Policy Diffusion and Polarization across U.S. States*

Stefano DellaVigna
UC Berkeley and NBER

Woojin Kim
UC Berkeley

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Abstract

Economists have studied the impact of numerous state laws, from welfare rules to voting ID requirements. Yet for all this policy evaluation, what do we know about policy diffusion—how these policies spread from state to state? We present a series of facts based on a data set of over 700 U.S. state policies spanning the past 7 decades. First, for the introduction of new laws, state capacity seems to have a small role, in that larger and richer states are only slightly more likely to innovate policy. 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 demographics and voter policy preferences. Third, since 2000, political alignment is the strongest predictor of diffusion. Models of learning and correlated preferences can account for the earlier patterns, but the findings for the last two decades indicate a sharply increasing role of party control. We conclude that party polarization has emerged as a key factor recently for policy adoption, plausibly leading to a worse match between state policies and voter preferences.

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1 Introduction

Economists have long studied the diffusion of innovations going back at least to the pioneering analysis of Griliches (1957) of agricultural innovations, followed by an extensive literature in the context especially of developing countries (e.g., Conley and Udry, 2010).

They have paid much less attention to the diffusion of policy innovations across government units, with the notable exceptions of the study of tax competition across U.S. states (Case, Rosen, and Hines Jr., 1993; Besley and Case, 1995; de Paula, Rasul, and Souza, 2020), the theoretical literature on states as laboratories of democracy, (Callander and Harstad, 2015) and learning across countries (Buera, Monge-Naranjo, and Primiceri, 2011). This limited attention is surprising given that numerous studies across nearly each subfield of economics have examined the impact of policy innovations. A few recent examples are the impact of Medicaid adoption on health (Goodman-Bacon, 2021), voter ID laws on turnout (Cantoni and Pons, 2021), and minimum-wage laws on worker earnings (Cengiz et al., 2019). Better understanding the diffusion of such policies is not just of interest on its own, but could also inform our understanding of studies such as these.

In this paper, we study the innovation and diffusion of policies at the U.S. state level. While one could also consider the diffusion across countries or at other decision-making levels, the analysis of U.S. states has several advantages. The U.S. federalist system allows states to serve as "laboratories of democracy". At the same time, the states are still comparable, given similar political institutions. We also have a rich political science literature to build upon.[1] Further, a crucial benefit is the abundance of state-by-state data on policy adoptions.

Our main data source 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, provides a fairly representative coverage by topic of state laws, but only a limited coverage of the last decade. We thus extended its coverage through the 2010s for a subset of the policies.

While this data provides broad coverage, it may not necessarily cover the state-level policies of interest to economists. We thus constructed a second sample from economics papers. From the 11,316 NBER working papers from April 2012 to September 2021, we identify 169 papers with U.S. state-level policy variation. Out of this set, 91 papers meet our criteria, for a total of 57 policies (given that some policies are in multiple papers).

[1]Political scientists have studied the innovation and diffusion of policies across U.S. states as early as Walker (1969). See Graham, Shipan, and Volden (2012) for a review article and Mallinson (2020) for a meta-analysis.

The combined data set covers 705 policies adopted from the 1950s onward, 648 from the SPID data set and 57 from the NBER data set. The laws are most often about the provision of public services, law and crime, economics, and civil rights. Figure 1 presents three examples. Anti-bullying laws (Figure 1a) spread from the initial adoptions in Louisiana, West Virginia, and Colorado in 2001 in a fairly idiosyncratic way. In comparison, the Medicaid expansion from the Affordable Care Act (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 each policy, and thus cannot evaluate the role of effectiveness in the diffusion process. We nonetheless think that this descriptive evidence is valuable to cast light on different models and for predictive purposes, e.g., 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, capacity, or "legislative professionalism" 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). Nevertheless, population and income per capita are not reliable predictors of originating more laws. Overall, while there are specific states that consistently produce new policies (e.g., California) and those that do not (e.g., Mississippi), innovation appears to be mostly orthogonal to observable state characteristics.

How do policies diffuse? The diffusion may depend on competition, e.g., states raising expenditures when neighboring states do (Case, Rosen, and Hines Jr., 1993; de Paula, Rasul, and Souza, 2020), learning (Wang and Yang, 2021), 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 the different dimensions (e.g., geographic or political similarity). In the dynamic method, we use a logit hazard model outlining the dimensions along which policies tend to diffuse, given the observed adoption up to that period. The dimension of diffusion is informative about the underlying models. For example, diffusion along politically similar states would suggest the importance of ideological alignment.

We document that 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. Another important predictor is demographic similarity: a state is more likely to adopt a policy if other states with similar demographics (such as income or urban percentage) have already done so. The adoption by 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.

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 do not affect at all 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 associated with the governing state party, with no impact on bipartisan laws.

A final explanation is that different types of laws, for instance in more politically controversial topics, have become more common. While we find similar results even after reweighting for changes in the composition of policy areas over time, we also address this concern by focusing on one specific category of laws: public health policies for preventing infectious diseases. While COVID-related state laws and rules are strongly driven by political factors, there is no such pattern 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 dyadic 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 of laws; this approach allows us to use a larger sample of laws. Our findings for the last two decades indicate instead a decreased role of voter preferences and a comparatively stronger role for party control. We thus 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, forthcoming), documenting a sharp uptick at the state level since the 2000s that mimics, with a delay, the trend for politicians in Congress 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, 2021). While we do not observe the policy effectiveness, the increased impact of party politics suggests that factors other than policy impact are playing a growing role in policy adoption.

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, e.g., 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 estimate models that compare quantitatively the determinants of diffusion, allowing us to evaluate the role of different models. We also document that the recent polarization is even stronger for the 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 state political leaning 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. We present 50 randomly sampled examples of these laws in Table A.2a.

For each state law—for example on "Kinship Care Program" or on "Voter Registration by Mail"—the data set reports the name of the law, the source, its policy area, and the year of adoption in each state (if ever). The data set does not record if a law is rescinded, since it is a fairly rare event. Furthermore, the data set records only binary adoption, and not continuous variables such as the level of the minimum wage across states.

As with any data set, one wonders about the representativeness and reliability. While there was certainly selection by topic in some of the meta-analyses used to build the data set, the final product is representative of the policy areas in typical state laws (Boehmke et al., 2020). We also validated the adoption dates for a sample of laws with rare corrections.

A significant limitation of the data set is the limited coverage of the most recent decade, as Figure 3 shows. We thus extended its coverage especially from 2015 to 2020 for a subset of the policies using publicly available data sources.

NBER Data Set. While the SPID data set is extensive, there is no guarantee that it covers the type of state laws of interests to economists. We thus collected a similar, though smaller, sample from economics papers. From the 11,316 NBER working papers from April 2012 to September 2021, we manually checked and identified 169 papers with U.S. state-level policy variation, covering especially labor, public, and health economics (Column 2 in Table 1a). We then apply our sample restrictions, including the restriction to binary policy adoption, yielding 91 papers (Column 3). For 81 out of these 91 papers we can extract the timing of state-level policy adoption, typically from a table in the paper, covering 57 policies (given that, for example, multiple papers analyze the same policy of Medicaid expansion). Health economics is the most common field, followed by labor and public economics, and the share of published papers, 46 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.[2]

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, the data set does not include repeals and includes only binary measures of adoption (as opposed to, say, the minimum wage level).

As Table 1b shows, the data set includes 648 policies from the SPID data set, with an average of 24 states ultimately adopting each policy, and 57 policies from the NBER data set, with an average of 28 states ultimately adopting. As Table 1c documents, the most common topics, broadly grouped, are public services such as health and education, law and crime (especially in the SPID data set), economics (especially in the NBER data set), and civil rights (especially in the SPID data set). Over time, the topics covered have not changed much (Figure A.1a), and neither has the speed of adoption (Figure A.1b).

Outcome Variables. For 20 of the 57 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).

[2] 17 of the NBER policies are represented in the SPID data set to some extent. For example, one NBER policy is on the concealed carry of handguns, whereas a similar policy in SPID is on concealed carry in general. Some policies are present in both data sets, such as the state EITC, though the adoption dates tend to be more recently updated for the NBER source.

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).

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

Table 2 presents a statistical comparison between states in the top 20% of this innovation measure, versus states in the bottom 20%.[4] We find little evidence that states larger in population are more likely to be innovators, but some evidence only in the earlier period that states with higher per-capita income or higher "legislative professionalism" (Bowen and Greene, 2014) are more likely to be in the top-innovators group. Furthermore, innovations are not predicted by the pattern of voting in the state, and are not more likely to come from unified Republican or Democratic governments, compared to divided state governments. Innovative states do have a larger share of population in urban areas. Overall, while some states consistently produce new policies (e.g., California) and others less so (e.g., Mississippi), innovation appears to be mostly idiosyncratic on observable state characteristics.

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

[3] Figure A.2 presents similar plots splitting by the data source, SPID or NBER.

[4] In Table A.4 we present parallel evidence for the policies from the NBER papers.

(provided that this threshold of adoption was reached) with respect to the relevant dimension—e.g., 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.[5] If the states that are closer in the dimension are similar in policy adoptions, the weighted average of the differences in the numerator should be smaller than the unweighted average in the denominator. Consequently, values of this measure below 1 indicate clustering, values above 1 suggest the opposite, and a value of 1 is the null hypothesis.

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

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

In Figure 5a we display the geographic clustering of policies in the 1950s-70s (108 policies), 1980s-90s (222 policies), and 2000-10s (168 policies), indicating a degree of geographic clustering that is both substantial and persistent over time. For example, in the 1950-70s

[5] 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.

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:

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

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

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

Consider a state i that has yet to adopt a policy that has been adopted by $A_{-iqt} = 16$ states, of which $a^g_{-iqt} = 5$ are 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 adoption nationwide. 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 high 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 similarity, we take the average state-level log population, share of urban residents, and log income per capita over the last two years, 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 Democrat) and the case of divided split-party governments.

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

The four similarity parameters—β_g for geography, β_d for demographics, 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, though we pool the 1950s and 1960s given the more limited coverage for the earliest years. In each year t, only states that have not yet adopted policy q are in the sample. For each policy, we start the model in the first year of adoption and end it in the last year of adoption in the sample, and exclude policies that end with fewer than 5 adopters or span less than 3 years. We cluster the standard errors at the state level to capture autocorrelation, as well as correlations across policies.

We stress that we do not place a causal interpretation on the estimates in (1) (Manski, 1993). For example, the adoption of a policy by a state may be predicted by the adoption of geographic neighbors because of learning and diffusion of information (Banerjee, 1992; Bikhchandani, Hirshleifer, and Welch, 1992), or alternatively because of common demand for a policy 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 a specific variable, the change in state government control.

Hazard Estimates. As Table 3 shows, we do not find any reliable pattern that state-level demographics X_{it}, including state income or population, predict faster adoption.

We thus turn to the similarity predictors β_k. Demographic similarity is predictive of adoption: in the 1980s we estimate a coefficient of 0.21 (s.e.=0.06), which remains about constant up to the most recent decade, at 0.24 (s.e.=0.06). These estimates are certainly consistent with the impact of similar context and preferences, but can also be interpreted in light of models of competition and learning, if demographic similarity reflects these margins.

Next, we consider the impact of geographic closeness, which we expect to capture the impact of competition across neighboring states, learning about policies, and similarity in contexts and preferences. Geographic similarity is highly predictive, with a larger impact than demographic similarity, and with consistent importance over time, with a coefficient of 0.38 (s.e.=0.07) in the 1970s and of 0.36 (s.e.=0.07) in the most recent decade.

Third, we consider the role of similarity in the state-level Republican vote share. For the first five decades, political similarity is a modest predictor, with an effect size mostly between a third to a half of the one for geographic similarity: 0.13 (s.e.=0.06) in the 1970s, 0.06 (s.e.=0.05) in the 1980s, and 0.18 (s.e.=0.05) in the 1990s. In the last two decades, however, the impact *triples*, at 0.38 (s.e.=0.05) in the 2000s and 0.38 (s.e.=0.06) in the 2010s.

The impact of similarity in political voting could capture similarity in voter political preferences, or the impact of state parties. To capture the latter component, we include party control of the state government. In all the decades up to the 1990s, similarity in state party control matters relatively little and is not statistically significant. Yet in the 2000-10s period, previous adoption by other governments with the same state party control becomes the strongest predictor of adoption (estimate of 0.52, s.e.=0.07) for states under a unified state government. For states with split governments, there is no predictive power of adoption by other states with split governments, which further underscores the role of party control.

Figure 6 summarizes the evidence from the hazard regressions. Geographic and demographic similarity between states has consistently predicted the likelihood of passing the same laws. Meanwhile, similarities in the state-level voting and party control explained little in the past, but in the last two decades, have become the most important predictors. We interpret this change as evidence of a shift in the model of state policy-making, with party discipline taking on a newfound key role in the 21st century.

We note that the pseudo R-squared has generally increased over time from 0.13 in the 1970s to 0.20 in the 2010s. Thus, the process of adoption has become more predictable.

Simulated Diffusion. In Figure 7a we present counterfactuals for the 1990s (Figure 7a) versus for the 2010s (Figure 7b). 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 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 7a) diffuses geographically in the West, as well as in some demographically similar states such as Florida and politically aligned states in the Northeast. Meanwhile, with the estimated 2010s coefficients (Figure 7b), the spread of the policy becomes highly concentrated in the states with similar political leaning in the Northeast and along the West Coast in Oregon and Washington, while geographically close but politically distanced states such as Nevada, Utah, and Arizona become less likely to adopt.

In Figures A.5a-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.5a-b); (ii) Texas, a large, Republican state (Figure A.5c-d); and (iii) Ohio, a Republican-leaning Midwestern state (Figure A.5e-f).

Robustness. In Table A.6 we explore the robustness of the results in Table 3. 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.

We estimate (i) a linear probability model instead of a logit; (ii) a reweighted version that holds the composition of policy areas fixed over decades, (iii) a model with an expanded set of controls;[6] (iv) a parsimonious specification which drops the state characteristics X_{it} (e.g., the level of urban %), which are typically not significant. The results are similar across these specifications. We adopt the parsimonious specification in the panels to follow.

Next, we adopt alternative measures of adoptions among similar states: (i) using thresholds of the closest fifth, fourth, third, or half (Figure A.6) instead of the closest third in Equation 2; (ii) adoption by other states up to year $t-1$, instead of up to year t; (iii) a weighted average of the adoption status of all other 47 states, with weights proportional to the other state's rank in similarity; e.g., the most distal state carries 1/47th of the weight of the most similar state. 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-specification issues (Online Appendix Section A), all point to the increasing role of politics.

Heterogeneity. In Table 4 we estimate the parsimonious specification in row 5 of Table A.6 for different subsamples. In the NBER sample of policies studied by economists, the recent rise in importance of vote-share is even larger, with a coefficient of 0.50 (s.e.=0.08), compared to 0.35 (s.e.=0.04) in the SPID sample. For Interstate Compacts on which states cooperate to address a common problem, such as the Interstate Wildlife Violator Compact, we see less evidence of party polarization, as expected.

In Panel B we vary the policy area. For economic policies, we find a fairly constant role of politics and a decrease in the role of geography over time. The latter result seems to run counter to strong competition across neighboring states. For non-economic policies, the role of geography is about constant, and the impact of political polarization is especially strong, as one would expect given the polarizing nature of social issues.

In Panel C we split the states into thirds based on their vote-share as Republican-voting, Democratic-voting, and "battleground" states. The increased importance of politics is mostly

[6] 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 state government partisanship, 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.7a also shows the estimates for each demographic variable separately.

driven by the Republican-voting states and especially the Democratic-voting states, fitting with a party-driven model for the polarization. In the battleground states, the party in control varies from Democratic to Republican, so battleground states do not specifically adopt policies from one another, as opposed to states at the polar opposites that do.

Finally, returning to the "state capacity" model, we may expect a smaller impact of geographical closeness for larger states if state capacity enables them to learn from a broader range of other states. We find only suggestive evidence of such heterogeneity.

Comparison to Results in the Literature. The diffusion of policy along geographical and demographic lines is consistent with the results on tax legislation and competition across U.S. states in Besley and Case (1995) and de Paula, Rasul, and Souza (2020), for example, and with findings in the political science literature as early as Walker (1969) and in Mallinson (2020) who 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 and demographic similarity, we present results for the most recent years, and we document even stronger patterns for the 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 then 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.7a), we use the remaining 33 contiguous states (with the closest third now including only 10 of the other 32 states) throughout the analysis. Further, we use an index of existing measures of voter policy preferences in the literature to provide an alternative measure. We provide more detail on the policy preference questions and the sample coverage for ANES and GSS, as well as on the measures from the literature, in Online Appendix Section B.

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 decades in Column 1-3 and including only the 33 states consistently represented in ANES and GSS. Then in Columns 4-6 we add controls for similarity in voter preferences as well as in migration flows. The measure of migration flows has modest explanatory power, while the two measures of similarity in voter preferences are stronger predictors, though somewhat less so recently. The measure based on the ANES and GSS has coefficients of 0.26 (s.e.=0.09) and 0.28 (s.e.=0.09) in the earlier decades, but only 0.15 (s.e.=0.08) for the most recent 2000-10s decades. The coefficients on the index of public opinion measures in the literature are fairly constant over time ranging from 0.16 (s.e.=0.04) to 0.20 (s.e.=0.04).

What is the impact of controlling for voter preferences and migration flows on the predictive power of the other variables? The addition of these variables reduces by nearly half the explanatory power of geography and demographics, especially in the most time periods. The predictive power of Republican vote-share in the most recent decades also falls, from 0.38 (s.e.=0.05) to 0.27 (s.e.=0.05). Strikingly, these variables leave the coefficient on the similarity in state government party control essentially unaffected, from 0.44 (s.e.=0.08) to 0.42 (s.e.=0.08). The lack of movement in the coefficient even after including measures of voter preferences suggests that its rise in recent decades likely reflects top-down partisanship rather than bottom-up demand from the voters.[7]

[7] In Table A.7a we examine separately the impact of each policy opinion measure used in the index. In Table A.7b we analyze the impact of the GSS-ANES similarity variable considering separately questions that either match or do not match the 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 B discusses these results.

Evidence from Outcome Variables. As a final piece of evidence, we consider variables that are typical policy outcomes, such as the state-level opioid mortality rate, income, and poverty rate. If 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 between the outcomes and politics may not have changed over time.

We compute the Geary's C statistic using the closest third of states by vote-share for these variables, first for the period 1980-85 and then for the period 2005-10. Figure A.8a provides no evidence that these variables have become more politically correlated.[8]

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 mostly to other factors.

5.2 Evidence Within Area: Vaccination Policies

A possible confound for the findings thus far is that the composition of policies in the sample has changed over time, for example, to include more politically controversial laws. Reassuringly, Figure A.1a shows that the composition of policy areas has remained fairly stable, except for the last 5 years, and re-weighting to hold the composition of policy areas fixed over the decades does not affect the estimates (Row 3 in Table A.6). Nonetheless, it would be useful to consider a narrower class of policies. We thus 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 Table 6. We estimate a significant impact of demographic and geographic similarity, but especially of state party control.[9] 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.

Even in this narrower topic of infectious disease prevention laws, we reproduce our key result: while geographic and demographic similarity have historically been the most important predictors of policy diffusion, recently party politics has become the foremost driver.

[8]Figure A.8b documents that the outcomes have become less geographically correlated in recent times.

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

5.3 Event Study on Party Discipline

The hazard estimates so far provide descriptive evidence on 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

$$Y_{iqt} = \sum_{s} \sum_{d=-4}^{4} \delta_d 1\left\{t - e_i^s = d\right\} + \Pi X_{it} + \boldsymbol{\alpha}_i + \gamma_{qt} + \varepsilon_{iqt}$$

where e_i^s is the year of switch s to unified party control in state i (with the state elections typically occurring late in the prior year, $t = e_i^s - 1$), and the key parameter δ_d is allowed to depend on the ideology of the policy q. We categorize the ideology of policies using the vote-share of the states that have adopted the law so far.[10] 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 8a displays the event study coefficients for the period 1990-2020. A switch to a unified state 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 t, as one would expect, and appears to be persistent. In contrast, in the earlier 1950-1989 time period (Figure 8b) we do not uncover any partisan impact of a switch in party control.[11] We find similar results using the event study estimator from Chaisemartin

[10] We take the average 2-party Republican vote-share (demeaned by year) in the latest Presidential election as of 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 Republican-leaning, and conversely for Democratic-leaning policies. If the average vote-share of states adopting a policy is within the 2 percentage-point buffer, 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 fraction of policies that switch from left- to right-leaning or vice versa at some point in their life-cycle. Figure A.9a shows the distribution of the average demeaned Republican vote-share among adopters over the last 30 years. Figure A.9b follows the ideological evolution of the three most left-, right-, and neutral-leaning policies in 1990 until 2020. Figure A.9c displays the classification of policies for thresholds other than 1 pp.

