarterly Journal of Economics*, 130 (2), 951–1002.

Canen, Nathan, Chad Kendall, and Francesco Trebbi. 2020. "Unbundling polarization." *Econometrica*, 88 (3), 1197-1233.

Case, Anne C., Harvey S. Rosen, and James R. Hines Jr. 1993. "Budget spillovers and fiscal policy interdependence: Evidence from the states." *Journal of Public Economics*, 52 (3), 285-307.

Caughey, Devin, and Christopher Warshaw. 2016. "The Dynamics of State Policy Liberalism, 1936–2014." *American Journal of Political Science,* 60 (4), 899–913.

Caughey, Devin, Christopher Warshaw, and Yiqing Xu. 2017. "Incremental democracy: The policy effects of partisan control of state government." *The Journal of Politics*, 79 (4), 1342-1358.

Cantoni, Enrico and Vincent Pons. 2021. “Strict ID Laws Don’t Stop Voters: Evidence from a U.S. Nationwide Panel, 2008–2018.” *The Quarterly Journal of Economics*, 136 (4), 2615-2660.

Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer. 2019. “The Effect of Minimum Wages on Low-Wage Jobs.” *The Quarterly Journal of Economics*, 134 (3), 1405-1454.

Collins, William J. 2003. “The Political Economy of State-level Fair Employment Laws, 1940-64.” *Explorations in Economic History*, 40, 24-51.

Cui, Zhihan, Geoffrey Heal, Howard Kunreuther and Lu Li. 2021. “The Political Economy of Responses to COVID-19 in the U.S.A.” NBER Working Paper 28578.

de Chaisemartin, Clément and Xavier D’Haultfœuille. 2020. “Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects.” *American Economic Review*, 110 (9): 2964-96.

DellaVigna, Stefano, Guido Imbens, Woojin Kim, David Ritzwoller. 2024. “Using Multiple Outcomes to Adjust Standard Errors for Spatial Correlation.” Working paper.

de Paula, Aureo, Imran Rasul, and Pedro CL Souza. Forthcoming. “Identifying Network Ties from Panel Data: Theory and an Application to Tax Competition.” *Review of Economic Studies*.

Erikson, Robert S. Gerald C. Wright, Jr., and John P. McIver. 1989. “Political Parties, Public Opinion, and State Policy in the United States.” *American Political Science Review*, 83: 729-750.

Freyaldenhoven, Simon, Christian Hansen, Jorge Perez Perez, and Jesse M. Shapiro. Forthcoming. “Visualization, Identification, and Estimation in the Linear Panel Event-Study Design.” *Advances in Economics and Econometrics: Twelfth World Congress*.

Fiorina, Morris P. and Samuel J. Abrams. 2008. “Political polarization in the American public.” *Annual Review of Political Science*, 11, 563-588.

Gamm, Gerald and Thad Kousser. 2010. “Broad Bills or Particularistic Policy? Historical Patterns in American State Legislatures.” *American Political Science Review*, 104 (1), 151-170.

Geary, R. C. 1954. “The Contiguity Ratio and Statistical Mapping.” *The Incorporated Statistician*, 5 (3), 115-146.

Graham, E. R., Charles R. Shipan, and Craig Volden. 2012. “Review Article: The Diffusion of Policy Diffusion Research in Political Science.” *British Journal of Political Science*, 43, 673-701.

Gruber, Jonathan and Benjamin Sommers. 2020. “Fiscal Federalism and the Budget Impacts of the Affordable Care Act’s Medicaid Expansion.” Working paper.

Grumbach, J. M. 2018. “From Backwaters to Major Policymakers: Policy Polarization in the States, 1970–2014.” *Perspectives on Politics*, 16 (2), 416-435.

Goodman-Bacon, Andrew. 2021. “The Long-Run Effects of Childhood Insurance Coverage:

Medicaid Implementation, Adult Health, and Labor Market Outcomes." *American Economic Review,* 111 (8), 2550-2593.

Heckman, James and Sidharth Moktan. 2020. "Publishing and Promotion in Economics: The Tyranny of the Top Five." *Journal of Economic Literature*, 58 (2), 419-470.

Hjort, Jonas, Diana Moreira, Gautam Rao and Juan Francisco Santini. 2021. "How Research Affects Policy: Experimental Evidence from 2,150 Brazilian Municipalities." *American Economic Review*, 111 (5), 1442-80.

Hoynes, Hilary W. and Diane Whitmore Schanzenbach. 2009. "Consumption Responses to In-Kind Transfers: Evidence from the Introduction of the Food Stamp Program." *American Economic Journal: Applied Economics,* 1 (4), 109-139.

Kim, Woojin. 2024. "Political polarization in medicine." Working paper.

Knight, Brian. 2013. "State Gun Policy and Cross-State Externalities: Evidence from Crime Gun Tracing." *American Economic Journal: Economic Policy*, 5 (4): 200–229.

Mallinson, Daniel J. 2020. "The spread of policy diffusion studies: A systematic review and meta-analysis, 1990-2018." Working paper.

Mallinson, Daniel J. 2021. "Who are your neighbors? The role of ideology and decline of geographic proximity in the diffusion of policy innovations." *Policy Studies Journal*, 49 (1), 67-88.

Manski, C. 1993. "Identification of endogenous social effects: The reflection problem." *The Review of Economic Studies*, 60 (3): 531-542.

McCarty, Nolan. 2019. *Polarization: What Everyone Needs to Know*. Oxford University Press.

Mulligan, Casey B. and Andrei Shleifer. 2005. "The Extent of the Market and the Supply of Regulation." *The Quarterly Journal of Economics*, 120 (4), 1445-1473.

Poole, Keith T. and Howard Rosenthal. 1985. "A spatial model for legislative roll call analysis." *American Journal of Political Science*. 29 (2), 357-384.

Shor, Boris and Nolan McCarty. 2011. "The ideological mapping of American legislatures." *American Political Science Review*, 105 (3), 530-551.

Snyder Jr., James M. and David Strömberg. 2010. "Press Coverage and Political Accountability." *Journal of Political Economy*, 118 (2), 355-408.

Strumpf, Koleman S., and Felix Oberholzer-Gee. 2002. "Endogenous policy decentralization: Testing the central tenet of economic federalism." *Journal of Political Economy*, 110 (1), 1-36.

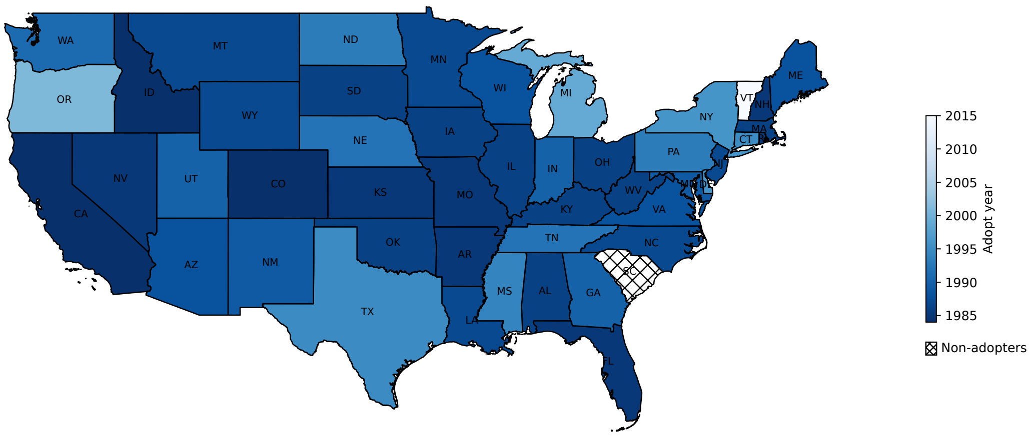
Volden, Craig, Michael Ting, and Daniel Carpenter. 2008. "A formal model of learning and policy diffusion." *American Political Science Review*, 102 (3), 319-332.

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

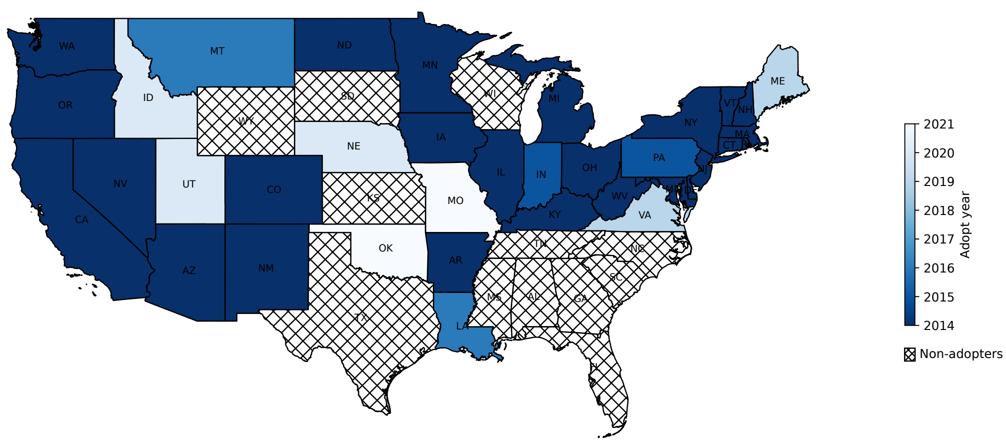
Wang, Shaoda and David Y. Yang. Forthcoming. "Policy Experimentations in China: the Political Economy of Policy Learning." *Journal of Political Economy.*

Figure 1: Three policy examples

(a) Uniform Transfers to Minors Act



(b) 2014 Medicaid expansion (Affordable Care Act)



(c) Initial prescription drug monitoring program

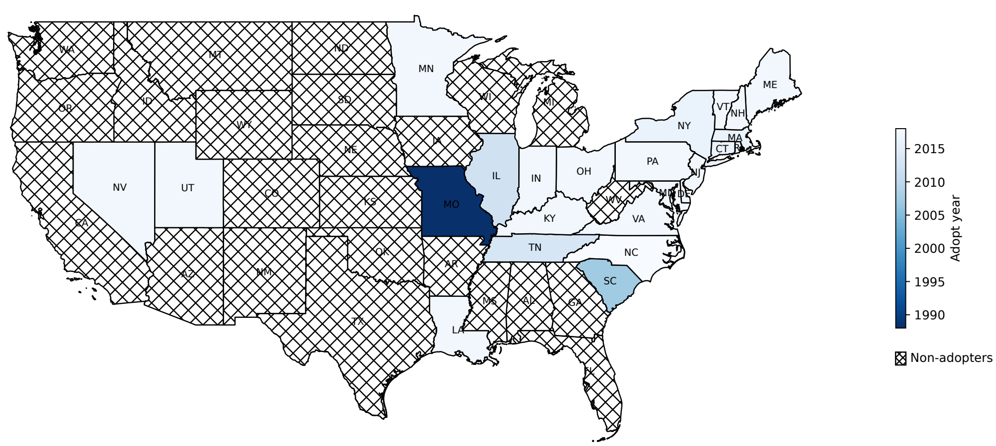
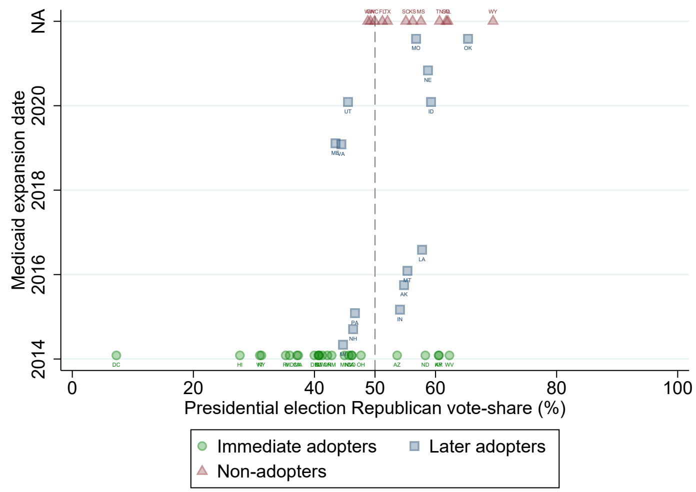
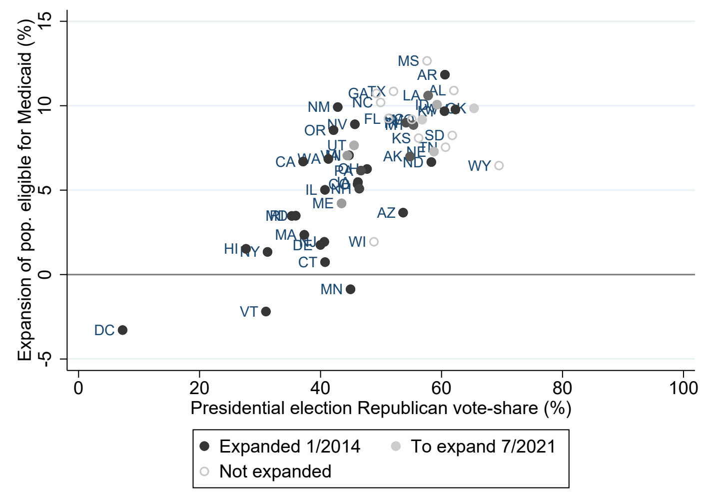


Figure 2: Case studies of welfare programs

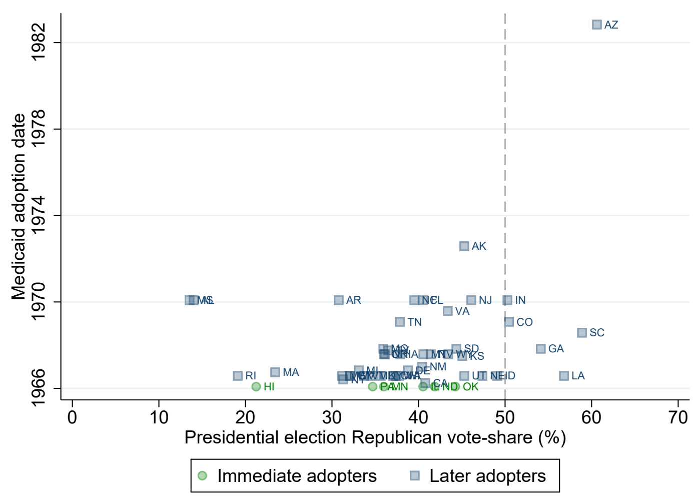
(a) 2014 Medicaid expansion (ACA)



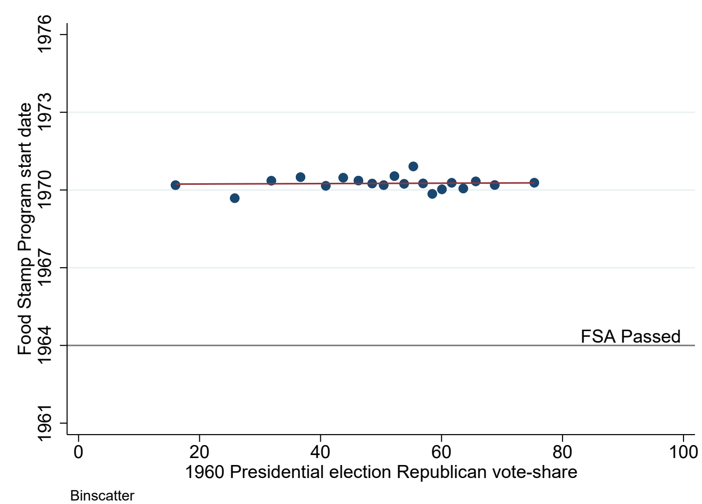
(b) 2014 Medicaid expansion coverage



(c) 1960s Initial Medicaid adoption

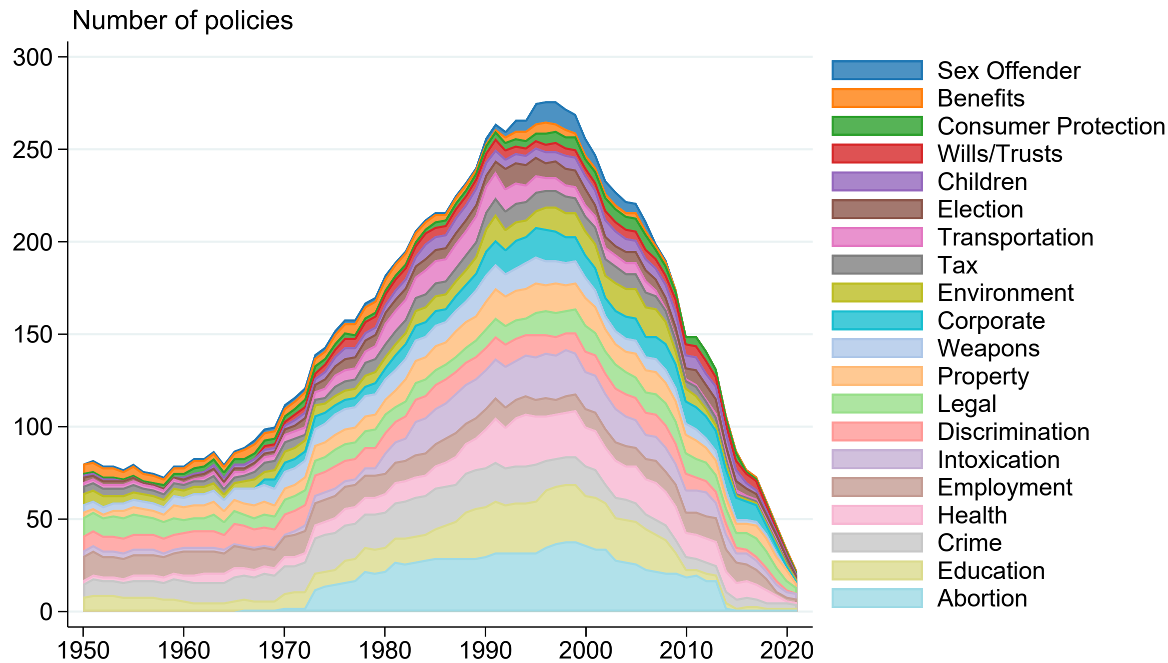


(d) 1960-70s Food Stamp Program adoption (county-level)



For Figures 2a-2c, the Presidential vote-share is from the most recent election to the year of adoption, and for non-adopters in Figures 2a-2b, the vote-share is from the 2020 election.

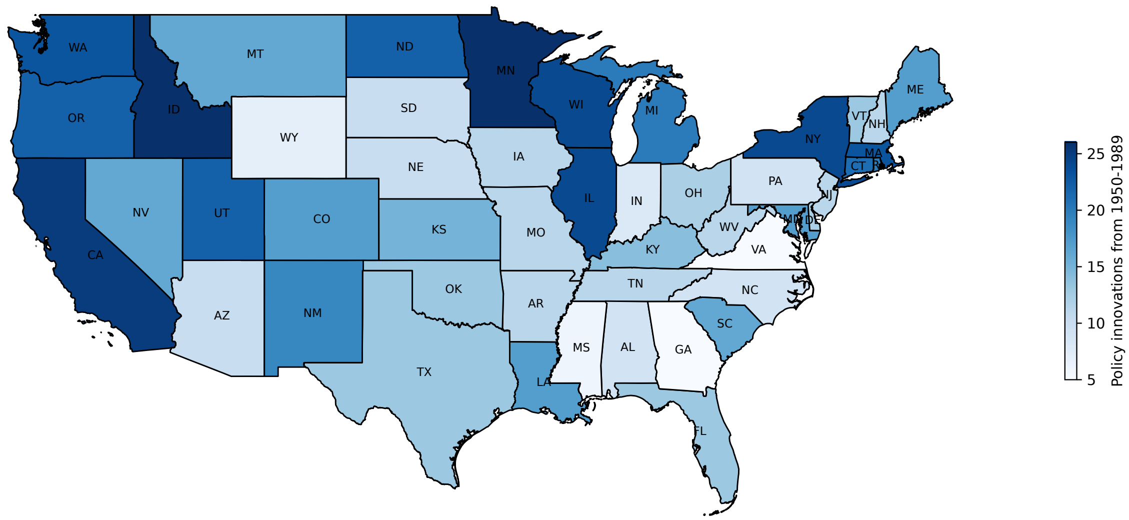
Figure 3: Number of policies by keyword category



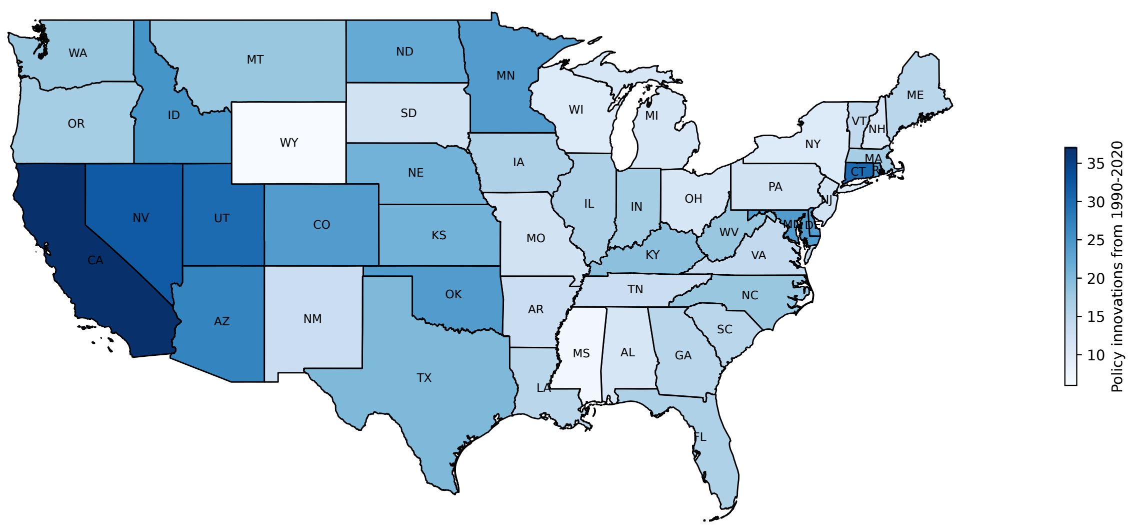
This figure shows the number of policies in each keyword category over time. Keyword categories are groups of policies sharing common keywords in the description of the policies. The keywords are listed in Table 1a.

Figure 4: Innovating states

(a) Policies innovated 1950-1989



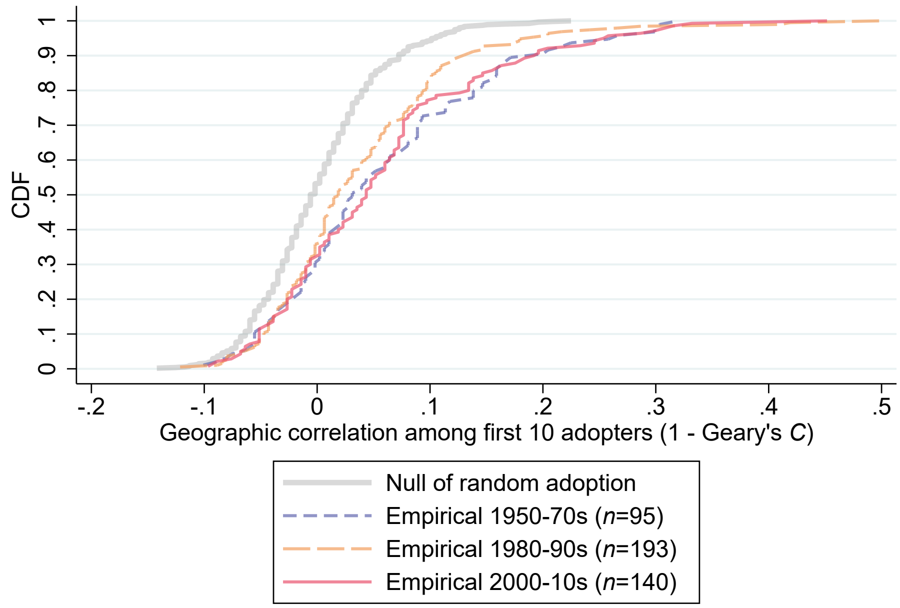
(b) Policies innovated 1990-2020



These maps show the number of policies that each state innovated (i.e., adopted in the first year that the policy enters the sample) during 1950-1989 (Figure 4a) and 1990-2020 (Figure 4b).

