Policy Diffusion and Polarization across U.S. States*

Stefano DellaVigna
UC Berkeley and NBER

Woojin Kim
Stanford University

July 2025

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.

*We thank Elliott Ash, Frederick Boehmke, Tim Besley, Davide Cantoni, David Card, Maria Carreri, Janet Currie, Alexander Fouirnaies, Jeffrey Frieden, Matthew Gentzkow, Bryan Graham, Jonathan Gruber, Jonas Hjort, Lawrence Katz, Pat Kline, Brian Knight, Sendhil Mullainathan, Angel O'Mahony, Vincent Pons, Giacomo Ponzetto, Andrea Prat, Gautam Rao, Emmanuel Saez, Jesse Shapiro, James Snyder, Francesco Trebbi, Clemence Tricaud, Brian Wheaton, David Yang, Jorg Spenkuch for his discussion at the NBER Summer Institute, and participants in presentations at the University of Chicago (Harris), at NUS, at the Turin workshop on Political Economy, the Social Economics conference (Chicago), and at and the NBER Summer Institute (Political Economy) for helpful comments. We are grateful to a team of undergraduate research assistants—YeJin Ahn, Christian Alamos, Iden Azad, Emma Berman, Rupsha Debnath, Yifan Ding, AJ Grover, Rohan Jha, Chenxi Jiang, Chloe Liu, Matthew Liu, Junru Lu, Louis McKinnon, Akhalya Valluvan, Randol Yao, Owen Yeung, and Yi Yu—for exceptional research assistance. Woojin Kim gratefully acknowledges funding from the National Institute on Aging to the National Bureau of Economic Research through grant number T32-AG000186.

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, 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 have adopted are close in this dimension, the weighted average of the differences in the numerator should be smaller than the unweighted average in the denominator.

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.

Consequently, values of this measure below 1 indicate that adoptions are clustered in this dimension. On the other hand, values above 1 suggest that adopting states tend to be far apart in this dimension. The 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:

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

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:

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

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:

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

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 and economics, 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 0.23 (s.e.=0.06), which has remained similar in the most recent decade, at 0.20 (s.e.=0.08). 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 consistent importance over time, with a coefficient of 0.36 (s.e.=0.08) in the 1970s and of 0.42 (s.e.=0.08) 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: 0.10 (s.e.=0.06) in the 1970s, 0.07 (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 0.46 (s.e.=0.05) in the 2000s and 0.48 (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.=0.11 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, have 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 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 distant 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 0.20 (s.e.=0.11) in the earliest time period and 0.23 (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 0.14 (s.e.=0.06) to 0.19 (s.e.=0.05).

What is the impact of controlling for voter preferences and migration flows? The addition of these variables reduces by over a third the explanatory power of geography and demographics. The predictive power of Republican vote-share in the most recent decades also falls, from 0.41 (s.e.=0.05) to 0.29 (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

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

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). Such welfare externalities arising from ideological polarization can be seen in the selection out of ACA marketplaces by healthy Republicans, which generates adverse selection in 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 (Hertel-Fernandez, 2014; Angelucci, Ash, and Longuet Marx, 2025). 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. (2025).

Data Availability Statement

The data underlying this article are available in Zenodo at `https://doi.org/10.5281/zenodo.15590121`.

References

Angelucci, Charles, Elliott Ash, and Nicolas Longuet Marx. 2025. "The Polarization of State Legislatures? 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, and David Ritzwoller. 2025. "Using Multiple Outcomes to Adjust Standard Errors for Spatial Correlation." NBER Working Paper 33716.

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." NBER Working Paper 26862.

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.

Hertel-Fernandez, Alexander. 2014. "Who Passes Business's "Model Bills"? Policy Capacity and Corporate Influence in U.S. State Politics." *Perspectives on Politics*, 12(3), 582-602.

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.

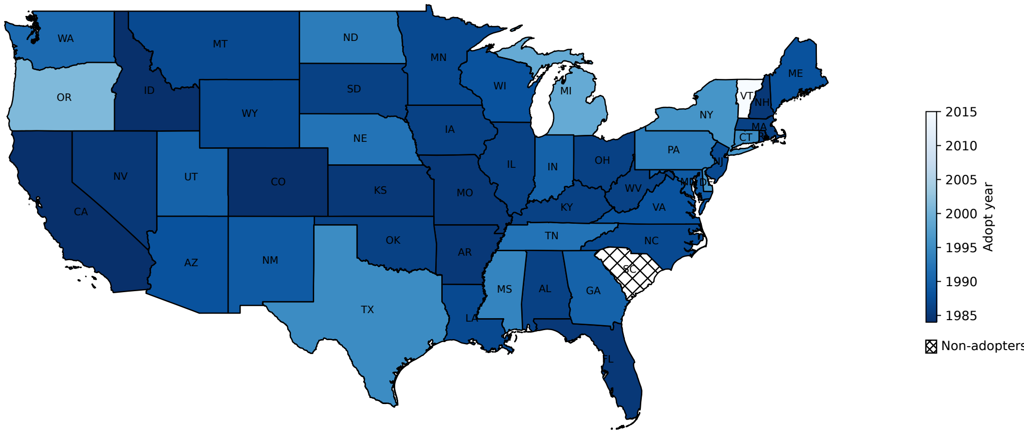
Volden, Craig, Michael Ting, and Daniel Carpenter. 2008. "A formal model of learning and policy diffusion." *American Political Science Review*, 102 (3), 319-332.

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

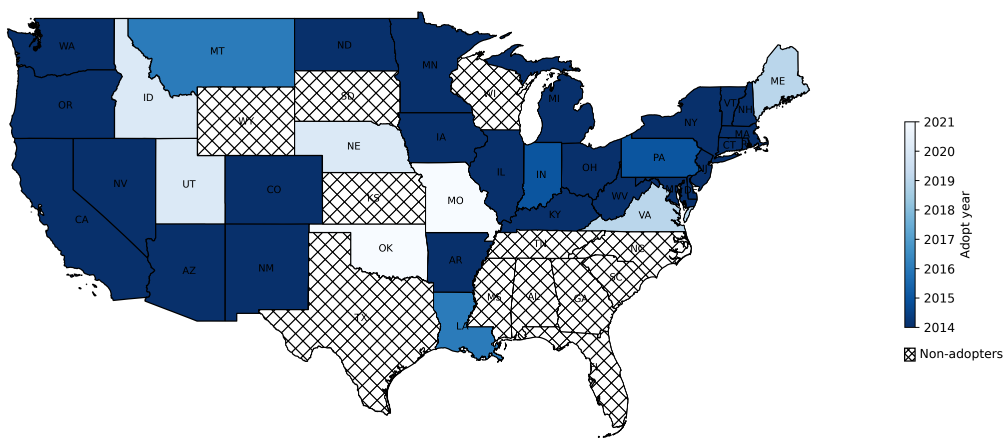
Wang, Shaoda and David Y. Yang. Forthcoming. "Policy Experimentations in China: the Political Economy of Policy Learning." *Journal of Political Economy*.