[11] In Figure A.10a-b, we also show the event study estimates with the most plausible confound path

and D'Haultfœuille (2020) (Figure A.10c-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

We documented a series of facts about the diffusion of state-level policies in the U.S., and related them to different 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 9 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 were not polarizing.[12]

One of the most touted advantages of the U.S. federalist system is the ability of independent states to tailor their policies swiftly and optimally to voter preferences and state-specific needs. Yet the current trends suggest that the adoption of state policies is becoming if anything less responsive to local economic demands, and instead bending more to partisan forces. While measuring the welfare implications of such top-down policy choices is beyond the scope of the paper, we note the implications about the quality of the match between policies and state voter preferences, as well as welfare externalities on other states (e.g., Knight, 2013).

Our findings raise a number of 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

(Freyaldenhoven et al., forthcoming). In Table A.8 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.

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

the American Legislative Exchange Council (Angelucci, Ash, and Longuet Marx, 2022). It would also be useful to know whether this trend of polarization has reached even lower levels of governments, such as city policy-making, or other decisions in the public interest, such as the content of textbook or medical rules.

Our findings also suggest that researchers can assess the extent to which any particular law diffuses more geographically or politically. As a first approximation, in Figure 10 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, which includes Anti-Bullying Laws, appears to be fairly idiosyncratic, at least based on these parsimonious measures.

We envision that this categorization can guide researchers studying a policy change to identify the degree of correlation in the diffusion process of their policy, relative to the average paper of this kind. For example, the presence of geographic versus political diffusion suggests different concerns for identification, a topic which we leave for future work.

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

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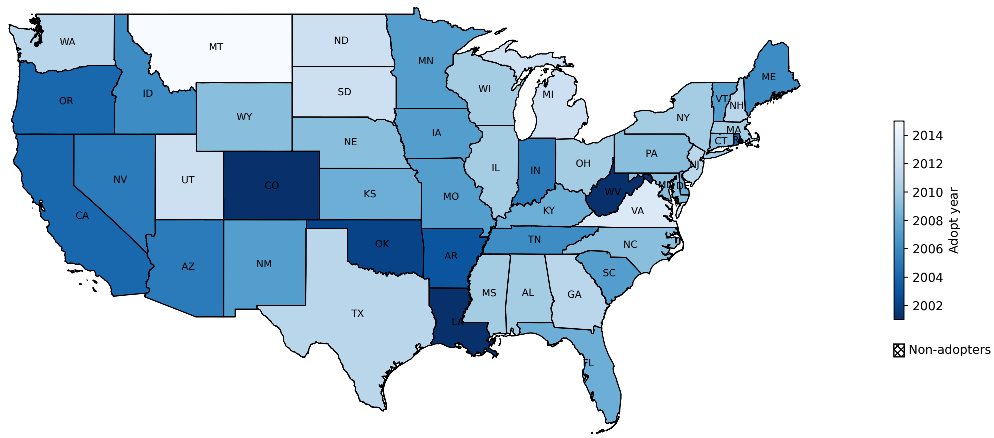
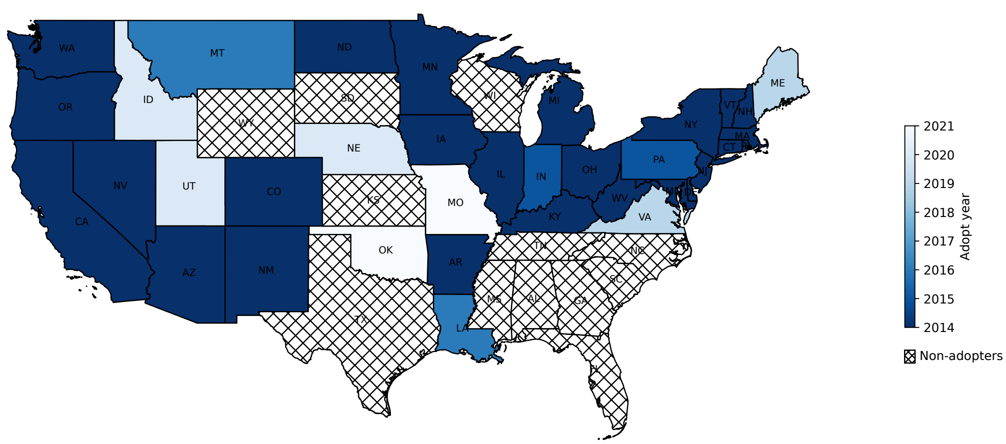
Figure 1: Three policy examples

(a) Anti-bullying laws



(b) 2014 Medicaid expansion (Affordable Care Act)



(c) Initial prescription drug monitoring program

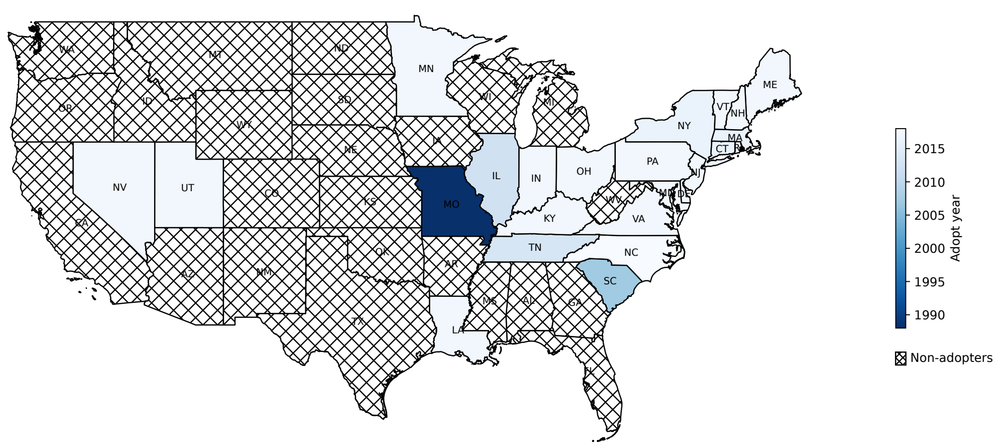
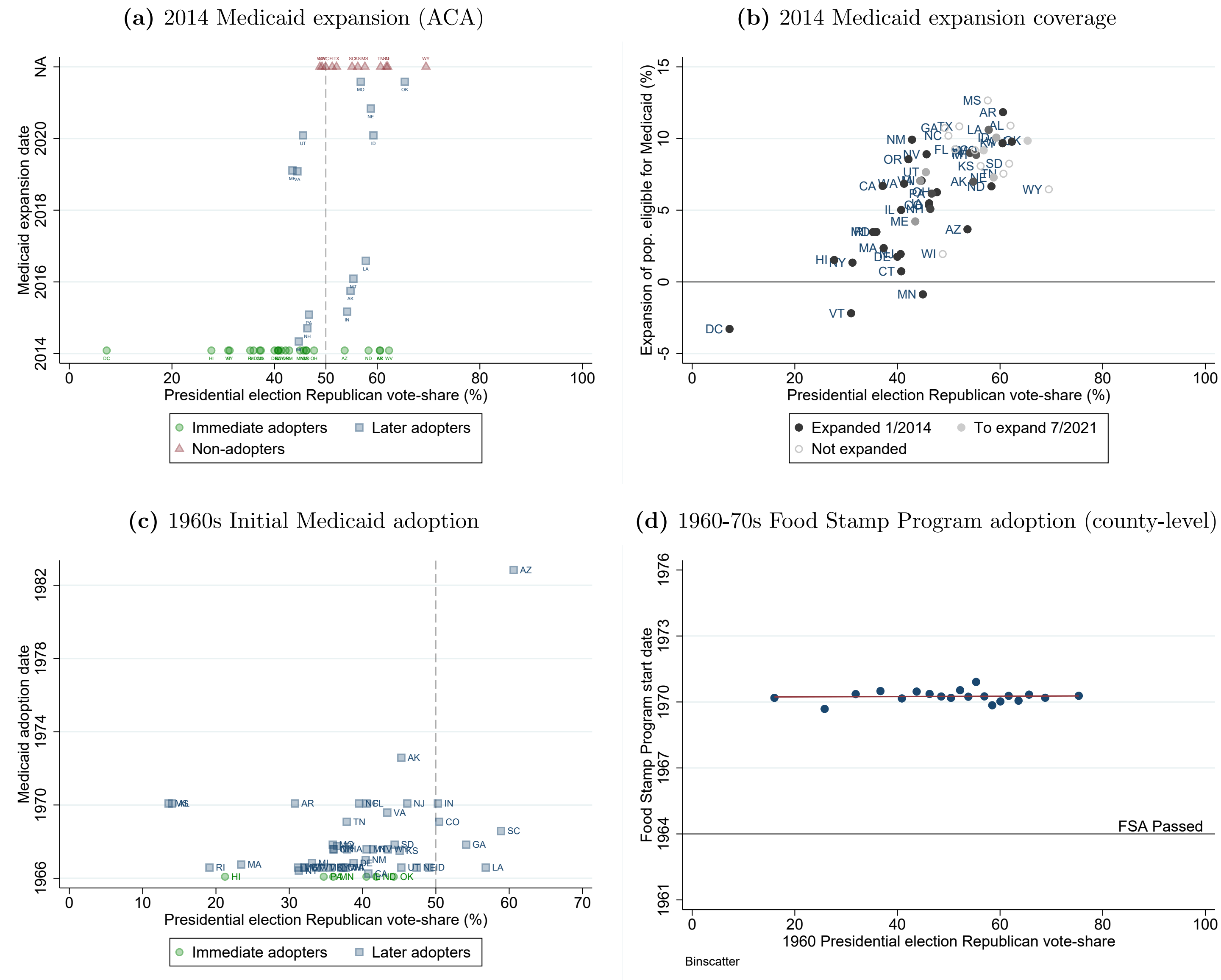


Figure 2: Case studies of welfare programs



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: Policy sources

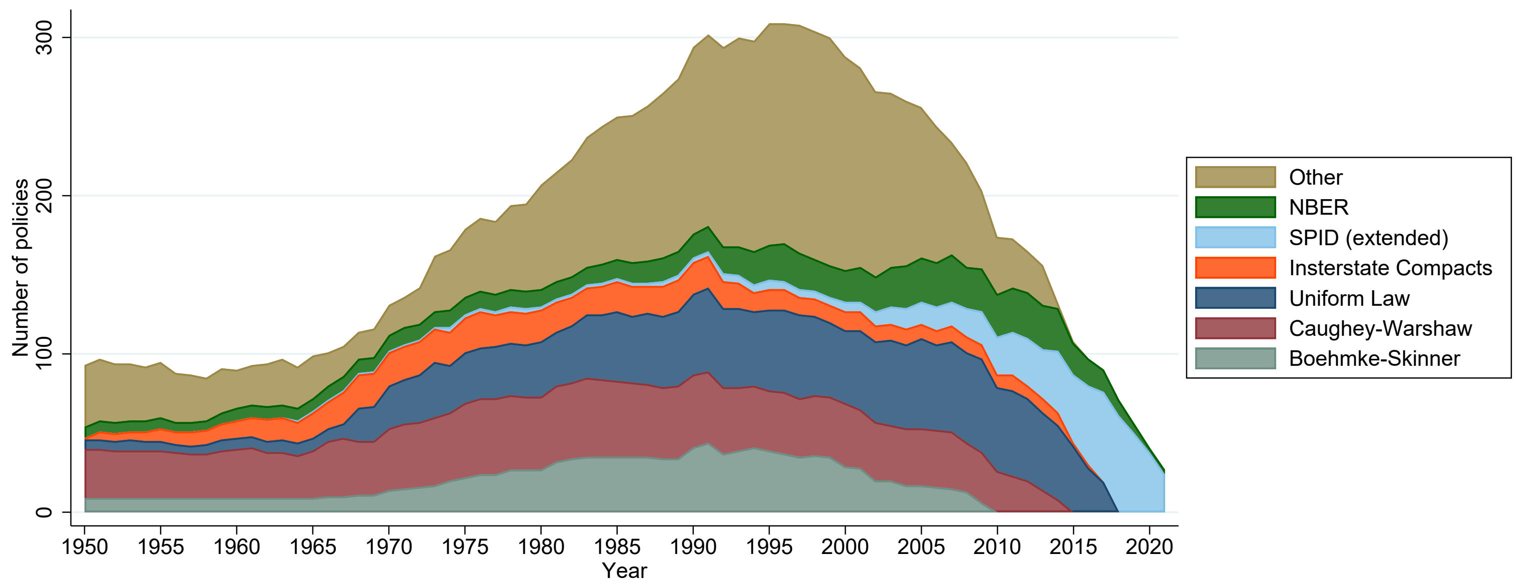
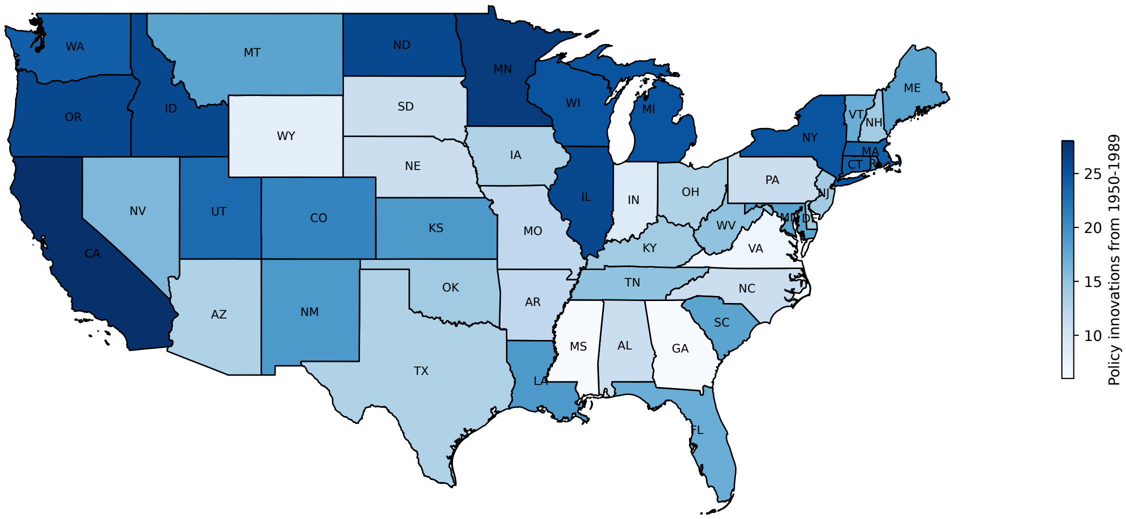


Figure 3 shows the number of active policies with ongoing adoptions for each year by the source of the policy. All sources are from the SPID dataset, except for the NBER policies. The "SPID (extended)" subgroup refers to policies from SPID that this paper extended for further coverage of adoption in recent decades.

Figure 4: Innovating states

(a) Policies innovated 1950-1989



(b) Policies innovated 1990-2020

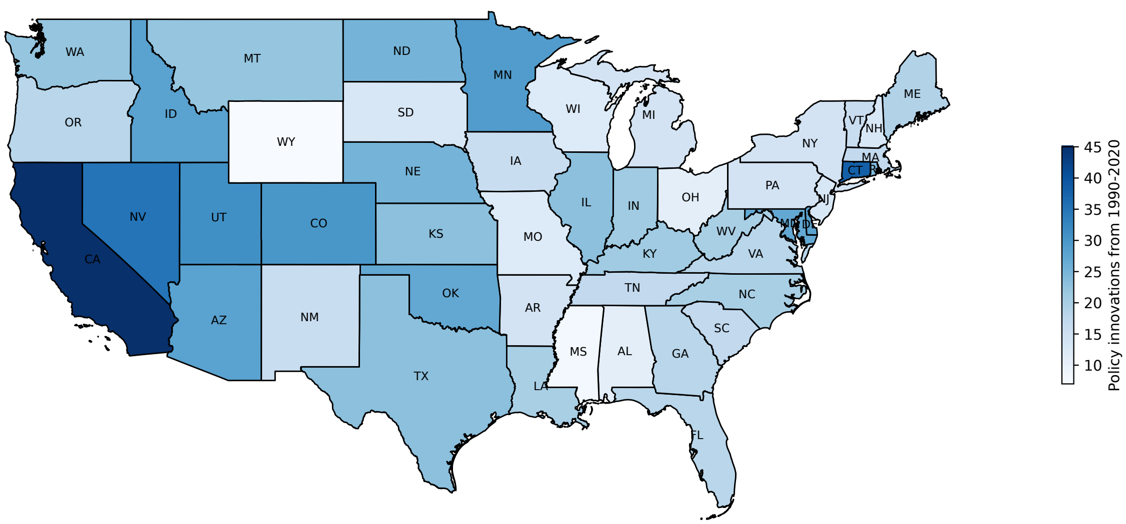
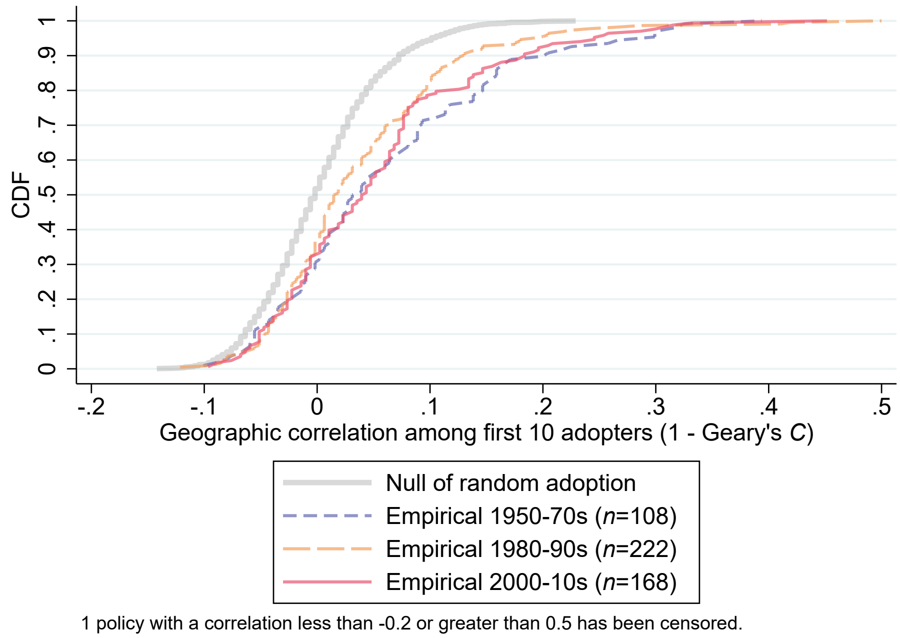
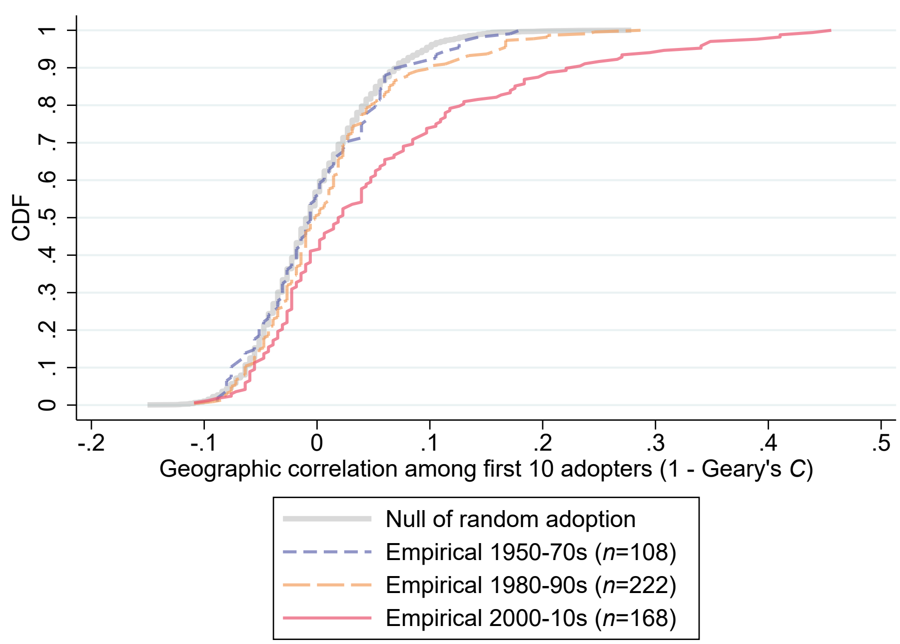