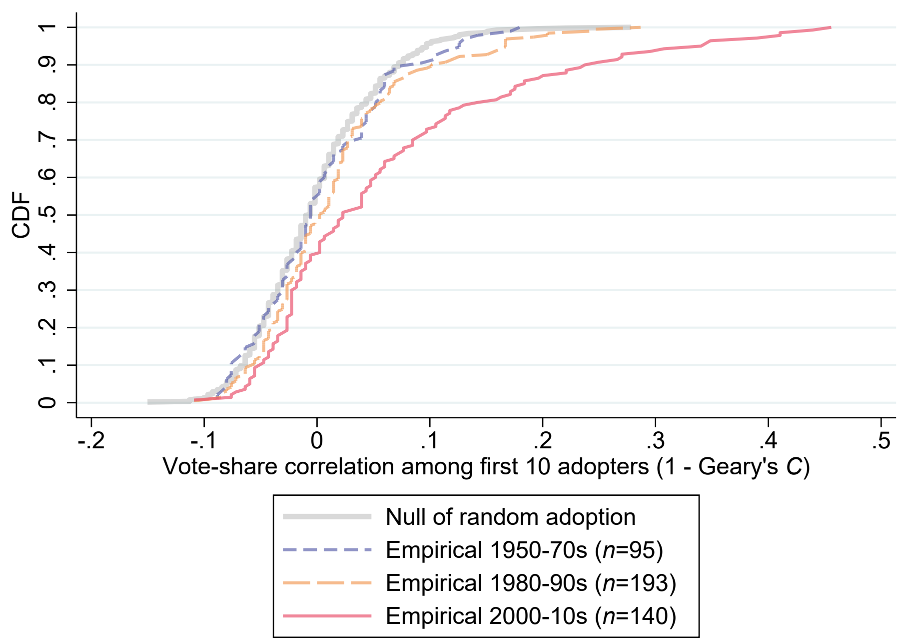
Figure 5: Correlation in geography and politics among adopters (random and observed)

(a) Correlation in geographic distance (first 10 adopters)



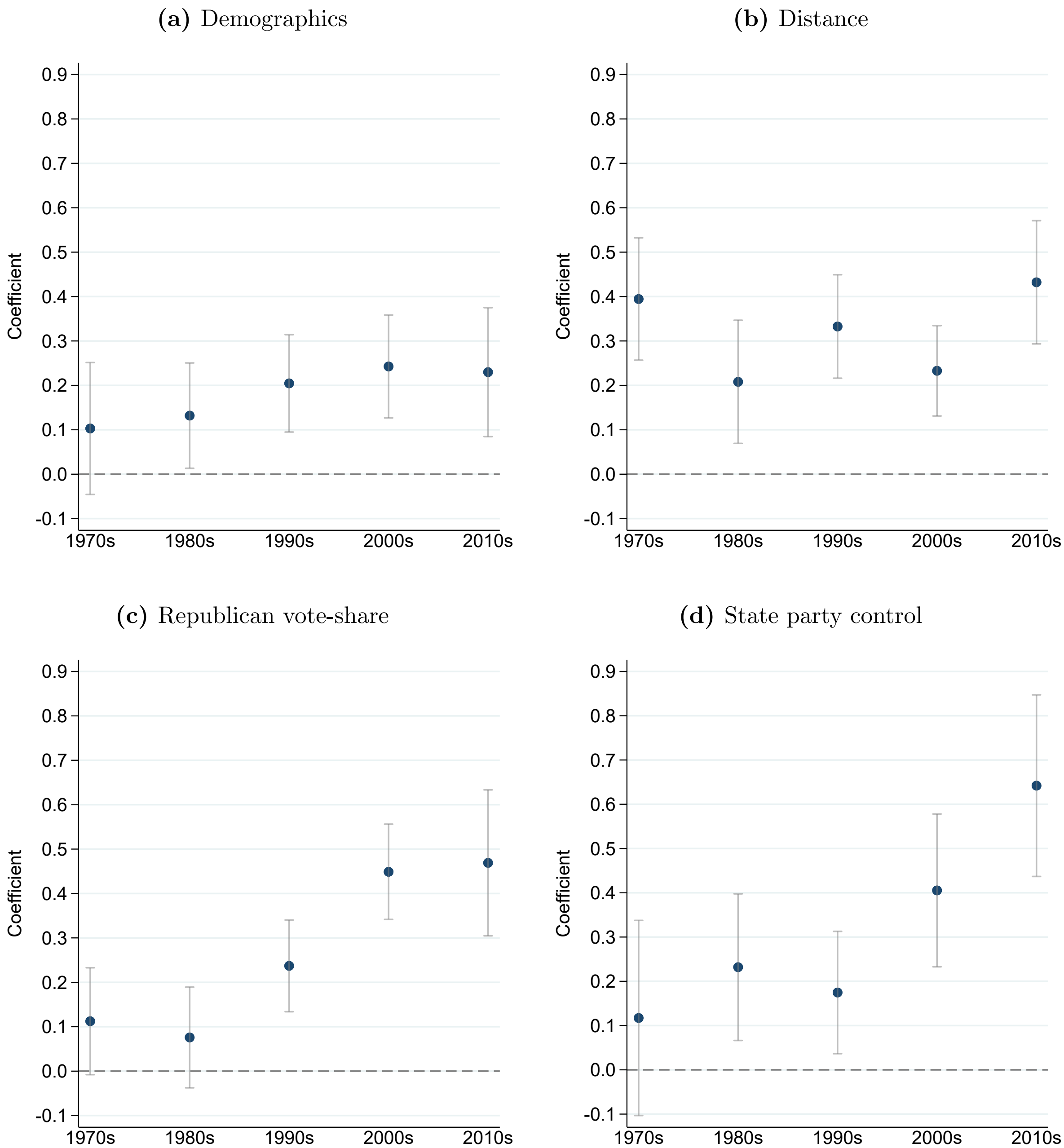
1 policy with a correlation less than -0.2 or greater than 0.5 has been censored.

(b) Correlation in Republican vote-share (first 10 adopters)



This figure plots the CDF of the 1−Geary's C statistic for policy adoptions, which measures the correlation of adoptions within a specified dimension. Geary's C is calculated by taking the weighted average of the pairwise squared differences in adoptions, where the weights are increasing in the similarity between the pair of states along the specified dimension. The weighted average is then divided by the unweighted average of the pairwise squared differences across all pairs of states. This figure uses a simple weighting scheme, in which for each state, the other states in the closest third by geographic distance (Figure 5a) or by Republican vote-share (Figure 5b) are given equal weight, and the remaining states outside the closest third are assigned zero weight. The measure is calculated in year that the policy reaches 10 adopters with ties are broken randomly. Under the null of uniformly random adoptions, the expected value of 1 - Geary's C is 0.

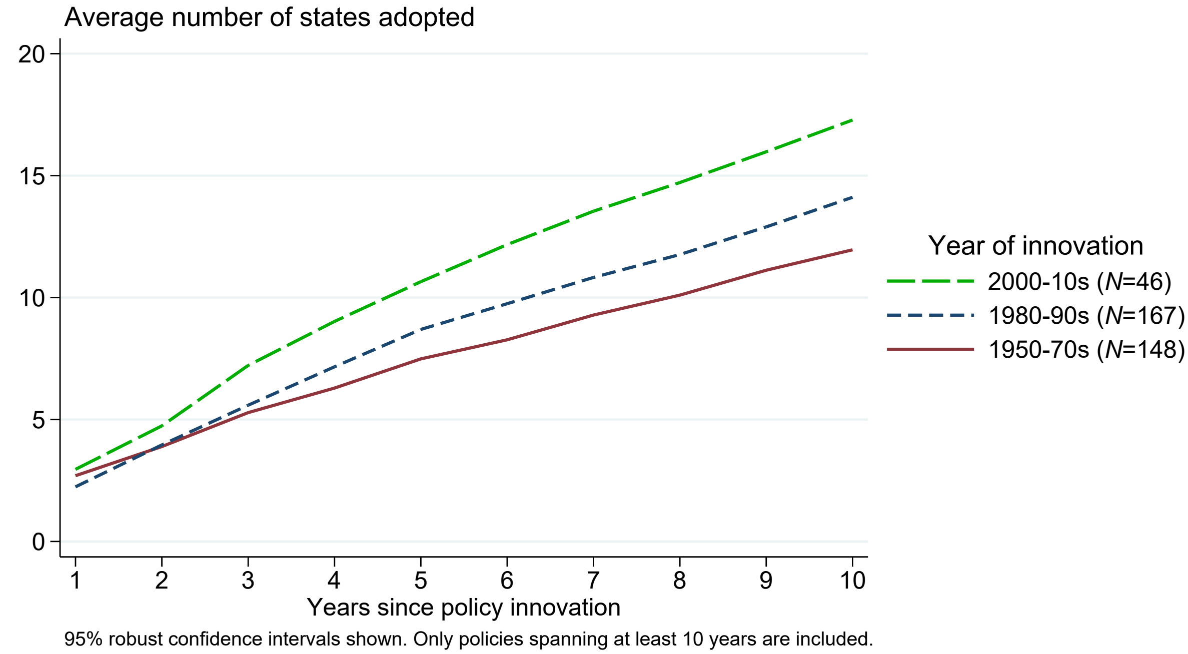
Figure 6: Dynamics of policy diffusion dimensions



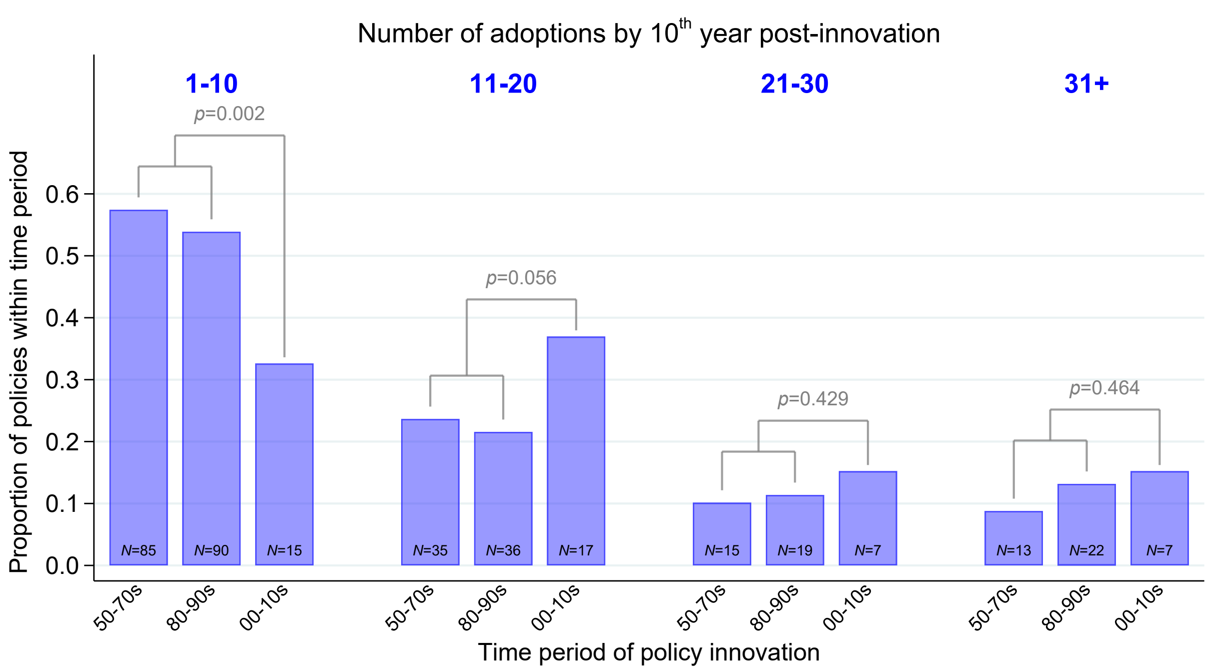
This figure plots the decade-by-decade estimates from Table 3 for the coefficients on the measure of adoption among the closest states in each dimension. The coefficient for the 1950-60s decade is not shown due to the scale of the confidence intervals. 95% confidence intervals are shown with standard errors clustered by state.

Figure 7: Speed of adoption

(a) Number of adoptions within first 10 years



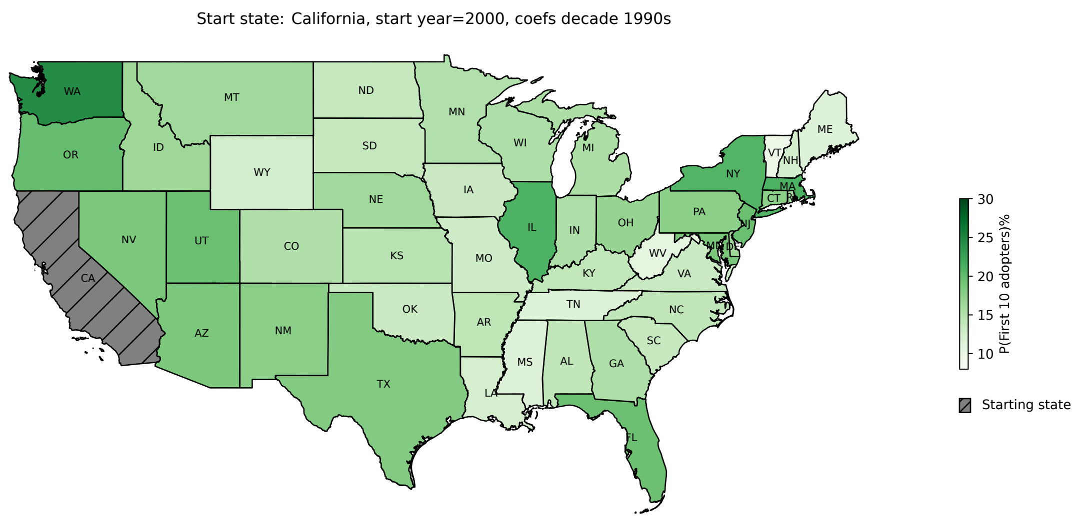
(b) Number of total adoptions by year 10



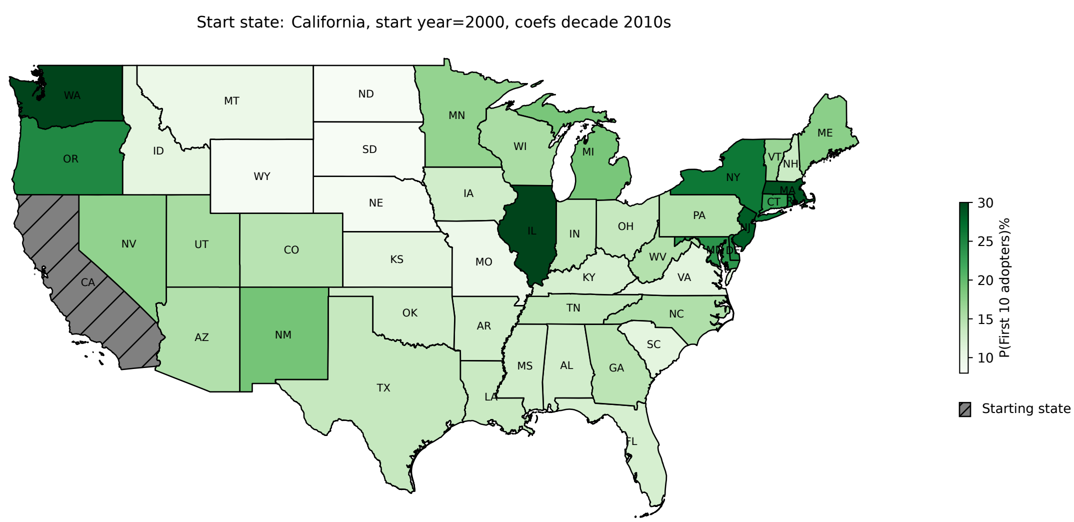
In Figures 7a-7b, policies are grouped into time periods based on the year of innovation. Only policies that span at least 10 years are included. Figure 7a shows the average number of states that have adopted a policy over the first 10 years. Figure 7b shows the proportion of policies after 10 years that have 1-10, 11-20, 21-30, or more than 30 adopters.

Figure 8: Simulated policy diffusion

(a) Coefficients from 1990s



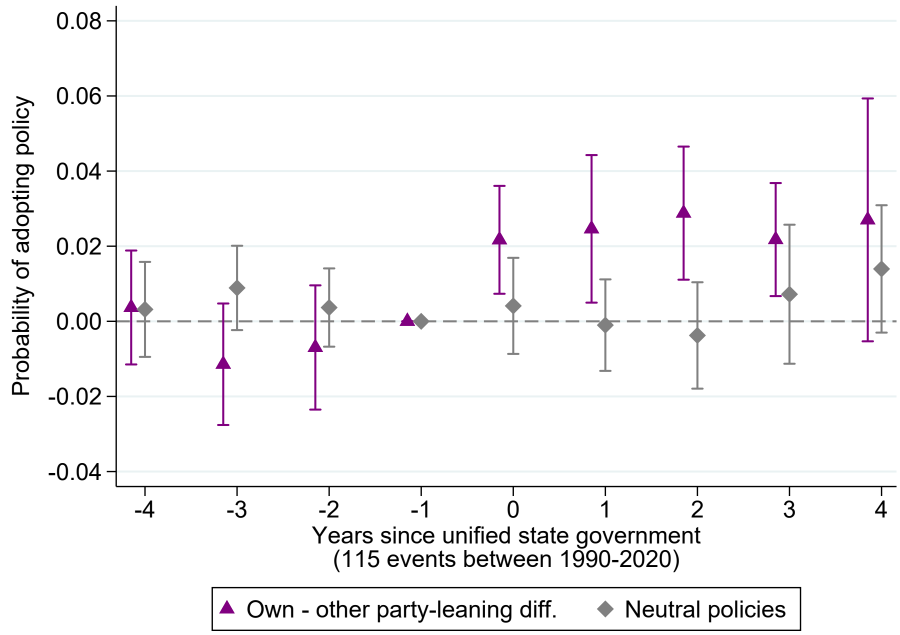
(b) Coefficients from 2010s



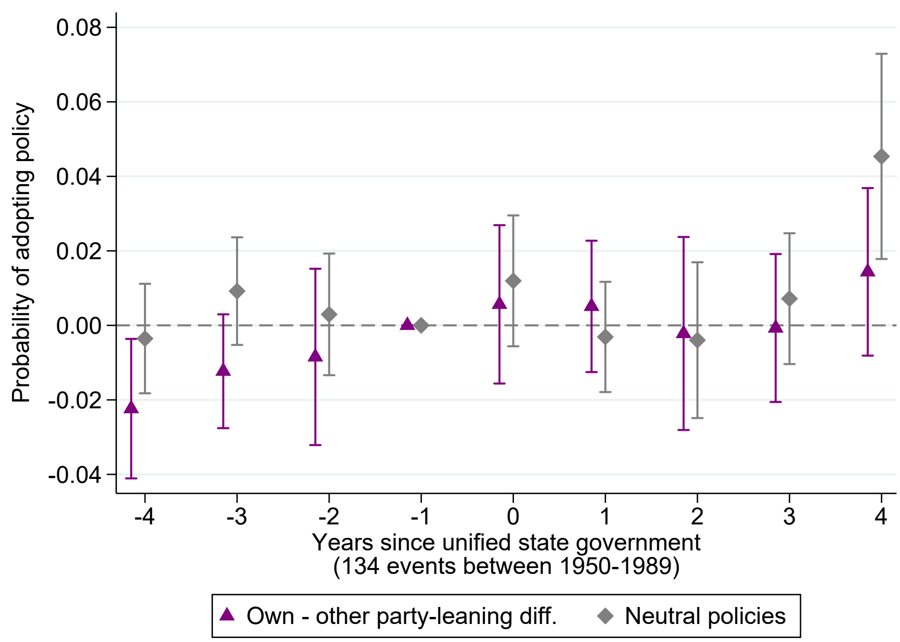
These maps show the probability of each state being among the first 10 adopters within 20 years after a policy is innovated by California in 2000, based on the model estimated in Table 3. Figure 8a uses estimated coefficients from the 1990s decade, and Figure 8b from the 2010s decade.

Figure 9: Event study from switches in state government party control

(a) Events during 1990-2020

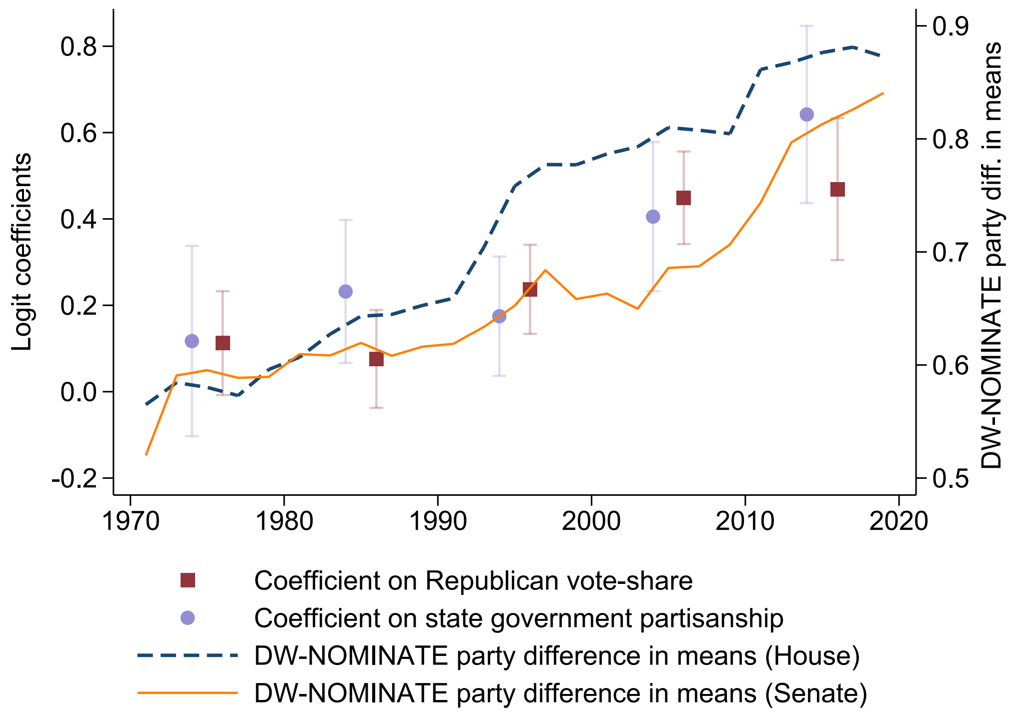


(b) Events during 1950-1989



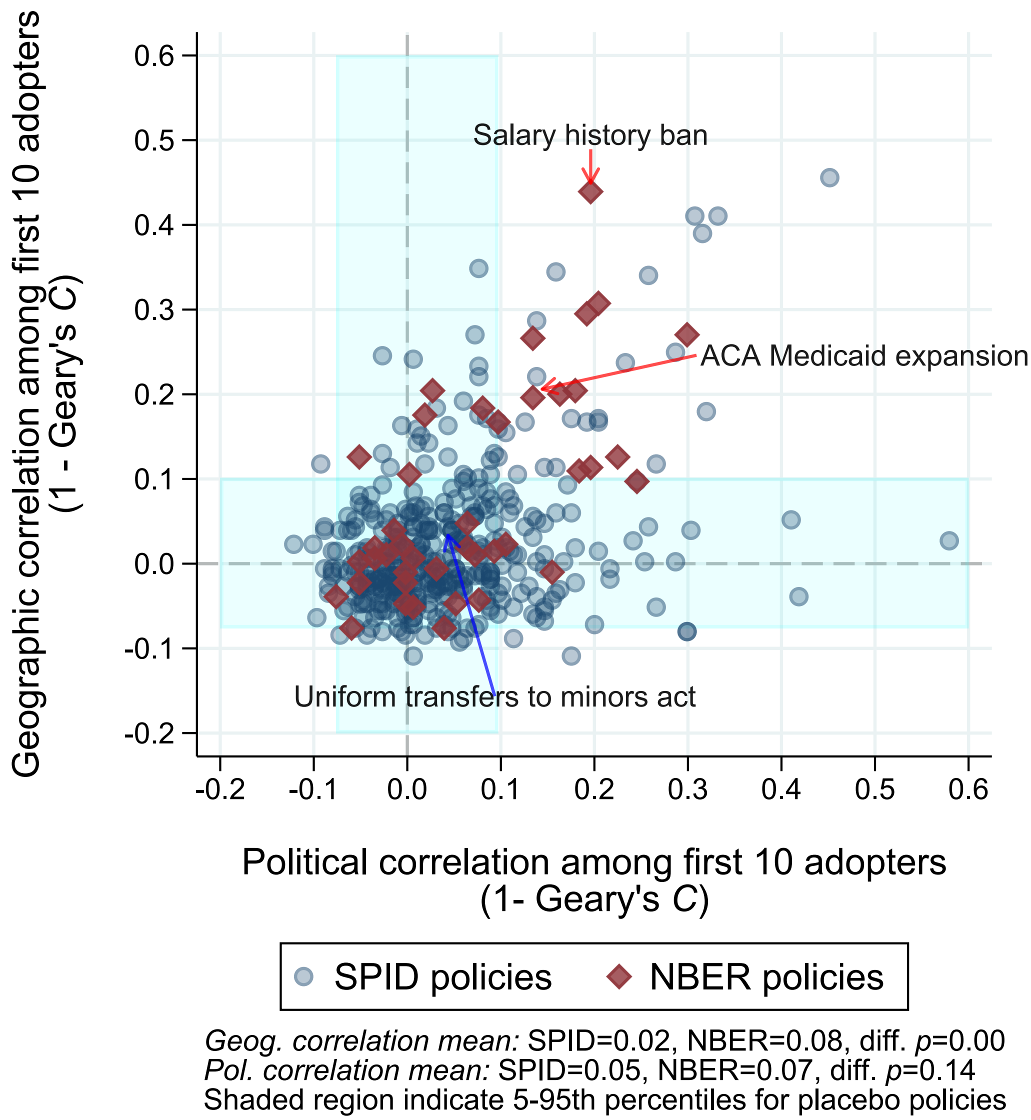
This figure shows the event-study estimates around a switch to unified party control of state government. The purple triangles show the difference in the probability of adopting a policy that is ideologically aligned with the incoming party versus a policy that is ideologically opposed. The gray diamonds show the probability of adopting a neutral policy. The ideology of a policy is categorized based on the vote-share of the adopters (see Section 5.3 for details). Policies are included after reaching five adopters. Policies that ever switch ideological categorization (e.g., from Right- to Left-leaning) are excluded. 95% confidence intervals are shown with standard errors clustered by state.