Figure 1: Three policy examples

(a) Uniform Transfers to Minors Act (1984-2015)



(b) Medicaid expansion (2014-2021)



(c) Initial prescription drug monitoring program (1988-2018)

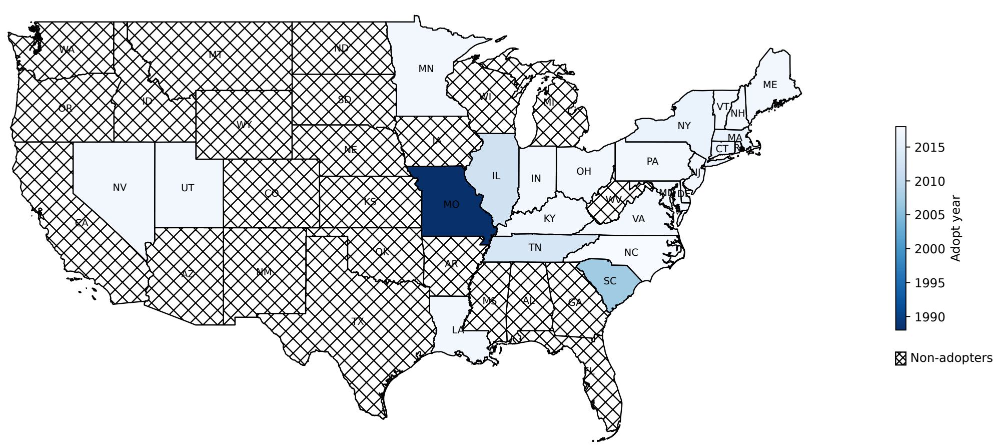
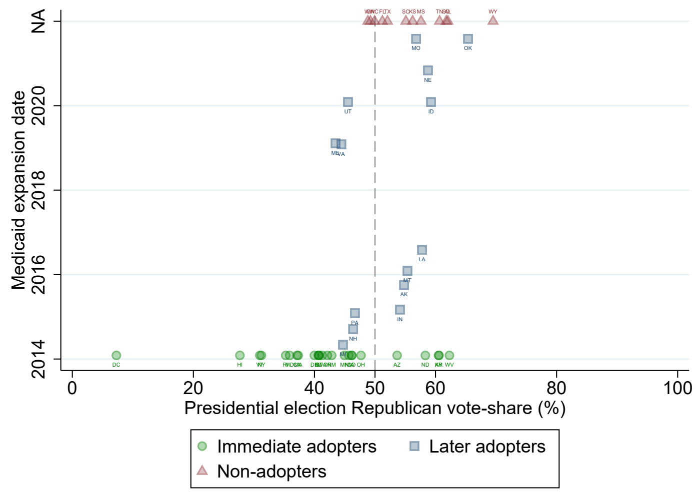
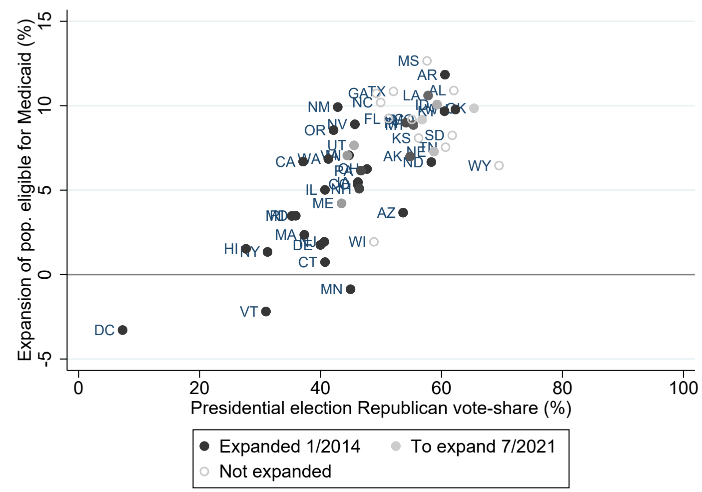


Figure 2: Case studies of welfare programs

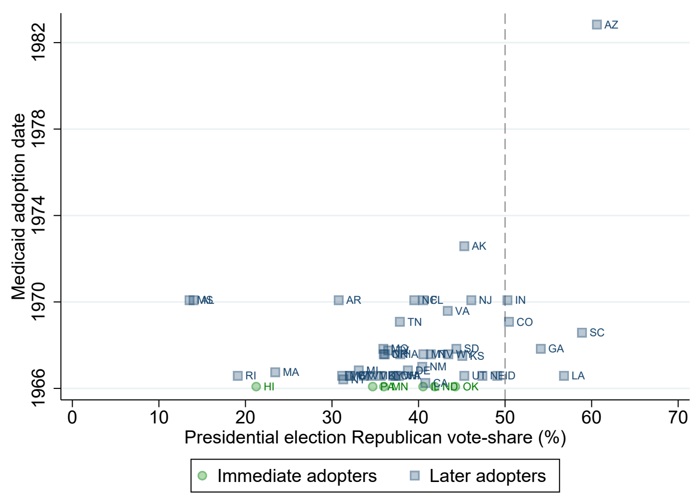
(a) 2014 Medicaid expansion (Affordable Care Act)