Figure 5: Correlation in geography and politics among adopters (random and observed)

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

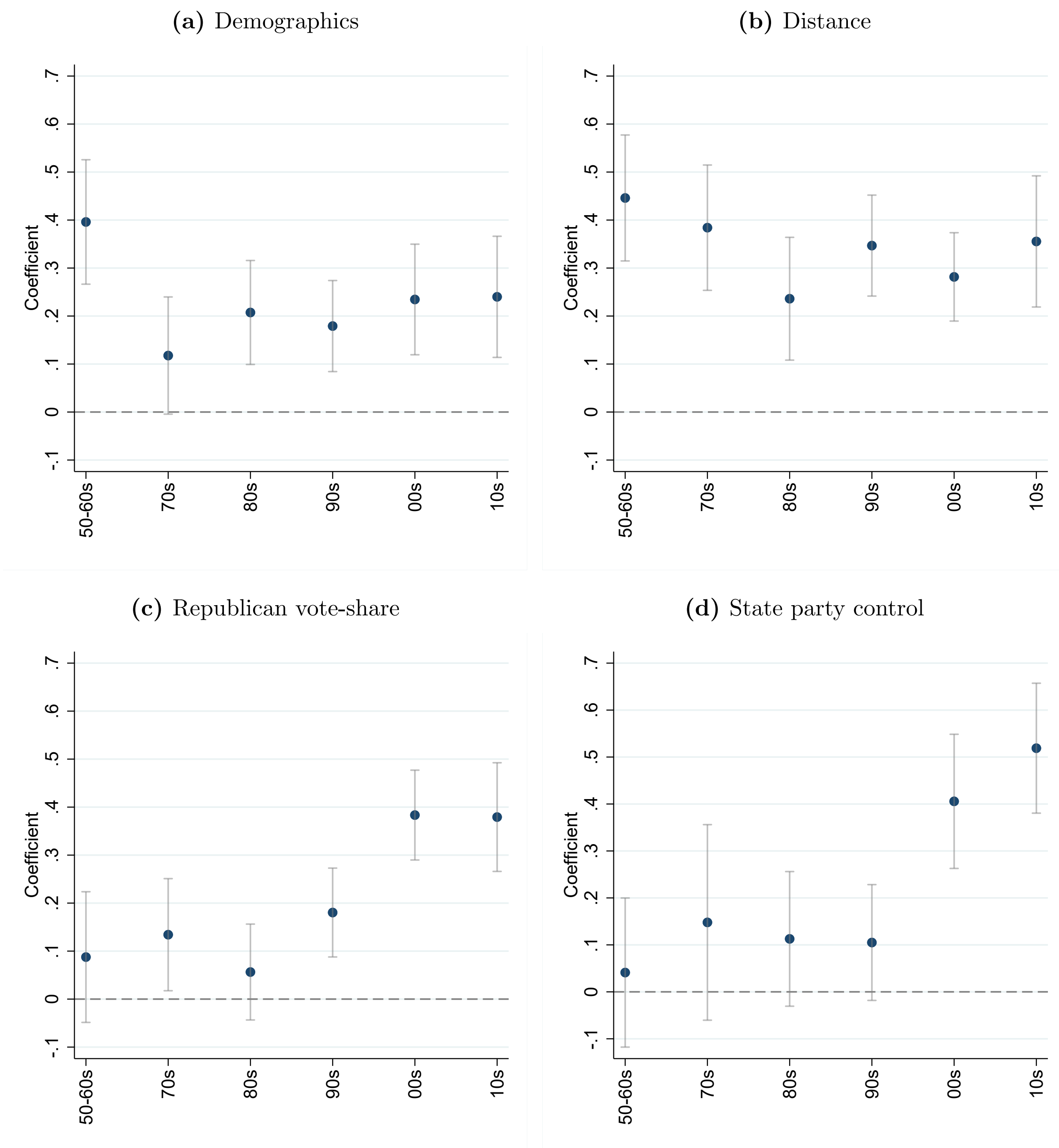


(b) Correlation in Republican vote-share (first 10 adopters)



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.

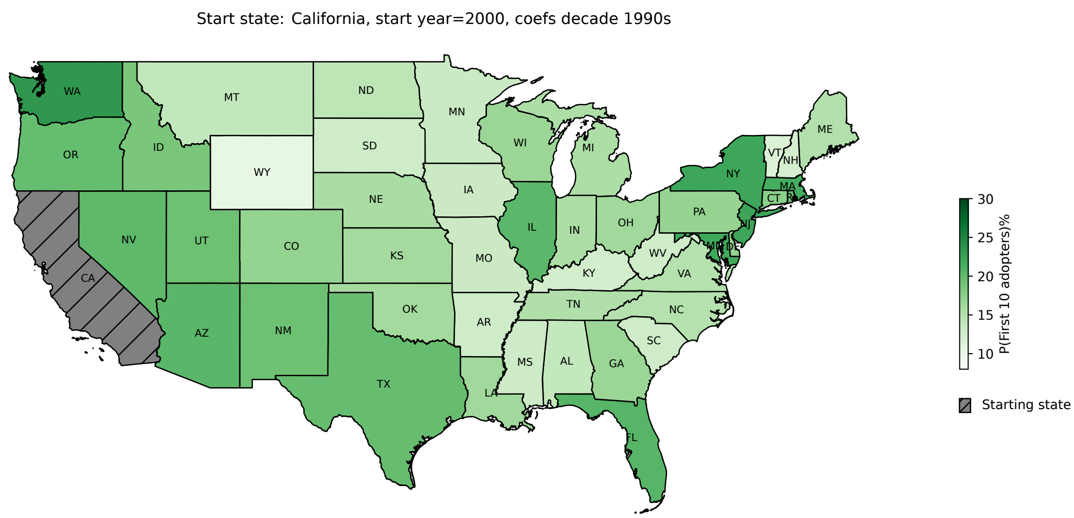
Figure 6: Dynamics of policy diffusion dimensions



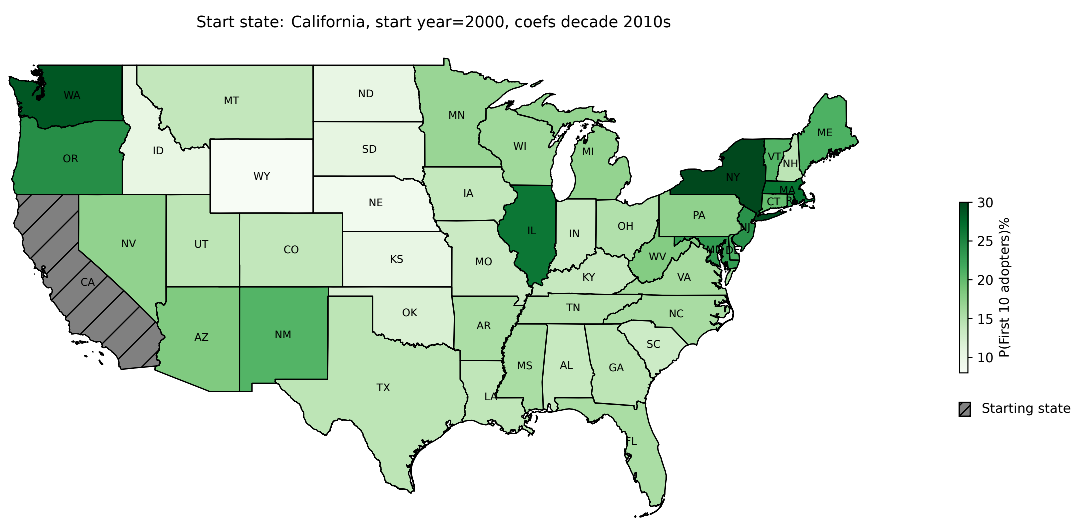
This figure plots the decade-by-decade estimates from the model in Table 3 for the coefficients on the measure of adoption among the closest states in each dimension. 95% confidence intervals are shown with standard errors clustered by state.

Figure 7: Simulated policy diffusion

(a) Coefficients from 1990s



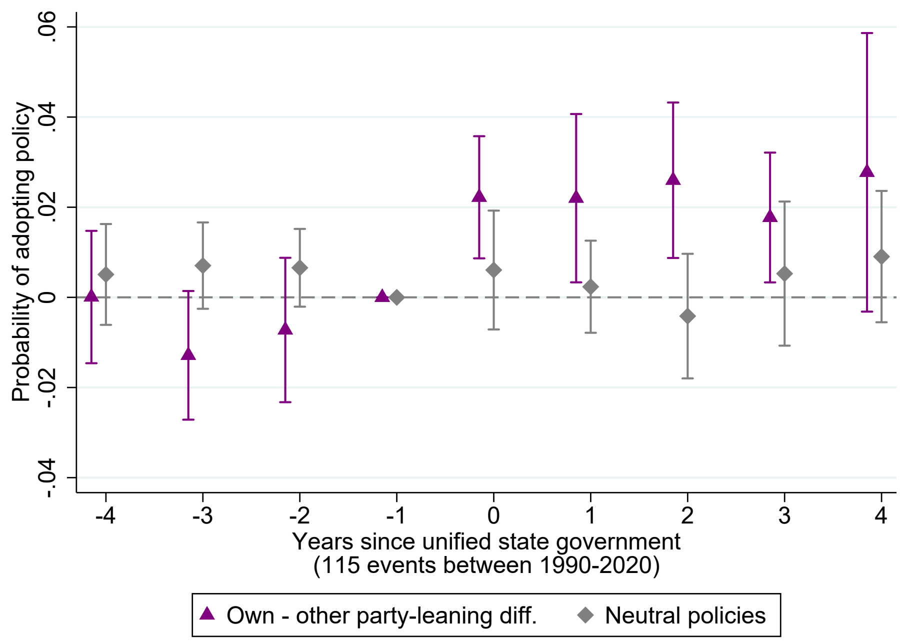
(b) Coefficients from 2010s



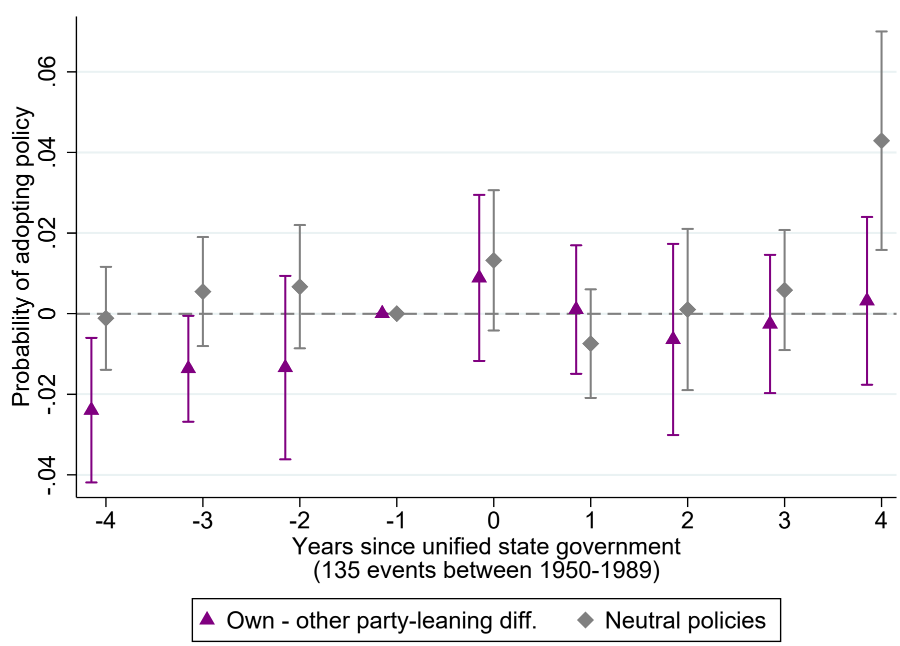
These maps show the probability of the diffusion of a policy innovated by California in 2009 for each of the other states based on the model estimated in Table 3. Figure 7a uses estimated coefficients from the 1990s decade, and Figure 7b from the 2010s decade.

Figure 8: Event study from switches in state government party control

(a) Events during 1990-2020



(b) Events during 1950-1989



Policies are included after 5 adoptions. Policies that ever switch ideological categorization from one party to the other (e.g., from left to right) are excluded. 95% confidence intervals are shown with standard errors clustered by state.

Figure 9: Comparison to polarization in DW-NOMINATE

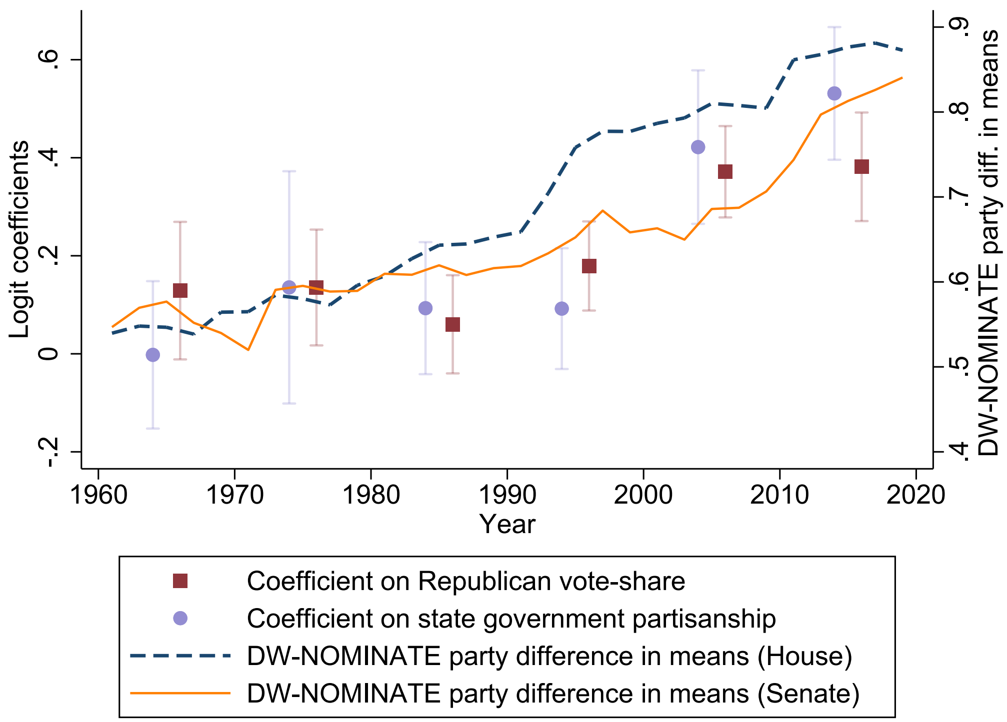


Figure 10: Policy-by-policy diffusion patterns

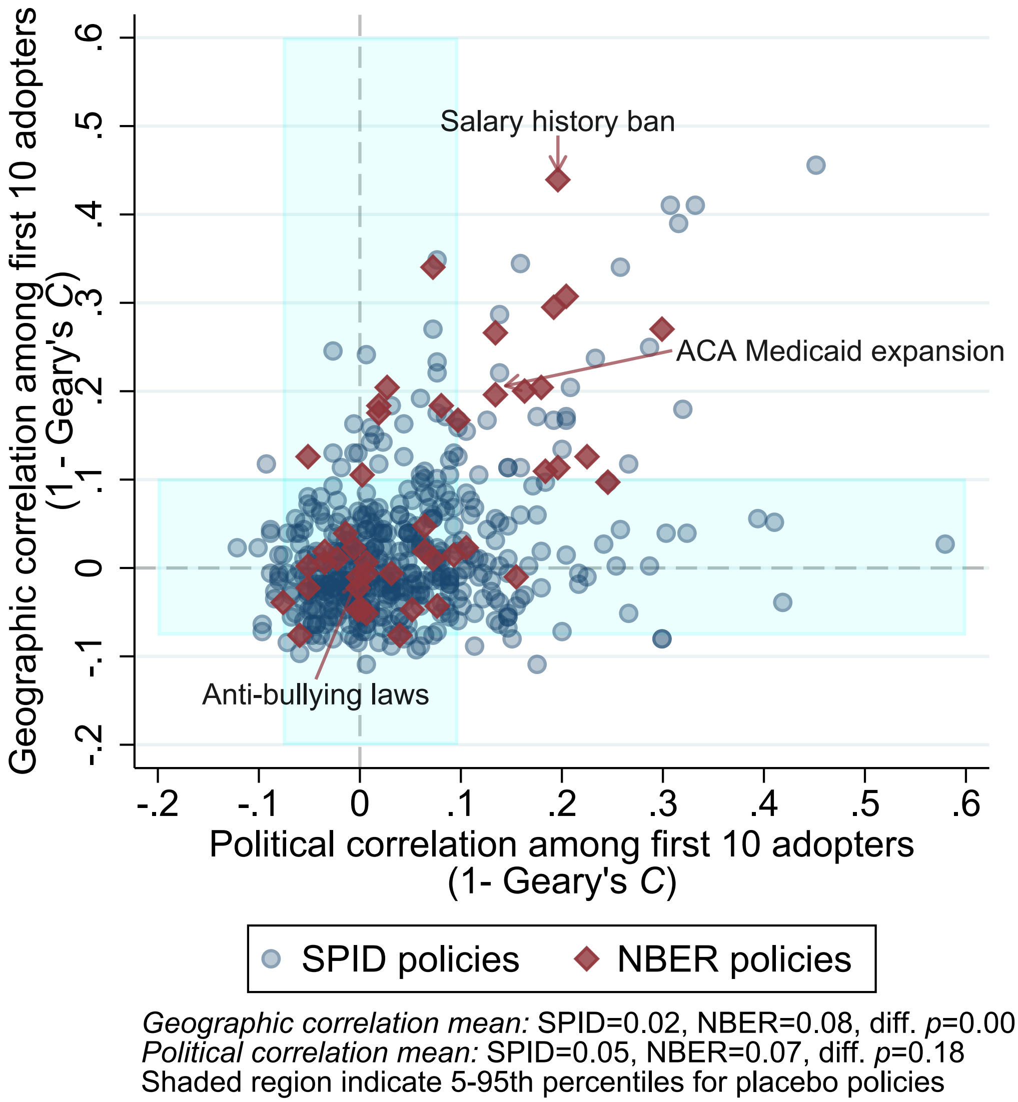


Table 1a: Summary of NBER data set

	(1) All (4/12 - 9/21)	(2) Cross-state policy	(3) Meets criteria*	(4) Sample
Total	11316	169	91	81
Issue date	2017.3 [2.7]	2017.6 [2.8]	2017.2 [2.8]	2017.5 [2.7]
Field				
% in Labor Studies	23	32	30	28
% in Public Economics	23	40	32	31
% in Economic Fluctuations and Growth	22	7	1	1
% in Health Economics	12	52	62	67
Other	41	15	11	10
Publication				
% Published	48	46	49	46
% Published in "Top General Interest"	9	4	1	0
% Published in "Tier A"	14	15	19	20
Year published	2017.3 [2.4]	2016.9 [2.3]	2016.6 [2.5]	2016.8 [2.6]
% Policy adoption data available	–	–	89	100
% Replication data available	–	–	–	9

Working papers numbered 18000-29318 are included. Means are reported with standard deviations in brackets for dates. Working papers can be listed under multiple fields. Papers on the same policy are all included in the sample. *Criteria: Policy must be binary and active after the 1950s. Covid-19 policies are also excluded.