Figure 10: Comparison to polarization in DW-NOMINATE



This figure shows the estimated coefficients from the model in Table 3 for the political dimensions of state policy diffusion (i.e., vote-share and party control) alongside the average partisan differences in DW-NOMINATE ideology scores among members of Congress over time.

Figure 11: Policy-by-policy diffusion patterns



This figure shows the 1-Geary's C statistic for each policy (see notes in Figures 5a-5b). "Political correlation" is measured using similarity in Republican vote-share.

Table 1a: Policy areas

Policy area	Keywords	Example	Number of policies		
			1950-70s	1980-90s	2000-10s
Abortion	abortion, fetal, roe, contraception, ru486	Minor abortion parental consent	23	41	42
Education	college, education, school, tuition, student, teacher, higher ed, remedia, enrollment, exam, merit	Merit-aid programs	22	36	36
Health	health, medical, prescription, doctor, nurse, physician, cancer, breast, treatment, screening, physician, organ, clinic, fertility, screening	Pill mill laws	11	39	29
Crime	crime, criminal, prison, inmate, corrections, juvenile, corrections, victim, penalty, felon, convict, theft, penal, sentencing, probat, convict, detain, wanted	Probation Law	24	33	19
Intoxication	smoking, cigarette, alcohol, drinking, tobacco, intoxication, dui, drug, beer, meth, salvi divinorum, bac, marijuana	Smoking ban	7	28	27
Legal	court, commission, judicial, deposition, limitation, action, legal, judgment, legislative, civil, witness, judge	Juvenile Court Law	18	19	23
Property	property, housing, real estate, condo, rent, building, time share, development, mortgage	Building Code Adoption	13	23	22
Corporate	business, securities, investment, transaction, trade, corporate, enterprise, companies, instrument, sales, goods, bank	Interstate bank branching laws	8	25	23
Employment	employment, bargain, minimum wage, labor, right to work, right-to-work, eitc, licens, wage, discharge, employer, leave, salary	State EITC	20	16	20
Discrimination	discrimination, gay, racial, equal, sodomy, same-sex	Same-sex marriage	18	19	13
Environment	environment, pollution, conservation, renewable, electricity, emission, recycling, energy, waste, forest, river, renewal, endangered, wildlife, nox	NOx cap-and-trade	11	19	18
Children	child, minor, adoption, guardian, abuse, kinship	Kinship Care Program	8	15	14
Weapons	gun, weapon, rifle, carry, stand your ground	Stand Your Ground laws	10	16	11
Election	voter, election, campaign, voting, ballot, referendum, direct primary	Strict voter ID	9	12	12
Tax	tax	Coporate income tax	11	10	11
Transportation	transportation, seat belt, automobile, helmet, vehicle, bus, highway, seatbelt, license, rail, car	Bicycle helmet laws	9	16	7
Benefits	welfare, afdc, dependent, disabled, blind, medicaid, retirement, medicaid, tanf, retarded	TANF	11	11	4
Consumer Protection	credit card, credit score, creditor, contract, consumer, debt, payment, identity theft, consumption	Commonsense Consumption Acts	4	7	12
Sex Offender	sex offender, offender	Internet Registry Of Sex Offenders	2	12	9
Wills/Trusts	will, real estate, trust	Codifies Trust Laws	6	8	9

Table 1b: Summary statistics of policy data sets

	SPID				NBER			
	Mean (SD)	Min	Median	Max	Mean (SD)	Min	Median	Max
Number of policies	549	–	–	–	53	–	–	–
First year of adoption	1977.73 (27.53)	1842	1983	2017	1986.66 (25.92)	1911	1994	2017
Last year of adoption	1998.96 (16.85)	1950	2002	2022	2006.58 (14.07)	1955	2013	2021
Number of states adopted	24.01 (15.15)	1	22	48	26.98 (14.68)	5	26	48

Policies with the last adoption before 1950 are dropped. Alaska, Hawaii, and Washington D.C. are excluded.

Table 2: Predictors of policy innovation

Innovated during:	1950-1989				1990-2020			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var.: No. policies innovated×100	All	Right-leaning	Left-leaning	Non-partisan	All	Right-leaning	Left-leaning	Non-partisan
Standardized 2-party Rep. vote-share	-4.09	0.84	-1.32	-3.61	3.98	3.06	-3.33	4.25
	(1.61)	(0.52)	(0.58)	(1.22)	(3.84)	(0.91)	(1.13)	(3.27)
Unified Democratic government	-5.65	-1.38	1.47	-5.74	5.35	-0.29	3.13	2.51
	(3.89)	(1.14)	(1.75)	(3.37)	(5.25)	(1.53)	(1.89)	(4.78)
Unified Republican government	-8.17	-1.66	-1.29	-5.22	-9.42	-3.29	0.53	-6.66
	(4.38)	(1.17)	(1.17)	(3.64)	(5.86)	(1.95)	(2.03)	(4.29)
Standardized log(population)	-2.23	-0.46	-0.37	-1.41	-4.68	0.99	1.89	-7.56
	(2.40)	(0.56)	(0.59)	(1.78)	(3.99)	(1.05)	(2.24)	(2.47)
Standardized log(income per capita)	2.35	-0.89	1.87	1.37	-0.73	-1.33	-0.75	1.34
	(2.93)	(1.10)	(0.83)	(1.97)	(4.59)	(0.87)	(1.19)	(3.73)
Standardized urban %	9.09	2.24	2.33	4.51	14.50	2.26	3.25	8.98
	(3.70)	(1.07)	(0.90)	(2.58)	(3.62)	(0.84)	(1.63)	(2.55)
Standardized agriculture employed %	7.04	1.53	2.90	2.61	3.04	0.75	2.05	0.24
	(3.50)	(0.52)	(1.03)	(2.78)	(3.25)	(0.67)	(1.82)	(2.15)
Standardized manufacturing employed %	1.98	0.45	1.27	0.27	0.64	-0.29	0.07	0.86
	(2.26)	(0.49)	(0.82)	(1.66)	(3.07)	(0.71)	(0.91)	(2.37)
No. policies	280	51	67	162	248	48	58	142
Average no. innovations/year	0.38	0.03	0.06	0.29	0.58	0.06	0.06	0.45
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1920	1920	1920	1920	1488	1488	1488	1488
R^2	0.25	0.05	0.07	0.26	0.29	0.08	0.09	0.34

Coefficients and standard errors have been multiplied by a factor of 100. Standard errors clustered by state are shown in parentheses. The ideology of a policy is determined by the average demeaned Republican vote-share among non-innovating states that eventually adopt the policy, based on the vote-share in the years of adoption. The innovating states are excluded from the mean vote-share calculation each year. If the average demeaned vote-share is 1 percentage point or above, the policy is classified as right-leaning; if it is -1 percentage point or below, as left-leaning; and if it falls between -1 and 1 percentage points, as non-partisan. Policies adopted by fewer than five non-innovating states are categorized as non-partisan, as there are too few adopters to reliably determine ideology. Similarly, policies with more than five innovating states are also categorized as non-partisan, as excluding the innovators when demeaning vote-share may lead to unreliable estimates. Independent variables have been standardized to have mean zero unit and standard deviation across states within each year, except the indicators for unified Democratic/Republican state governments.

Table 3: Policy diffusion predictors by decade

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. var.: Policy adoption (logit)	50-60s	70s	80s	90s	00s	10s	00-10s - 80-90s
Measure of adoption among other states closest in:							Diff. p-value
Demographic and economic index	0.17	0.10	0.13	0.20	0.24	0.23	0.22
	(0.15)	(0.08)	(0.06)	(0.06)	(0.06)	(0.07)	
Distance	0.36	0.39	0.21	0.33	0.23	0.43	0.96
	(0.13)	(0.07)	(0.07)	(0.06)	(0.05)	(0.07)	
Republican vote-share	0.29	0.11	0.08	0.24	0.45	0.47	0.00
	(0.21)	(0.06)	(0.06)	(0.05)	(0.05)	(0.08)	
State gvnt. partisanship	-0.21	0.12	0.23	0.17	0.41	0.64	0.00
	(0.19)	(0.11)	(0.08)	(0.07)	(0.09)	(0.10)	
State gvnt. partisanship×Divided gvnt.	0.43	-0.41	-0.30	-0.06	-0.41	-0.88	0.00
	(0.45)	(0.25)	(0.17)	(0.15)	(0.14)	(0.19)	
Baseline P(Adopt)	0.03	0.03	0.03	0.05	0.05	0.05	
Observations	50804	44349	65585	79691	58881	28104	
Policies	138	167	238	333	286	167	
Pseudo R^2	0.20	0.13	0.14	0.20	0.18	0.19	

This table shows the coefficients from a logit regression. Standard errors are clustered by state. The baseline hazard for each policy is parametrized by policy fixed effects for each decade. The closest states are defined as the third of all the states with the smallest absolute value difference in each characteristic. The difference in the demographic index is calculated by first standardizing the two-year moving averages of log population, urban %, log income per capita, % employed in the agricultural sector, and % employed in the manufacturing sector across all states in each year, then taking the absolute difference in each of the five standardized demographic and economic variables, and finally averaging the five absolute standardized differences. The closest states in terms of distance are the third of states that have the smallest distance calculated using the centroid of the states. For Republican vote-share, the closest states are defined as the third with the smallest absolute difference in the vote-share for the Republican presidential candidate averaged over the most recent two elections. For state government partisanship, the closest states are defined as those with the same party control of state government (unified Republican, unified Democratic, or divided). We assign Nebraska, which has a unicameral nonpartisan state legislature, to the party of its governor. Alaska, Hawaii, and Washington D.C. are excluded from the analyses. The last year in the dataset is 2020, which is included in the 2010s decade. Only policies spanning at least 3 years with at least 5 adopters are included. Policies are weighted to keep the composition of keyword categories constant over time periods. All regressions include controls for: the proportion of states adopted, an indicator for divided state government, and standardized values of log population, income per capita, % urban, % employed in agriculture, % employed in manufacturing, and Republican vote-share (estimates are reported in Table A.6).

Table 4: Robustness and heterogeneity in policy diffusion

Distance			Republican vote-share			State gvnt. party control		
1950-70s	1980-90s	2000-10s	1950-70s	1980-90s	2000-10s	1950-70s	1980-90s	2000-10s
Dep. var.: Policy adoption (logit)								
Panel A. Alternate measures of political affiliation								
Excluding Southern states (N_{pol}: 214, 357, 309)								
0.38	0.22	0.16	0.03	0.15	0.36	0.05	0.05	0.63
(0.08)	(0.07)	(0.08)	(0.07)	(0.06)	(0.08)	(0.08)	(0.09)	(0.10)
Holding political affiliation constant at 2000-10 levels (N_{pol}: 227, 369, 325)								
0.38	0.28	0.28	0.21	0.23	0.38	0.09	0.07	0.52
(0.05)	(0.05)	(0.05)	(0.06)	(0.04)	(0.05)	(0.06)	(0.06)	(0.06)
Panel B. Source of policy								
NBER (N_{pol}: 14, 30, 39)								
0.62	0.40	0.50	0.08	0.30	0.61	-0.55	0.05	0.55
(0.17)	(0.12)	(0.11)	(0.16)	(0.12)	(0.10)	(0.25)	(0.16)	(0.09)
SPID (N_{pol}: 213, 339, 286)								
0.42	0.29	0.25	0.09	0.15	0.40	0.10	0.11	0.54
(0.05)	(0.06)	(0.06)	(0.04)	(0.04)	(0.05)	(0.08)	(0.05)	(0.08)
Panel C. Policy area								
Economics (N_{pol}: 38, 55, 62)								
0.46	0.44	0.26	-0.00	0.15	0.35	0.42	0.15	0.44
(0.11)	(0.08)	(0.08)	(0.13)	(0.09)	(0.09)	(0.14)	(0.11)	(0.13)
Non-economics (N_{pol}: 189, 314, 263)								
0.42	0.27	0.29	0.12	0.17	0.45	-0.01	0.11	0.58
(0.06)	(0.06)	(0.06)	(0.05)	(0.04)	(0.05)	(0.08)	(0.05)	(0.07)
Panel D. Vote-share								
Third of states with highest Republican vote-share (N_{pol}: 227, 369, 325)								
0.53	0.27	0.33	0.08	0.26	0.59	0.05	0.13	0.68
(0.08)	(0.11)	(0.08)	(0.11)	(0.09)	(0.11)	(0.11)	(0.09)	(0.12)
Third of states with highest Democratic vote-share (N_{pol}: 227, 369, 325)								
0.35	0.32	0.25	0.13	0.15	0.46	0.07	0.13	0.45
(0.08)	(0.06)	(0.09)	(0.09)	(0.08)	(0.09)	(0.08)	(0.06)	(0.10)
Panel E. Policy effectiveness from NBER papers								
NBER policies with null, negative, or mixed effects in papers (N_{pol}: 12, 18)								
	0.93	0.49		0.62	0.68		-0.11	0.61
	(0.15)	(0.15)		(0.18)	(0.15)		(0.29)	(0.15)
NBER policies with positive effects in papers (N_{pol}: 19, 19)								
	0.31	0.61		0.04	0.54		-0.15	0.59
	(0.13)	(0.14)		(0.11)	(0.13)		(0.14)	(0.12)
Panel F. Analysis within keyword categories (N_{pol}: 229, 374, 328)								
0.40	0.29	0.34	0.18	0.23	0.42	-0.10	0.01	0.48
(0.06)	(0.06)	(0.05)	(0.05)	(0.04)	(0.05)	(0.06)	(0.05)	(0.06)

This table predicts the diffusion of policies along geographic and political lines across various cuts and modifications of the main sample. For each analysis and time period (1950-70s, 1980-90s, and 2000-10s), a parsimonious diffusion model is estimated, which includes only (i) policy fixed effects, (ii) the proportion of adopters in all states, and the measure of adoption among the closest third of states in (iii) a demographic index combining population, income per capita, and urban % (see notes in Table 3 for details), (iv) geography, (v) Republican vote-share in the most recent presidential election, and (vi) state government party control (unified Democratic, unified Republican, or divided). The table shows coefficients on (iv), (v), and (vi) from the logit regression with standard errors clustered by state below in parentheses. The pseudo-R^2 and number of policies are reported in parentheses in chronological order corresponding to the three time periods. In Panels A-E, policies are weighted to keep the composition of keyword categories constant over time periods.

Panel A contains two robustness checks for the diffusion of policies along political lines. The first excludes states in the South census region (TX, OK, AR, LA, MS, AL, GA, FL, TN, SC, NC, KY, VA, WV, MD, DE). Measures of the closest third are readjusted accordingly. The second calculates the average vote-share and state party control over 2000-10s, and holds constant which states are in the politically closest third states according to the 2000-10s averages across all time periods. In Panel B, the model is estimated separately for policies in NBER working papers and the SPID data set. In Panel C, the results are reported separately for policies in the "Economics" policy area and all other policies. In Panel D, the states are first partitioned into thirds each year based on Republican vote-share in the most recent presidential election. The coefficients are then allowed to differ and reported separately for each third. Panel E shows the diffusion estimates of policies studied in NBER papers, separately for policies that were found to have null, negative, or mixed effects in the papers and for those that were found to have positive effects. The direction of the policy outcome is normalized such that a "positive" effect indicates a desirable impact. For example, if a paper finds that a policy led to an increase in homicides, then that policy is categorized as having a negative effect, even though it had a "positive" effect on homicides. See Table A.2b for the categorization of effective policies. The 1950-90s decades are grouped together due to a low number of observations in the 1950-70s time period. Panel F pools all time periods and estimates the average diffusion along each dimension for each time period, with the 1950-70s as the omitted base period, while interacting the diffusion along each dimension with an indicator for each keyword policy category from Table 1a. Policy category by time period fixed effects are included, as well as the interaction terms for the proportion of adopters with an indicator for each time period. The estimates for the 1950-70s base period are from a separate specification without the interactions with each keyword policy category along each dimension. The coefficients for the subsequent 1980-90s and 2000-10s periods are the average diffusion along each dimension in that time period (controlling for the diffusion patterns for each keyword policy category) added to the diffusion along that dimension in the base 1950-70s period.

Table 5: Models of policy diffusion: Role of migration and voter preferences

Dep. var.: Policy adoption (logit)	(1) 60-70s	(2) 80-90s	(3) 00-10s	(4) 60-70s	(5) 80-90s	(6) 00-10s
Measure of adoption among other states closest in:						
Demographic and economic index	0.24	0.07	0.18	0.13	-0.03	0.07
	(0.09)	(0.06)	(0.08)	(0.09)	(0.06)	(0.07)
Distance	0.41	0.31	0.27	0.24	0.19	0.11
	(0.08)	(0.07)	(0.07)	(0.11)	(0.08)	(0.07)
Republican vote-share	0.15	0.16	0.43	0.12	0.12	0.30
	(0.05)	(0.05)	(0.06)	(0.05)	(0.04)	(0.06)
State gvnt. partisanship	0.14	0.11	0.58	0.13	0.11	0.55
	(0.13)	(0.06)	(0.09)	(0.13)	(0.06)	(0.09)
State gvnt. partisanship $\times$ Divided gvnt.	-0.36	-0.00	-0.70	-0.38	-0.03	-0.63
	(0.26)	(0.13)	(0.15)	(0.25)	(0.14)	(0.14)
Migration flows				0.17	0.06	0.24
				(0.15)	(0.09)	(0.09)
Voter preferences (ANES & GSS)				0.22	0.31	0.25
				(0.10)	(0.08)	(0.08)
Index of public opinion measures				0.16	0.18	0.22
				(0.06)	(0.04)	(0.05)
Observations	51192	102544	61250	51192	102544	61250
Policies	196	364	310	196	364	310
Pseudo R^2	0.15	0.17	0.17	0.15	0.17	0.18

This table shows the correlation in policy adoption among states that are closer in demographics, distance, Republican vote-share, state government partisanship, migration flows, voter preferences stated on ANES and GSS surveys, and an index of public opinion measures from political science. See Table 3 for the definition of the states closest in the demographic and economic index, distance, Republican vote-share, and state government partisanship. All regressions include the proportion of states that have adopted the policy so far as well as an indicator for divided state governments (coefficients not reported). For migration flows, the closest states are defined as the third with the highest sum of in- and out-migration. For voter preferences, the closest states are those with the smallest average difference in standardized responses on ANES and GSS questions regarding policy preferences. 15 states are excluded as they do not have sufficient representation to measure voter preferences in the ANES and GSS surveys (see Online Appendix Section C). For the index of public opinion measures, we standardize the Berry et al. (1998) revised 1960-2016 citizen ideology series, the Lagodny et al. (2022) state-level public policy mood measure, and the Caughey and Warshaw (2017) mass social and economic liberalism scores in each year, and average the absolute differences between each pair of states. The closest states are defined as the third with the smallest average difference. Each column reports a separate logit regression within the time period indicated in the header. Policy-by-decade fixed effects are included as the baseline hazard rate for each policy. Policies are weighted to keep the composition of keyword categories constant over time periods. Standard errors clustered by states are in parentheses.

Online Appendix

A Data Details

Overlap between SPID and NBER. The two data sources for the state law adoption are SPID and the NBER working papers. There is some overlap between the policies. Of the NBER policies, 17 are represented in the SPID data set to some extent. For example, one NBER policy is on the concealed carry of handguns, whereas a similar policy in SPID is on concealed carry in general. Some policies are present in both data sets, such as the state EITC, though the adoption dates tend to be more recently updated for the NBER source.

Extension of SPID. As mentioned in the text, the coverage of the SPID data set is limited for the years after 2015. We thus extended its coverage for 104 policies in total following methods as similar as possible to those used to build the original SPID data set. We first checked whether the original sources used in SPID had been updated since the publication of SPID. We extend 71 policies by scraping more recent updates from the Uniform Law Commission website and 3 more policies from the Caughey-Warshaw data set. For the remaining policies, we reviewed which policy descriptions were specific enough to return valid matches in other sources. We attempted to find those policies in online resources, academic papers, and state bills to assess whether there had been more recent developments. If so, we then confirmed whether the existing policy adoption data in SPID matched the dates in the source. Through this method, we find additional adoption data for 24 policies from online sources such as the National Conference of State Legislatures, 4 policies directly from state bills, and 2 policies based on academic papers that record the adoption dates.

Definition of Areas. To define the 20 areas of legislation, we use a keyword search on the one-line description of each law. There are 130 cases in which a law belongs to multiple areas by this classification, in that it contains multiple keywords in different categories. Two examples are "Does The State's Medicaid System Pay For Abortions?" and "Legal Framework For Public Intoxication Law." In these cases, we manually coded these laws and assigned them to the area deemed to be the most relevant.

B Alternate measures of correlated adoptions

In the hazard model analysis (Section 4.2), we use a two-sided "likelihood" as the baseline measure of how concentrated the adoption of a policy has been among states that are (dis)similar in each dimension. We tried other measures that may be simpler but did not perform as well in specification checks. In this section, we define three alternate measures and discuss their shortcomings. Reassuringly, as shown in Table A.7, we find that the dynamic patterns of policy diffusion remain similar regardless of the measure used.