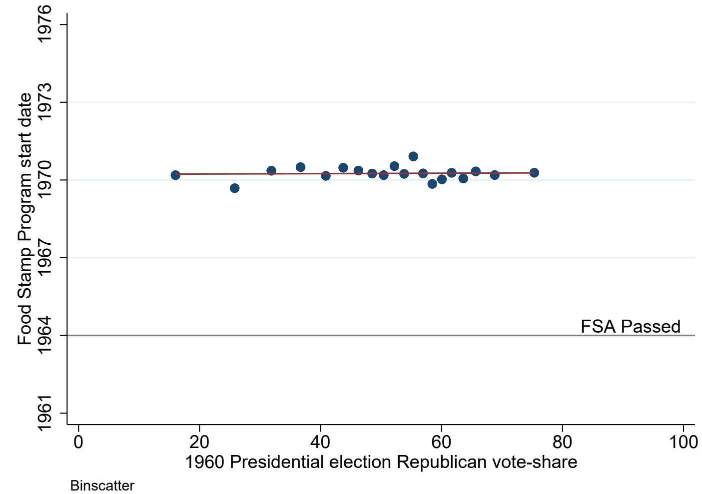
(b) 2014 Medicaid expansion coverage



(c) 1960s Initial Medicaid adoption

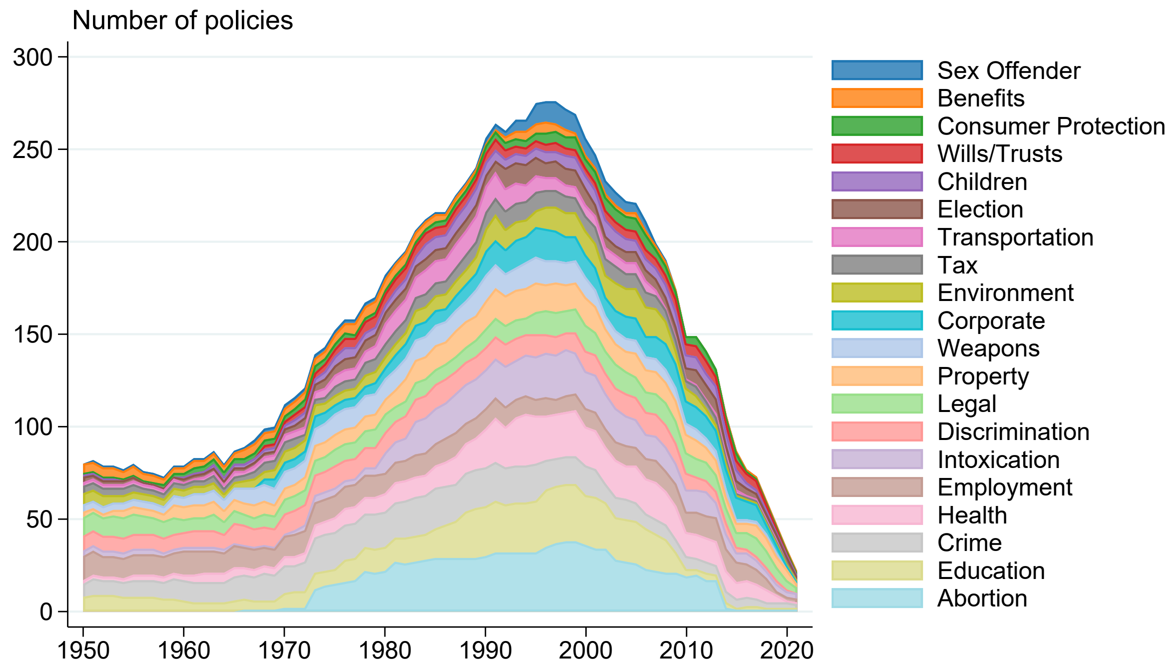


(d) 1960-70s Food Stamp Program adoption (county-level)



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.

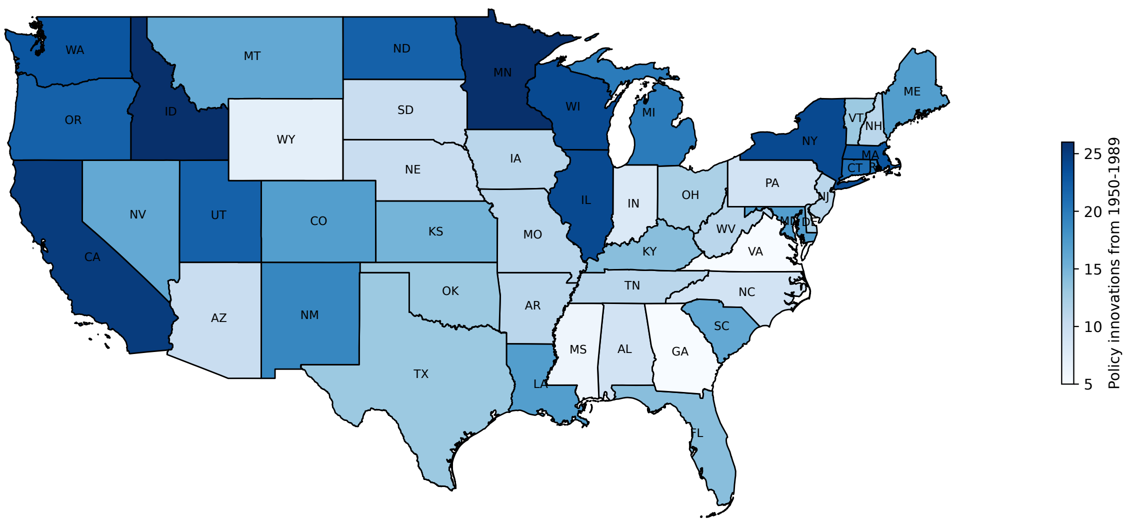
Figure 3: Number of policies by keyword category



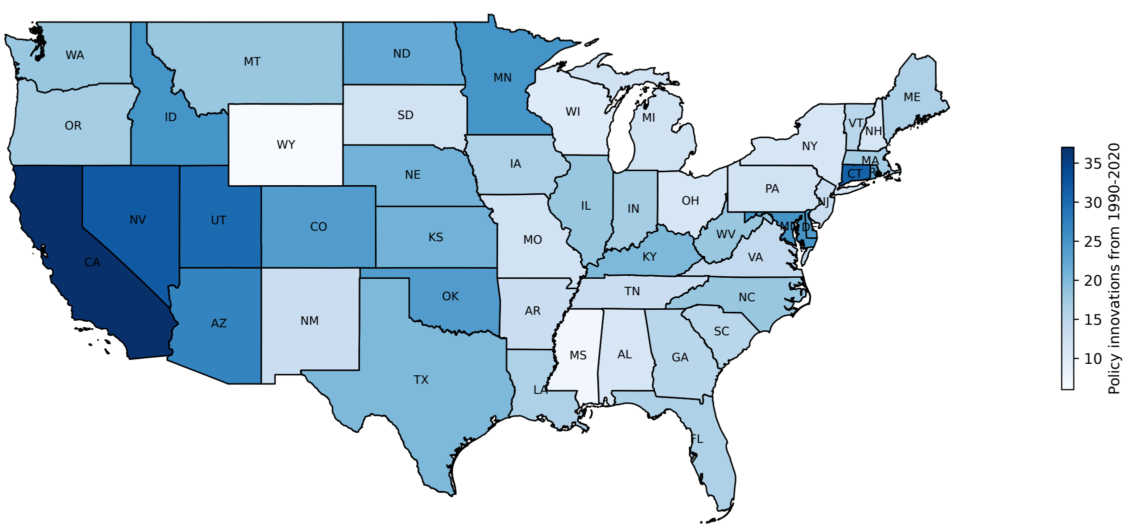
This figure shows the number of policies in each keyword category over time. Keyword categories are groups of policies sharing common keywords in the description of the policies. The keywords are listed in Table 1a.