Table 1b: Summary statistics of policy data sets

	SPID				NBER			
	Mean (SD)	Min	Median	Max	Mean (SD)	Min	Median	Max
Number of policies	648	–	–	–	57	–	–	–
First year of adoption	1977.76 (28.55)	1811	1983	2017	1987.81 (25.34)	1911	1995	2017
Last year of adoption	1998.89 (17.10)	1950	2002.5	2022	2007.30 (13.82)	1955	2014	2021
Number of states adopted	23.70 (15.23)	1	22	48	28.40 (15.08)	5	27	48

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

Table 1c: Policy areas

			Number of policies (freq.)	
Policy area	Main subgroups	Example	SPID	NBER
Public Services	Health, Education	Medical savings accounts	174 (27%)	28 (49%)
Law & Crime	Law & Crime	Gun open carry laws	184 (28%)	4 (7%)
Economics	Domestic Commerce, Labor	Bankrupcy laws	117 (18%)	20 (35%)
Civil Rights	Civil Rights, Immigration	Gender discrimination laws	105 (16%)	2 (4%)
Environment & Energy	Energy, Environment	Renewable energy standards	35 (5%)	2 (4%)
Gvnt. Operations & Foreign Affairs	Government Operations, Defense	Direct democracy	33 (5%)	1 (2%)

Table 2: Highest and lowest innovators (20%)

	1950-1990		1991-2020		Difference (SE)	
	(1) Top 20%	(2) Bottom 20%	(3) Top 20%	(4) Bottom 20%	(1)-(2)	(3)-(4)
Rep. two-party vote-share %	52.64	54.83	50.81	50.51	-2.19	0.30
	[8.67]	[13.42]	[10.09]	[9.80]	(2.30)	(3.94)
|Demeaned two-party vote-share|	5.06	8.48	8.23	7.57	-3.42	0.66
	[4.25]	[9.55]	[5.40]	[5.56]	(1.81)	(2.00)
Unified Dem. state gvt.	0.22	0.52	0.21	0.15	-0.30	0.06
	[0.42]	[0.50]	[0.41]	[0.36]	(0.14)	(0.08)
Unified Rep. state gvt.	0.23	0.25	0.33	0.37	-0.02	-0.05
	[0.42]	[0.43]	[0.47]	[0.48]	(0.10)	(0.15)
Legislative professionalism	0.81	-0.68	0.35	0.42	1.48	-0.07
	[1.90]	[0.84]	[2.23]	[1.95]	(0.63)	(0.90)
Log(population)	15.17	14.71	14.99	15.16	0.46	-0.17
	[1.07]	[0.98]	[1.05]	[1.08]	(0.45)	(0.46)
Income per capita	0.70	0.58	3.79	3.77	0.11	0.02
	[0.57]	[0.49]	[1.32]	[1.36]	(0.04)	(0.27)
Log(income per cap.)	8.53	8.31	10.48	10.47	0.21	0.01
	[0.80]	[0.86]	[0.35]	[0.37]	(0.06)	(0.07)
Urban pop. %	69.43	54.17	80.92	69.59	15.25	11.33
	[15.55]	[11.03]	[11.60]	[14.69]	(5.51)	(5.66)
Minority %	10.30	16.60	27.55	22.09	-6.30	5.46
	[8.81]	[10.51]	[14.46]	[11.98]	(4.03)	(5.50)
Unemployed %	6.72	6.56	5.27	5.41	0.16	-0.14
	[1.99]	[2.33]	[2.07]	[1.82]	(0.65)	(0.45)
States	11	10	11	11		

This table compares characteristics of the states in the highest and lowest 20% for first innovations. Averages are taken over the entire time period. Standard deviations are in brackets and standard errors in parentheses. Standard errors for the difference are clustered by state. Hawaii, Washington D.C., and Alaska are excluded.

Table 3: Policy diffusion predictors by decade

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.: Policy adoption (logit)	50-60s	70s	80s	90s	00s	10s
Proportion of states adopted	2.93	-0.03	1.72	2.99	2.20	2.84
	(0.22)	(0.23)	(0.17)	(0.13)	(0.19)	(0.24)
Standardized log(pop)	0.05	0.03	-0.01	0.04	-0.02	0.06
	(0.07)	(0.06)	(0.03)	(0.05)	(0.04)	(0.06)
Standardized income per cap.	0.11	0.23	-0.06	-0.04	-0.13	-0.07
	(0.10)	(0.06)	(0.04)	(0.06)	(0.04)	(0.08)
Standardized urban %	0.08	-0.12	0.13	0.12	0.16	-0.01
	(0.09)	(0.07)	(0.03)	(0.03)	(0.06)	(0.07)
Standardized Republican vote-share	-0.08	-0.11	-0.06	-0.00	-0.03	-0.10
	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)	(0.07)
Divided state government	0.10	-0.15	0.09	-0.03	-0.12	-0.04
	(0.10)	(0.08)	(0.06)	(0.05)	(0.08)	(0.09)
Measure of adoption among other states closest in:						
Demographic index (pop., income per cap., urban %)	0.40	0.12	0.21	0.18	0.23	0.24
	(0.07)	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)
Distance	0.45	0.38	0.24	0.35	0.28	0.36
	(0.07)	(0.07)	(0.07)	(0.05)	(0.05)	(0.07)
Republican vote-share	0.09	0.13	0.06	0.18	0.38	0.38
	(0.07)	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)
State gvnt. partisanship (unified Dem./unified Rep./divided)	0.04	0.15	0.11	0.11	0.41	0.52
	(0.08)	(0.11)	(0.07)	(0.06)	(0.07)	(0.07)
State gvnt. partisanship×Divided gvnt.	0.15	-0.41	-0.02	0.02	-0.45	-0.82
	(0.17)	(0.24)	(0.15)	(0.14)	(0.13)	(0.13)
Baseline P(Adopt)	0.03	0.03	0.03	0.05	0.05	0.06
Observations	58814	53268	75259	90165	69305	32602
Policies	162	196	272	380	330	194
Pseudo R^2	0.22	0.13	0.14	0.20	0.18	0.20

This table shows the coefficients from a logit regression. Standard errors are clustered by state. The baseline hazard for each policy is parametrized by policy fixed effects for each decade. The closest states are defined as the third of all the states with the smallest absolute value difference in each characteristic. The difference in the demographic index is calculated by first standardizing the two-year moving averages of log population, urban %, and log income per capita across all states in each year, then taking the absolute difference in each of the three standardized demographic variables, and finally averaging the three 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 Republic 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.

Table 4: 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. Source of policy								
NBER (R^2: $0.23, 0.25, 0.20$; $N_{\text{pol.}}$: $14, 30, 43$)								
0.63	0.36	0.46	0.09	0.27	0.50	-0.71	0.07	0.51
(0.15)	(0.11)	(0.10)	(0.15)	(0.11)	(0.08)	(0.21)	(0.14)	(0.08)
SPID (R^2: $0.16, 0.16, 0.17$; $N_{\text{pol.}}$: $253, 390, 332$)								
0.42	0.30	0.27	0.15	0.12	0.35	0.07	0.05	0.49
(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.06)	(0.04)	(0.06)
Interstate Compacts (within SPID) (R^2: $0.14, 0.13, 0.22$; $N_{\text{pol.}}$: $22, 26, 15$)								
0.47	0.70	0.09	0.13	-0.07	0.04	0.03	-0.12	0.28
(0.11)	(0.13)	(0.13)	(0.09)	(0.18)	(0.13)	(0.11)	(0.26)	(0.20)
Panel B. Policy area								
Economics (R^2: $0.10, 0.21, 0.19$; $N_{\text{pol.}}$: $48, 63, 71$)								
0.64	0.36	0.22	0.14	0.14	0.22	0.12	0.12	0.29
(0.09)	(0.07)	(0.07)	(0.12)	(0.07)	(0.08)	(0.09)	(0.10)	(0.10)
Non-Economics (R^2: $0.17, 0.16, 0.17$; $N_{\text{pol.}}$: $219, 357, 304$)								
0.38	0.29	0.33	0.15	0.13	0.41	0.02	0.05	0.53
(0.06)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.07)	(0.05)	(0.06)
Panel C. By state characteristics								
Third of states with highest Republican vote-share (R^2: $0.16, 0.17, 0.18$; $N_{\text{pol.}}$: $267, 420, 375$)								
0.32	0.32	0.28	0.10	0.12	0.34	0.08	0.07	0.43
(0.09)	(0.05)	(0.07)	(0.10)	(0.07)	(0.08)	(0.08)	(0.06)	(0.09)
Third of states with most neutral vote-share (R^2: $0.16, 0.17, 0.18$; $N_{\text{pol.}}$: $267, 420, 375$)								
0.38	0.30	0.27	0.11	0.05	0.16	0.03	0.07	0.43
(0.08)	(0.06)	(0.08)	(0.07)	(0.05)	(0.06)	(0.11)	(0.06)	(0.10)
Third of states with highest Democratic vote-share (R^2: $0.16, 0.17, 0.18$; $N_{\text{pol.}}$: $267, 420, 375$)								
0.58	0.30	0.34	0.16	0.19	0.57	0.05	0.04	0.59
(0.08)	(0.10)	(0.08)	(0.10)	(0.08)	(0.09)	(0.10)	(0.08)	(0.09)
Third of states with highest population (R^2: $0.16, 0.17, 0.18$; $N_{\text{pol.}}$: $267, 420, 375$)								
0.39	0.22	0.27	0.27	0.04	0.33	0.11	0.02	0.59
(0.09)	(0.09)	(0.09)	(0.06)	(0.05)	(0.06)	(0.12)	(0.08)	(0.05)
Third of states with lowest population (R^2: $0.16, 0.17, 0.18$; $N_{\text{pol.}}$: $267, 420, 375$)								
0.50	0.37	0.39	0.07	0.17	0.38	-0.05	0.02	0.39
(0.09)	(0.07)	(0.09)	(0.08)	(0.04)	(0.07)	(0.08)	(0.06)	(0.09)

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

In Panel A, the model is estimated separately for policies in NBER working papers, the SPID data set, and the Interstate Compacts source from the SPID data set. The Interstate Compacts are policies on which states cooperate to address a common problem.

In Panel B, the results are reported separately for policies in the "Economics" policy area and all other policies.

In Panel C, the states are first partitioned into thirds each year based on a characteristic (e.g., Republican vote-share in the most recent presidential election). The coefficients are then allowed to differ and reported separately for each third. The exercise is implemented for two characteristics: Republican vote-share and population.

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
Proportion of states adopted	0.95	2.27	2.38	0.92	2.28	2.41
	(0.20)	(0.14)	(0.20)	(0.20)	(0.15)	(0.21)
Measure of adoption among other states closest in:						
Demographic index	0.46	0.18	0.21	0.32	0.09	0.13
	(0.08)	(0.05)	(0.06)	(0.08)	(0.05)	(0.06)
Distance	0.38	0.29	0.25	0.21	0.19	0.16
	(0.06)	(0.07)	(0.06)	(0.10)	(0.08)	(0.07)
Republican vote-share	0.19	0.13	0.38	0.14	0.09	0.27
	(0.07)	(0.04)	(0.05)	(0.06)	(0.04)	(0.05)
State gvnt. partisanship	0.09	0.10	0.44	0.08	0.10	0.42
	(0.13)	(0.07)	(0.08)	(0.12)	(0.07)	(0.08)
State gvnt. partisanship×Divided gvnt.	-0.15	-0.01	-0.55	-0.18	-0.04	-0.50
	(0.23)	(0.15)	(0.15)	(0.22)	(0.15)	(0.14)
Migration flows				0.14	0.01	0.12
				(0.13)	(0.10)	(0.09)
Voter preferences (ANES & GSS)				0.26	0.28	0.15
				(0.09)	(0.09)	(0.08)
Index of public opinion measures				0.19	0.16	0.20
				(0.06)	(0.04)	(0.04)
Observations	53757	107999	67504	53757	107999	67504
Policies	227	414	359	227	414	359
Pseudo R^2	0.16	0.17	0.19	0.16	0.17	0.19

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 demographics, distance, Republican vote-share, and state government partisanship. All regressions include an indicator for divided state governments as a control (coefficient 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 B). 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 (2018) 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. Standard errors clustered by states are in parentheses.

Table 6: Vaccine regulations and COVID-19 policies

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

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

Online Appendix

A Alternate measures of correlated adoptions

In the hazard model analysis (Section 4.2), we use a two-sided "likelihood" as the baseline measure of how concentrated the adoption of a policy has been among states that are (dis)similar in each dimension. We tried other measures that may be simpler but did not perform as well in specification checks. In this section, we define three alternate measures and discuss their shortcomings. Reassuringly, as shown in Table A.6, we find that the dynamic patterns of policy diffusion remain similar regardless of the measure used.

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

To start with the baseline likelihood measure, Figure A.11a shows that its range goes from -1 to 1 and is fairly consistent across the domain of total adopters. Figure A.11e then plots the coefficients on the first three groups of 5 adopters and on the following adopters for the two dimensions of interest, distance and Republican vote-share. There does not appear to be any systematic ordering or reversals in the coefficients across the bins, and the coefficients generally remain within each other's confidence intervals. These checks return a favorable evaluation of the baseline measure.

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

Proportion of states in the closest third that are adopters ($a^k/15$)**.** As Figure A.11b shows, the range of this measure is limited in both the early and late stages of a policy's life-cycle. For instance, if there are 5 total adopters of the policy, then the measure can range only from 0/15 to 5/15. From 16 to 32 total adopters, the measure ranges from 0 to 1. After 32 total adopters, the range shrinks toward the upper region. Another downside is that this measure does not incorporate information about the total number of adopters, though intuitively, we should consider a case when there are 10 total adopters of a policy and all 10 are in the closest third as a stronger sign of correlated adoptions than the case when there are 30 total adopters of which 10 are in the closest third. In light of these drawbacks, Figure A.11f finds that the coefficients on the first bin of 5 adopters are significantly lower, and even become negative, compared to the coefficients for the rest of the bins. Hence using this measure in the main specification would lead to a poor fit of the early stage diffusion process.

Proportion of all adopters that are in the closest third (a^k/A)**.**[13] As shown in Figure A.11c, this measure ranges from 0 to 1 until there are 16 total adopters, at which point there must be more total adopters than adopters in the closest third and thus the upper bound of the range decreases. From 33 total adopters, the lower bound of the range becomes strictly positive, since there must be at least one adopter in the closest third, and continues to increase. Given this narrowing range, similar concerns arise as with the previous measure. Figure A.11g confirms these issues, and shows that the coefficients are systematically increasing in the bins. For this measure, a single coefficient in the specification would be overly sensitive for the early adopters and too unresponsive for the later adopters.

Proportion of states in the closest third that adopters minus proportion of all states that are adopters $\left(\frac{a^k}{15} - \frac{A}{47}\right)$**.** Figure A.11d plots the range of this measure. The difference between the upper and lower bounds linearly increases in the number of total adopters and is maximized at 1 while the number of total adopters is between 15 and 32. After 32 total adopters, the range begins to linearly decrease. Figure A.11h shows that this measure is not as poorly behaved as the previous two in the logit model, but the coefficients do seem to systematically decrease across the bins in the distance dimension. The pseudo-R^2 from Row 10 of Table A.6 also indicates that this measure provides a poorer fit of the data compared to the baseline measure (Row 5 of Table A.6).

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

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

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

opinion from political science. This section describes the construction of these measures in detail.

B.1 Measuring voter preferences using the ANES and GSS

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

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

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

- (ANES: VCF0837) *There has been some discussion about abortion during recent years. Which one of the opinions on this page best agrees with your view?*

    1. *By law, abortion should never be permitted.*
    2. *The law should permit abortion only in case of rape, incest, or when the woman's life is in danger.*
    3. *The law should permit abortion for reasons other than rape, incest, or danger to the woman's life, but only after the need for the abortion has been clearly established.*
    4. *By law, a woman should always be able to obtain an abortion as a matter of personal choice.*

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

- (GSS: cuthours) *Here are some things the government might do for the economy. Circle one number for each action to show whether you are in favor of it or against it. "Reducing the work week to create more jobs." (5-POINT SCALE SHOWN TO RESPONDENT)*

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

We then restrict the final sample to 49 questions in the ANES and 196 in the GSS that have been asked for at least 10 years, to ensure the responses reflect voter preferences on longstanding, key issues and to reduce noise from compositional changes in the sample. For example, this restriction drops a question asking whether the respondent thought the United States should cooperate more with the Soviet Union, which was asked only from 1980-88. We link questions in the GSS that are under different variable names but are qualitatively on the same policy preference. For example, the GSS variable *aidneedy* asks, *"For students whose parents have a low income, should the government provide grants that would not have to be paid back, provide loans which the student would have to pay back, or should the government not provide any financial assistance?"* This question is only asked in the 1985 survey, but we link this question to *aidcol* (shown in the last example above), which has been asked for 26 years over 1990-2016. Hence, we keep *aidneedy* as well. Overall, Figure A.7b shows that there are typically over 10 questions represented from the 1960s, and over 20 from the 1970s.

State representation One downside of the ANES and GSS surveys, depicted in Figure A.7a, is that not all states are sufficiently represented in every wave of the survey. In fact, there are 15 states (Delaware, Idaho, Kansas, Maine, Montana, Nebraska, Nevada, New Hampshire, New Mexico, North Dakota, Rhode Island, South Dakota, Vermont, West Virginia, and Wyoming) that are missing for at least a decade. To prevent the results being contaminated from the addition of these states only in certain time periods, we drop them entirely when we use the ANES and GSS measure of voter preferences. This means that whenever we include the ANES and GSS measure, we also re-calculate the measure of similarity in Equation 2 for all the other dimensions, since there are now 33 states in the sample.

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

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

Matching voter preference questions to policy areas In Columns 1-3 of Table A.7b, we extend the analysis by constructing measures of voter preferences that are specific to each policy area. A team of 10 undergraduate research assistants categorized each question used in the ANES and GSS measure into one of the six policy areas (Table 1c) or as none of them, based on the set of SPID and NBER policies classified under each policy area. Each question was assigned to two research assistants to code independently. The coders agreed on the policy area for 71% of the questions on the first attempt, which indicates that most of the questions were straightforward to classify. For the remaining 29%, we discussed each question as a group before settling on the final categorization. The composition of the questions over time by policy area is shown in Figure A.7c. The questions in the "Environment and Energy" policy area are missing until the 1970s, and even then, there are no respondents for those questions in Kentucky, Mississippi, and Kentucky until the 1980s; hence, we drop policies in "Environment and Energy" for this analysis.

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

Including voter sentiment In Columns 4-6 of Table A.7b, we use a broader measure to also capture voter sentiment that could be relevant for their policy positions. We add questions such as "thermometers" about specific groups, (e.g., on a scale of 0-100, how the respondent feels about labor unions, homosexuals, or people on welfare), whether society should make sure that everyone has an equal opportunity to succeed, and whether it matters that the respondent votes or not. Figure A.7b shows the number of voter sentiment questions in this broader measure over time. Reassuringly, this broader measure finds similar results.

B.2 Measures of public opinion from political science research

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

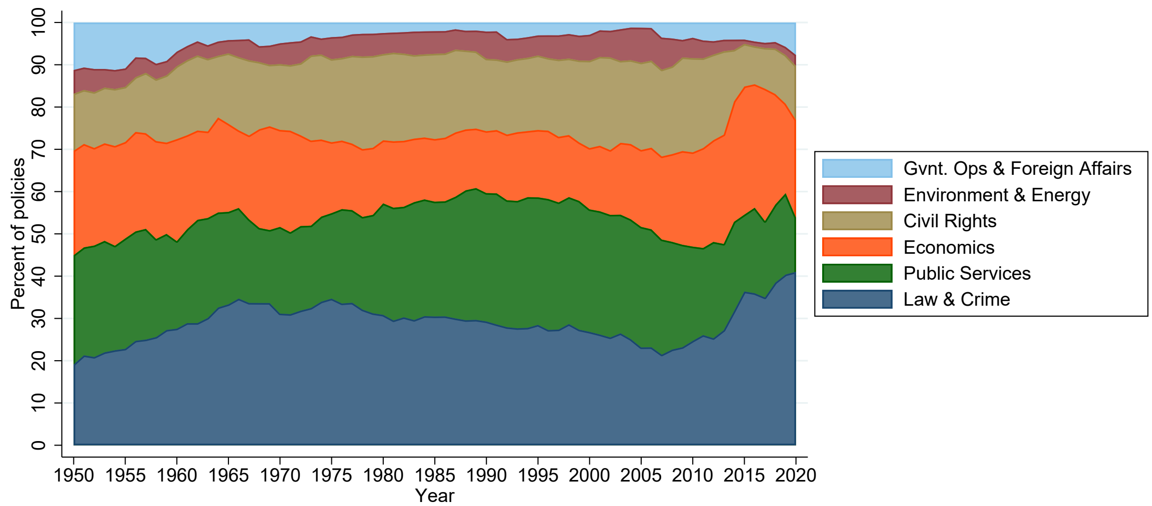
- the mass social and economic policy liberalism scores (1936-2014) from Caughey and Warshaw (2018), which are estimated from surveys (including the ANES and GSS) as well as polling data (such as the Gallup),
- the state policy mood measure (1956-2020) from Lagodny et al. (2022), which also aggregates data from public opinion surveys, and
- the updated citizen ideology measure (1960-2016) from Berry et al. (1998), which is based on interest group ratings of state representatives in Congress and state election results.