We assess two attributes of each measure. First, we consider its range of possible values as a function of the number of total adopters. Drastic variation in the range may lead to mis-specification when entering the measure as a linear term in the logit, as done in the main analysis of Table 3, since this assumes that the same coefficient applies to early as well as to late adopters of the policy. In the second assessment, we check directly for this mis-specification by allowing the coefficient on the measure to vary by the number of total adopters so far: for the first five adopters (1-5), the second five adopters (6-10), the third five adopters (11-15), and the later adopters (>15). Stable coefficients are encouraging, but coefficients that systematically differ between the early and the later adopters indicate that the estimates from the model under- or over-estimate the responsiveness to adoption among similar states at some stage of the policy's life-cycle.

To start with the baseline likelihood measure, Figure A.12a shows that its range goes from -1 to 1 and is fairly consistent across the domain of total adopters. Figure A.12e then plots the coefficients on the first three groups of 5 adopters and on the following adopters for the two dimensions of interest, distance and Republican vote-share. There does not appear to be any systematic ordering or reversals in the coefficients across the bins, and the coefficients generally remain within each other's confidence intervals. These checks return a favorable evaluation of the baseline measure.

Now for the three alternate measures below, we notate $a^k \in \{0, 1, ..., 15\}$ as the number of adopters among the 15 states that compose the closest third in dimension k, and $A \in \{0, 1, ..., 47\}, A \geq a^k$, as the number of adopters among all other 47 contiguous states.

Proportion of states in the closest third that are adopters $(a^k/15)$**.** As Figure A.12b shows, the range of this measure is limited in both the early and late stages of a policy's life-cycle. For instance, if there are 5 total adopters of the policy, then the measure can range only from 0/15 to 5/15. From 16 to 32 total adopters, the measure ranges from 0 to 1. After 32 total adopters, the range shrinks toward the upper region. Another downside is that this measure does not incorporate information about the total number of adopters, though intuitively, we should consider a case when there are 10 total adopters of a policy and all 10 are in the closest third as a stronger sign of correlated adoptions than the case when there are 30 total adopters of which 10 are in the closest third. In light of these drawbacks, Figure A.12f finds that the coefficients on the first bin of 5 adopters are significantly lower, and even become negative, compared to the coefficients for the rest of the bins. Hence using this measure in the main specification would lead to a poor fit of the early stage diffusion process.

Proportion of all adopters that are in the closest third (a^k/A)**.**[15] As shown in Figure A.12c, this measure ranges from 0 to 1 until there are 16 total adopters, at which point there must be more total adopters than adopters in the closest third and thus the upper bound of the range decreases. From 33 total adopters, the lower bound of the range becomes strictly positive, since there must be at least one adopter in the closest third, and continues to increase. Given this narrowing range, similar concerns arise as with the previous measure. Figure A.12g confirms these issues, and shows that the coefficients are systematically increasing in the bins. For this measure, a single coefficient in the specification would be overly sensitive for the early adopters and too unresponsive for the later adopters.

Proportion of states in the closest third that adopters minus proportion of all states that are adopters $\left(\frac{a^k}{15} - \frac{A}{47}\right)$**.** Figure A.12d plots the range of this measure. The difference between the upper and lower bounds linearly increases in the number of total adopters and is maximized at 1 while the number of total adopters is between 15 and 32. After 32 total adopters, the range begins to linearly decrease. Figure A.12h shows that this measure is not as poorly behaved as the previous two in the logit model, but the coefficients do seem to systematically decrease across the bins in the distance dimension. The pseudo-R^2 from row 10 of Table A.7 also indicates that this measure provides a poorer fit of the data compared to the baseline measure (row 5).

[15] Another interpretation of this measure is the ratio of the proportion of states in the closest third that are adopters to the proportion of all states that are adopters, or $(a^k/15)/(A/47)$, multiplied by a constant (15/47).

C Estimating voter preferences using the ANES, GSS, and measures from political science

In Section 5.1, we introduce two measures of the similarity between states in voter preferences and public opinion. The first uses survey data from the American National Election Studies (ANES) and the General Social Survey (GSS), which are national surveys of American voters frequently featured in political research. The second draws on existing measures of public opinion from political science. This section describes the construction of these measures in detail.

C.1 Measuring voter preferences using the ANES and GSS

The ANES and GSS surveys collect demographic and background information about voters, their views on societal issues, knowledge about politics, and voting behavior. We use the cumulative ANES data set including surveys conducted over 1948-2020 and the GSS data set covering surveys over 1972-2018.

Question selection. We filter through all the survey items to identify 59 questions in the ANES and 468 in the GSS that asked voters about their preference for a specific policy on an ordinal response scale. For example, these include:

• (ANES: VCF0806) *There is much concern about the rapid rise in medical and hospital costs. Some people feel there should be a government insurance plan which would cover all medical and hospital expenses for everyone. Others feel that all medical expenses should be paid by individuals, and through private insurance plans like Blue Cross or other company paid plans. Where would you place yourself on this scale, or haven't you thought much about this? (7-POINT SCALE SHOWN TO RESPONDENT)*

• (ANES: VCF0877) *Do you think homosexuals should be allowed to serve in the United States Armed Forces or don't you think so? (5-POINT SCALE SHOWN TO RESPONDENT)*

• (GSS: aidcol) *On the whole, do you think it should or should not be the government's responsibility to give financial assistance to college students from low-income families? (4-POINT SCALE SHOWN TO RESPONDENT)*

We then restrict the final sample to 49 questions in the ANES and 196 in the GSS that have been asked for at least 10 years, to ensure the responses reflect voter preferences on longstanding, key issues and to reduce noise from compositional changes in the sample. For example, this restriction drops a question asking whether the respondent thought the United States should cooperate more with the Soviet Union, which was asked only from 1980-88. We link questions in the GSS that are under different variable names but are qualitatively on the same policy preference. For example, the GSS variable *aidneedy* asks, *"For students whose parents have a low income, should the government provide grants that would not have to be paid back, provide loans which the student would have to pay back, or should the government not provide any financial assistance?"* This question is only asked in the 1985 survey, but we link this question to *aidcol* (shown in the last example above), which has been asked for 26 years over 1990-2016. Hence, we keep *aidneedy* as well. Overall, Figure A.8b shows that there are typically over 10 questions represented from the 1960s, and over 20 from the 1970s.

State representation. One downside of the ANES and GSS surveys, depicted in Figure A.8a, is that not all states are sufficiently represented in every wave of the survey. In fact, there are 15 states (Delaware, Idaho, Kansas, Maine, Montana, Nebraska, Nevada, New Hampshire, New Mexico, North Dakota, Rhode Island, South Dakota, Vermont, West Virginia, and Wyoming) that are missing for at least a decade. To prevent the results being contaminated from the addition of these states only in certain time periods, we drop them entirely when we use the ANES and GSS measure of voter preferences. This means that whenever we include the ANES and GSS measure, we also re-calculate the measure of similarity in Equation 2 for all the other dimensions, since there are now 33 states in the sample.

Respondent weighting and measure construction. Respondents in the ANES and GSS are sampled to be representative at the national level, not at the state level. Therefore, we use propensity weighting to provide a more accurate measure of voter preferences at the state level. We reweight the respondents in each survey wave based on their age, gender, and race to match the population distribution in the official Census and American Community Survey data for their state. We then calculate state-level yearly averages of the responses to each question using these propensity weights.

Next, we standardize the state average responses for each question in each year, subtracting by the mean and dividing by the standard deviation, to bring all responses (e.g., 5-point Likert vs. 2-point Likert) to the same scale. For every pair of states in each year of the survey, we compute the absolute difference in the standardized state average response to each question, and then take the average of the absolute differences across all questions in that year. At this point, we have a measure between every pair of states for how similarly their average voter responded to the policy preference questions. To smooth the measure, we use a moving average including the previous five years and next five years of the average standardized difference between each pair of states. Finally, for each state, we consider the third of other states (i.e., 10 out of the other 32) with the smallest average standardized difference in the responses to be the closest in voter preferences for that year. Figure A.4 shows the stability of this measure, and Table A.5b lists examples of states that are close in these voter preferences.

Matching voter preference questions to policy areas. In Columns 1-3 of Table A.8b, we extend the analysis by constructing measures of voter preferences that are specific to each policy area. A team of 10 undergraduate research assistants categorized each question used in the ANES and GSS measure into one of the six policy areas (Figure A.8c) or as none of them, based on the set of SPID and NBER policies classified under each policy area. Each question was assigned to two research assistants to code independently. The coders agreed on the policy area for 71% of the questions on the first attempt, which indicates that most of the questions were straightforward to classify. For the remaining 29%, we discussed each question as a group before settling on the final categorization. The questions in the "Environment and Energy" policy area are missing until the 1970s, and even then, there are no respondents for those questions in Kentucky, Mississippi, and Kentucky until the 1980s; hence, we drop policies in "Environment and Energy" for this analysis.

For each policy, we then calculate the Equation 2 measure of adoption among states closest in voter preferences (i) for questions specifically in that policy area, as well as (ii) for the remaining questions in all the other policy areas. That is, we explore whether states are more likely to adopt Economic policies from other states with voters who express similar preferences on questions specifically related to the economy, more so than states with voters who express similar preferences in other policy areas such as Civil Rights and Public Services. We find that both measures of voter preferences—specific to the policy area and in other policy areas—are comparably predictive of policy diffusion in each time period.

Including voter sentiment. In Columns 4-6 of Table A.8b, we use a broader measure to also capture voter sentiment that could be relevant for their policy positions. We add questions such as "thermometers" about specific groups, (e.g., on a scale of 0-100, how the respondent feels about labor unions, homosexuals, or people on welfare), whether society should make sure that everyone has an equal opportunity to succeed, and whether it matters that the respondent votes or not. Figure A.8b shows the number of voter sentiment questions in this broader measure over time. Reassuringly, this broader measure finds similar results.

C.2 Measures of public opinion from political science research

As another measure of state-level voter policy preferences, we combine prominent measures from political science research that span policy topics and decades from at least the 1960s to the 2010s. In particular, we use:

• the mass social and economic policy liberalism scores (1936-2014) from Caughey and Warshaw (2018), which are estimated from surveys (including the ANES and GSS) as well as polling data (such as the Gallup),

• the state policy mood measure (1956-2020) from Lagodny et al. (2022), which also aggregates data from public opinion surveys, and

• the updated citizen ideology measure (1960-2016) from Berry et al. (1998), which is based on interest group ratings of state representatives in Congress and state election results.

From these measures, we construct an index in the same method as for demographics. We standardize each measure within each year across states, calculate the absolute difference in each standardized measure, and average the absolute differences to create the index. The states that have the smallest averaged absolute difference in this index are defined as the closest in public opinion.

In addition to the analysis in Table 5, we also investigate the role of each measure in the index separately in Columns 4-6 of Table A.8a. For the measures that end before 2020, we extend the measure from the last year (2014 in Caughey and Warshaw, 2018, and 2016 in Berry et al., 1998) through 2020. The Berry et al. (1998) measure strongly predicts policy diffusion in the 1960-70s, but less so in the later time periods. Interestingly, the Caughey and Warshaw (2018) measures have become more predictive in recent times, and more so for the social liberalism measure, which is consistent with the results in Caughey and Warshaw (2018). Nevertheless, the escalating role of state government partisanship far exceeds the explanatory power of any measure of voter preferences in the last two decades.

References

Berry, William D., Evan J. Ringquist, Richard C. Fording, and Russell L. Hanson. 1998. "Measuring Citizen and Government Ideology in the American States, 1960-93." *American Journal of Political Science*, 42 (1), 327-348.

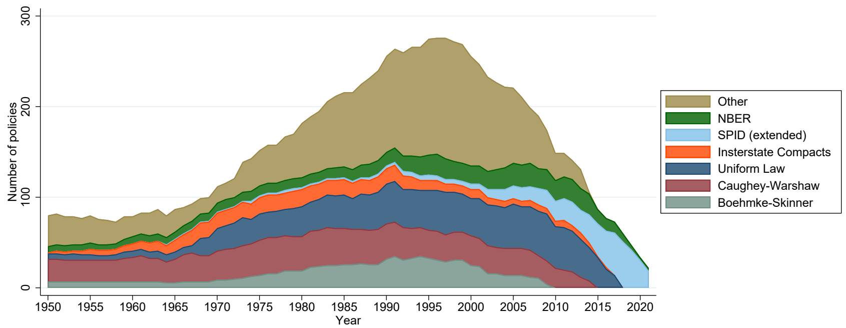
Caughey, Devin, and Christopher Warshaw. 2018. "Policy Preferences and Policy Change: Dynamic Responsiveness in the American States, 1936–2014." *American Political Science Review,* 112 (2), 249–266.

Desmarais, Bruce A., Jeffrey J. Harden, and Frederick J. Boehmke. 2015. "Persistent Policy Pathways: Inferring Diffusion Networks in the American States." *American Political Science Review*, 109 (2), 392-406.

Lagodny, Julius, Rebekah Jones, Julianna Koch, and Peter K. Enns. 2022. "A Validation and Extension of State-Level Public Policy Mood: 1956 to 2020." *State Politics and Policy Quarterly*, 1-14.

Figure A.1: Summary statistics of policies

(a) Source of policies



(b) Word cloud of policy descriptions

(c) Proportion of all policies by keyword

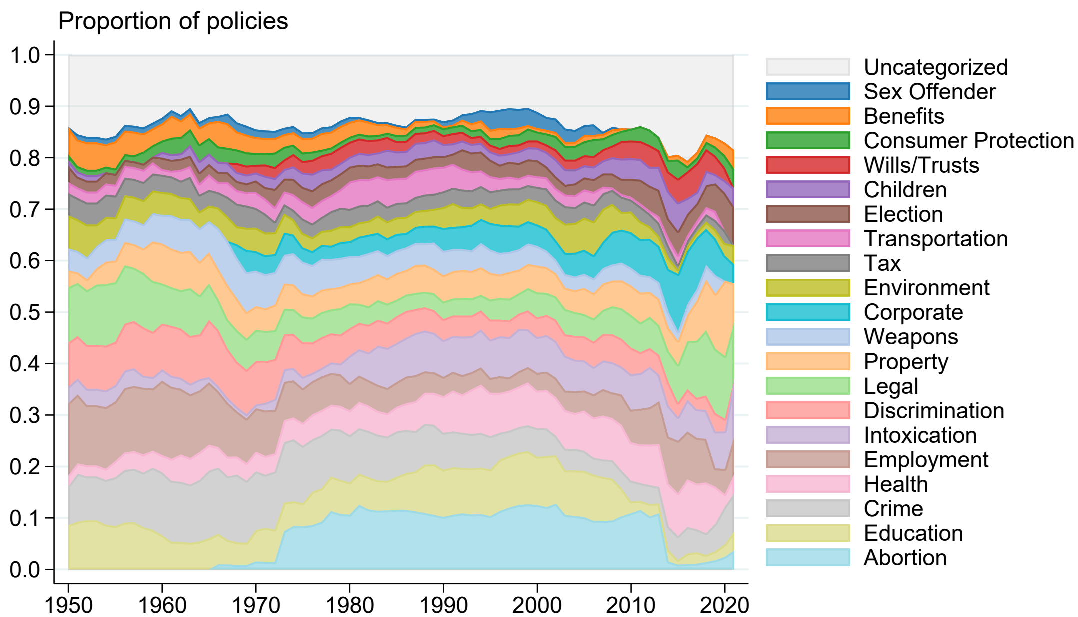
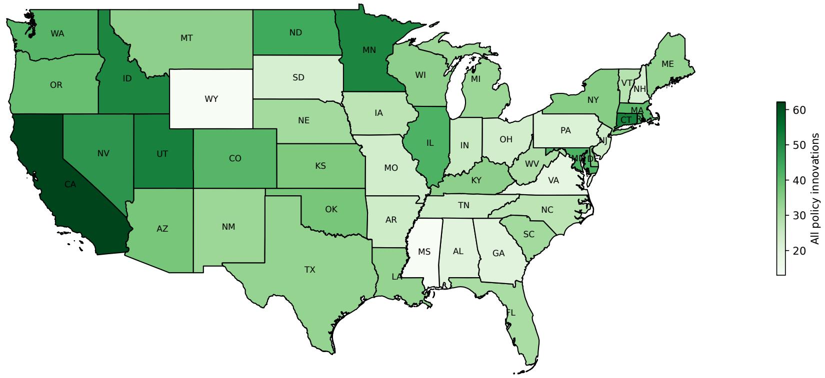


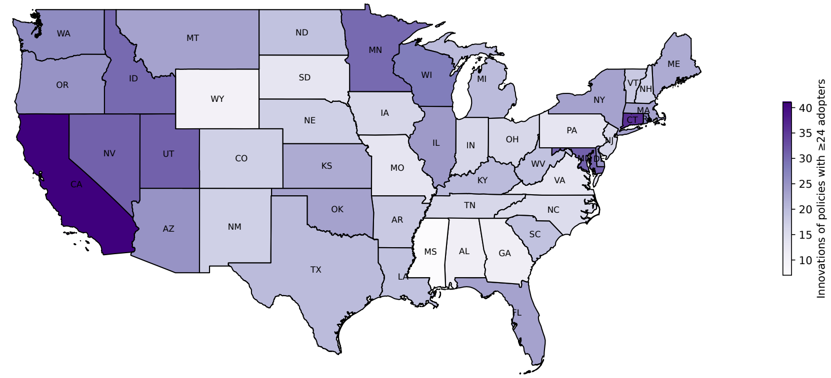
Figure A.1a shows the number of policies in each policy area over time. Figure A.1b shows a word cloud of keywords in policy descriptions. Words are proportional to their frequency in the policy descriptions. Figure A.1c show the proportion of policies in each keyword category over time (see Table 1a for details). Policies that are not categorized under any keyword category are grouped under "Uncategorized". The uncategorized policies are not included in the analyses.

Figure A.2: Policy innovations by state

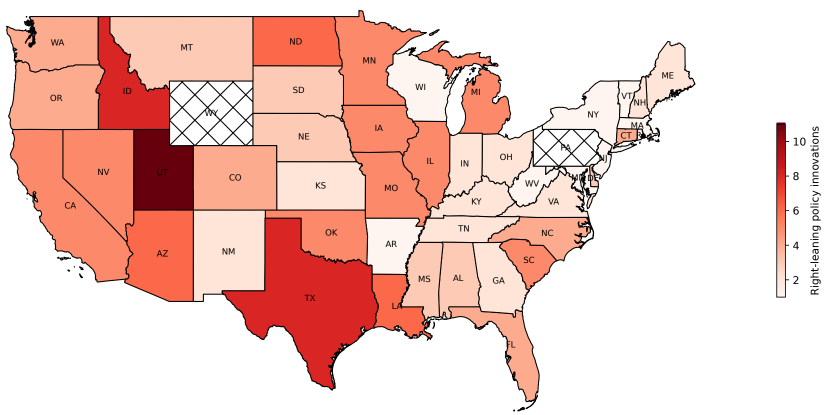
(a) All policy innovations



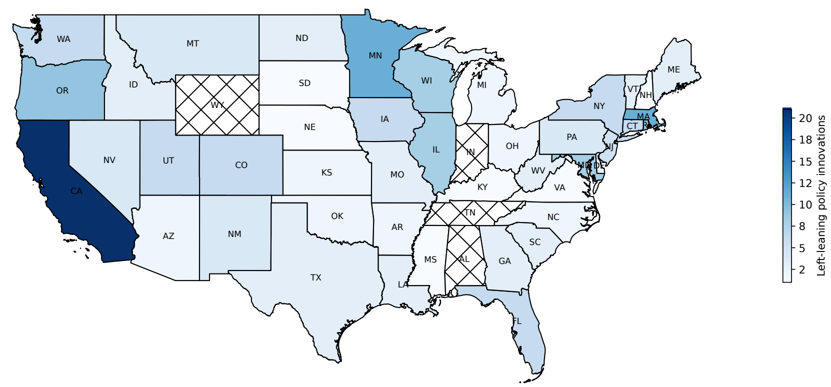
(b) Innovations of policies with $\geq$ 24 adopters



(c) Right-leaning policy innovations



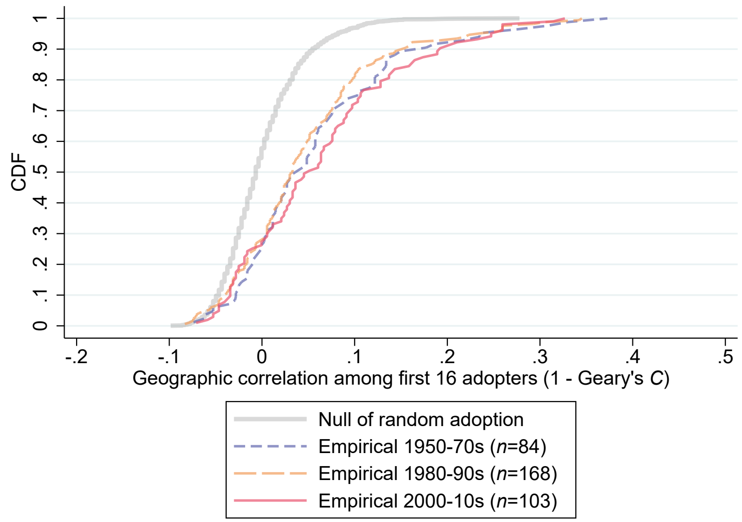
(d) Left-leaning policy innovations



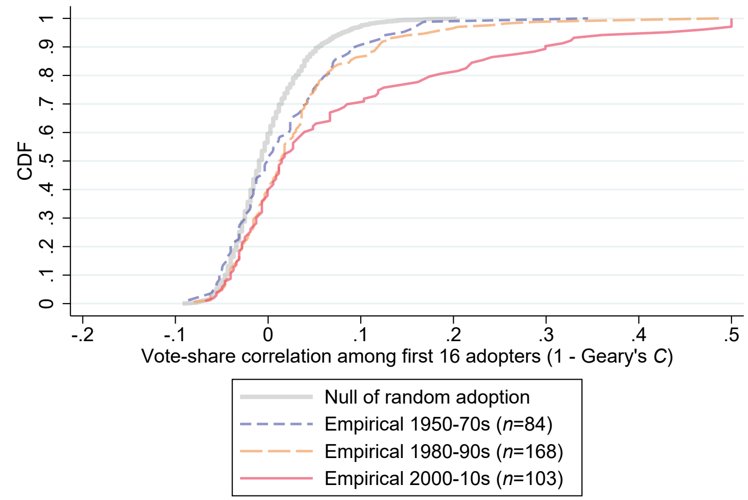
Figures A.2a-A.2d show the number of innovations by each state for: all policies (A.2a), policies with 24 or more adopters (A.2b), Right-leaning policies (A.2c), and Left-leaning policies (A.2d). See notes in Table 2 for the categorization of Right- and Left-leaning policies.