Figure 4: Innovating states

(a) Policies innovated 1950-1989



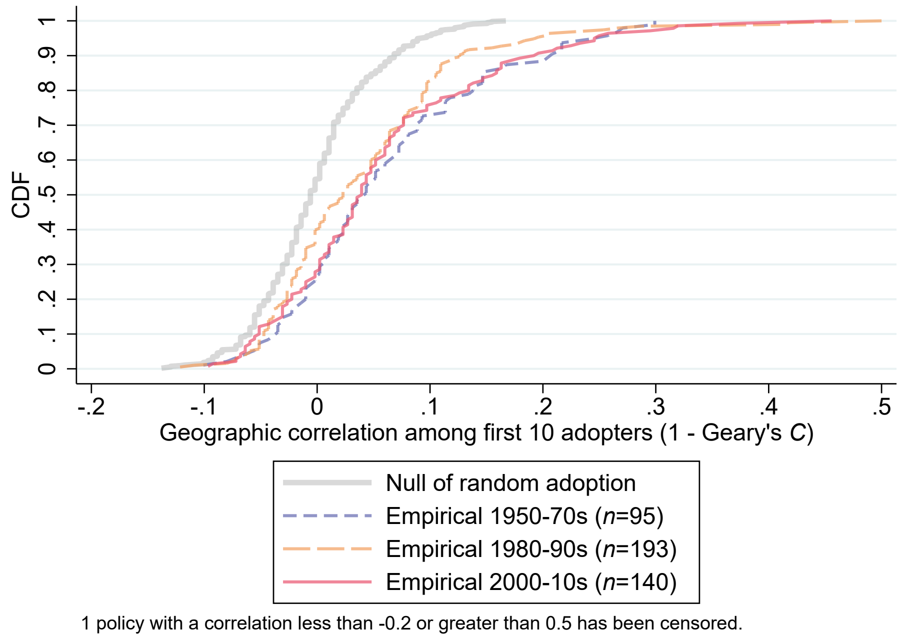
(b) Policies innovated 1990-2020



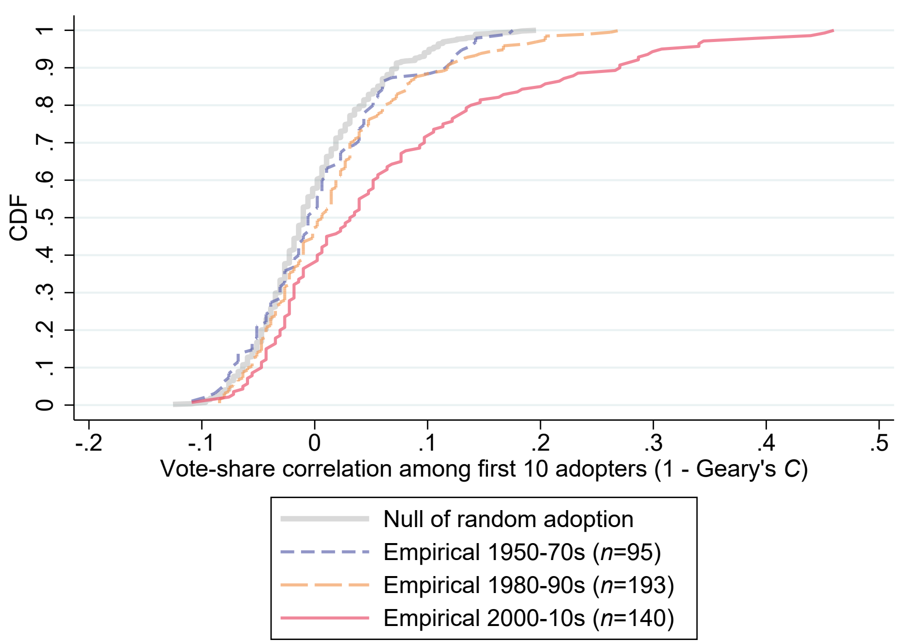
These maps show the number of policies that each state innovated (i.e., adopted in the first year that the policy enters the sample) during 1950-1989 (Figure 4a) and 1990-2020 (Figure 4b).