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

In addition to the analysis in Table 5, we also investigate the role of each measure in the index separately in Columns 4-6 of Table A.7a. For the measures that end before 2020, we extend the measure from the last year (2014 in Caughey and Warshaw, 2018, and 2016 in Berry et al., 1998) through 2020. The Berry et al. (1998) measure strongly predicts policy diffusion in the 1960-70s, but less so in the later time periods. Interestingly, the Caughey and Warshaw (2018) measures have become more predictive in recent times, and more so for the social liberalism measure, which is consistent with the results in Caughey and Warshaw (2018). Nevertheless, the escalating role of state government partisanship far exceeds the explanatory power of any measure of voter preferences in the last two decades.

Figure A.1: Summary statistics: Policy area composition and adoption speed

(a) Composition of policy areas over time



(b) Speed of adoption by time period

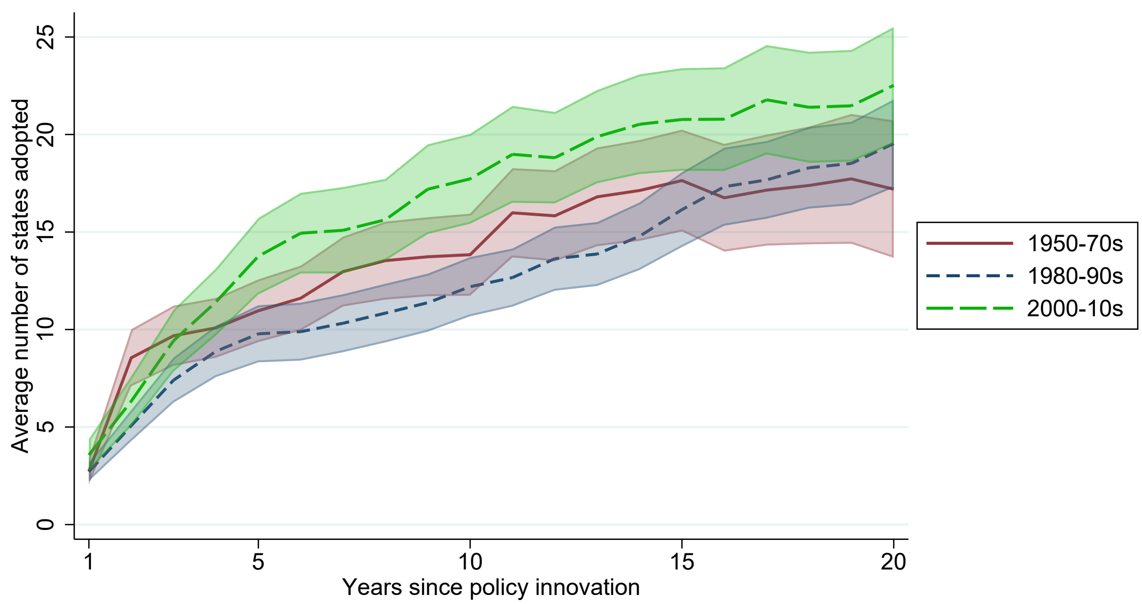
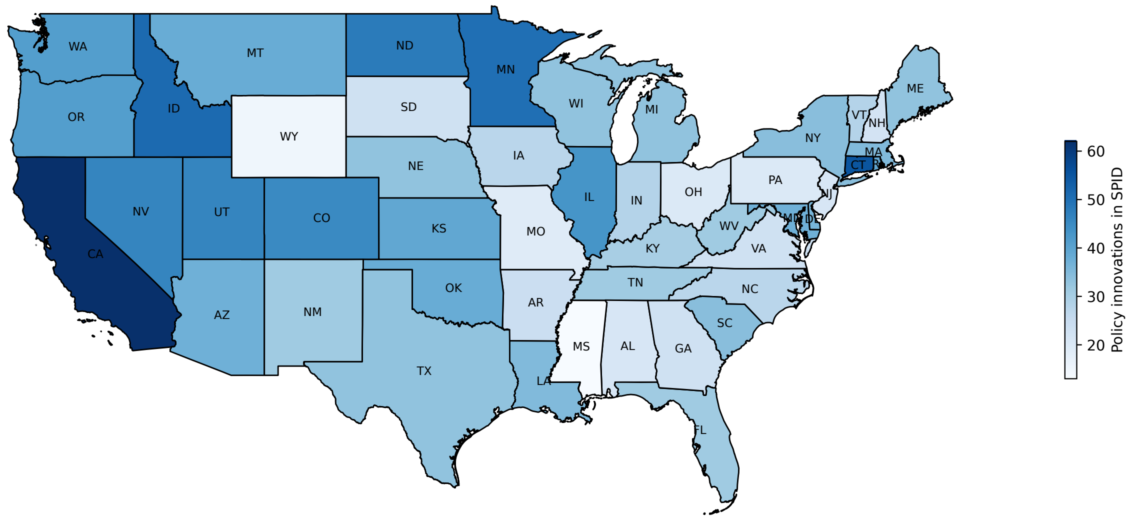


Figure A.2: Innovating states

(a) SPID policies



(b) NBER policies

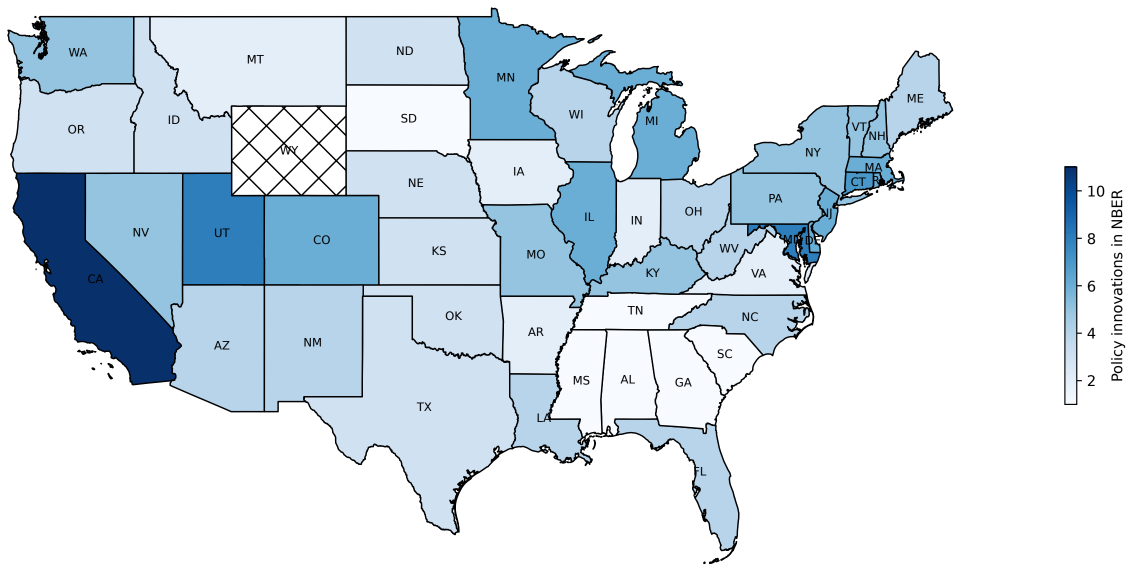
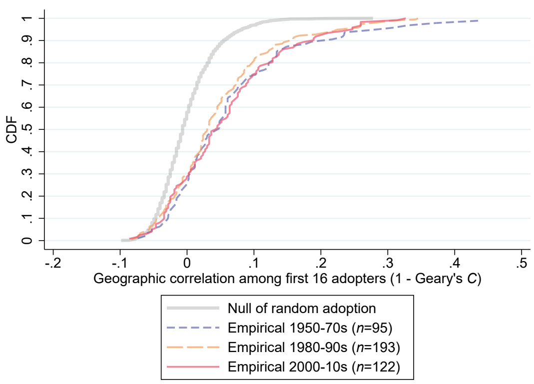
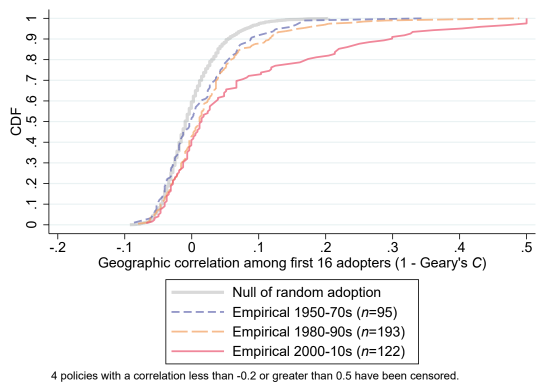


Figure A.3: Correlation in geography and politics among adopters (alternate thresholds)

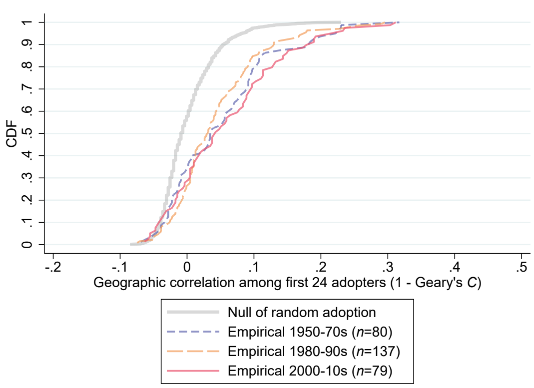
(a) Correlation in geographic distance (first **16** adopters)



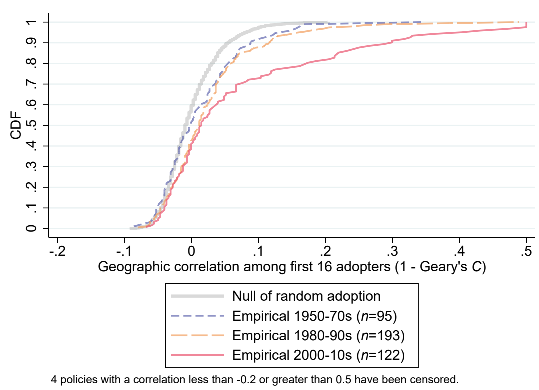
(b) Correlation in Republican vote-share (first **16** adopters)



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



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



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

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

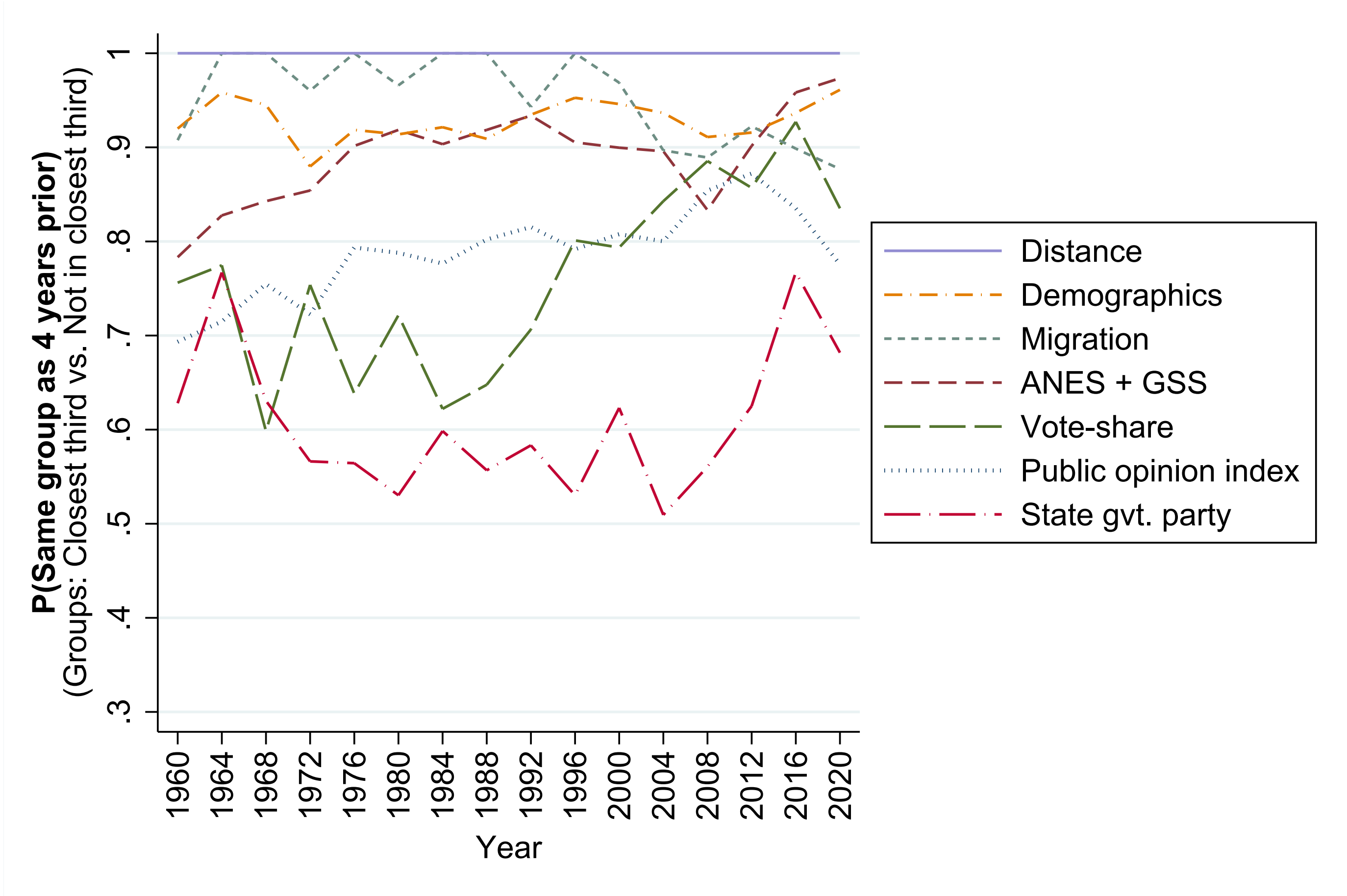
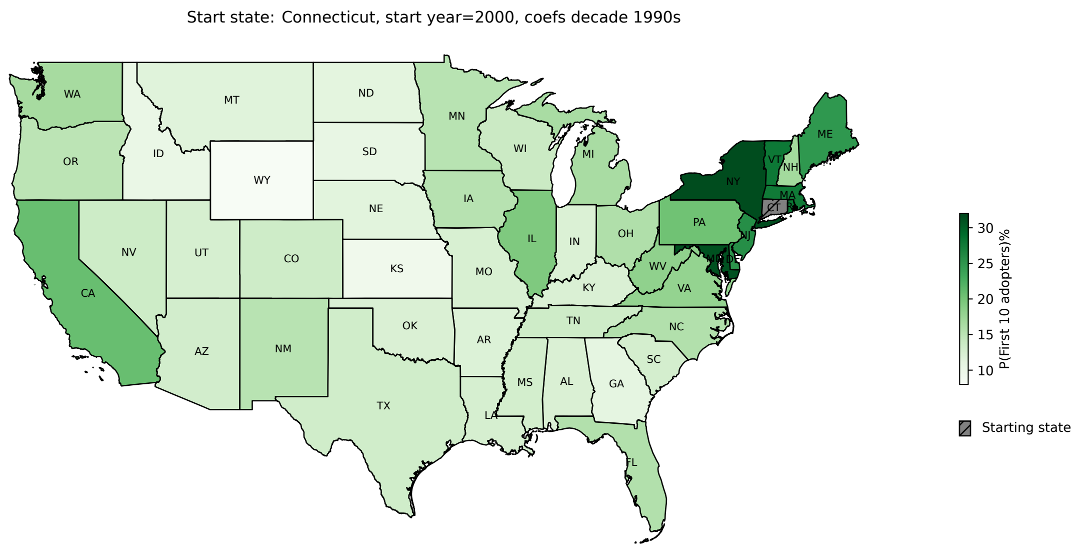


Figure A.5: Simulated policy diffusion

(a) Coefficients from 1990s (Connecticut)



(b) Coefficients from 2010s (Connecticut)

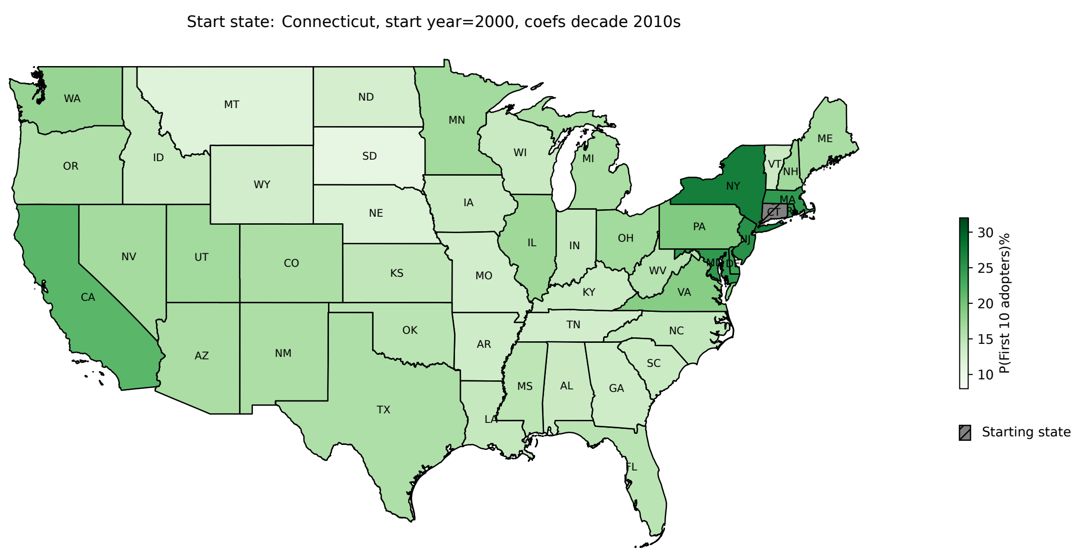
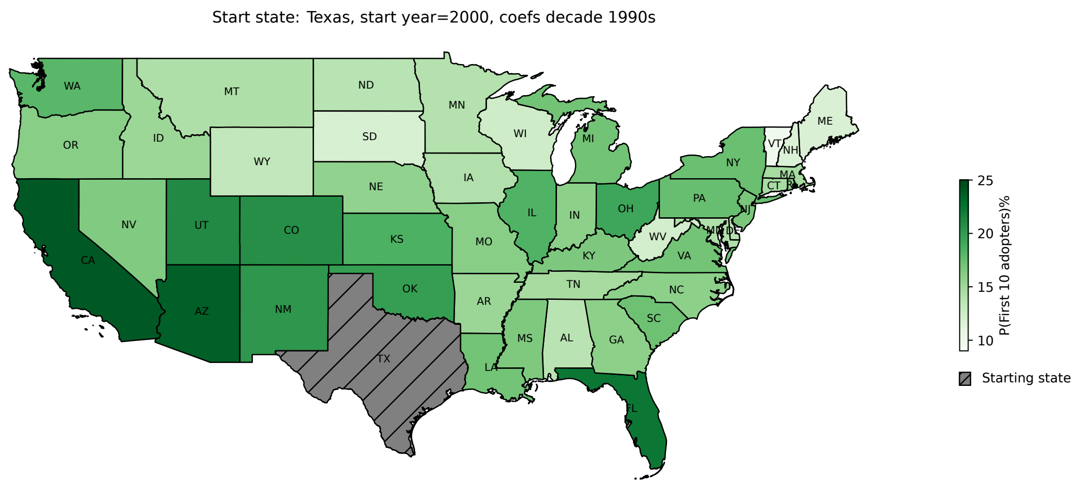