Figure A.3: Correlation in geography and politics among adopters (alternate thresholds)

(a) Correlation in geographic distance (first **16** adopters)

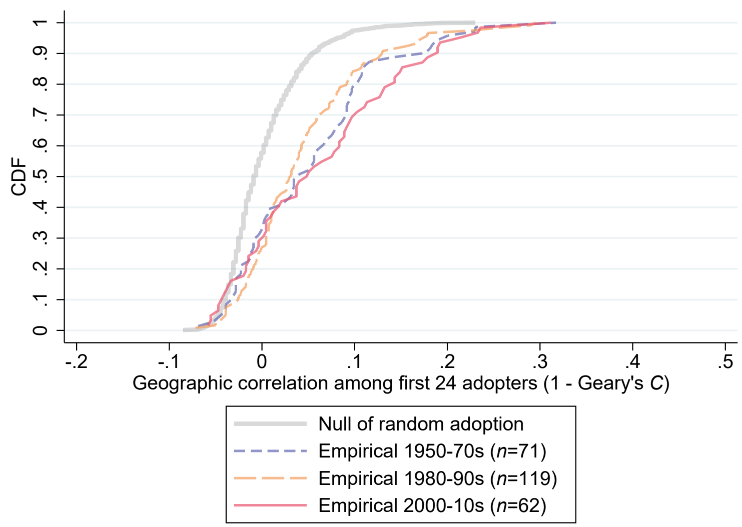


(b) Correlation in Republican vote-share (first **16** adopters)

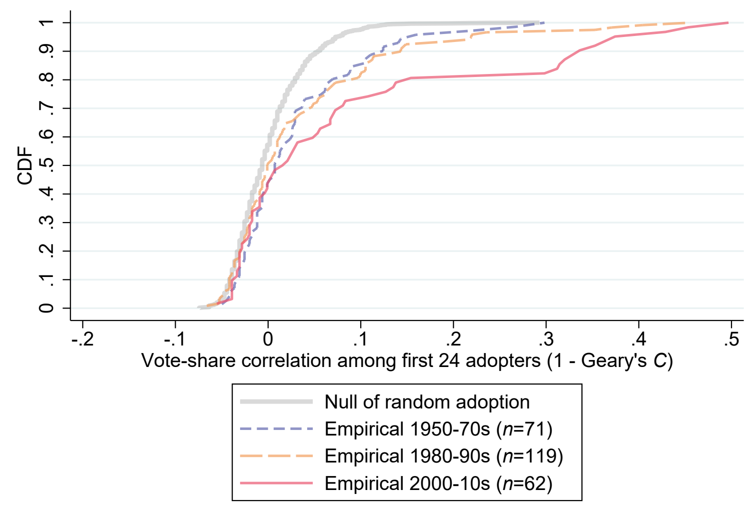


4 policies with a correlation less than -0.2 or greater than 0.5 have been censored.

(c) Correlation in geographic distance (first **24** adopters)



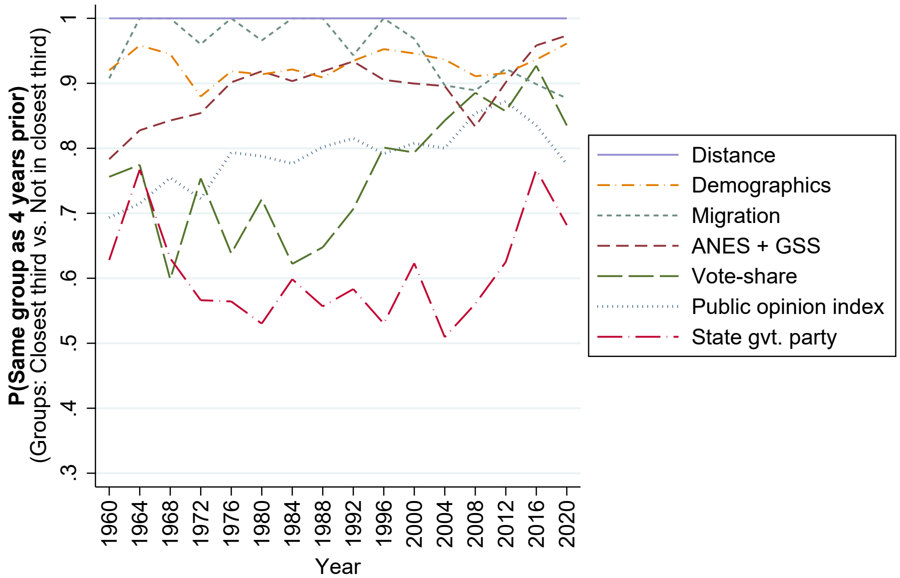
(d) Correlation in Republican vote-share (first **24** adopters)



1 policy with a correlation less than -0.2 or greater than 0.5 has been censored.

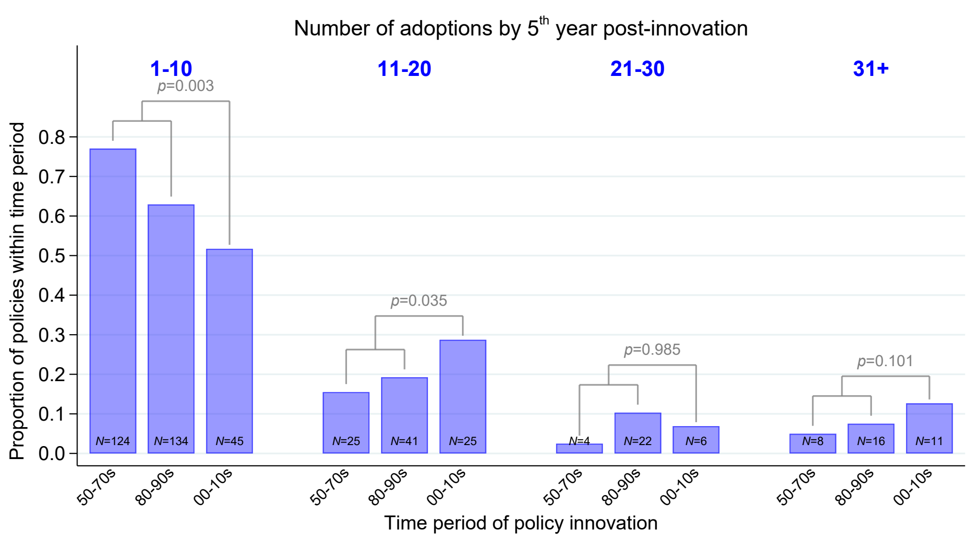
This figure replicates the analysis in Figures 5a-5b, but instead uses a threshold of the first 16 (Figures A.3a-A.3b) and of the first 24 (Figures A.3c-A.3d) adopters of a policy. The assignment of each policy to a decade is held constant at the year in which it reached 10 adopters. The sample of policies shrinks with higher thresholds as there are fewer policies that reach those thresholds.

Figure A.4: Stability of closest thirds in each dimension



This figure shows the average likelihood of being in the closest third of states conditional on being in the closest third four years prior, along different dimensions of similarity.

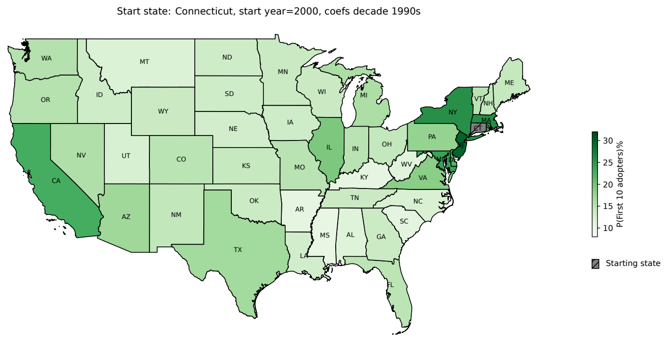
Figure A.5: Number of total adoptions by year 5



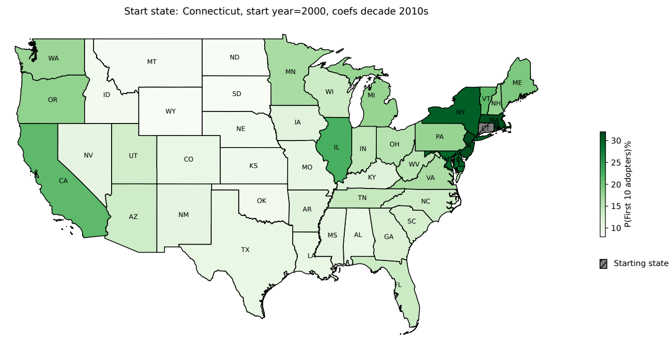
This figure shows the proportion of policies after 5 years that have 1-10, 11-20, 21-30, or more than 30 adopters. Policies are grouped into time periods based on the year of innovation.

Figure A.6: Simulated policy diffusion

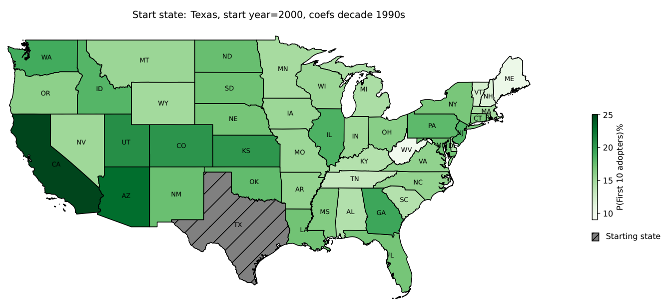
(a) Coefficients from 1990s (Connecticut)



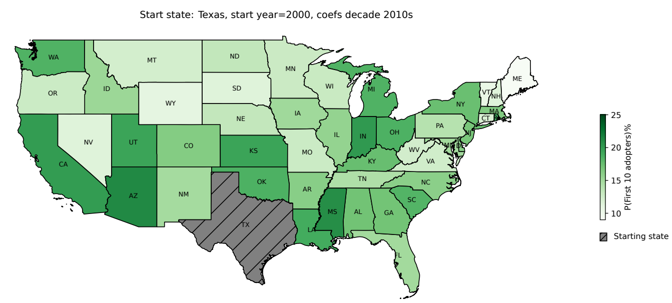
(b) Coefficients from 2010s (Connecticut)



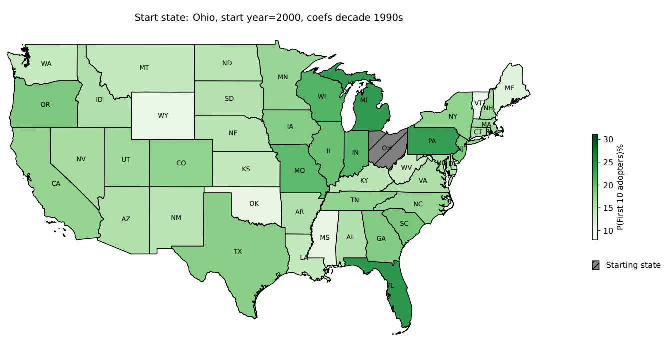
(c) Coefficients from 1990s (Texas)



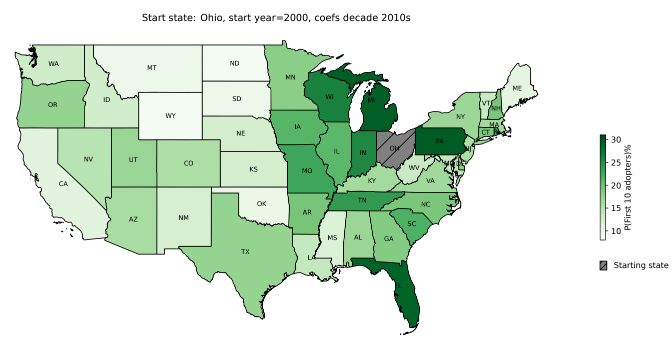
(d) Coefficients from 2010s (Texas)



(e) Coefficients from 1990s (Ohio)



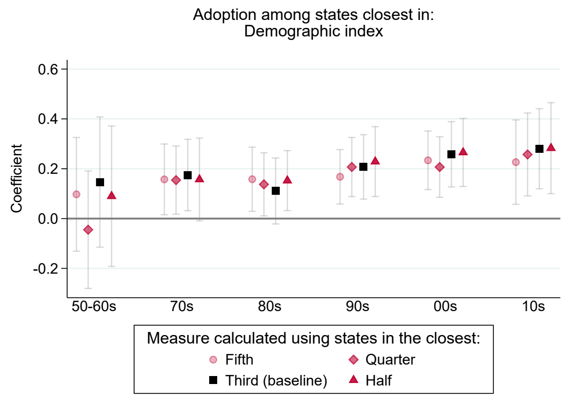
(f) Coefficients from 2010s (Ohio)



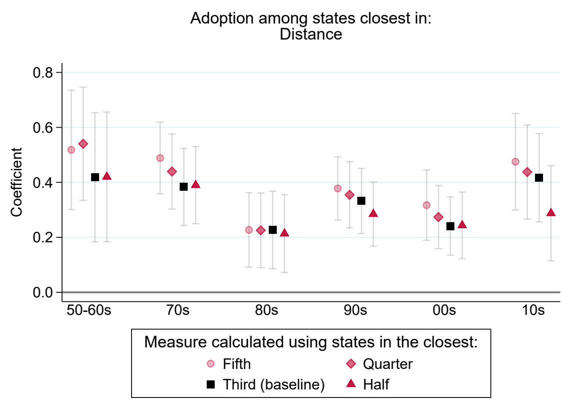
These figure show the simulated diffusion of policies as in Figures 8a-8b, but with different innovating states: Connecticut (A.6a-A.6a), Texas (A.6c-A.6c), and Ohio (A.6e-A.6e).

Figure A.7: Robustness checks: Threshold of closest states

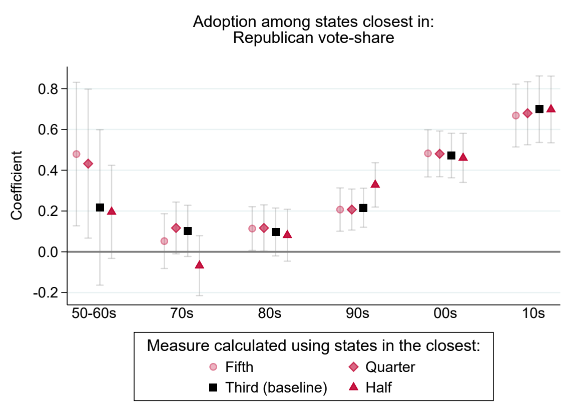
(a) Dimension: Demographic index



(b) Dimension: Distance



(c) Dimension: Republican vote-share



This figure shows the point estimates and 95% confidence intervals for the measure of adoption among closest states in Equation 2, but at different thresholds to determine the closest states (i.e., the fifth, quarter, or half closest states).

Figure A.8: Measuring voter policy preference from ANES and GSS

(a) State representation in ANES and GSS **(b)** Number of questions **(c)** Questions by policy area

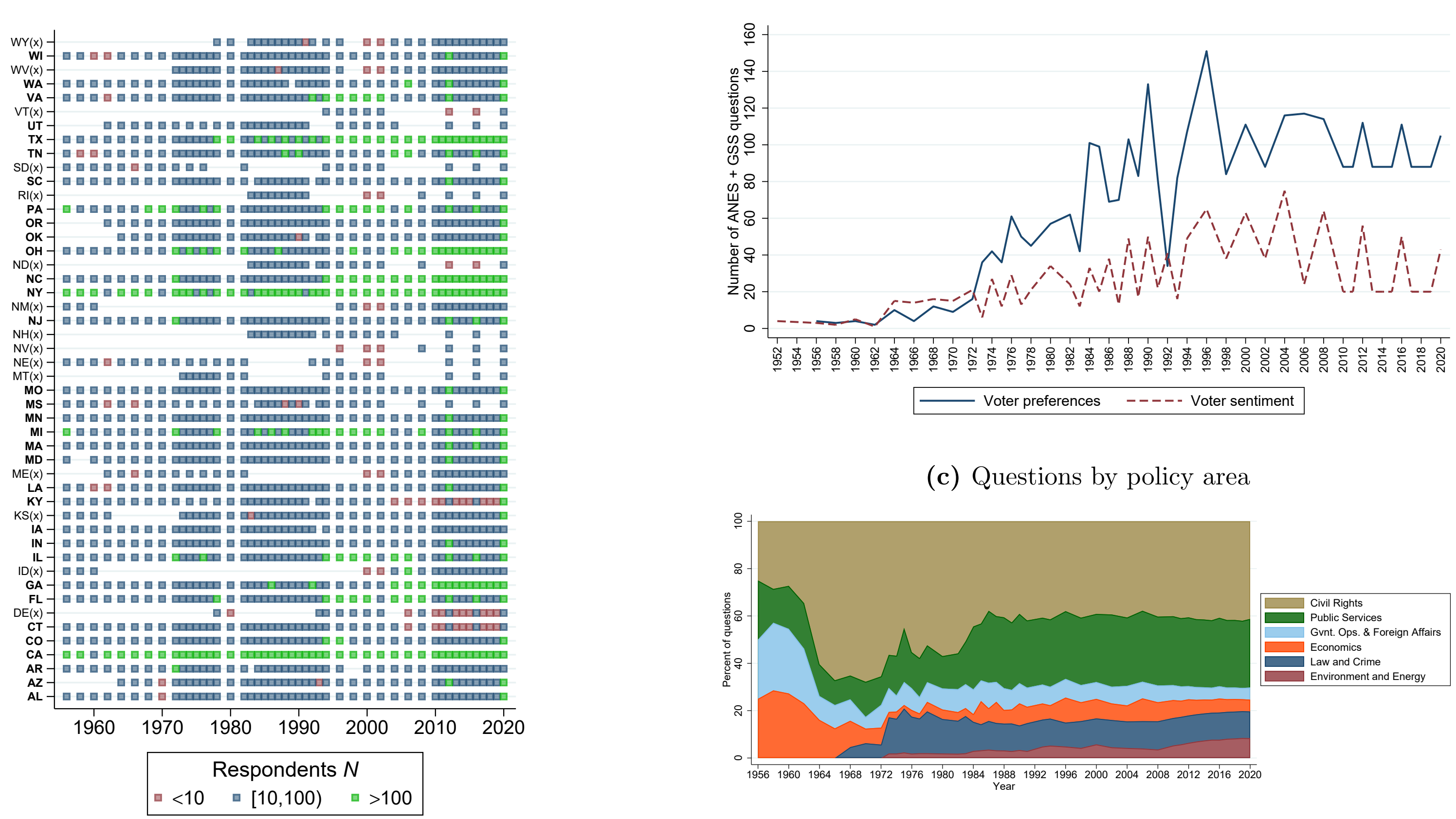
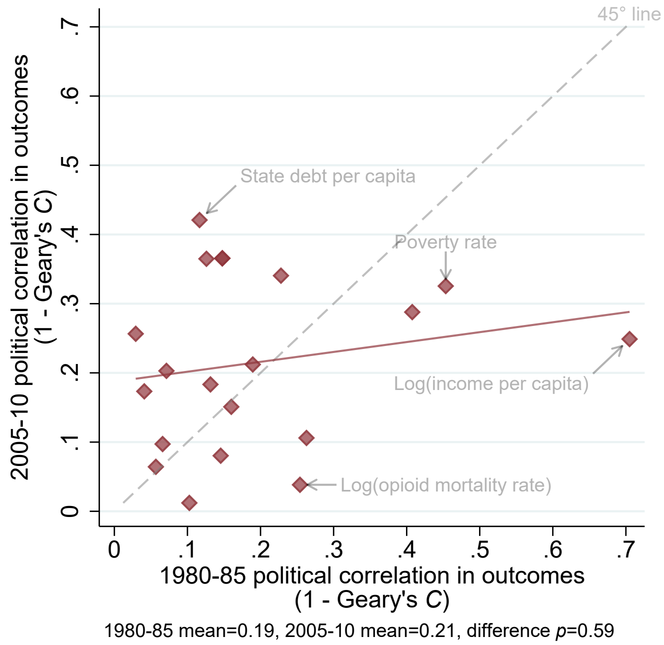


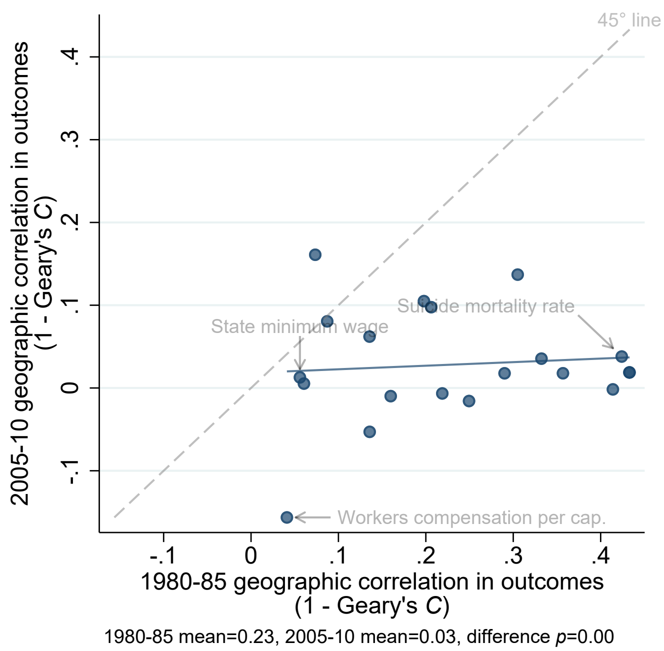
Figure A.8a shows the number of respondents in each state for across the ANES and GSS survey waves. States marked by "(x)" in Figure A.8a are excluded from the analyses using this voter preference measure due to insufficient coverage. Figure A.8b shows the number of policy questions from the ANES and GSS surveys that are used for measures of voter preferences and sentiment. Figure A.8c shows the composition of the questions by policy area over time.

Figure A.10: Correlation of policy outcomes: 1980-85 vs. 2005-10

(a) Political correlation



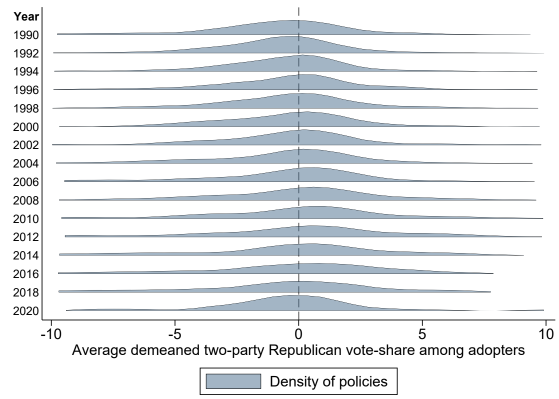
(b) Geographic correlation



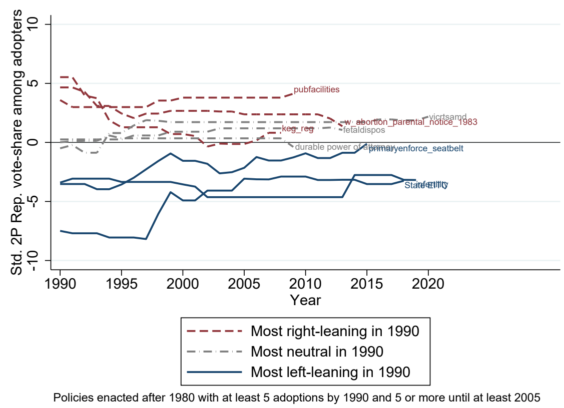
This figure shows the 1-Geary's C measure for the geographic and political correlation in typical outcomes studied in NBER papers (see Table A.3a). "Political correlation" in Figure A.10a is calculated using Republican vote-share. The correlations are shown for 1980-85 and 2005-2010, the time periods with the most overlap in outcome data.