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

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

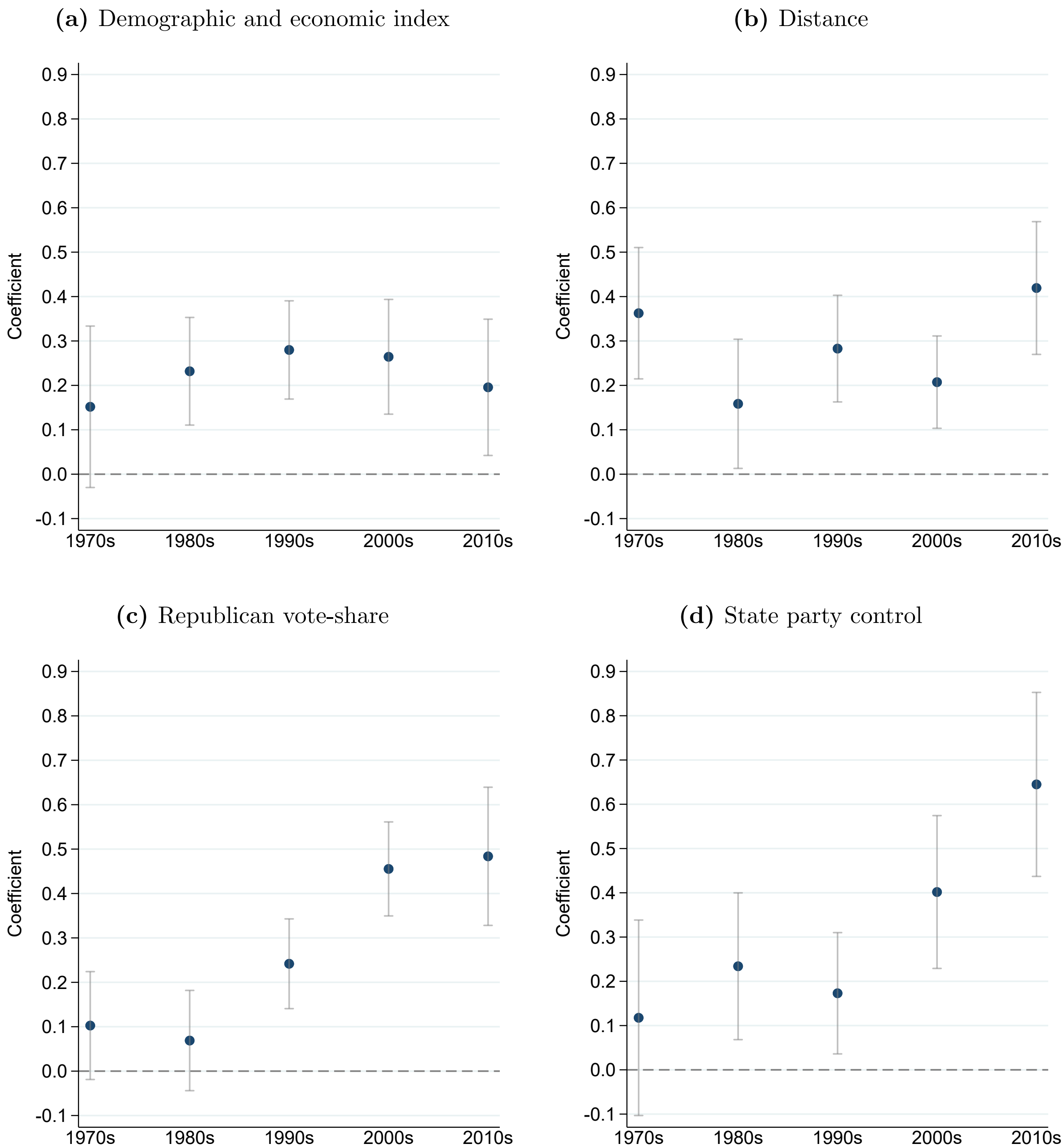


(b) Correlation in Republican vote-share (first 10 adopters)



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.

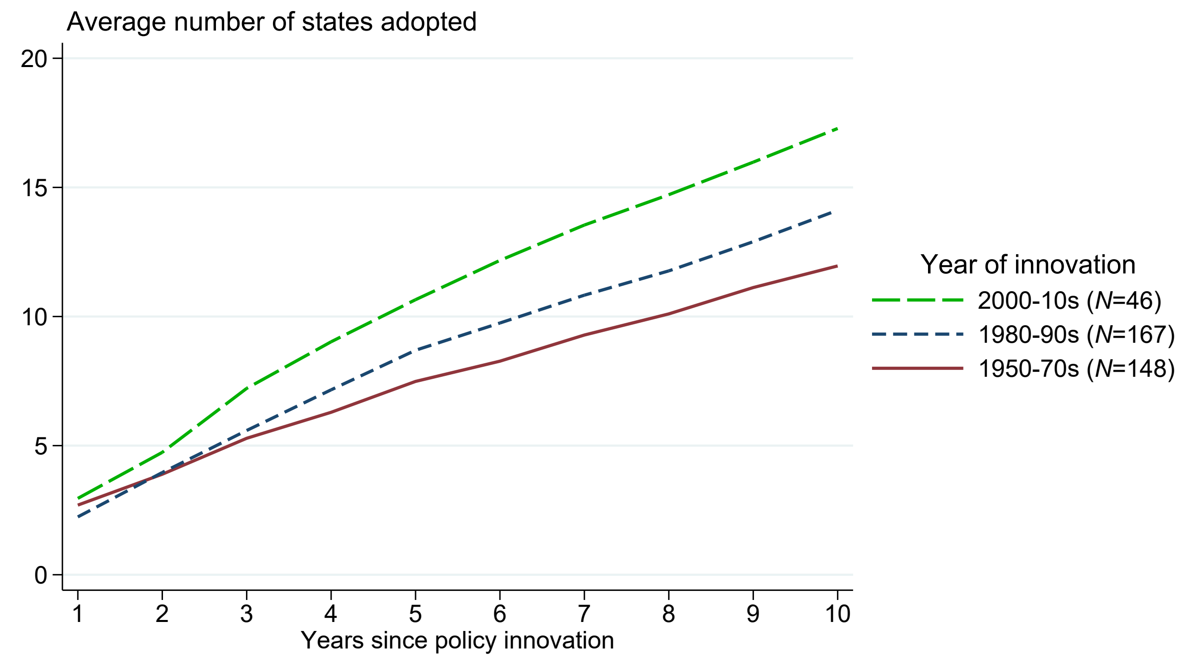
Figure 6: Dynamics of policy diffusion dimensions



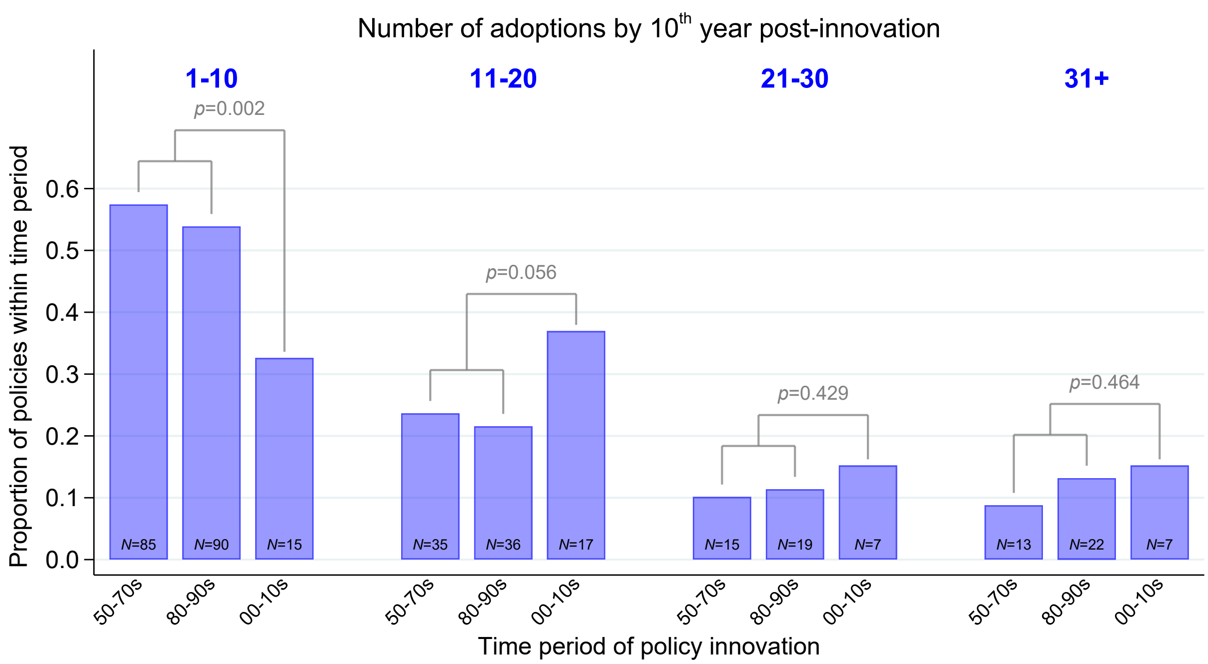
This figure plots the decade-by-decade estimates from Table 3 for the coefficients on the measure of adoption among the closest states in each dimension. The coefficient for the 1950-60s decade is not shown due to the scale of the confidence intervals. 95% confidence intervals are shown with standard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