Figure A.5: Simulated policy diffusion

(c) Coefficients from 1990s (Texas)



(d) Coefficients from 2010s (Texas)

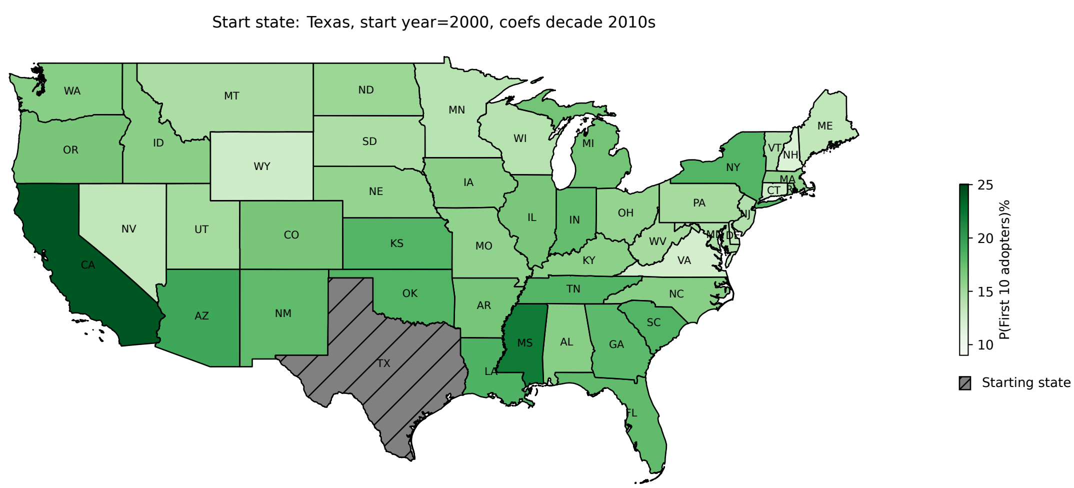
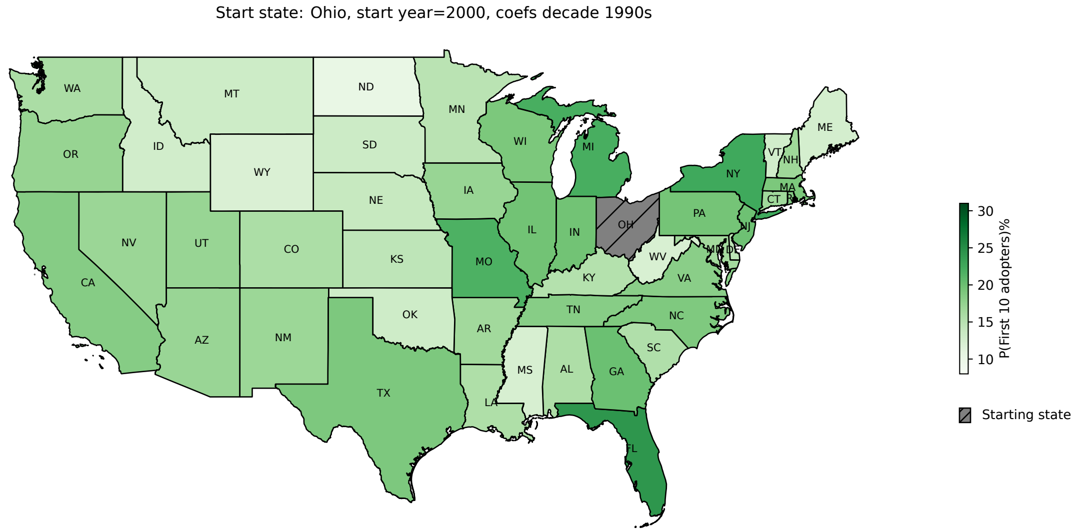


Figure A.5: Simulated policy diffusion

(e) Coefficients from 1990s (Ohio)



(f) Coefficients from 2010s (Ohio)

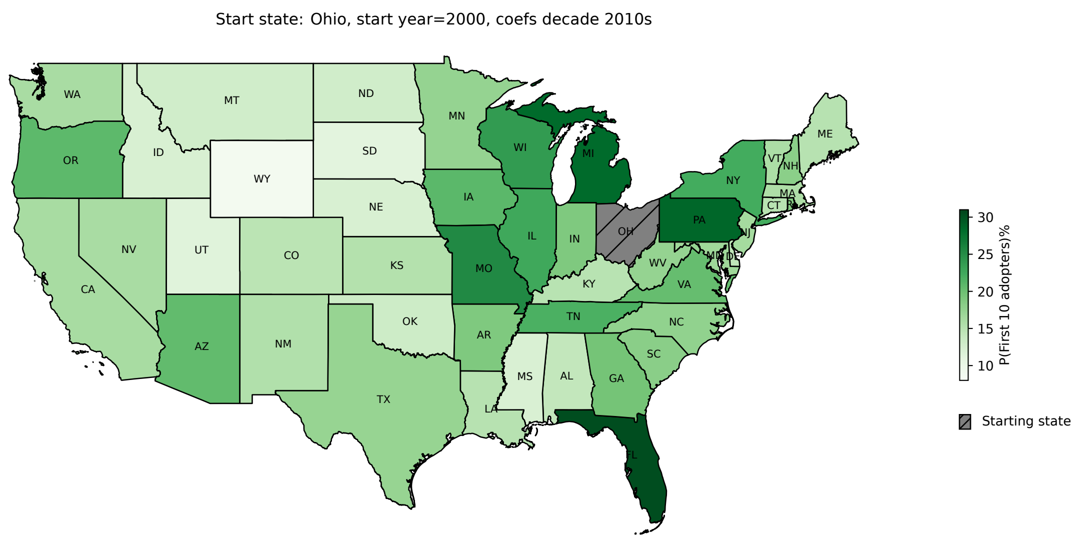
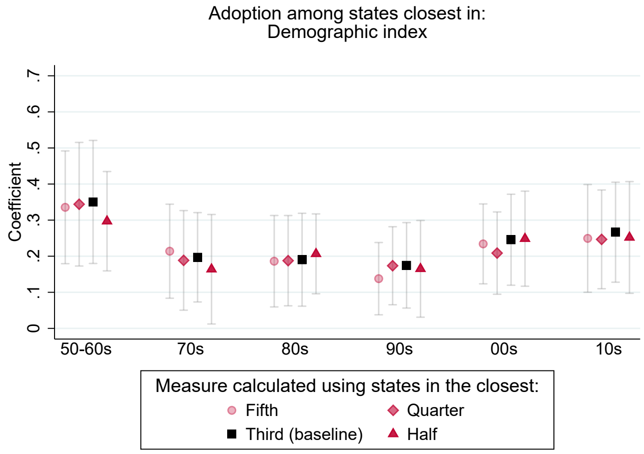
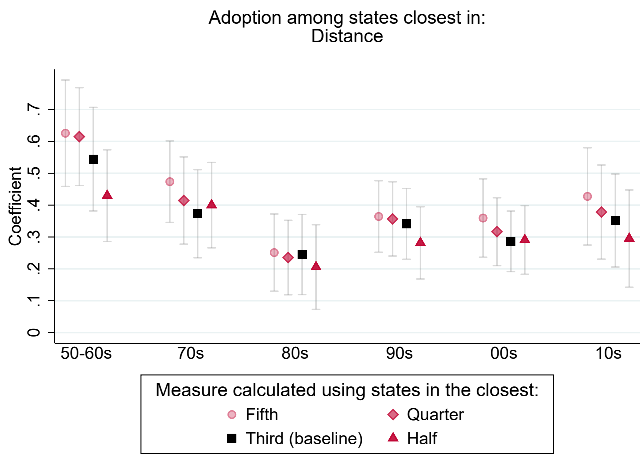


Figure A.6: Robustness checks: Threshold of closest states

(a) Dimension: Demographic index



(b) Dimension: Distance



(c) Dimension: Republican vote-share

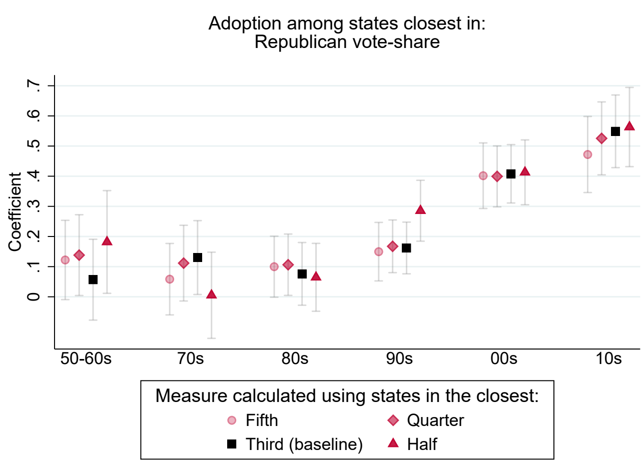
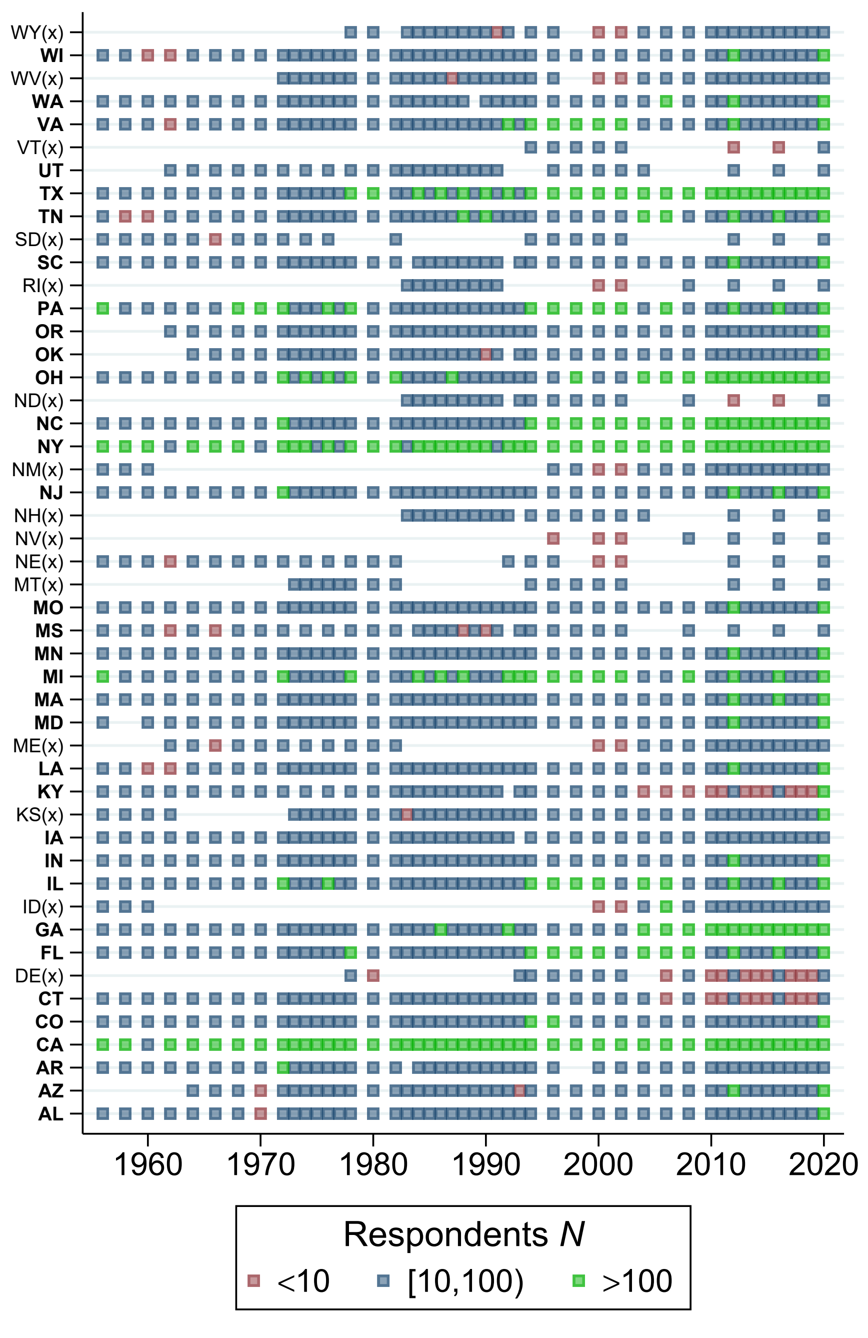


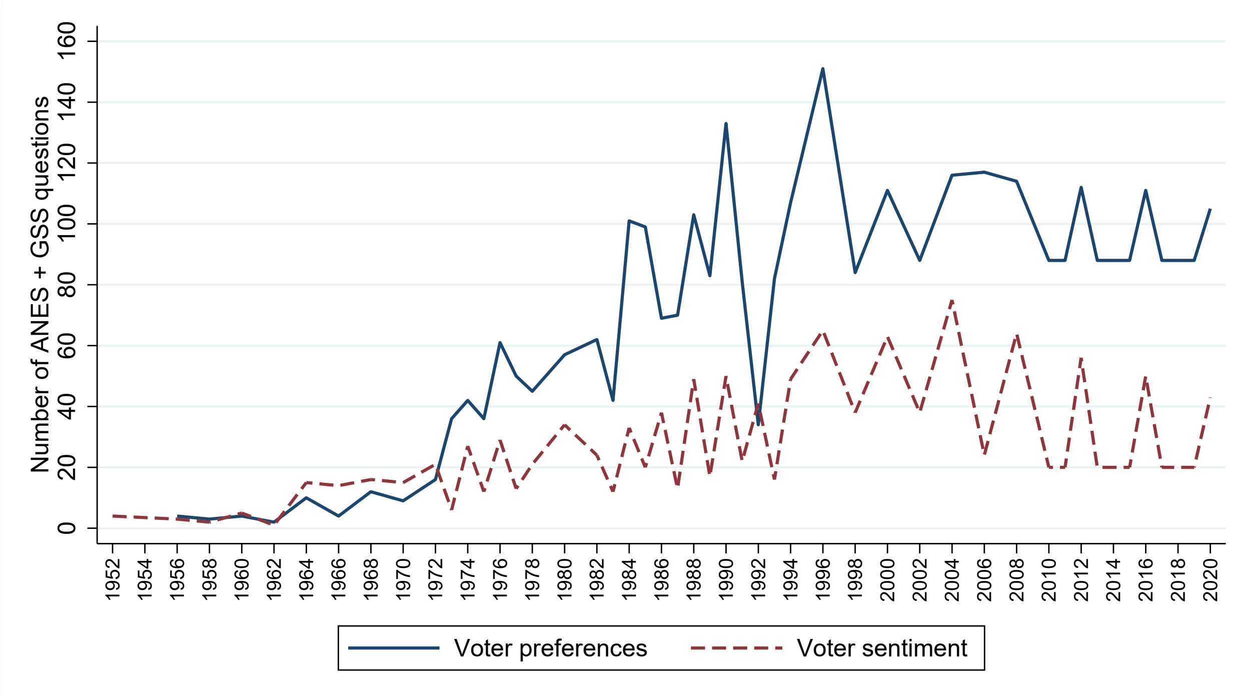
Figure A.7: Measuring voter policy preference from ANES and GSS

(a) State representation in ANES



States marked by "(x)" in Figure A.7a are excluded from the analysis using this voter preference measure due to insufficient coverage.

(b) Number of questions



(c) Questions by policy area

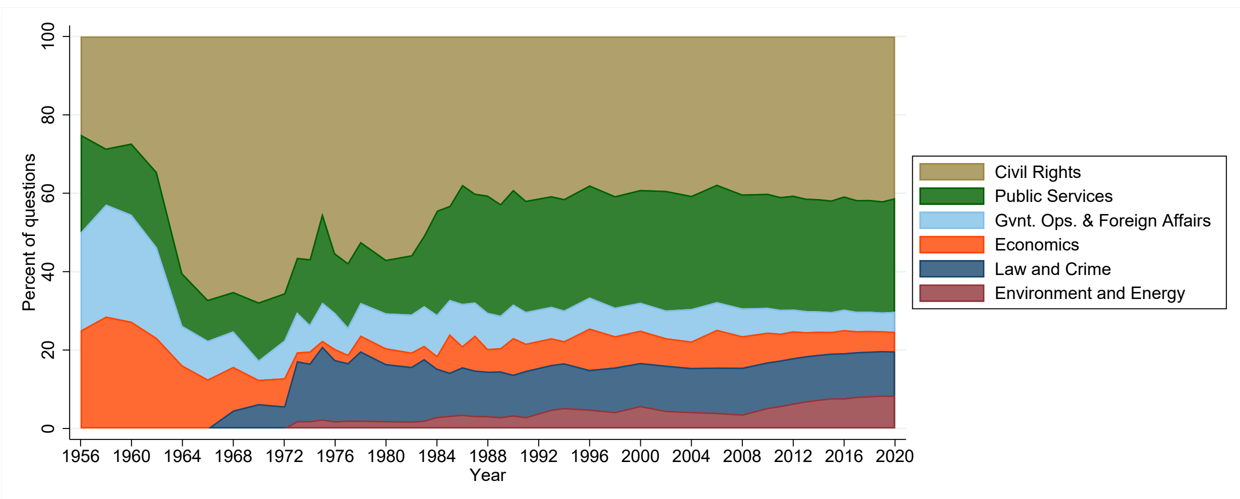
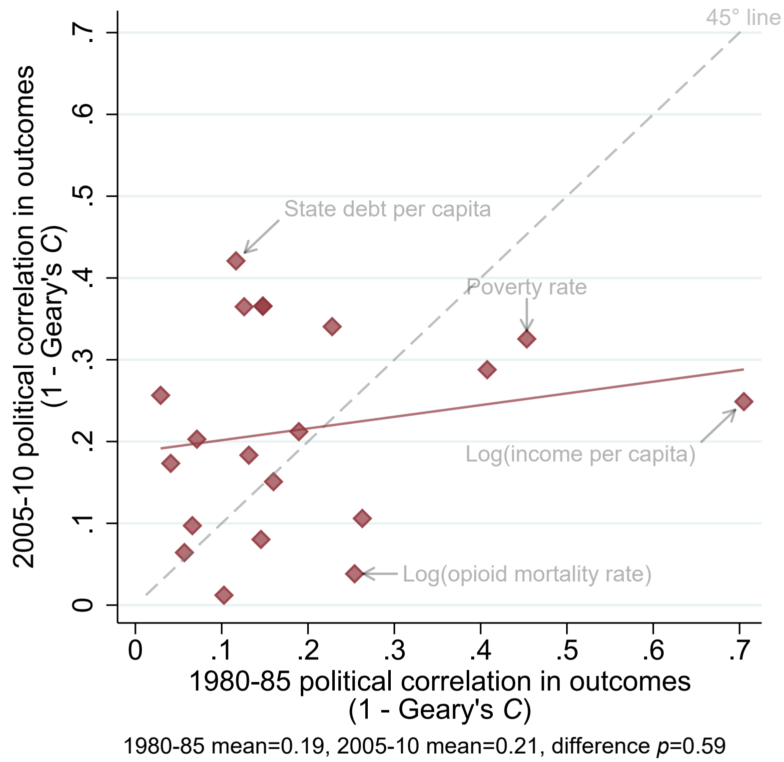