Figure A.11: Categorizing the ideology of policies for event study analysis

(a) Distribution of policy ideologies



(b) Ideology of most extreme and neutral policies over time



(c) Number of policies under each ideology as a function of the threshold

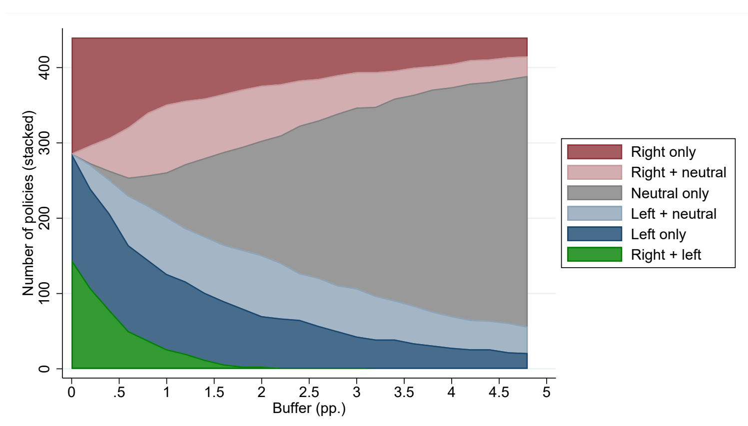
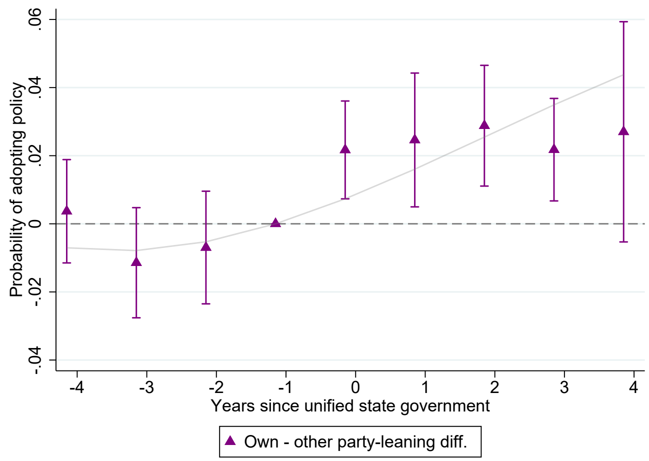


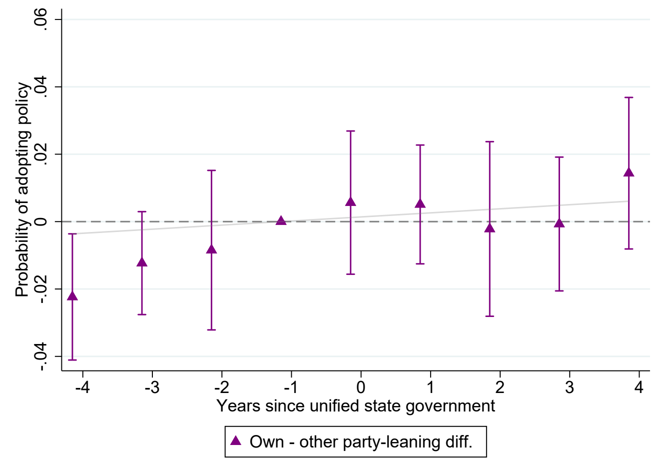
Figure A.11a shows the distribution of policies by the average demeaned Republican vote-share among adopters over the last 30 years. Figure A.11b follows the ideological evolution of the three most Left-, Right-, and Neutral-leaning policies in 1990 until 2020. Figure A.11c displays the ideological classification of policies for different thresholds of average demeaned vote-share.

Figure A.12: Event study from switches in state government party control

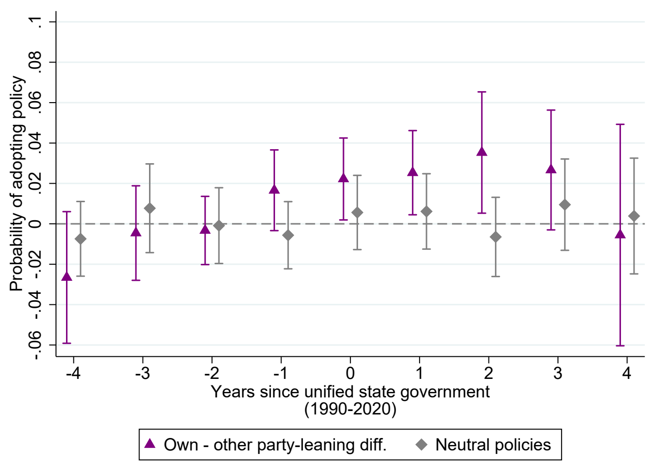
(a) Events during 1990-2020



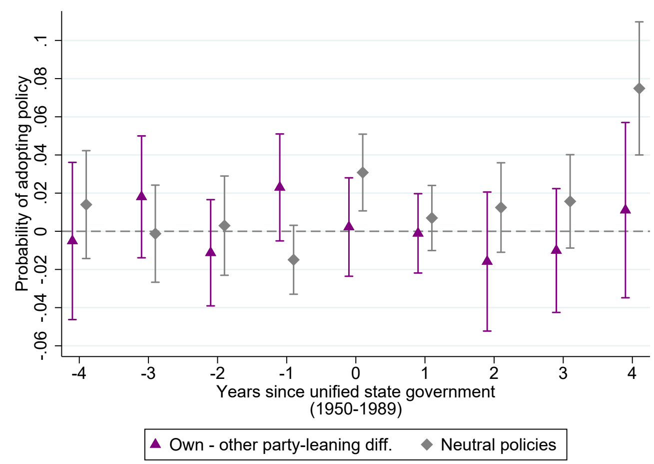
(b) Events during 1950-1989



(c) de Chaisemartin and D'Haultfœuille estimator (1990-2020)



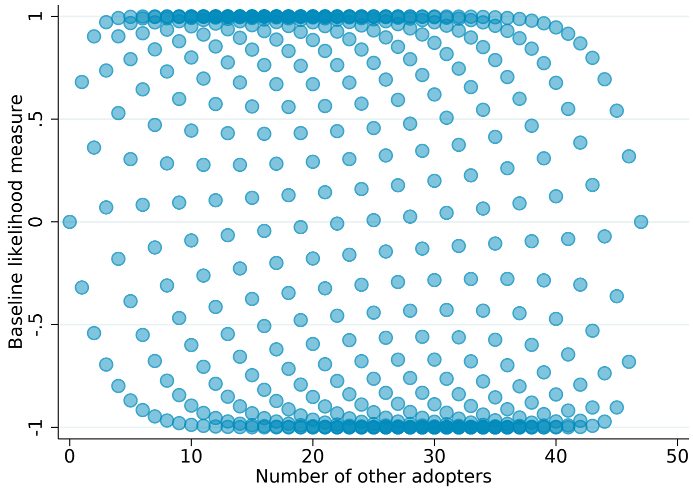
(d) de Chaisemartin and D'Haultfœuille estimator (1950-1989)



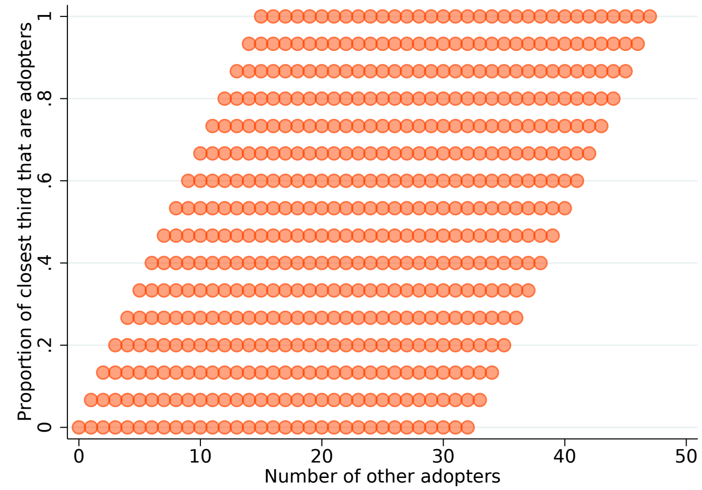
Figures A.12a-A.12b show the event studies estimates from Figures 9a-9b with the most plausible confound path (Freyaldenhoven et al., forthcoming) traced in the gray curve. Figures A.12c-A.12d show the event study estimates for switches to unified party control of state governments from the de Chaisemartin and D'Haultfœuille (2020) estimator. To run the event study using the de Chaisemartin and D'Haultfœuille estimator, the state-policy-year panel is collapsed to the state-year average rates of adoption for aligned, not aligned, and neutral policies. The treated effects from switching to unified state governments are estimated separately for these three types of policies. 95% confidence intervals are shown from bootstrap standard errors resampling at the state level.

Figure A.13: Specification checks: Range of measure by number of adopters

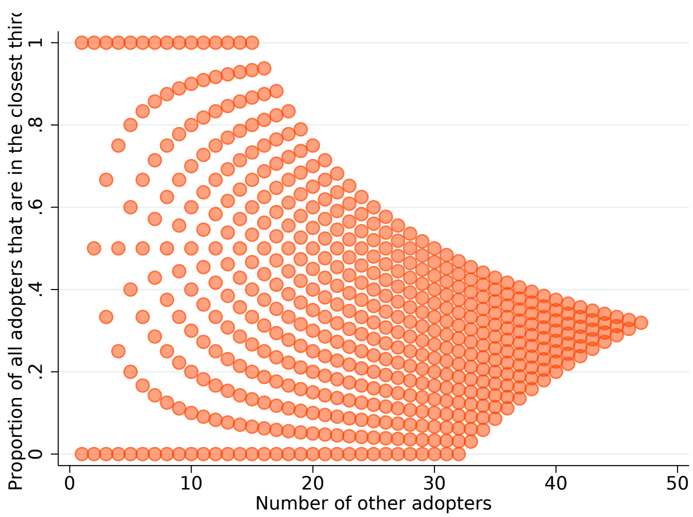
(a) Baseline two-sided likelihood measure



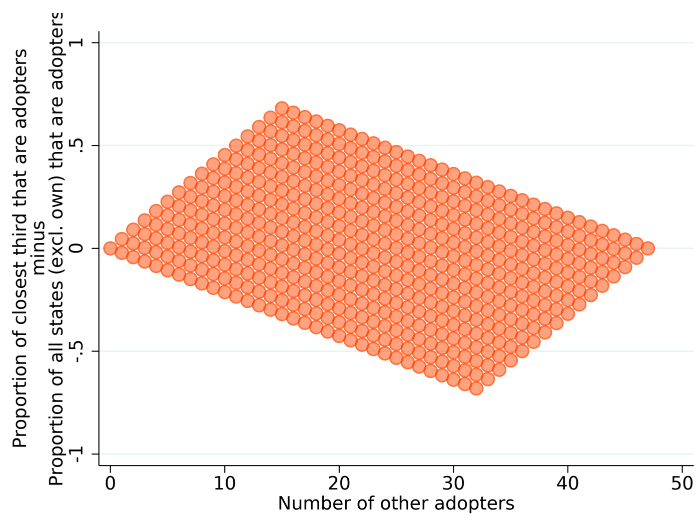
(b) Proportion of states in the closest third that are adopters



(c) Proportion of all adopters that are in the closest third

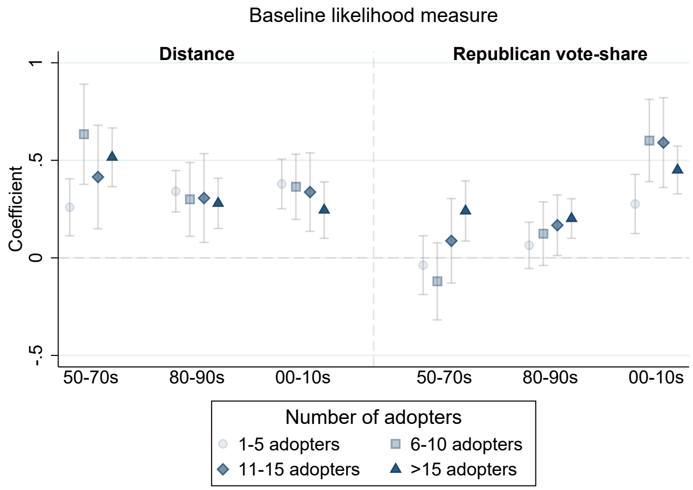


(d) Proportion of closest third that are adopters − Proportion of all states (excluding own) that are adopters

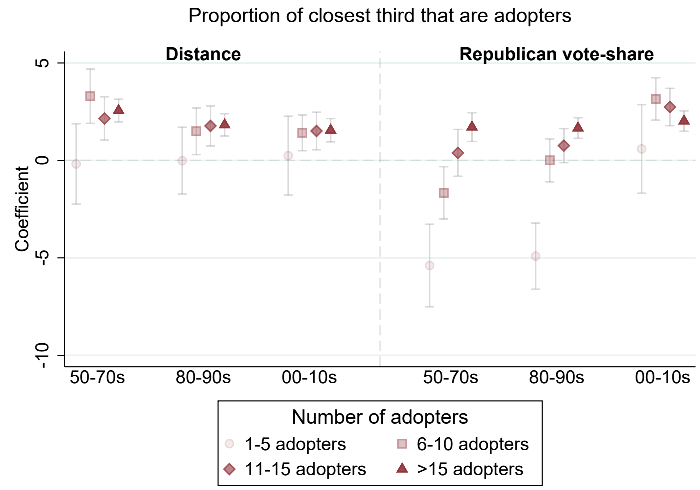


This figure shows the range of different measures of adoption in the closest third of states across the number of adopters.

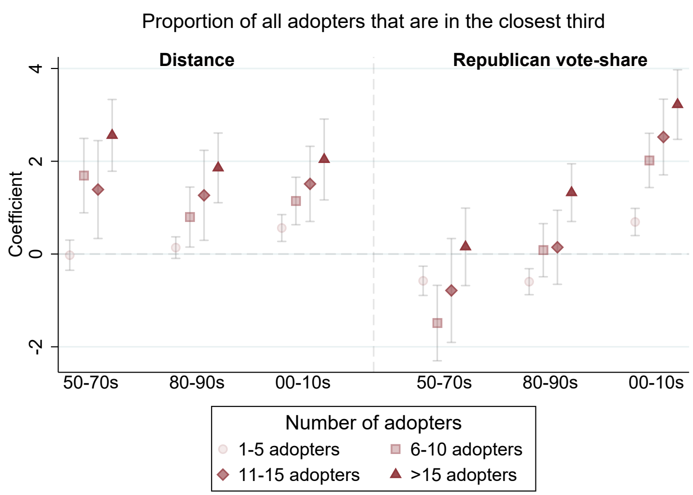
Figure A.13: Specification checks: Stability in coefficients by number of adopters



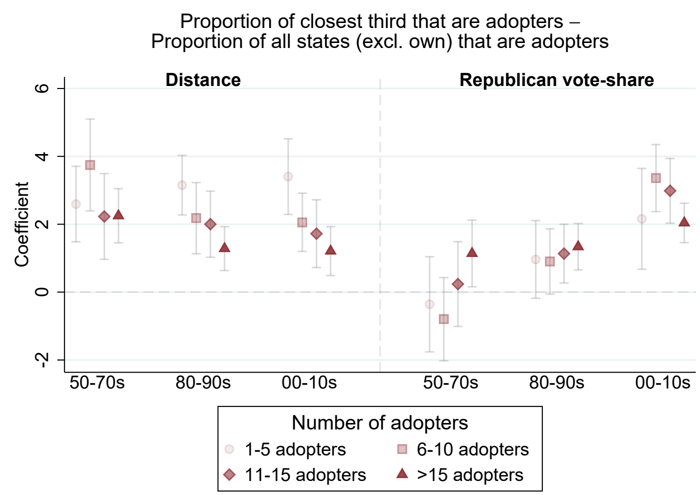
(e) Baseline two-sided likelihood measure



(f) Proportion of states in the closest third that are adopters



(g) Proportion of all adopters that are in the closest third



(h) Proportion of closest third that are adopters − Proportion of all states (excluding own) that are adopters

This figure shows the coefficients on different measures of adoption in geographically or politically close states, where the measures are interacted with dummies for whether the policy has 1-5, 6-10, 11-15, or more than 15 adopters. Point estimates and 95% confidence intervals are shown.

Table A.1: Summary of recent papers on policy diffusion in political science and examples in economics

Paper	(1) No. of Policies	(2) Time Period	(3) Source of Policies	(4) Methodology	(5) Determinants	(6) Quantitative Comparison across Determinants	(7) Main Results
DellaVigna and Kim (2022)	705	1950-2020	SPID, self-collected from NBER working papers	Logit hazard model	Geographic distance, Demographics, Migration, State government partisanship, Voter preferences	Yes	1950-1990s: Geographic and demographic diffusion, 2000-2020: Political diffusion
Desmarais, Harden, and Boehmke (2015)	151	1960-1999	Boehmke and Skinner (2012)	Multilevel logit model (dyadic)	Geographic contiguity, Ideology, Legislative professionalism, Diversity, Income, Population, State government partisanship	No	Diffusion predicted by: Geographic proximity; Citizen ideology; Demographics; Legislative professionalism difference; State party control
Caughey, Warshaw, and Xu (2017)	148	1936-2014	Caughey and Warshaw (2016)	Regression discontinuity, Dynamic panel analysis	State party control	No	Pre-2000: State party had little impact, Post-2000: State party control has strong impact on policy liberalism
Caughey and Warshaw (2018)	148	1936-2014	Caughey and Warshaw (2016)	Dynamic panel analysis	Mass liberalism, State party control, Suffrage, Campaign contribution limits, Reforms for citizen participation, Legislative professionalism	No	Role of public opinion has increased over time
Grumbach (2018)	135	1970-2014	Self-collected, Jordan and Grossmann (2016), Caughey and Warshaw (2016), Boehmke and Skinner (2012)	Dynamic panel analysis	State party control	No	Pre-2000: Little polarization, Post-2000: Substantial polarization in certain policy areas
Maillinson (2021)	556	1960-2014	SPID	Multilevel logit model	Geographic distance, Ideological similarity, Congressional hearings, Initiative availability, Initiative qualification difficulty, Legislative professionalism, Slack resources (per capita income and population), State party control, Salience, Policy complexity	No	Geographic diffusion has decreased over time, Role of ideology has remained stable
Case, Rosen, and Hines Jr. (1993)	1	1970-1985	Direct state expenditures per capita	Two-way fixed effects	Expenditures of similar states	Yes	Expenditure by other states similar in geography, income, and racial composition predict own state's expenditures
Strumpf and Oberholzer-Gee (2002)	1	1934-1970	Liquor control	Latent taste model for liquor controls; Probit estimation of policy choice on latent taste heterogeneity	Preference heterogeneity within state	No	Greater heterogeneity in local taste for liquor controls predicts the state adopting decentralized liquor laws

Table A.2a: SPID sample examples

Number	Source	Description	Keyword Category	Adoptions	First year	Last year
4	Boehmke-Skinner	Abortion Pre-Roe	Abortion	16	1966	1972
8	Caughey-Warshaw	Does The State Ban Late-Term Or Partial Birth Abortions?	Abortion	15	1996	2000
32	Uniform Law	Framework For Donation Of Organs Other Body Parts (2006 Version)	Health	44	2007	2013
47	Uniform Law	Provides Judicial Facilitation Of Private Dispute Resolution	Legal	21	1968	1997
53	Uniform Law	Governs Relations Among Student Athletes, Athlete Agents, And Educational Institutions	Education	39	2001	2010
67	Walker	Aid To The Blind (Social Security)	Benefits	48	1936	1953
72	Boehmke-Skinner	Child Access Gun Protection Law	Weapons	16	1989	2000
74	Mallinson	Allows Public Breastfeeding	Health	46	1993	2009
75	Boehmke-Skinner	Requiring Broad Community Notification Of Sex Offenders	Sex Offender	18	1990	1997
77	Min Hee Go	Building Code Adoption	Property	43	1953	2010
83	Boushey	Laws Regulating Punishment And Protection Of Credit Card Theft	Consumer Protection	48	1961	1999
116	Karch	System For Transferring Professional Education Employees' Pension	Education	2	1989	1991
135	Uniform Law	Crystallize The Best Elements Of Contemporary Federal And State Regulation Of Consumer Sales Practices	Consumer Protection	3	1972	1973
139	Matisoff	Corporate Incentives	Corporate	22	1990	2008
174	Uniform Law	Allow Every Sort Of Disclaimer, Including Those That Are Useful For Tax Planning Purposes.	Tax	9	1978	1995
177	Uniform Law	Preserves The Rights Of Each Spouse In Property That Was Community Property Before The Spouses Moved To The Non-Community Property State,	Property	14	1973	2013
182	Karch	System For States To Exchange License Suspension/Violation Between States	Employment	43	1961	1996
193	Uniform Law	Establishes Power Of Attorney For Medical Care And Finances	Health	17	1980	2009
204	Boehmke-Skinner	Election Day Registration	Election	7	1974	1994
239	Uniform Law	Require Delegates In Electoral College To Vote In Accordance With Voters	Election	7	2011	2021
244	Kreitzer	Bans Abortion After Fetal Heartbeat	Abortion	2	2013	2013
254	Uniform Law	Provides The Rules For Fair Conversions Of Foreign Money Judgments Into Dollar Amounts	Legal	21	1989	2010
261	Kreitzer	Bans Public Funding To Be Used For Abortion	Abortion	35	1977	1990
325	Michiganstate	Individual Limit On Campaigns	Election	48	1992	2000
339	Lacy	Instate Tuition For Veterans	Education	7	2006	2009
346	Karch	Establishes Procedure For Out Of State Supervision Of Juveniles And Procedures For Their Return	Crime	48	1955	1986
377	Boehmke-Skinner	Kinship Care Program	Children	26	1998	2006
388	Caughey-Warshaw	Does The State Ban Discrimination Against Disabled People?	Discrimination	39	1965	1986
456	Kreitzer	Near Total Abortion Ban	Abortion	2	1991	1991
502	Sheprd	Length License Suspension For First Dui, Pre-Conviction	Intoxication	40	1980	2004
506	Other	State Adoption Of Prepaid Tuition	Education	20	1986	1999
527	Kreitzer	Ban On Public Employees Conducting Abortions	Abortion	2	1990	2005
592	Other	College Tuition Saving Plans	Education	31	1988	1999
645	Mallinson	Targeted Regulation Of Abortion Providers (Trap) Laws	Abortion	19	1978	2005
647	Kreitzer	Requires Additional Licensure For Abortion Providers	Abortion	27	1973	2013
652	Lacy	States Allowing For Less Central Control Over Tuition Setting	Education	20	1987	2006
665	Uniform Law	Governs Transfer Of Investment Securities	Corporate	21	1987	1994
682	Walker	Urban Renewal- Enabling Legislation	Environment	34	1941	1952
686	Kreitzer	Requires Testing To Ascertain Viability Before Abortions	Abortion	6	1984	1999
696	Caughey-Warshaw	Has The State Expanded Access To Emergency Contraception?	Abortion	8	1998	2007

Table A.2b: NBER working paper sample

Number	Policy	Title	Keyword Category	Adoptions	First year	Last year	Effective
18187	Stand Your Ground laws	Stand Your Ground Laws, Homicides, and Injuries	Weapons	25	1994	2009	No
18299	Leave for state employee organ donors	Removing Financial Barriers to Organ and Bone Marrow Donation: The Effect of Leave and Tax Legislation in the U.S.	Health	29	1989	2007	Yes
18341	Physical education requirement	The Impact of Physical Education on Obesity among Elementary School Children	Education	38	1940	2007	Yes
18516	Wrongful discharge laws	Wrongful Discharge Laws and Innovation	Employment	45	1970	1998	Yes
18773	Bicycle helmet laws	Effects of Bicycle Helmet Laws on Children's Injuries	Transportation	19	1987	2006	No
18887	AFDC waiver	Effects of Welfare Reform on Women's Crime	Benefits	27	1992	1996	Yes
18887	TANF	Effects of Welfare Reform on Women's Crime	Benefits	48	1996	1998	Yes
19294	Biotech tax incentives	State Incentives for Innovation, Star Scientists and Jobs: Evidence from Biotech	Tax	7	1984	2003	Yes
19904	Community rating regulations	Regulatory Redistribution in the Market for Health Insurance	Health	7	1993	1997	Yes
20149	Interstate bank branching laws	Does Financing Spur Small Business Productivity? Evidence from a Natural Experiment	Corporate	48	1995	1997	Yes
20565	Medical record copy fee cap	Expanding Patients' Property Rights In Their Medical Records	Health	42	1972	2007	Yes
20808	NOx cap-and-trade	Who Loses Under Power Plant Cap-and-Trade Programs?	Environment	20	2003	2007	No
21170	Commonsense Consumption Acts	Do Ã¢Â€Â˜Cheeseburger BillsÃ¢Â€Â™ Work? Effects of Tort Reform for Fast Food	Consumer Protection	26	2003	2013	Yes
21345	Medical marijuana laws	Do Medical Marijuana Laws Reduce Addictions and Deaths Related to Pain Killers?	Intoxication	21	1996	2014	No
21373	Individual income tax	Broadening State Capacity	Tax	42	1911	1971	No
21373	Coporate income tax	Broadening State Capacity	Tax	43	1911	1971	No
22344	Nurse Licensure Compact	Labor Supply Effects of Occupational Regulation: Evidence from the Nurse Licensure Compact	Employment	25	1999	2015	No
22899	Initial Medicaid implementation	The Long-Run Effects of Childhood Insurance Coverage: Medicaid Implementation, Adult Health, and Labor Market Outcomes	Benefits	48	1966	1982	Yes
23313	E-cigarette minimum age law	The Effects of E-Cigarette Minimum Legal Sale Age Laws on Youth Substance Use	Intoxication	48	2010	2016	No
23388	Substance use disorder parity laws	Health Insurance and Traffic Fatalities: The Effects of Substance Use Disorder Parity Laws	Health	12	1994	2009	Yes
23510	Concealed handgun carry law	Right-to-Carry Laws and Violent Crime: A Comprehensive Assessment Using Panel Data and a State-Level Synthetic Control Analysis	Weapons	41	1959	2014	No
23995	Smoking ban	Impact of Comprehensive Smoking Bans on the Health of Infants and Children	Intoxication	34	1994	2012	Yes
24153	Interstate tax audit info sharing	Intergovernmental Cooperation and Tax Enforcement	Tax	5	1950	1955	Yes
24259	Right-to-work laws	From the Bargaining Table to the Ballot Box: Political Effects of Right to Work Laws	Employment	27	1943	2017	N/A
24381	Ban-the-box laws	Do Ban the Box Laws Increase Crime?	Employment	11	2009	2014	No
24651	Same-sex marriage	Effects of Access to Legal Same-Sex Marriage on Marriage and Health: Evidence from BRFSS	Discrimination	33	2004	2014	Yes

The "Effective" column indicates whether the policy had a desirable impact based on the estimates in the NBER paper. We code the policy effect mainly from the abstracts, consulting the text in ambiguous cases and taking the position of the paper wherever possible. Outcomes that cannot be classified as either positive or negative (e.g., Democratic vote-share) are shown as "N/A".