Figure 7: Speed of adoption

(a) Number of adoptions within first 10 years



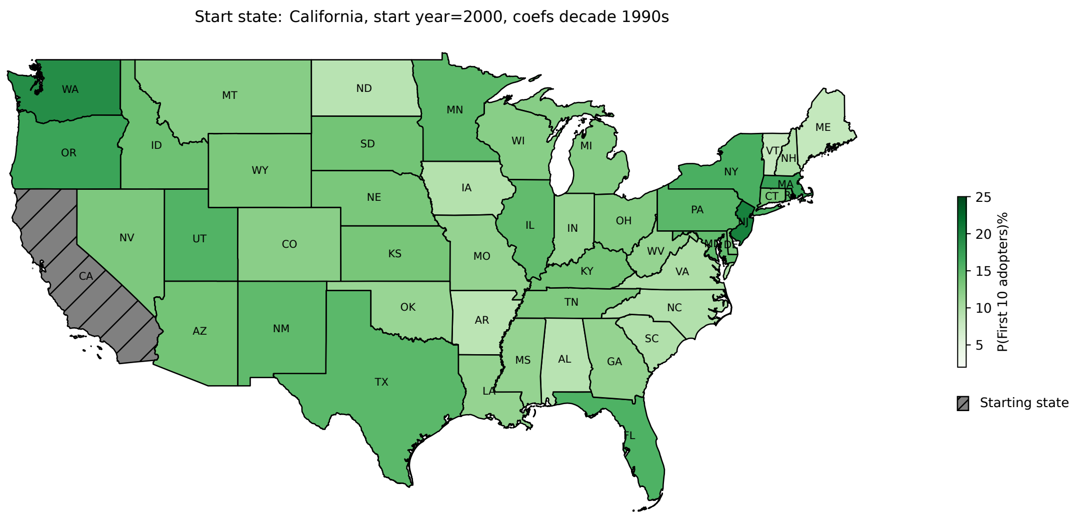
(b) Number of total adoptions by year 10



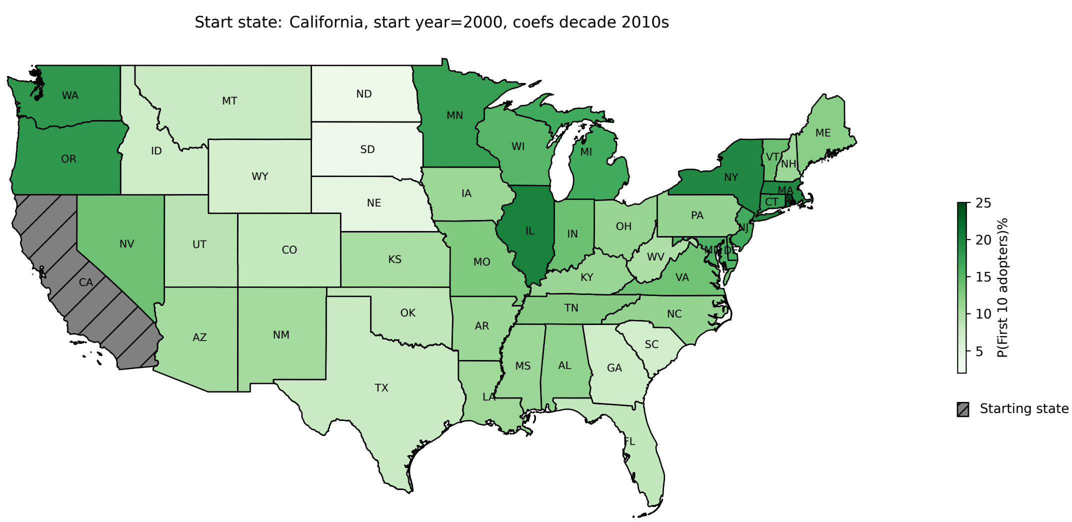
In Figures 7a-7b, policies are grouped into time periods based on the year of innovation. Only policies that span at least 10 years are included. Figure 7a shows the average number of states that have adopted a policy over the first 10 years. Figure 7b shows the proportion of policies after 10 years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