Figure A.8: Correlation of policy outcomes: 1980-85 vs. 2005-10

(a) Political correlation



(b) Geographic correlation

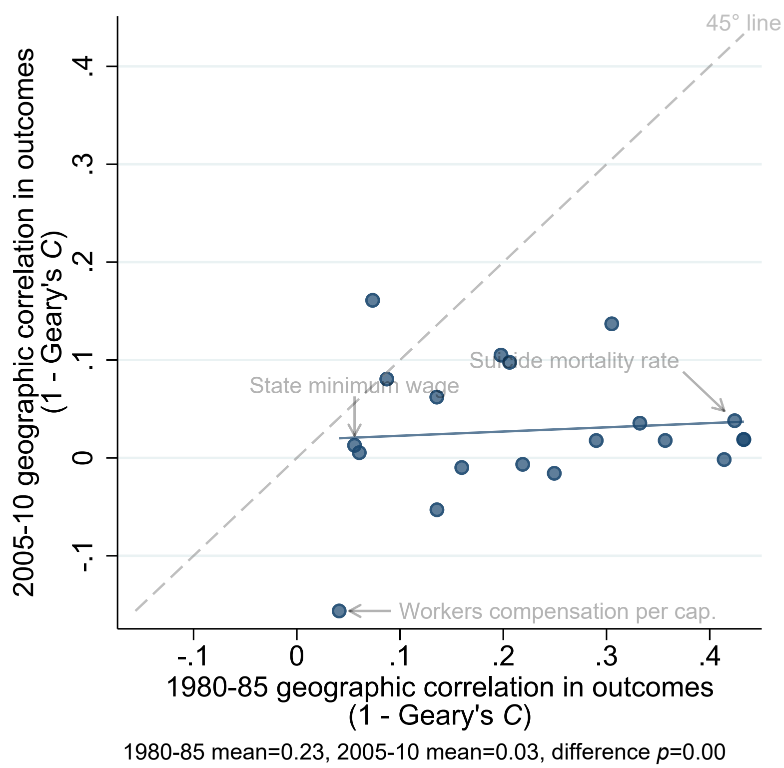
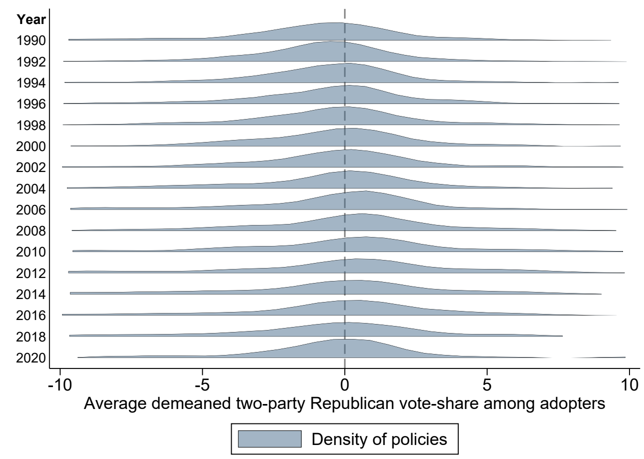
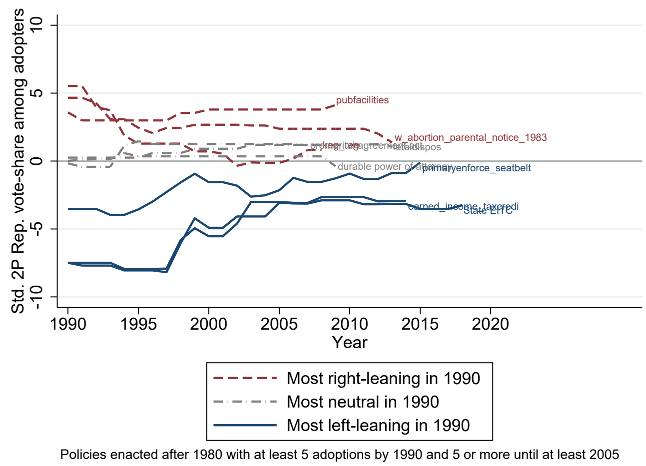


Figure A.9: Categorizing the ideology of policies for event study analysis

(a) Distribution of policy ideologies



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



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

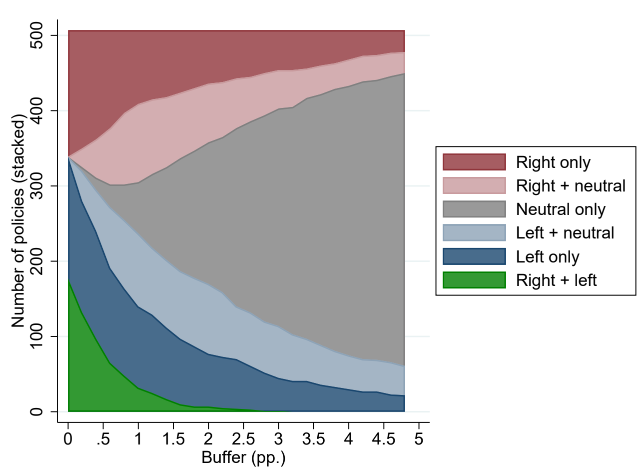
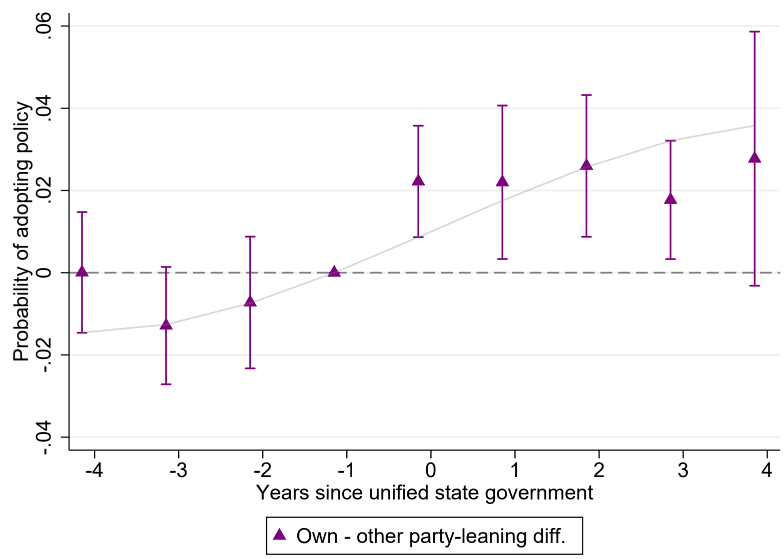
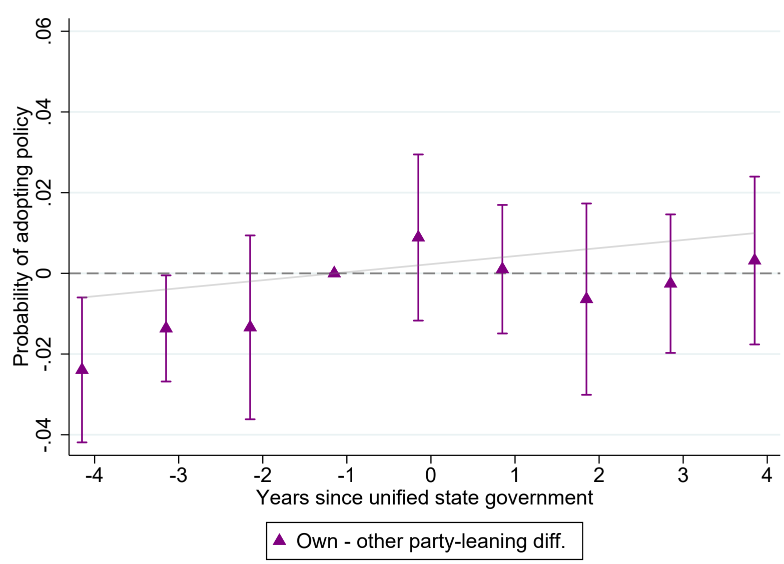


Figure A.10: Event study from switches in state government party control

(a) Events during 1990-2020



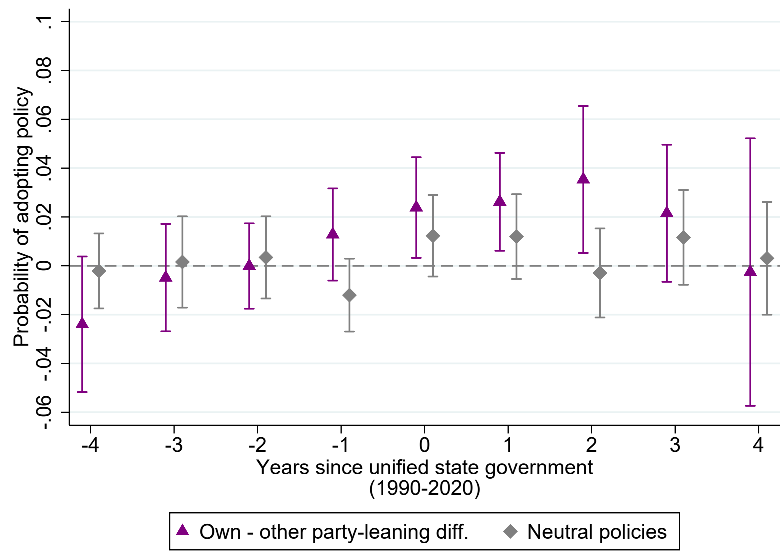
(b) Events during 1950-1989



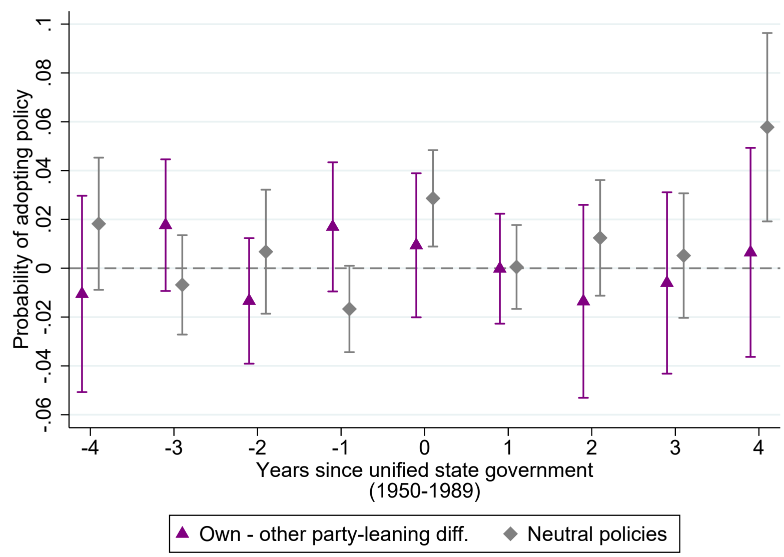
These figures show the event studies estimates from Figures 8a-8b with the most plausible confound path (Freyaldenhoven et al., forthcoming) traced in the gray curve.

Figure A.10: Event study from switches in state government party control (de Chaisemartin and D'Haultfœuille estimator)

(c) Events during 1990-2020



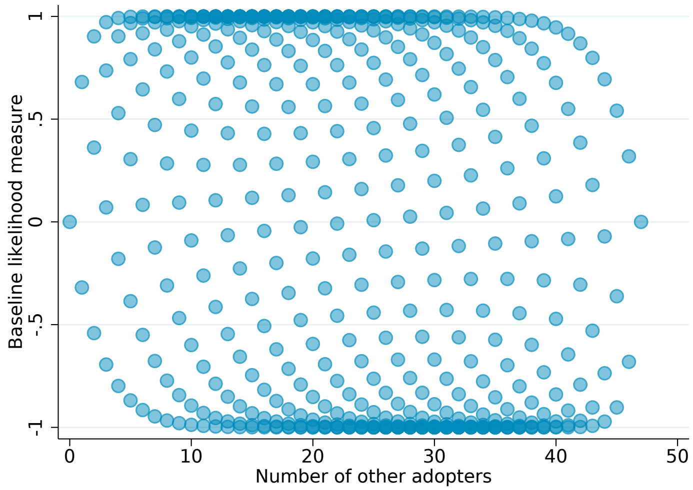
(d) Events during 1950-1989



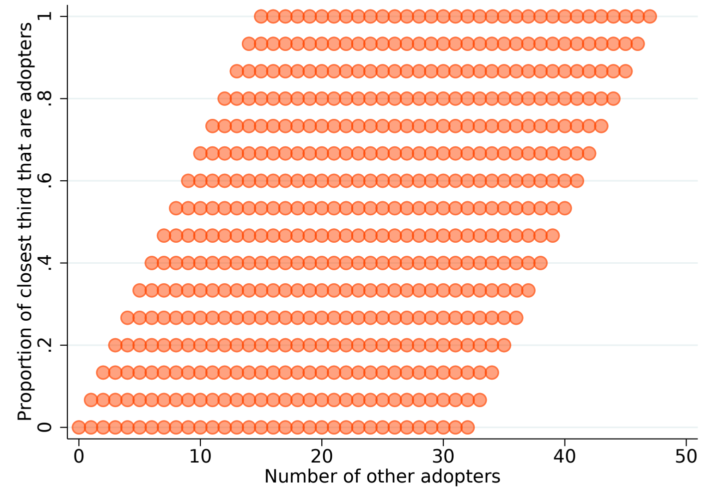
These figures show the event study estimates for switches to unified party control of state governments from the de Chaisemartin and D'Haultfœuille (2020) estimator. Spells of unified state party control are defined as the 4 years prior to and after the switch to the unified government. During these spells for each state, policies are categorized as aligning with the party in control, not aligning, or neither, based on the procedure described in Footnote 10. For example, the policy of medical marijuana legalization is a left-learning policy based on the standardized vote-share of past adopters. In 2011, Alabama had a unified Republican state government, and thus medical marijuana legalization is categorized as a policy not in alignment with the party in control. On the other hand, Massachusetts had a unified Democratic state government, and thus the policy is categorized as being aligned with the party in control. Outside these event windows of unified state governments, all policies for that state are categorized as neutral. To run the event study using the de Chaisemartin and D'Haultfœuille estimator, the state-policy-year panel is collapsed to the state-year average rates of adoption for aligned, not aligned, and neutral policies. The treated effects from switching to unified state governments are estimated separately for these three types of policies. 95% confidence intervals are shown from bootstrap standard errors resampling at the state level.

Figure A.11: Specification checks: Range of measure by number of adopters

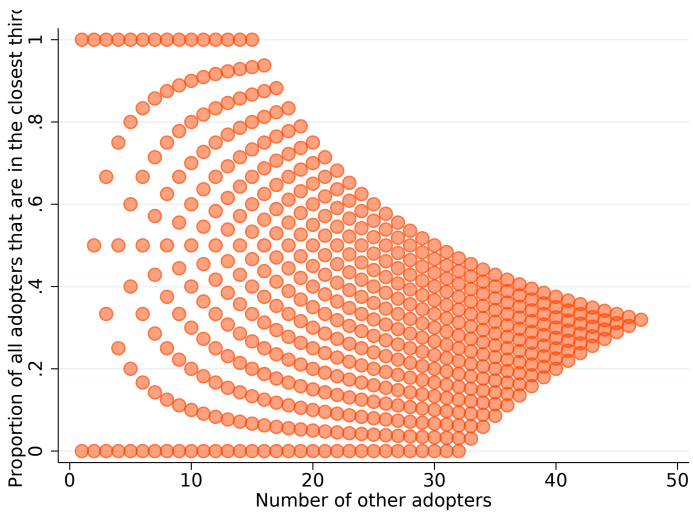
(a) Baseline two-sided likelihood measure



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



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



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

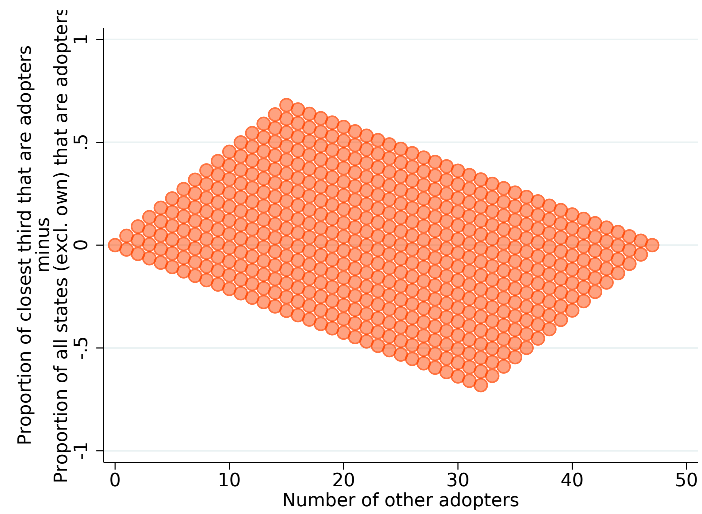
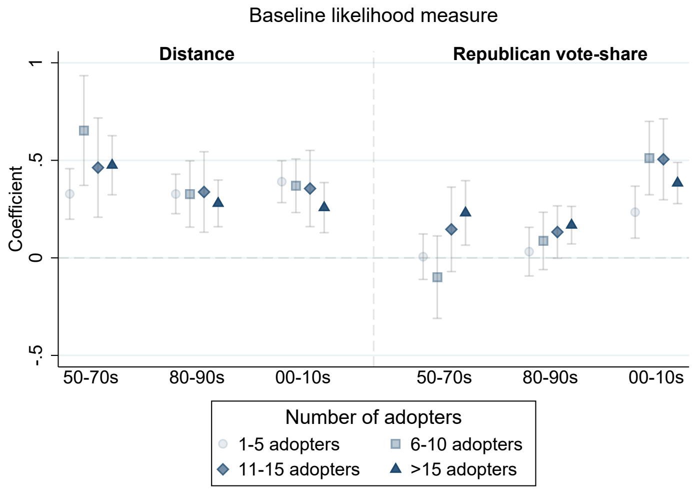
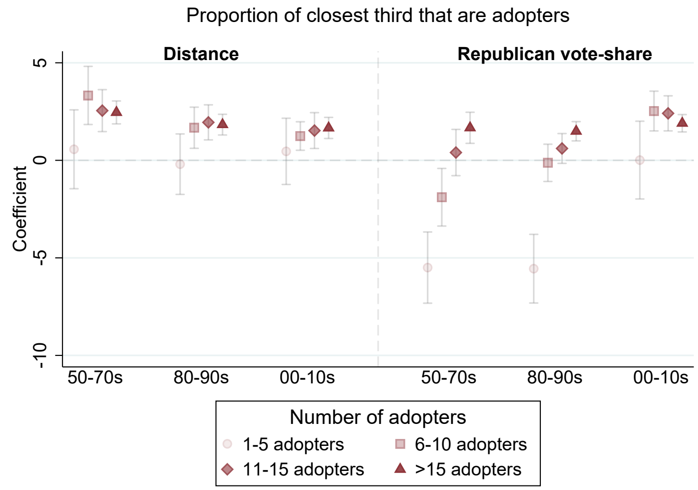


Figure A.11: Specification checks: Stability in coefficients by number of adopters

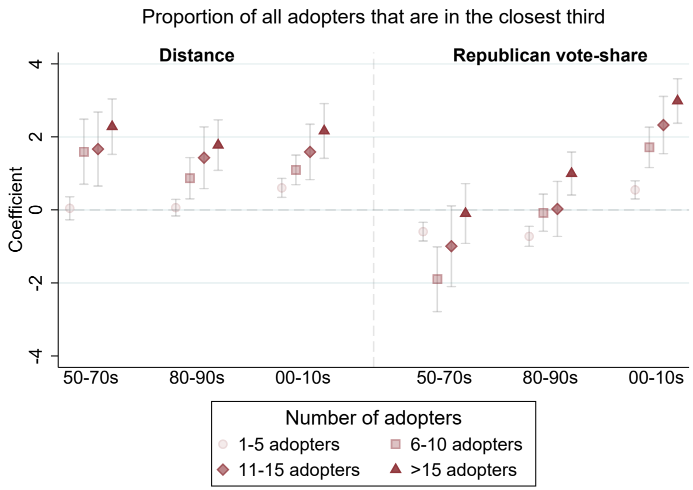
(e) Baseline two-sided likelihood measure



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



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



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

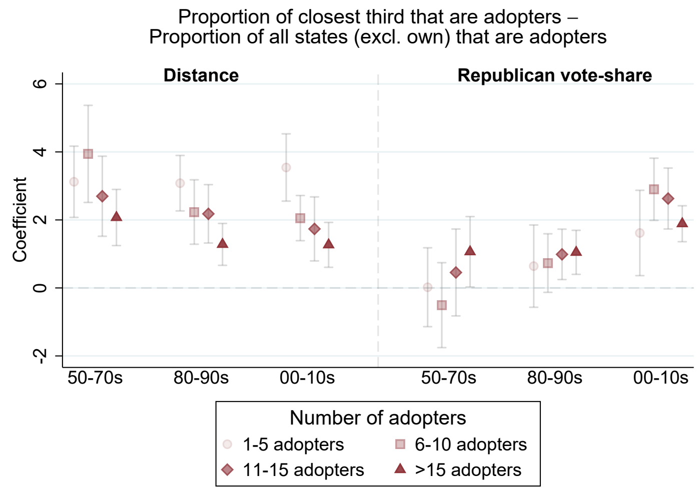


Table A.1: Summary of recent papers on policy diffusion in political science and examples in economics