Table A.2b: NBER working paper sample

Number	Policy	Title	Keyword Category	Adoptions	First year	Last year	Effective
24662	Merit-aid programs	State Merit Aid Programs and Youth Labor Market Attachment	Education	18	1988	2005	N/A
24782	Duty-to-bargain laws	The Long-run Effects of Teacher Collective Bargaining	Employment	31	1960	1987	No
24986	Community eligibility provision	School Nutrition and Student Discipline: Effects of Schoolwide Free Meals	Education	10	2012	2014	Yes
25209	Child gun access prevention laws	Child Access Prevention Laws and Juvenile Firearm-Related Homicides	Weapons	25	1989	2001	Yes
25369	Age anti-discrimination	Do State Laws Protecting Older Workers from Discrimination Reduce Age Discrimination in Hiring? Evidence from a Field Experiment	Discrimination	45	1934	1997	Yes
25369	Disability anti-discrimination	Do State Laws Protecting Older Workers from Discrimination Reduce Age Discrimination in Hiring? Evidence from a Field Experiment	Discrimination	46	1971	1988	Yes
25390	Wind energy incentives	Technological Spillover Effects of State Renewable Energy Policy: Evidence from Patent Counts	Environment	48	2000	2011	Yes
25758	Minor abortion parental consent	The Impact of Parental Involvement Laws on Minor Abortion	Abortion	37	1974	2013	No
25974	Initial prescription drug monitoring	Can Policy Affect Initiation of Addictive Substance Use? Evidence from Opioid Prescribing	Health	24	1988	2018	No
25974	Must-access prescription drug monitoring	Can Policy Affect Initiation of Addictive Substance Use? Evidence from Opioid Prescribing	Health	29	2007	2019	Yes
26017	E-cigarette tax	The Effects of Traditional Cigarette and E-Cigarette Taxes on Adult Tobacco Product Use	Intoxication	7	2010	2017	No
26135	Pill mill laws	Mortality and Socioeconomic Consequences of Prescription Opioids: Evidence from State Policies	Health	8	2005	2014	Yes
26140	NBCCEDP cancer screenings	Effects of Direct Care Provision to the Uninsured: Evidence from Federal Breast and Cervical Cancer Programs	Health	48	1991	1999	Yes
26206	Strict voter ID	Strict Voter Identification Laws, Turnout, and Election Outcomes	Election	11	2004	2016	No
26405	State EITC	The EITC and the Extensive Margin: A Reappraisal	Employment	28	1986	2018	No
26500	Triplicate prescription	Origins of the Opioid Crisis and Its Enduring Impacts	Health	7	1939	1988	Yes
26676	E-verify for employment	States Taking the Reins? Employment Verification Requirements and Local Labor Market Outcomes	Employment	22	2006	2015	No
26749	Modern prescription drug monitoring	Effect of Prescription Opioids and Prescription Opioid Control Policies on Infant Health	Health	47	1999	2017	Yes
26832	Mandated sick pay	Mandated Sick Pay: Coverage, Utilization, and Welfare Effects	Employment	10	2011	2018	Yes
27054	Salary history ban	Information and the Persistence of the Gender Wage Gap: Early Evidence from California's Salary History Ban	Employment	12	2017	2021	Yes
27306	Medicaid expansion	Medicaid Expansion and the Mental Health of College Students	Benefits	36	2014	2021	Yes
27520	Tramadol as Schedule IV drug	Competitive Effects of Federal and State Opioid Restrictions: Evidence from the Controlled Substance Laws	Intoxication	12	2007	2014	No
27788	Paid family leave	Paid Leave Pays Off: The Effects of Paid Family Leave on Firm Performance	Employment	6	2002	2018	Yes
28173	Tobacco 21 laws	Do State Tobacco 21 Laws Work?	Intoxication	15	2016	2019	Yes
28903	Right of workers to talk law	Equilibrium Effects of Pay Transparency	Employment	12	2004	2016	No
29087	Recreational marijuana legalization	Recreational Marijuana Laws and the Use of Opioids: Evidence from NSDUH Microdata	Intoxication	17	2012	2021	No

The "Effective" column indicates whether the policy had a desirable impact based on the estimates in the NBER paper. We code the policy effect mainly from the abstracts, consulting the text in ambiguous cases and taking the position of the paper wherever possible. Outcomes that cannot be classified as either positive or negative (e.g., Democratic vote-share) are shown as "N/A".

Table A.2c: Summary of NBER data set

	(1) All (4/12 - 9/21)	(2) Cross-state policy	(3) Meets criteria*	(4) Has data	(5) Sample
Total	11316	170	91	80	77
Issue date	2017.3 [2.7]	2017.6 [2.8]	2017.2 [2.8]	2017.5 [2.7]	2017.4 [2.7]
Field					
% in Labor Studies	23	32	30	28	29
% in Public Economics	23	40	31	30	30
% in Economic Fluctuations and Growth	22	6	1	1	1
% in Health Economics	12	52	62	68	66
Other	41	15	11	10	10
Publication					
% Published	48	46	49	46	45
% Published in "Top General Interest"	9	4	1	0	0
% Published in "Tier A"	14	15	19	20	21
Year published	2017.3 [2.4]	2016.9 [2.3]	2016.6 [2.5]	2016.8 [2.6]	2016.6 [2.5]
% Policy adoption data available	–	–	88	100	100
% Replication data available	–	–	–	9	8

Working papers numbered 18000-29318 are included. Means are reported with standard deviations in brackets for dates. Working papers can be listed under multiple fields. Papers on the same policy are all included in the sample. *Criteria: Policy must be binary and active after the 1950s. Covid-19 policies are also excluded. The final sample consists of policies for which there are adoption data from the papers and can be categorized into one of the main keyword groups.

Table A.3a: Summary statistics: Policy outcomes from NBER papers

Outcome	Coverage	Example NBER policy	NBER WP numbers
Log(income per capita)	1950-2020	Partial paid leave for pregnancy	19294
Voter turnout rate	1980-2019	Strict voter ID	26206, 24259
Log(opioid mortality rate)	1968-2014	Naloxone Access Law	25974, 26135, 26500, 27520, 29087
Employment rate in energy-intensive industry	1975-2018	NOx cap-and-trade	20808
Private insurance coverage rate	1987-2006	Community rating regulations	19904
Log(state revenue per capita)	1950-2016	Tax audit info sharing	21373, 24153
Log(state expenditure per capita)	1950-2016	State income and corporate taxes	21373, 24153
Average BMI	1987-2020	Physical education requirements	18341, 21170
Firearm mortality rate	1968-2016	Stand Your Ground laws	18187, 23510, 25209
Alcohol-induced traffic mortality rate	1975-2015	Substance use disorder parity laws	23388

This table shows a set of outcomes studied in the NBER paper sample used in Figures A.10a-A.10b.

Table A.3b: COVID-19 policies

Example policy	Coverage (MM/DD/YYYY)	Num. adopted states
Modify Medicaid requirements with 1135 waivers (date of CMS approval)	3/16/2020-4/22/2020	48
SNAP Waiver - Pandemic EBT during school year 2020-2021	12/15/2020-3/23/2021	25
Late Fee Ban Start	2/29/2020-5/22/2020	11
Date K-12 school employees became eligible for COVID-19 vaccination	1/8/2021-4/5/2021	48
Date banned visitors to nursing homes	3/9/2020-8/13/2020	30
Stopped visitation in state prisons x2	7/15/2020-12/30/2020	9
Date adults ages 55+ became eligible for COVID-19 vaccination	3/1/2021-4/19/2021	48
SNAP Waiver - Emergency Allotments to Current SNAP Households	3/24/2020-4/15/2020	48
Reopened bars (x2)	8/11/2020-5/7/2021	18
Face mask mandate in public spaces	4/8/2020-12/9/2020	38
SNAP Waiver - Temporary Suspension of Claims Collection	4/2/2020-5/13/2020	24
Face mask mandate in schools for 2021-22 school year	5/1/2020-4/16/2021	15
Closed movie theaters (x2)	6/29/2020-12/12/2020	6
Closed gyms (x2)	6/29/2020-12/12/2020	7
State of emergency issued	2/29/2020-3/16/2020	48
Reopened ACA enrollment using a special enrollment period	3/10/2020-4/1/2020	11
Date closed K-12 public schools	3/16/2020-4/3/2020	47
First eviction enforcement ban start	3/16/2020-4/30/2020	27
Utilities reconnection start	3/4/2020-4/13/2020	8
Date adults ages 75+ became eligible for COVID-19 vaccination	12/23/2020-2/15/2021	48
SNAP Waiver - Pandemic EBT during school year 2019-2020	4/9/2020-8/13/2020	48
Allowed restaurants to sell takeout alcohol	3/16/2020-5/8/2020	42
Allow audio-only telehealth	1/1/2020-6/22/2020	45
Exceptions to emergency oral prescriptions	3/11/2020-4/6/2020	6
Closed restaurants except take out	3/16/2020-4/3/2020	47
Date adults ages 40+ became eligible for COVID-19 vaccination	3/16/2021-4/19/2021	48
Reopened hair salons/barber shops	4/24/2020-8/28/2020	47
Date adults ages 50+ became eligible for COVID-19 vaccination	3/3/2021-4/19/2021	48
Reopened religious gatherings	4/26/2020-6/22/2020	34
Closed gyms	3/16/2020-4/3/2020	47
Average (all 76 policies)	6/30/2020-9/27/2020	30.62

This table shows 30 randomly selected COVID-19 policies in the data set as well as the overall average. Policies are kept in data set until the first repeal. Source: COVID-19 US State Policies (CUSP)

Table A.3c: Vaccine regulations

Policy	Coverage	Num. adopted states
Hepatitis A Vaccine Mandates for Child Care	1998-2021	22
Hepatitis A Vaccine Mandates for K-12	1988-2021	15
Hepatitis B Vaccine Mandates for Child Care	1993-2018	43
Hepatitis B Vaccine Mandates for Colleges and Universities	1992-2011	15
Hepatitis B Vaccine Mandates for elementary	1994-2008	44
Hepatitis B Vaccine Mandates for secondary	1995-2014	41
Influenza Vaccine Mandates for Child Care and Pre-K	1999-2020	7
MenACWY Vaccine Mandates for Colleges and Universities	2001-2020	23
MenACWY Vaccine Mandates for Elementary and Secondary Schools	2005-2021	33
PCV Vaccine Mandates for Childcare	2001-2018	39
Rotavirus Vaccine Mandates for Child Care and Pre-K	1999-2021	8
Tdap Vaccine Mandates for Elementary and Secondary Schools	2006-2017	48
Varicella Vaccine Mandates for Child Care	1997-2016	47
Varicella Vaccine Mandates for Elementary School	1998-2015	48
Varicella Vaccine Mandates for Middle/junior/senior high	1999-2015	39
Hep B vaccine is either offered or mandated in hospitals	1993-2016	8
Hep B vaccine is either offered or mandated in long-term care facilities	1993-2018	9
Hep B vaccine is either offered or mandated in ambulatory care facilities	1993-2016	12
Any of the MMR vaccines are either offered or mandated in hospitals	1980-2014	14
Any of the MMR vaccines are either offered or mandated in long-term care facilities	1981-2020	10
Any of the MMR vaccines are either offered or mandated in ambulatory care facilities	1992-2022	12
Pertussis vaccine is either offered or mandated in hospitals	2002-2013	5
Pneumococcal vaccine is either offered or mandated in hospitals	2002-2017	13
Pneumococcal vaccine is either offered or mandated in long-term care facilities	1991-2015	26
Varicella vaccine is either offered or mandated in ambulatory care facilities	1995-2017	5
Influenza vaccine is either offered or mandated in hospitals	1995-2019	24
Influenza vaccine is either offered or mandated in long-term care facilities	1995-2020	33
Influenza vaccine is either offered or mandated in ambulatory care facilities	1998-2021	12
Average (28 policies)	1996-2017	23.39

This table lists all 28 policies in the vaccine regulations data set.

Table A.4: Predictors of policy innovation (with legislative professionalism)

Innovated during:	1973-1989				1990-2014			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var.: No. policies innovated×100	All	Right-leaning	Left-leaning	Non-partisan	All	Right-leaning	Left-leaning	Non-partisan
Standardized 2-party Rep. vote-share	-6.24	1.36	-3.44	-4.16	4.82	2.63	-2.40	4.59
	(3.56)	(1.10)	(1.09)	(2.67)	(5.23)	(0.98)	(1.46)	(4.52)
Unified Democratic government	-4.50	-1.22	-0.22	-3.06	8.13	-1.17	4.07	5.23
	(5.94)	(2.14)	(2.00)	(4.60)	(6.23)	(1.85)	(2.53)	(5.48)
Unified Republican government	-19.28	-2.42	-6.41	-10.45	-10.65	-3.82	0.41	-7.24
	(9.90)	(2.57)	(2.39)	(8.96)	(6.55)	(2.32)	(2.35)	(5.04)
Standardized log(population)	-4.34	-1.40	-0.28	-2.66	-7.61	3.04	-0.86	-9.79
	(4.39)	(0.96)	(1.71)	(3.10)	(5.02)	(1.63)	(1.92)	(3.92)
Standardized log(income per capita)	-3.14	-0.93	0.71	-2.92	0.29	-1.10	-1.17	2.55
	(4.50)	(1.75)	(1.31)	(2.69)	(5.78)	(1.03)	(1.42)	(4.63)
Standardized urban %	11.73	3.85	2.64	5.24	15.15	2.40	2.77	9.98
	(4.78)	(2.13)	(1.79)	(2.44)	(4.15)	(0.97)	(1.70)	(3.11)
Standardized agriculture employed %	9.72	2.87	3.12	3.73	1.80	1.37	1.27	-0.84
	(4.22)	(1.02)	(1.34)	(3.45)	(3.32)	(0.85)	(1.26)	(2.70)
Standardized manufacturing employed %	1.47	2.26	0.52	-1.31	0.11	-0.60	-0.25	0.96
	(3.18)	(0.89)	(1.27)	(2.54)	(3.96)	(0.86)	(1.19)	(3.05)
Standardized legislative professionalism	2.65	-0.24	0.16	2.72	3.82	-2.26	5.50	0.58
	(3.74)	(0.94)	(1.14)	(2.95)	(7.51)	(1.14)	(4.03)	(4.00)
Year range	1973-1989	1973-1989	1973-1989	1973-1989	1990-2014	1990-2014	1990-2014	1990-2014
Average no. innovations/year	0.43	0.05	0.08	0.30	0.68	0.07	0.07	0.54
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Observations	816	816	816	816	1200	1200	1200	1200
R^2	0.17	0.04	0.08	0.16	0.26	0.08	0.10	0.32

Coefficients and standard errors have been multiplied by a factor of 100. Standard errors clustered by state are shown in parentheses. See notes in Table 2. The measure of legislative professionalism is the first-dimension measure from Bowen and Greene (2014), and is available from 1973-2014.

Table A.5a: Examples of states in closest thirds

Decade	Demographics	Distance	Vote-share	State party	Migration
1960s	NM ← NH,	VT ← MI,	AR ← LA,	SC ← NC,	AR ← OH,
	TN ← SC,	VA ← RI,	VT ← CO,	VA ← NC,	UT ← NV,
	WV ← SD,	WI ← PA,	KS ← WY,	MS ← NC,	MD ← CA,
	WI ← CO,	NM ← ID,	CT ← NJ,	GA ← NC,	MD ← NC,
	KS ← MO	OR ← AZ	MD ← NY	GA ← TX	ND ← WA
1970s	GA ← AL,	KY ← PA,	VA ← NH,	WY ← NY,	WV ← VA,
	MO ← PA,	MT ← KS,	ID ← NE,	MD ← GA,	WA ← MN,
	NH ← WY,	AZ ← CA,	IL ← GA,	GA ← MS,	OR ← NY,
	VT ← NE,	NE ← CO,	ID ← VA,	RI ← MS,	TX ← FL,
	IL ← TX	MO ← OK	GA ← DE	OH ← ID	OR ← UT
1980s	PA ← VA,	TX ← CO,	IN ← KS,	PA ← ND,	IL ← AZ,
	NM ← KS,	MA ← NJ,	MT ← NJ,	RI ← NM,	ND ← TX,
	TN ← WI,	MD ← KY,	MA ← MN,	WY ← DE,	CT ← NY,
	NM ← MT,	MS ← OK,	CT ← OH,	CO ← NY,	ID ← NV,
	KY ← IN	IN ← MO	OR ← WI	MA ← MD	WI ← MN
1990s	MI ← MO,	AR ← LA,	NM ← MI,	TX ← OK,	ME ← CA,
	VA ← MD,	RI ← MA,	UT ← VA,	NC ← AL,	NJ ← AZ,
	MD ← CO,	IL ← KY,	MD ← WV,	DE ← NY,	NJ ← OH,
	DE ← NV,	MD ← NJ,	MA ← WV,	MT ← WY,	NY ← NJ,
	KY ← AL	MA ← PA	WA ← MD	KY ← GA	NH ← NY
2000s	ID ← KY,	VA ← DE,	VT ← DE,	ND ← NE,	MD ← GA,
	WI ← PA,	SD ← ND,	RI ← MI,	OR ← MA,	ID ← OR,
	CA ← CO,	ND ← OK,	NM ← PA,	NE ← SD,	IN ← FL,
	MA ← AZ,	MN ← OK,	NV ← NM,	FL ← ID,	MN ← AZ,
	MA ← NY	CO ← NE	DE ← MD	KS ← WY	NE ← IA
2010s	OK ← SC,	MS ← OK,	WY ← MS,	ND ← ID,	MD ← OH,
	LA ← OR,	VT ← NJ,	NV ← MN,	KS ← MI,	VT ← FL,
	DE ← NV,	MN ← KY,	AZ ← FL,	UT ← FL,	KY ← TN,
	NM ← IN,	NY ← NH,	MD ← NJ,	NE ← GA,	NJ ← GA,
	GA ← WI	NH ← ME	OR ← DE	AZ ← ID	OR ← TX

XX ← YY means state YY is most consistently in the third of states closest to state XX averaged over the decade. Ties are randomly broken.

Table A.5b: Examples of states in closest thirds of voter preferences (ANES & GSS)

Decade	All policy areas	Within policy area				
		Civic Rights	Economics	Government	Law and Crime	Public Services
1960s	NJ ← PA, IL ← CA, CA ← IL, NC ← FL, OK ← FL	WA ← CA, UT ← CA, IN ← PA, PA ← NY, NC ← KY	MS ← MA, WI ← MO, TN ← CT, MD ← MA, IN ← TX	AZ ← WA, UT ← CT, TN ← AR, KY ← OH, OK ← NJ	OR ← WA, AR ← FL, MI ← MO, LA ← TX, CO ← WA	WI ← GA, WA ← NY, KY ← PA, WA ← SC, LA ← OH
1970s	LA ← TX, AR ← VA, MI ← TX, AL ← MI, OH ← VA	AL ← NC, VA ← MI, IL ← NJ, MN ← MI, CA ← NY	TN ← IA, IA ← IN, AR ← OH, MN ← WI, KY ← MI	SC ← KY, TX ← VA, MO ← OH, IN ← VA, TN ← CA	TX ← AL, IN ← PA, MD ← PA, WI ← PA, AL ← TX	MA ← NJ, UT ← SC, NJ ← OH, NC ← MI, SC ← IL
1980s	NY ← MA, PA ← IL, CA ← NY, FL ← IL, LA ← TX	MI ← MO, NY ← CA, CO ← IL, OK ← FL, WI ← IL	CA ← PA, OR ← MI, MA ← VA, OR ← CA, IN ← CA	MI ← CA, MA ← CA, MS ← OH, MN ← NY, CO ← PA	NJ ← OH, GA ← PA, MA ← IL, OR ← CA, MI ← OH	KY ← MI, MN ← CA, IL ← CA, NY ← PA, GA ← VA
1990s	CT ← PA, FL ← TX, OR ← NY, MI ← PA, CA ← IL	KY ← NC, TX ← IN, IN ← FL, MO ← OH, KY ← OH	AR ← IN, KY ← MI, FL ← CA, FL ← OH, NY ← CA	IN ← VA, OH ← IL, FL ← PA, VA ← PA, OH ← TN	CO ← MI, AZ ← CA, IL ← NY, PA ← CA, MO ← MI	MI ← PA, MO ← CA, TX ← MI, IL ← PA, MI ← OH
2000s	IA ← FL, MD ← NJ, MA ← CA, NY ← PA, GA ← NC	MO ← NC, WA ← CA, LA ← TX, NC ← TN, NJ ← WA	WI ← MI, NC ← NY, MI ← OH, TN ← TX, GA ← FL	GA ← PA, AL ← PA, MS ← TX, IA ← GA, NY ← CA	PA ← NC, FL ← NC, IN ← FL, MA ← IL, IA ← NY	FL ← CA, NJ ← PA, CT ← MI, MD ← FL, CA ← TX
2010s	AR ← MI, LA ← PA, WI ← TX, NJ ← TX, SC ← MA	MA ← FL, OH ← NJ, AZ ← MI, SC ← IL, PA ← GA	OR ← CA, AZ ← WI, UT ← GA, AZ ← FL, SC ← TN	MA ← CO, CA ← OR, VA ← IA, MN ← CA, SC ← CO	CO ← OH, KY ← OH, OR ← UT, SC ← WI, VA ← IA	AR ← TN, MA ← MI, NY ← MI, CO ← CA, NY ← NJ

XX ← YY means state YY is most consistently in the third of states closest to state XX averaged over the decade. Ties are randomly broken.