Figure 8: Simulated policy diffusion

(a) Coefficients from 1990s



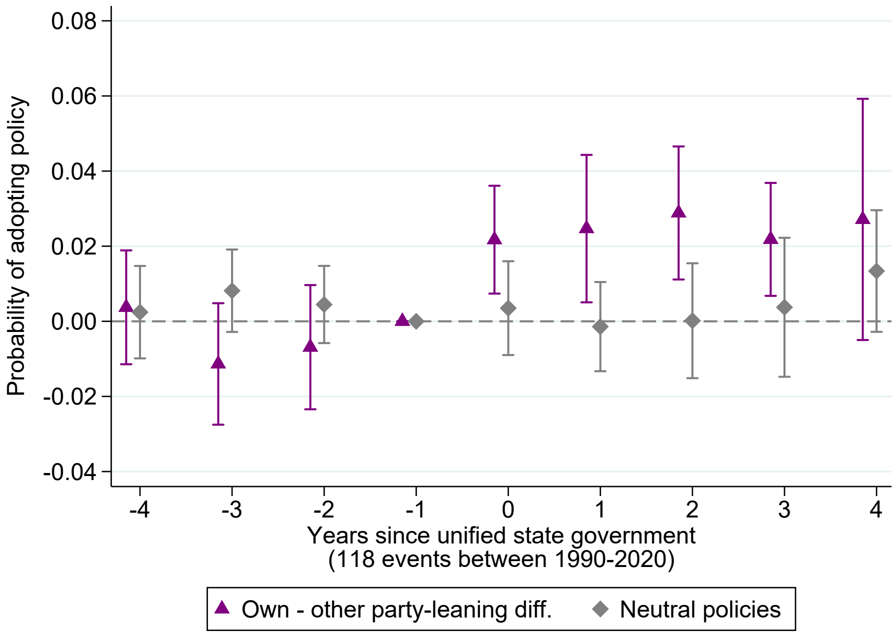
(b) Coefficients from 2010s



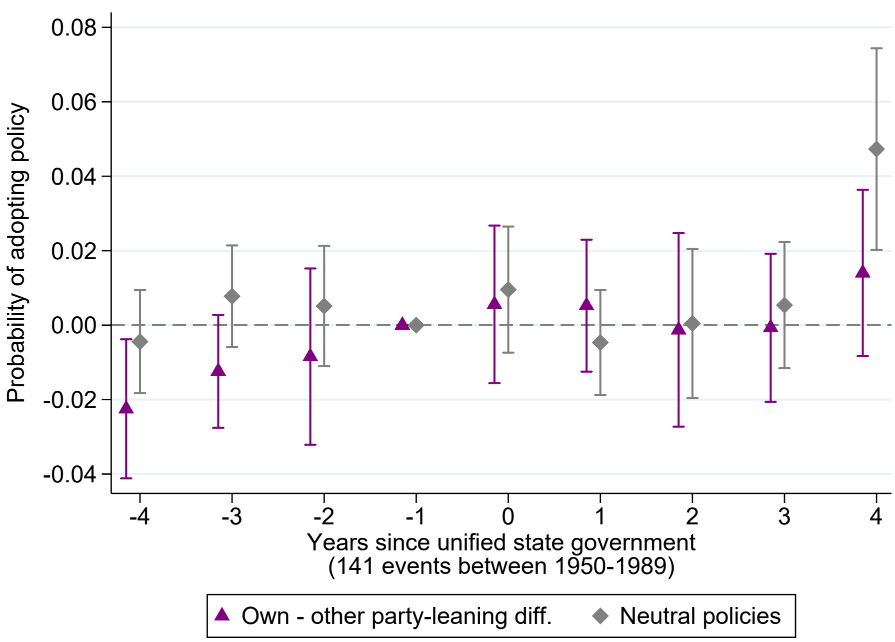
These maps show the probability of each state being among the first 10 adopters within 20 years after a policy is innovated by California in 2000, based on the model estimated in Table 3. Figure 8a uses estimated coefficients from the 1990s decade, and Figure 8b from the 2010s decade.

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

(a) Events during 1990-2020

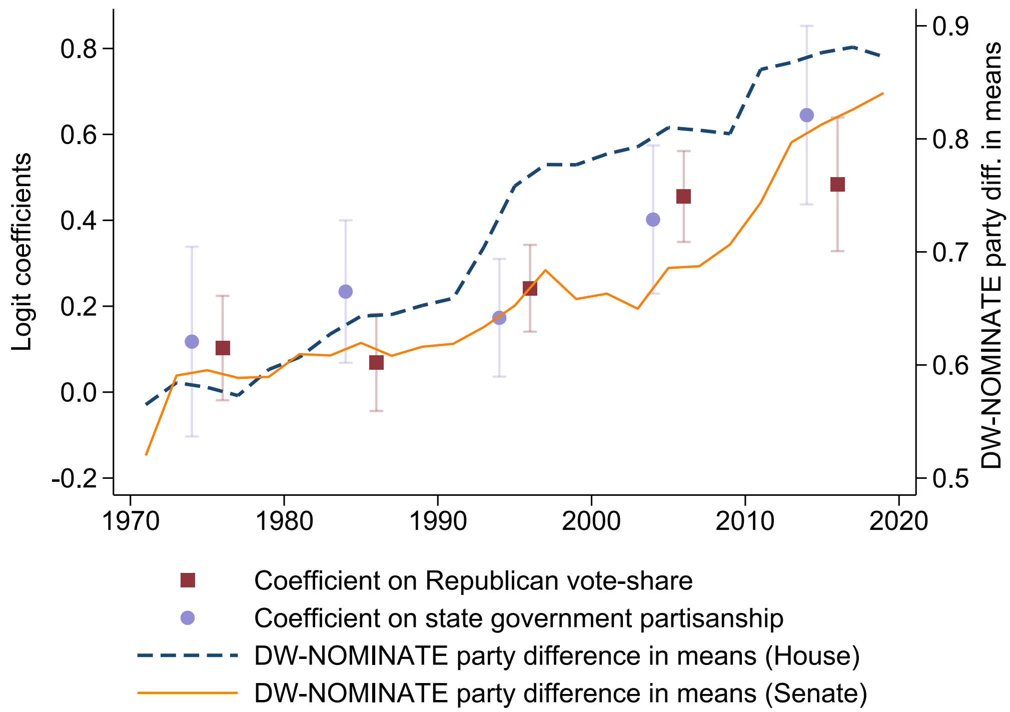


(b) Events during 1950-1989



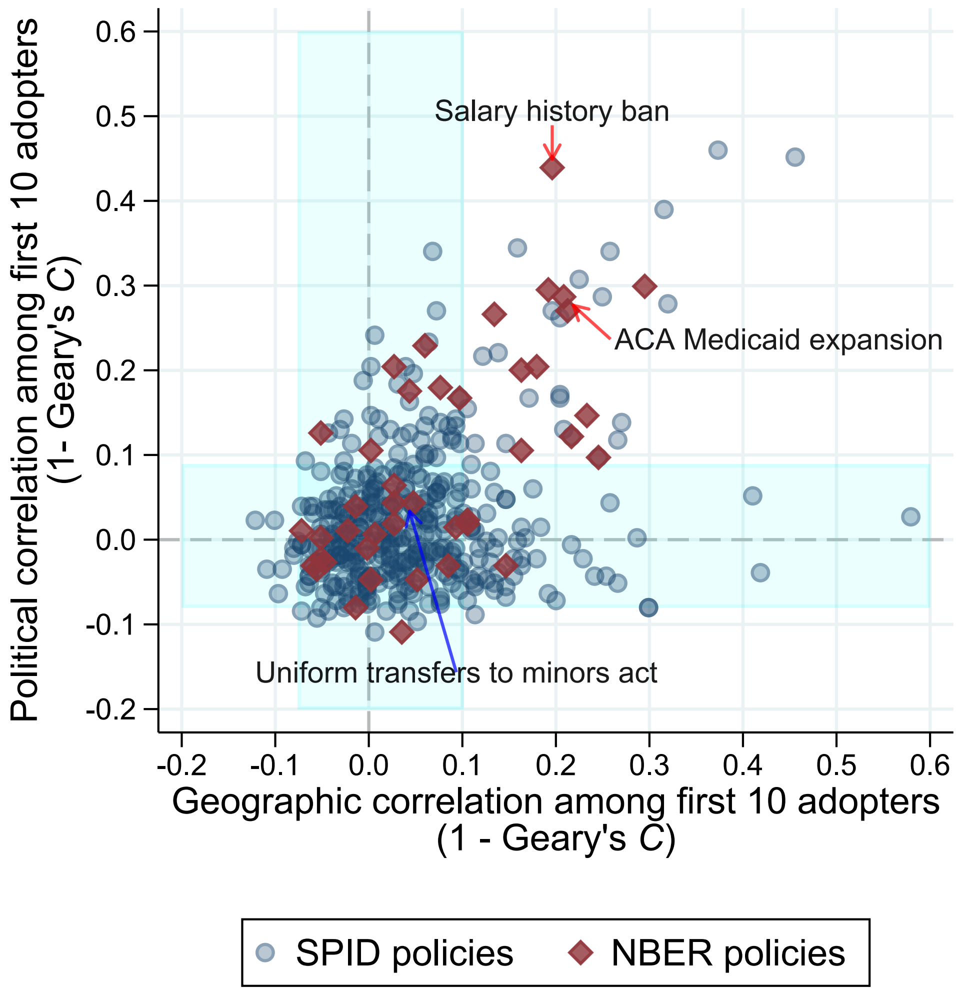
This figure shows the event-study estimates around a switch to unified party control of state government. The purple triangles show the difference in the probability of adopting a policy that is ideologically aligned with the incoming party versus a policy that is ideologically opposed. The gray diamonds 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