Table A.6: Policy diffusion predictors by decade

Dep. var.: Policy adoption (logit)	(1) 50-60s	(2) 70s	(3) 80s	(4) 90s	(5) 00s	(6) 10s
Proportion of states adopted	3.02	-0.67	1.67	2.92	2.16	2.93
	(0.36)	(0.27)	(0.20)	(0.13)	(0.20)	(0.31)
Standardized log(pop)	0.06	0.05	-0.01	0.06	-0.01	-0.01
	(0.15)	(0.06)	(0.03)	(0.06)	(0.05)	(0.08)
Standardized income per cap.	-0.00	0.19	-0.06	-0.01	-0.13	-0.06
	(0.19)	(0.07)	(0.03)	(0.07)	(0.05)	(0.09)
Standardized urban %	0.22	0.00	0.18	0.14	0.14	0.13
	(0.21)	(0.09)	(0.05)	(0.05)	(0.07)	(0.09)
Standardized % employed in agriculture	0.16	0.18	0.09	0.07	-0.03	-0.05
	(0.17)	(0.06)	(0.06)	(0.04)	(0.03)	(0.08)
Standardized % employed in manufacturing	0.08	0.04	0.02	0.01	-0.05	0.11
	(0.13)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
Standardized Republican vote-share	0.14	-0.12	-0.06	0.02	-0.03	-0.06
	(0.12)	(0.04)	(0.04)	(0.05)	(0.07)	(0.08)
Divided state government	0.26	-0.12	0.06	-0.02	-0.10	-0.08
	(0.23)	(0.08)	(0.07)	(0.06)	(0.08)	(0.12)
Measure of adoption among other states closest in:						
Demographic and economic index	0.17	0.10	0.13	0.20	0.24	0.23
	(0.15)	(0.08)	(0.06)	(0.06)	(0.06)	(0.07)
Distance	0.36	0.39	0.21	0.33	0.23	0.43
	(0.13)	(0.07)	(0.07)	(0.06)	(0.05)	(0.07)
Republican vote-share	0.29	0.11	0.08	0.24	0.45	0.47
	(0.21)	(0.06)	(0.06)	(0.05)	(0.05)	(0.08)
State gvnt. partisanship	-0.21	0.12	0.23	0.17	0.41	0.64
	(0.19)	(0.11)	(0.08)	(0.07)	(0.09)	(0.10)
State gvnt. partisanship×Divided gvnt.	0.43	-0.41	-0.30	-0.06	-0.41	-0.88
	(0.45)	(0.25)	(0.17)	(0.15)	(0.14)	(0.19)
Baseline $P(\text{Adopt})$	0.03	0.03	0.03	0.05	0.05	0.05
Observations	50804	44349	65585	79691	58881	28104
Policies	138	167	238	333	286	167
Pseudo R^2	0.20	0.13	0.14	0.20	0.18	0.19

This table shows the coefficients from a logit regression. Standard errors are clustered by state. The baseline hazard for each policy is parametrized by policy fixed effects for each decade. The closest states are defined as the third of all the states with the smallest absolute value difference in each characteristic. The difference in the demographic index is calculated by first standardizing the two-year moving averages of log population, urban %, log income per capita, % employed in the agricultural sector, and % employed in the manufacturing sector across all states in each year, then taking the absolute difference in each of the five standardized demographic and economic variables, and finally averaging the five absolute standardized differences. The closest states in terms of distance are the third of states that have the smallest distance calculated using the centroid of the states. For Republican vote-share, the closest states are defined as the third with the smallest absolute difference in the vote-share for the Republican presidential candidate averaged over the most recent two elections. For state government partisanship, the closest states are defined as those with the same party control of state government (unified Republican, unified Democratic, or divided). We assign Nebraska, which has a unicameral nonpartisan state legislature, to the party of its governor. Alaska, Hawaii, and Washington D.C. are excluded from the analyses. The last year in the dataset is 2020, which is included in the 2010s decade. Only policies spanning at least 3 years with at least 5 adopters are included. Policies are weighted to keep the composition of keyword categories constant over time periods.

Table A.7: Robustness checks

Distance			Republican vote-share			State gvnt. party control		
1950-70s	1980-90s	2000-10s	1950-70s	1980-90s	2000-10s	1950-70s	1980-90s	2000-10s
Dep. var.: Policy adoption (all logit except (2))								
(1) Baseline (Table 3) (R^2: 0.17, 0.17, 0.17; $N_{\text{pol.}}$: 227, 369, 325)								
0.45	0.29	0.33	0.13	0.16	0.41	0.02	0.11	0.55
(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.07)	(0.04)	(0.07)
(2) Baseline linear probability model (coefficients and SEs ×100) (R^2: 0.17, 0.17, 0.17; $N_{\text{pol.}}$: 229, 374, 328)								
1.32	0.98	1.41	0.35	0.58	1.83	0.11	0.40	2.64
(0.16)	(0.17)	(0.22)	(0.13)	(0.13)	(0.20)	(0.17)	(0.17)	(0.33)
(3) Expanded state-level controls (R^2: 0.19, 0.18, 0.20; $N_{\text{pol.}}$: 225, 369, 325)								
0.26	0.20	0.20	0.12	0.18	0.43	0.04	0.14	0.52
(0.07)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.06)	(0.05)	(0.06)
(4) Without SPID extensions (R^2: 0.17, 0.17, 0.18; $N_{\text{pol.}}$: 227, 368, 319)								
0.44	0.29	0.34	0.14	0.16	0.41	0.00	0.11	0.54
(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.07)	(0.05)	(0.07)
(5) Parsimonious model (R^2: 0.16, 0.17, 0.17; $N_{\text{pol.}}$: 227, 369, 325)								
0.44	0.29	0.33	0.15	0.16	0.40	0.00	0.10	0.54
(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.07)	(0.05)	(0.07)
(6) Adoption measure: Lagged by one year (R^2: 0.14, 0.16, 0.16; $N_{\text{pol.}}$: 205, 344, 325)								
0.46	0.30	0.28	0.10	0.15	0.43	-0.03	0.07	0.51
(0.06)	(0.05)	(0.06)	(0.05)	(0.04)	(0.05)	(0.07)	(0.05)	(0.07)
(7) Adoption measure: Rank-inverse weighted average (R^2: 0.17, 0.17, 0.17; $N_{\text{pol.}}$: 227, 369, 325)								
2.60	1.88	1.75	0.34	0.99	1.76	0.66	1.41	3.56
(0.26)	(0.24)	(0.31)	(0.25)	(0.19)	(0.24)	(0.60)	(0.33)	(0.52)
(8) Adoption measure: Proportion of closest third that are adopters (R^2: 0.17, 0.17, 0.17; $N_{\text{pol.}}$: 227, 369, 325)								
2.39	1.67	1.66	0.82	1.09	2.18	0.33	0.68	1.57
(0.29)	(0.30)	(0.28)	(0.35)	(0.25)	(0.23)	(0.29)	(0.16)	(0.25)
(9) Adoption measure: Proportion of all adopters in the closest third (R^2: 0.15, 0.14, 0.15; $N_{\text{pol.}}$: 207, 352, 325)								
0.76	0.71	0.91	0.05	0.28	1.12	-0.04	-0.38	1.53
(0.09)	(0.09)	(0.11)	(0.07)	(0.08)	(0.09)	(0.13)	(0.14)	(0.17)
(10) Adoption measure: $P(Adopt)$ closest third$-P(Adopt)$ all states (R^2: 0.15, 0.15, 0.16; $N_{\text{pol.}}$: 227, 369, 325)								
2.30	1.60	1.64	0.79	1.18	2.18	-0.53	0.11	2.15
(0.31)	(0.29)	(0.28)	(0.38)	(0.26)	(0.23)	(0.37)	(0.22)	(0.32)

This table presents results from alternate specifications of the policy diffusion model. The table shows coefficients on the measure of adopters among the "closest" states (i.e., the closest third unless otherwise noted) in terms of distance, the average Republication vote-share in the two most recent presidential election, and state government party control. Standard errors clustered by state are in parentheses. Each model is estimated over three separate time periods (1950-70s, 1980-90s, and 2000-10s). The (pseudo-)R^2 and number of policies are reported in parentheses in chronological order corresponding to the three time periods. Policies are weighted to keep the composition of keyword categories constant over time periods.

Baseline: replicates the specification from Table 3 over the longer time periods.

Baseline linear probability model: uses the same covariates in the Baseline specification but estimates the coefficients using a linear probability model.

Expanded state-level controls: takes the specification from Table 3 and adds: non-white % and unemployed %; quadratic terms for the proportion of all other states adopted, Republican vote-share, log population, income per capita, urban %, non-white %, and unemployed %; adoption measures among the closest third of states in migration flows, non-white %, and unemployed %; a more flexible policy-specific baseline hazard parametrized as a step function that can vary every five years; and state fixed-effects.

Without SPID extensions: uses the baseline specification but excludes policy-state-year observations from extending policy adoption data in the existing SPID dataset.

Parsimonious model: includes only policy fixed effects and the proportion of adopters among all other states, and the adoption measure among the closest third of other states in the demographic index (not shown), geography, Republican vote-share in the most recent presidential election, and state government party control. (This specification is also used in Table 4.)

The following specifications use alternate measures of concentrated adoptions among the similar states, in place of the baseline two-sided likelihood measure. Each specification is "parsimonious" in that the only controls included are policy fixed effects and, except for specifications (8) and (9), the proportion of adopters among all other states.

Lagged by one year: uses the Parsimonious model but takes the adoption measure among the closest other states up to the *prior* (not current) year.

Rank-inverse weighted average: instead of defining the closest states as the third with smallest absolute difference, this measure weights the other states' adoptions by the inverse of their rank in absolute distance, where the closest state is is ranked 1 and the furthest state is ranked 47.

Proportion of closest third that are adopters: uses the proportion of states in the closest third that have adopted.

Proportion of all adopters in the closest third: uses the proportion of all adopters that are in the closest third of states.

$P(Adopt)$ closest third$-P(Adopt)$ all states: uses the proportion of states in the closest third that have adopted minus the proportion of all states (excluding one's own) that have adopted.

Table A.8a: Models of policy diffusion: Role of migration and voter preferences (expanded demographics and public opinion)

Dep. var.: Policy adoption (logit)	(1) 60-70s	(2) 80-90s	(3) 00-10s	(4) 60-70s	(5) 80-90s	(6) 00-10s
Proportion of states adopted	0.89	2.35	2.35	1.02	2.35	2.46
	(0.26)	(0.14)	(0.22)	(0.26)	(0.15)	(0.19)
Divided state government	0.07	0.01	-0.13	0.07	0.00	-0.13
	(0.11)	(0.05)	(0.07)	(0.11)	(0.05)	(0.08)
State gvnt./legis. election year	0.10	0.02	-0.03			
	(0.11)	(0.08)	(0.06)			
Presidential election year	-0.20	-0.01	-0.22			
	(0.11)	(0.08)	(0.09)			
Measure of adoption among other states closest in:						
Demographic index				0.11	-0.06	0.01
				(0.09)	(0.06)	(0.07)
Log(population)	0.10	0.05	-0.10			
	(0.08)	(0.05)	(0.05)			
Log(income per capita)	0.24	-0.02	0.11			
	(0.08)	(0.05)	(0.06)			
Urban population %	0.04	0.01	0.19			
	(0.09)	(0.06)	(0.05)			
Non-white %		0.00	0.02			
		(0.03)	(0.06)			
Unemployed %		0.05	0.02			
		(0.03)	(0.06)			
Distance	0.23	0.18	0.08	0.21	0.19	0.09
	(0.12)	(0.08)	(0.07)	(0.11)	(0.08)	(0.07)
Republican vote-share	0.12	0.12	0.27	0.09	0.10	0.17
	(0.05)	(0.04)	(0.06)	(0.05)	(0.04)	(0.06)
State gvnt. partisanship	0.11	0.11	0.54	0.11	0.12	0.53
	(0.13)	(0.06)	(0.09)	(0.13)	(0.07)	(0.09)
State gvnt. partisanship×Divided gvnt.	-0.36	-0.03	-0.61	-0.37	-0.04	-0.58
	(0.25)	(0.14)	(0.15)	(0.25)	(0.14)	(0.15)
Migration flows	0.16	0.06	0.23	0.17	0.05	0.23
	(0.16)	(0.09)	(0.09)	(0.15)	(0.09)	(0.09)
Voter preferences (ANES & GSS)	0.17	0.31	0.21	0.17	0.28	0.23
	(0.11)	(0.08)	(0.08)	(0.11)	(0.08)	(0.08)
Index of public opinion measures	0.12	0.17	0.18			
	(0.06)	(0.05)	(0.05)			
Citizen ideology (Berry et al., 1998)				0.27	0.07	0.20
				(0.06)	(0.04)	(0.05)
Public policy mood (Lagodny et al., 2022)				-0.10	-0.02	-0.01
				(0.06)	(0.05)	(0.04)
Mass social liberalism (Caughey and Warshaw, 2018)				0.06	0.20	0.25
				(0.07)	(0.05)	(0.06)
Mass economic liberalism (Caughey and Warshaw, 2018)				0.01	0.05	0.08
				(0.09)	(0.04)	(0.06)
Observations	51192	102544	60649	51192	102544	60322
Policies	196	364	310	196	364	303
Pseudo R^2	0.16	0.17	0.18	0.16	0.17	0.18

This table reports the role of each individual factor included in the demographic and public opinion indices from Table 5 and shows the results for additional predictors, such as election years and similarity in non-white % and unemployment rates (available from the 1970s). The three factors included in the demographic index are population, income per capita, and urban %. See the notes for Table 5 for a description of each factor included in the public opinion index. Policies are weighted to keep the composition of keyword categories constant over time periods. Standard errors clustered by states are in parentheses.

Table A.8b: Models of policy diffusion: Role of migration and voter preferences (expanded ANES & GSS voter preferences)

Dep. var.: Policy adoption (logit)	(1) 60-70s	(2) 80-90s	(3) 00-10s	(4) 60-70s	(5) 80-90s	(6) 00-10s
Proportion of states adopted	0.79	2.34	2.42	0.81	2.36	2.43
	(0.27)	(0.14)	(0.19)	(0.27)	(0.14)	(0.19)
Divided state government	0.06	0.00	-0.14	0.07	-0.00	-0.14
	(0.12)	(0.05)	(0.08)	(0.12)	(0.05)	(0.08)
Measure of adoption among other states closest in:						
Demographic index	0.13	-0.04	0.07	0.14	-0.04	0.07
	(0.09)	(0.06)	(0.07)	(0.09)	(0.06)	(0.07)
Distance	0.25	0.18	0.09	0.25	0.18	0.08
	(0.11)	(0.08)	(0.07)	(0.11)	(0.08)	(0.07)
Republican vote-share	0.11	0.11	0.29	0.10	0.11	0.29
	(0.05)	(0.04)	(0.07)	(0.05)	(0.04)	(0.07)
State gvnt. partisanship	0.10	0.14	0.57	0.10	0.13	0.56
	(0.13)	(0.06)	(0.09)	(0.13)	(0.06)	(0.09)
State gvnt. partisanship×Divided gvnt.	-0.27	-0.05	-0.63	-0.28	-0.05	-0.62
	(0.26)	(0.13)	(0.15)	(0.25)	(0.13)	(0.15)
Migration flows	0.15	0.06	0.23	0.15	0.06	0.23
	(0.15)	(0.09)	(0.09)	(0.15)	(0.09)	(0.09)
Voter preferences (ANES & GSS) in policy area	0.24	0.19	0.13			
	(0.10)	(0.06)	(0.07)			
Voter preferences in other policy areas	0.10	0.16	0.15			
	(0.09)	(0.08)	(0.07)			
Voter preferences and sentiment (ANES & GSS)				0.27	0.29	0.26
				(0.11)	(0.08)	(0.09)
Index of public opinion measures	0.17	0.17	0.23	0.17	0.17	0.23
	(0.07)	(0.05)	(0.05)	(0.07)	(0.05)	(0.05)
Observations	48956	95719	57187	48956	95719	57187
Policies	186	342	289	186	342	289
Pseudo R^2	0.15	0.17	0.18	0.15	0.17	0.18

This table reports two extensions of the ANES & GSS measure of voter preferences from Table 5. In Columns 1-3, the ANES & GSS survey questions are categorized into the six policy areas shown in Table 1a. The measure of voter preferences is then calculated separately for questions in the relevant policy area and for all other questions related to the other policy areas. Policies in the "Environment and Energy" policy area are dropped due to insufficient representation of voter preferences in ANES & GSS survey questions for earlier time periods. In Columns 4-6, the set of ANES & GSS questions used to measure voter preferences is expanded to include questions about not only preferences regarding specific policies but also attitude toward policy topics more broadly. See Online Appendix Section C for details. Policies are weighted to keep the composition of keyword categories constant over time periods. Standard errors clustered by states are in parentheses.

Table A.9: Vaccine regulations and COVID-19 policies

	COVID		Vaccine laws	
Dep. var.: Policy adoption (logit)	(1)	(2)	(3)	(4)
Proportion of states adopted	3.31	3.04	1.37	1.46
	(0.24)	(0.27)	(0.46)	(0.47)
Measure of adoption among other states closest in:				
Demographic index	0.21	0.22	0.37	0.18
	(0.08)	(0.13)	(0.11)	(0.14)
Distance	0.31	0.37	0.20	-0.10
	(0.06)	(0.14)	(0.09)	(0.13)
Republican vote-share	0.16	-0.08	0.04	-0.07
	(0.09)	(0.10)	(0.10)	(0.11)
State gvnt. partisanship	0.47	0.58	-0.19	-0.26
	(0.10)	(0.14)	(0.12)	(0.16)
State gvnt. partisanship×Divided gvnt.	-0.30	-0.48	0.30	0.59
	(0.19)	(0.29)	(0.28)	(0.30)
Migration flows		0.21		0.45
		(0.16)		(0.11)
Voter preferences (ANES & GSS)		0.08		-0.18
		(0.18)		(0.22)
Index of public opinion measures		-0.15		0.01
		(0.11)		(0.12)
Observations	27751	10944	22646	15174
Policies	76	64	28	28
Pseudo R^2	0.33	0.33	0.17	0.19
Time unit	Weeks (Mo-Su)	Weeks (Mo-Su)	Years	Years
Time range	10/2019-8/2021	10/2019-12/2020	1980-2020	1980-2020

This table shows the coefficients from a logit regression. Standard errors are clustered by state. The baseline hazard is parametrized by policy-decade fixed effects for vaccine laws and policy-month fixed effects for COVID policies. See Tables 3 and 5 for the definition of closest states in each characteristic. Alaska, Hawaii, and Washington D.C. are excluded from the analyses. In Columns 2 and 4, only the 33 states with measures of voter preferences from the ANES and GSS surveys are included (see Table 5 notes). Only policies spanning at least 3 time periods with at least 5 adopters are included.

Table A.10: Event studies

	Uni. st. gvnt.	Unified Republican state government				Unified Democratic state government				Loss of uni.
	(1) Diff.	(2) Right-lean. policy	(3) Left-lean. policy	(4) Diff. (2-3)	(5) Neutral policy	(6) Left-lean. policy	(7) Right-lean. policy	(8) Diff. (6-7)	(9) Neutral policy	(10) Diff.
Events during years 1950 to 1989										
4 years pre-event	-0.022 (0.009)	-0.024 (0.012)	0.025 (0.013)	-0.049 (0.023)	0.017 (0.021)	-0.006 (0.008)	0.017 (0.011)	-0.023 (0.014)	-0.009 (0.009)	-0.001 (0.009)
3 years pre-event	-0.012 (0.008)	-0.015 (0.010)	0.013 (0.013)	-0.028 (0.020)	0.028 (0.016)	-0.013 (0.005)	-0.001 (0.007)	-0.012 (0.008)	-0.005 (0.007)	-0.003 (0.009)
2 years pre-event	-0.008 (0.012)	-0.008 (0.021)	0.031 (0.018)	-0.039 (0.037)	0.028 (0.020)	0.001 (0.008)	0.007 (0.006)	-0.006 (0.011)	0.001 (0.011)	0.002 (0.009)
1 year pre-event	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)
Year of event	0.006 (0.011)	-0.013 (0.014)	-0.006 (0.011)	-0.007 (0.018)	0.025 (0.022)	0.004 (0.006)	-0.006 (0.008)	0.010 (0.012)	0.006 (0.009)	0.000 (0.012)
1 year post-event	0.005 (0.009)	0.008 (0.012)	0.011 (0.011)	-0.003 (0.021)	0.003 (0.009)	0.004 (0.006)	-0.007 (0.006)	0.010 (0.008)	-0.006 (0.010)	0.005 (0.008)
2 years post-event	-0.002 (0.013)	0.001 (0.015)	0.011 (0.016)	-0.010 (0.026)	-0.020 (0.017)	0.007 (0.010)	0.008 (0.010)	-0.001 (0.015)	-0.000 (0.012)	0.001 (0.011)
3 years post-event	-0.001 (0.010)	0.003 (0.015)	0.006 (0.014)	-0.003 (0.024)	-0.005 (0.012)	-0.005 (0.007)	-0.007 (0.007)	0.003 (0.010)	0.011 (0.011)	-0.007 (0.007)
4 years post-event	0.014 (0.011)	-0.013 (0.016)	-0.009 (0.012)	-0.004 (0.017)	0.030 (0.025)	0.005 (0.011)	-0.014 (0.011)	0.019 (0.014)	0.052 (0.017)	-0.005 (0.012)
Observations	63567	50420	50420	50420	50420	63498	63498	63498	63498	64888
Policies	203	164	164	164	164	203	203	203	203	209
Events	134	51	51	51	51	82	82	82	82	148
Events during years 1990 to 2020										
4 years pre-event	0.004 (0.008)	0.001 (0.009)	-0.004 (0.008)	0.005 (0.015)	-0.000 (0.010)	0.007 (0.006)	0.002 (0.005)	0.004 (0.008)	0.005 (0.008)	0.020 (0.008)
3 years pre-event	-0.011 (0.008)	-0.003 (0.008)	0.003 (0.008)	-0.006 (0.015)	0.016 (0.007)	-0.004 (0.008)	0.010 (0.006)	-0.014 (0.009)	0.003 (0.007)	0.019 (0.007)
2 years pre-event	-0.007 (0.008)	-0.003 (0.008)	0.017 (0.008)	-0.020 (0.013)	0.019 (0.008)	0.002 (0.007)	-0.006 (0.006)	0.008 (0.010)	-0.008 (0.007)	0.020 (0.008)
1 year pre-event	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)
Year of event	0.022 (0.007)	0.005 (0.008)	0.001 (0.006)	0.004 (0.011)	0.013 (0.011)	0.029 (0.008)	-0.006 (0.007)	0.035 (0.010)	0.001 (0.007)	0.000 (0.009)
1 year post-event	0.025 (0.010)	0.012 (0.009)	-0.005 (0.006)	0.017 (0.012)	0.006 (0.011)	0.022 (0.009)	-0.011 (0.007)	0.033 (0.013)	-0.005 (0.006)	0.018 (0.009)
2 years post-event	0.029 (0.009)	0.012 (0.011)	-0.007 (0.008)	0.019 (0.015)	-0.000 (0.014)	0.025 (0.011)	-0.012 (0.008)	0.038 (0.013)	-0.006 (0.008)	0.012 (0.010)
3 years post-event	0.022 (0.007)	0.012 (0.010)	-0.017 (0.007)	0.028 (0.012)	0.013 (0.015)	0.015 (0.008)	-0.006 (0.007)	0.021 (0.010)	0.005 (0.011)	0.005 (0.008)
4 years post-event	0.027 (0.016)	-0.012 (0.009)	-0.009 (0.011)	-0.003 (0.016)	0.007 (0.013)	0.042 (0.024)	-0.021 (0.009)	0.063 (0.028)	0.021 (0.012)	0.002 (0.009)
Observations	110159	99469	99469	99469	99469	109408	109408	109408	109408	108061
Policies	373	365	365	365	365	372	372	372	372	374
Events	115	49	49	49	49	64	64	64	64	99

This table shows the event-study estimates underlying Figures 9a-9b. Standard errors clustered by state are shown in parentheses. Controls for gubernatorial and state assembly election years, state-policy-ideology fixed effects (e.g., separate dummies for California-Right-leaning, California-Left-leaning, and California-Neutral), and policy-year fixed effects are included. Policies that switch ideology (e.g., from Right- to Left-leaning) are excluded. Policies are included after reaching 5 adopters. Column 1 shows the estimates in Figures 9a-9b. Columns 2-5 separate the estimates for switches to unified Republican state government, and Columns 6-9 for unified Democratic state government. Column 10 shows the analogous estimates to Column 1, but for the loss of unified state government.