Geog. correlation mean: SPID=0.02, NBER=0.09, diff. *p*=0.00
Pol. correlation mean: SPID=0.05, NBER=0.07, diff. *p*=0.12
Shaded region indicate 5-95th percentiles for placebo policies

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	Corporate 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	0.33	0.15	0.23	0.28	0.26	0.20	0.79
	(0.14)	(0.09)	(0.06)	(0.06)	(0.07)	(0.08)	
Distance	0.28	0.36	0.16	0.28	0.21	0.42	0.50
	(0.12)	(0.08)	(0.07)	(0.06)	(0.05)	(0.08)	
Republican vote-share	0.28	0.10	0.07	0.24	0.46	0.48	0.00
	(0.21)	(0.06)	(0.06)	(0.05)	(0.05)	(0.08)	
State gvnt. partisanship	-0.19	0.12	0.23	0.17	0.40	0.64	0.00
	(0.19)	(0.11)	(0.08)	(0.07)	(0.09)	(0.11)	
State gvnt. partisanship×Divided gvnt.	0.38	-0.40	-0.30	-0.07	-0.41	-0.90	0.00
	(0.45)	(0.25)	(0.17)	(0.15)	(0.15)	(0.19)	
Baseline P(Adopt)	0.03	0.03	0.03	0.05	0.05	0.05	
Observations	50804	44434	65585	79695	58881	28104	
Policies	138	167	238	333	286	167	
Pseudo R^2	0.21	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 and economic 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)								
0.33	0.22	0.26	0.20	0.23	0.39	0.09	0.07	0.51
(0.05)	(0.06)	(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)								
0.58	0.37	0.47	0.07	0.30	0.61	-0.56	0.05	0.56
(0.16)	(0.12)	(0.12)	(0.16)	(0.12)	(0.10)	(0.26)	(0.16)	(0.09)
SPID (N_{pol}: 213, 339, 286)								
0.35	0.24	0.22	0.09	0.15	0.41	0.12	0.11	0.53
(0.05)	(0.06)	(0.06)	(0.04)	(0.04)	(0.04)	(0.07)	(0.05)	(0.08)
Panel C. Policy area								
Economics (N_{pol}: 38, 55, 62)								
0.43	0.37	0.26	-0.01	0.14	0.38	0.43	0.15	0.44
(0.11)	(0.10)	(0.09)	(0.13)	(0.09)	(0.09)	(0.14)	(0.11)	(0.13)
Non-economics (N_{pol}: 189, 314, 263)								
0.35	0.22	0.26	0.11	0.18	0.46	0.00	0.11	0.58
(0.06)	(0.06)	(0.06)	(0.05)	(0.04)	(0.05)	(0.08)	(0.06)	(0.07)
Panel D. Vote-share								
Third of states with highest Republican vote-share (N_{pol}: 227, 369, 325)								
0.45	0.23	0.30	0.08	0.26	0.59	0.05	0.11	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)								
0.29	0.26	0.20	0.11	0.16	0.49	0.09	0.13	0.45
(0.09)	(0.06)	(0.09)	(0.09)	(0.08)	(0.10)	(0.08)	(0.07)	(0.10)
Panel E. Policy effectiveness from NBER papers								
NBER policies with null, negative, or mixed effects in papers (N_{pol}: 12, 18)								
	0.83	0.47		0.59	0.72		-0.12	0.62
	(0.16)	(0.15)		(0.18)	(0.14)		(0.29)	(0.15)
NBER policies with positive effects in papers (N_{pol}: 19, 19)								
	0.32	0.58		0.05	0.53		-0.15	0.59
	(0.13)	(0.15)		(0.11)	(0.13)		(0.14)	(0.12)
Panel F. Analysis within keyword categories (N_{pol}: 229, 374, 328)								
0.33	0.23	0.29	0.16	0.23	0.42	-0.09	0.00	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 and economic index combining population, income per capita, urban %, and share of employment in the manufacturing and agricultural sectors (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	0.38	0.22	0.27	0.30	0.13	0.17
	(0.09)	(0.06)	(0.07)	(0.09)	(0.06)	(0.07)
Distance	0.31	0.26	0.22	0.17	0.16	0.09
	(0.08)	(0.07)	(0.07)	(0.12)	(0.08)	(0.07)
Republican vote-share	0.14	0.15	0.41	0.11	0.11	0.29
	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)	(0.06)
State gvnt. partisanship	0.14	0.10	0.58	0.13	0.11	0.55
	(0.13)	(0.06)	(0.09)	(0.13)	(0.06)	(0.09)
State gvnt. partisanship×Divided gvnt.	-0.38	0.01	-0.70	-0.40	-0.03	-0.63
	(0.26)	(0.13)	(0.15)	(0.25)	(0.13)	(0.14)
Migration flows				0.16	0.05	0.23
				(0.15)	(0.09)	(0.09)
Voter preferences (ANES & GSS)				0.20	0.28	0.23
				(0.11)	(0.09)	(0.08)
Index of public opinion measures				0.14	0.15	0.19
				(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	0.16	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.