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

Table A.2a: SPID sample examples

Number	Source	Description	Area	Adoptions	First year	Last year
4	Boehmke-Skinner	Abortion Pre-Roe	Civil Rights	16	1966	1972
31	Uniform Law	Framework For Donation Of Organs Other Body Parts (1987 Version)	Public Services	19	1989	2003
44	Biggers	Photo Id Voting Requirement	Civil Rights	20	1997	2013
49	Walker	Architects Licensing	Economics	47	1897	1951
61	Boehmke-Skinner	Ban On Financial Incentives For Doctors To Perform Less Costly Procedures/Prescribe Less Costly Drugs	Public Services	28	1996	2001
65	Sheprd	Requiring Helmet For Riding Bike	Public Services	20	1989	2007
67	Walker	Aid To The Blind (Social Security)	Public Services	48	1936	1953
70	Boushey	Short-Term Programs For Incarcerated Youth (Similar To Military School)	Law and Crime	22	1982	1999
77	Min Hee Go	Building Code Adoption	Public Services	43	1953	2010
102	Kreitzer	No-Protest Zone Around Abortion Clinic	Civil Rights	16	1973	2005
117	Karch	Provides All The Benefit Of Adoption Subsidy Agreement, Regardless Of State	Law and Crime	21	1984	2002
157	Uniform Law	Authorizes Courts To Adjudicate Actual Controversies Concerning Legal Rights And Duties Even Though Traditional Remedies For Damages Or Equitable Relief Are Not Available.	Law and Crime	41	1922	2008
161	Lacy	Comprehensive Remediation Reform	Public Services	17	1988	2009
166	Lacy	Placement Policies (Placement Examination, Changes To Placement Criteria	Public Services	3	1997	2008
176	Other	Notification Of Sex Offenders Is At Authority'S Discretion	Law and Crime	8	1995	2006
186	Caughey-Warshaw	Is It Legal To Use Marijuana For Medical Purposes?	Public Services	35	1996	2022
213	Uniform Law	Regulating Condemnation Of Property On Behalf Of Private And Public Entities	Public Services	1	1985	1985
219	Uniform Law	Allow Conversion Of One Kind Of Business Organization To Another, Or The Merger Of Two Or More Business Organizations Into One Organization	Economics	6	2009	2017
225	Caughey-Warshaw	Does The State Have A Public Benefit Fund For Renewable Energy And Energy Efficiency?	Environment and Energy	19	1996	2005
231	Caughey-Warshaw	Is There A State Estate Tax?	Economics	23	2009	2009
288	Caughey-Warshaw	Does The State Require Background Checks For Private Handgun Sales?	Law and Crime	13	1935	1996
295	Boehmke-Skinner	Harassment Crime	Law and Crime	10	1998	2001
333	Other	Reforms The Process Defendants Use To Claim Insanity, Including The Standard Or Burden Of Proof	Law and Crime	34	1975	1998
344	Other	Internet Registry Of Sex Offenders	Law and Crime	15	1997	2004
392	Uniform Law	Regulation On Promotional Sale Of Land	Economics	7	1967	1973
425	Lacy	Merit Based Aid Program	Public Services	12	1993	2005
442	Boehmke-Skinner	Voter Registration With Driver'S License Renewal	Civil Rights	47	1976	1995
490	Boehmke-Skinner	Interstate Pest Control Compact	Economics	36	1968	2009
534	Caughey-Warshaw	Does The State Have Fair Employment Laws	Civil Rights	41	1965	1992
536	Caughey-Warshaw	Does The State Have Fair Housing Laws For Owners	Civil Rights	13	1959	1968
571	Boushey	Repeal Sodomy Law	Civil Rights	48	1962	2003
574	Uniform Law	Regulating Mortgage Holder Rights	Economics	4	2005	2014
582	Boushey	Program To Combat Organized Crime	Law and Crime	29	1972	1995
620	Uniform Law	Defines Rights Of Convicted People	Law and Crime	1	1968	1968
651	Other	State Passes Truth-In-Sentencing Law Before 1997	Law and Crime	25	1911	1996
676	Uniform Law	Governs All Unincorporated Nonprofit Associations That Are Formed Or Operate In A State	Economics	5	2009	2015
698	Caughey-Warshaw	Does The State Mandate Ten Commandments Be Posted In Public Institutions/Schools?	Civil Rights	2	1935	1978
704	Caughey-Warshaw	Does The State Ban Discrimination In Public Accommodations On The Basis Of Gender Id?	Civil Rights	16	1993	2014
706	Caughey-Warshaw	Does The State Ban Discrimination In Public Accommodations On The Basis Of Sexual Orientation?	Civil Rights	20	1989	2009
714	Karch	Provides A Means Through Which States Can Participate In A Reciprocal Program To Enforce Wildlife Citations	Environment and Energy	20	1989	2014

Table A.2b: NBER working paper sample

Number	Policy	Title	Area	Adoptions	First year	Last year
18187	Stand Your Ground laws	Stand Your Ground Laws, Homicides, and Injuries	Law and Crime	25	1994	2009
18299	Leave for state employee organ donors	Removing Financial Barriers to Organ and Bone Marrow Donation: The Effect of Leave and Tax Legislation in the U.S.	Public Services	29	1989	2007
18341	Physical education requirement	The Impact of Physical Education on Obesity among Elementary School Children	Public Services	38	1940	2007
18516	Wrongful discharge laws	Wrongful Discharge Laws and Innovation	Economics	45	1970	1998
18773	Bicycle helmet laws	Effects of Bicycle Helmet Laws on Children's Injuries	Public Services	19	1987	2006
18887	AFDC waiver	Effects of Welfare Reform on Women's Crime	Economics	27	1992	1996
18887	TANF	Effects of Welfare Reform on Women's Crime	Economics	48	1996	1998
19294	Biotech tax incentives	State Incentives for Innovation, Star Scientists and Jobs: Evidence from Biotech	Economics	7	1984	2003
19904	Community rating regulations	Regulatory Redistribution in the Market for Health Insurance	Public Services	7	1993	1997
20149	Interstate bank branching laws	Does Financing Spur Small Business Productivity? Evidence from a Natural Experiment	Economics	48	1995	1997
20565	Medical record copy fee cap	Expanding Patients' Property Rights In Their Medical Records	Public Services	42	1972	2007
20808	NOx cap-and-trade	Who Loses Under Power Plant Cap-and-Trade Programs?	Environment and Energy	20	2003	2007
21170	Commonsense Consumption Acts	Do Ã¢Â€Â˜Cheeseburger BillsÃ¢Â€Â™ Work? Effects of Tort Reform for Fast Food	Economics	26	2003	2013
21345	Medical marijuana laws	Do Medical Marijuana Laws Reduce Addictions and Deaths Related to Pain Killers?	Public Services	21	1996	2014
21373	Individual income tax	Broadening State Capacity	Economics	42	1911	1971
21373	Coporate income tax	Broadening State Capacity	Economics	43	1911	1971
22344	Nurse Licensure Compact	Labor Supply Effects of Occupational Regulation: Evidence from the Nurse Licensure Compact	Public Services	25	1999	2015
22899	Initial Medicaid implementation	The Long-Run Effects of Childhood Insurance Coverage: Medicaid Implementation, Adult Health, and Labor Market Outcomes	Public Services	48	1966	1982
23171	Good Samaritan Law	With a Little Help from My Friends: The Effects of Naloxone Access and Good Samaritan Laws on Opioid-Related Deaths	Public Services	45	2007	2019
23171	Naloxone Access Law	With a Little Help from My Friends: The Effects of Naloxone Access and Good Samaritan Laws on Opioid-Related Deaths	Public Services	48	2001	2017
23313	E-cigarette minimum age law	The Effects of E-Cigarette Minimum Legal Sale Age Laws on Youth Substance Use	Public Services	48	2010	2016
23388	Substance use disorder parity laws	Health Insurance and Traffic Fatalities: The Effects of Substance Use Disorder Parity Laws	Public Services	12	1994	2009
23510	Concealed handgun carry law	Right-to-Carry Laws and Violent Crime: A Comprehensive Assessment Using Panel Data and a State-Level Synthetic Control Analysis	Law and Crime	41	1959	2014
23995	Smoking ban	Impact of Comprehensive Smoking Bans on the Health of Infants and Children	Public Services	34	1994	2012
24153	Interstate tax audit info sharing	Intergovernmental Cooperation and Tax Enforcement	Government Operations	5	1950	1955
24259	Right-to-work laws	From the Bargaining Table to the Ballot Box: Political Effects of Right to Work Laws	Economics	27	1943	2017
24381	Ban-the-box laws	Do Ban the Box Laws Increase Crime?	Economics	11	2009	2014
24651	Same-sex marriage	Effects of Access to Legal Same-Sex Marriage on Marriage and Health: Evidence from BRFSS	Civil Rights	33	2004	2014
24662	Merit-aid programs	State Merit Aid Programs and Youth Labor Market Attachment	Public Services	18	1988	2005
24782	Duty-to-bargain laws	The Long-run Effects of Teacher Collective Bargaining	Economics	31	1960	1987

Table A.2b: NBER working paper sample

Number	Policy	Title	Area	Adoptions	First year	Last year
24986	Community eligibility provision	School Nutrition and Student Discipline: Effects of Schoolwide Free Meals	Public Services	10	2012	2014
25209	Child gun access prevention laws	Child Access Prevention Laws and Juvenile Firearm-Related Homicides	Law and Crime	25	1989	2001
25369	Age anti-discrimination	Do State Laws Protecting Older Workers from Discrimination Reduce Age Discrimination in Hiring? Evidence from a Field Experiment	Economics	45	1934	1997
25369	Disability anti-discrimination	Do State Laws Protecting Older Workers from Discrimination Reduce Age Discrimination in Hiring? Evidence from a Field Experiment	Economics	46	1971	1988
25390	Wind energy incentives	Technological Spillover Effects of State Renewable Energy Policy: Evidence from Patent Counts	Environment and Energy	48	2000	2011
25758	Minor abortion parental consent	The Impact of Parental Involvement Laws on Minor Abortion	Public Services	37	1974	2013
25974	Initial prescription drug monitoring	Can Policy Affect Initiation of Addictive Substance Use? Evidence from Opioid Prescribing	Public Services	24	1988	2018
25974	Must-access prescription drug monitoring	Can Policy Affect Initiation of Addictive Substance Use? Evidence from Opioid Prescribing	Public Services	29	2007	2019
26017	E-cigarette tax	The Effects of Traditional Cigarette and E-Cigarette Taxes on Adult Tobacco Product Use	Public Services	7	2010	2017
26135	Pill mill laws	Mortality and Socioeconomic Consequences of Prescription Opioids: Evidence from State Policies	Public Services	8	2005	2014
26140	NBCCEDP cancer screenings	Effects of Direct Care Provision to the Uninsured: Evidence from Federal Breast and Cervical Cancer Programs	Public Services	48	1991	1999
26206	Strict voter ID	Strict Voter Identification Laws, Turnout, and Election Outcomes	Civil Rights	11	2004	2016
26405	State EITC	The EITC and the Extensive Margin: A Reappraisal	Economics	28	1986	2018
26500	Triplicate prescription	Origins of the Opioid Crisis and Its Enduring Impacts	Public Services	7	1939	1988
26676	E-verify for employment	States Taking the Reins? Employment Verification Requirements and Local Labor Market Outcomes	Economics	22	2006	2015
26749	Modern prescription drug monitoring	Effect of Prescription Opioids and Prescription Opioid Control Policies on Infant Health	Public Services	47	1999	2017
26777	Anti-bullying laws	Anti-Bullying Laws and Suicidal Behaviors among Teenagers	Law and Crime	48	2001	2015
26832	Mandated sick pay	Mandated Sick Pay: Coverage, Utilization, and Welfare Effects	Economics	10	2011	2018
27054	Salary history ban	Information and the Persistence of the Gender Wage Gap: Early Evidence from California's Salary History Ban	Economics	12	2017	2021
27306	Medicaid expansion	Medicaid Expansion and the Mental Health of College Students	Public Services	36	2014	2021
27520	Tramadol as Schedule IV drug	Competitive Effects of Federal and State Opioid Restrictions: Evidence from the Controlled Substance Laws	Public Services	12	2007	2014
27728	2003 standard certificate of live birth implementation	Heterogeneous Effects Of Health Insurance On Birth Related Outcomes: Unpacking Compositional Vs. Direct Changes	Public Services	48	2003	2016
27788	Paid family leave	Paid Leave Pays Off: The Effects of Paid Family Leave on Firm Performance	Economics	6	2002	2018
28173	Tobacco 21 laws	Do State Tobacco 21 Laws Work?	Public Services	15	2016	2019
28903	Right of workers to talk law	Equilibrium Effects of Pay Transparency	Economics	12	2004	2016
29087	Recreational marijuana legalization	Recreational Marijuana Laws and the Use of Opioids: Evidence from NSDUH Microdata	Public Services	17	2012	2021
29318	CPA 150-hour rule	Occupational Licensing and Accountant Quality: Evidence from the 150-Hour Rule	Economics	48	1983	2015

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

Outcome	Coverage	Example NBER policy	NBER WP numbers
Log(income per capita)	1950-2020	Partial paid leave for pregnancy	26416, 19294
Voter turnout rate	1980-2019	Strict voter ID	26206, 24259
Log(opioid mortality rate)	1968-2014	Naloxone Access Law	23171, 25974, 26135, 26500, 27520, 29087
Employment rate in energy-intensive industry	1975-2018	NOx cap-and-trade	20808
Private insurance coverage rate	1987-2006	Community rating regulations	19904
Log(state revenue per capita)	1950-2016	Tax audit info sharing	21373, 24153
Log(state expenditure per capita)	1950-2016	State income and corporate taxes	21373, 24153
Average BMI	1987-2020	Physical education requirements	18341, 21170
Firearm mortality rate	1968-2016	Stand Your Ground laws	18187, 23510, 25209
Alcohol-induced traffic mortality rate	1975-2015	Substance use disorder parity laws	23388

Table A.3b: COVID-19 policies

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

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

Table A.3c: Vaccine regulations

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

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

Table A.4: Highest and lowest innovators of NBER policies (20%)

	1991-2020		Difference (SE)
	(1) Top 20%	(2) Bottom 20%	(1)-(2)
Rep. two-party vote-share %	44.65	55.98	-11.33
	[8.59]	[6.54]	(2.59)
|Demeaned two-party vote-share|	9.20	6.19	3.01
	[5.05]	[4.41]	(1.49)
Unified Dem. state gvt.	0.31	0.13	0.18
	[0.46]	[0.34]	(0.07)
Unified Rep. state gvt.	0.16	0.42	-0.26
	[0.37]	[0.49]	(0.11)
Legislative professionalism	1.00	-0.84	1.84
	[2.11]	[0.45]	(0.63)
Log(population)	15.42	14.90	0.52
	[1.00]	[0.89]	(0.39)
Income per capita	40569.71	33051.67	7518.04
	[13543.22]	[11052.03]	(1987.49)
Log(income per cap.)	10.55	10.35	0.21
	[0.34]	[0.34]	(0.05)
Urban pop. %	85.05	61.06	23.99
	[7.27]	[7.83]	(2.95)
Minority %	27.91	23.25	4.66
	[12.19]	[11.45]	(4.66)
Unemployed %	5.69	5.28	0.41
	[2.09]	[1.79]	(0.40)
States	12	12	

This table compares characteristics of the states in the highest and lowest 20% for first innovations for the NBER policies. Averages are taken over the entire time period. Standard deviations are in brackets and standard errors in parentheses. Standard errors for the difference are clustered by state. Hawaii, Washington D.C., and Alaska are excluded.

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

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

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

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

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

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

Table A.6: Robustness checks

	Distance			Republican vote-share			State gvnt. party control	
1950-70s	1980-90s	2000-10s	1950-70s	1980-90s	2000-10s	1950-70s	1980-90s	2000-10s
Dep. var.: Policy adoption (all logit except (2))								
(1) Baseline (Table 3) (R^2: 0.16, 0.17, 0.18; $N_{\text{pol.}}$: 267, 420, 375)								
0.43	0.31	0.30	0.13	0.13	0.38	0.06	0.06	0.51
(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.06)	(0.04)	(0.05)
(2) Baseline linear probability model (coefficients and SEs ×100) (R^2: 0.18, 0.18, 0.18; $N_{\text{pol.}}$: 269, 425, 379)								
1.24	1.04	1.35	0.34	0.46	1.75	0.22	0.28	2.62
(0.15)	(0.16)	(0.22)	(0.12)	(0.12)	(0.19)	(0.15)	(0.16)	(0.29)
(3) Controlling for policy area composition over decades (R^2: 0.18, 0.17, 0.18; $N_{\text{pol.}}$: 267, 420, 375)								
0.46	0.30	0.33	0.12	0.12	0.36	0.04	0.06	0.52
(0.06)	(0.05)	(0.05)	(0.05)	(0.03)	(0.04)	(0.07)	(0.04)	(0.05)
(4) Expanded state-level controls (R^2: 0.18, 0.18, 0.20; $N_{\text{pol.}}$: 265, 420, 375)								
0.24	0.22	0.18	0.12	0.14	0.40	0.09	0.09	0.50
(0.06)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)	(0.04)	(0.05)
(5) Parsimonious model (R^2: 0.16, 0.17, 0.18; $N_{\text{pol.}}$: 267, 420, 375)								
0.43	0.31	0.31	0.15	0.13	0.37	0.04	0.05	0.50
(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.06)	(0.04)	(0.05)
(6) Adoption measure: Lagged by one year (R^2: 0.14, 0.15, 0.15; $N_{\text{pol.}}$: 267, 420, 375)								
0.34	0.26	0.22	0.06	0.12	0.33	0.03	0.04	0.41
(0.06)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)	(0.06)
(7) Adoption measure: Rank-inverse weighted average (R^2: 0.16, 0.17, 0.17; $N_{\text{pol.}}$: 267, 420, 375)								
2.59	1.85	1.74	0.25	0.77	1.62	0.89	1.26	3.39
(0.26)	(0.23)	(0.30)	(0.23)	(0.17)	(0.22)	(0.53)	(0.30)	(0.46)
(8) Adoption measure: Proportion of closest third that are adopters (R^2: 0.16, 0.17, 0.18; $N_{\text{pol.}}$: 267, 420, 375)								
2.40	1.76	1.59	0.79	0.91	2.07	0.42	0.60	1.49
(0.29)	(0.28)	(0.27)	(0.33)	(0.23)	(0.21)	(0.25)	(0.15)	(0.21)
(9) Adoption measure: Proportion of all adopters in the closest third (R^2: 0.14, 0.15, 0.15; $N_{\text{pol.}}$: 243, 400, 375)								
0.77	0.72	0.86	0.12	0.20	0.94	0.09	-0.37	1.51
(0.09)	(0.09)	(0.10)	(0.07)	(0.08)	(0.08)	(0.12)	(0.13)	(0.13)
(10) Adoption measure: $P(Adopt)$ closest third$-P(Adopt)$ all states (R^2: 0.15, 0.15, 0.16; $N_{\text{pol.}}$: 267, 420, 375)								
2.31	1.71	1.56	0.76	0.95	2.09	-0.33	0.02	1.92
(0.32)	(0.27)	(0.28)	(0.36)	(0.24)	(0.21)	(0.32)	(0.20)	(0.28)

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

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

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

Controlling for policy area composition over decades: reweights policies in each decade to match the composition of policy areas in the 1980s.

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

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

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

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

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

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

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

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

Table A.7a: Models of policy diffusion: Role of migration and voter preferences (expanded demographics and public opinion)

Dep. var.: Policy adoption (logit)	(1) 60-70s	(2) 80-90s	(3) 00-10s	(4) 60-70s	(5) 80-90s	(6) 00-10s
Proportion of states adopted	0.83	2.27	2.37	1.33	2.34	2.49
	(0.20)	(0.14)	(0.23)	(0.28)	(0.13)	(0.20)
Divided state government	-0.00	0.02	-0.18	0.03	0.02	-0.16
	(0.10)	(0.05)	(0.07)	(0.11)	(0.05)	(0.07)
State gvnt./legis. election year	0.16	0.02	-0.01			
	(0.12)	(0.07)	(0.06)			
Presidential election year	-0.25	-0.00	-0.20			
	(0.13)	(0.07)	(0.09)			
Measure of adoption among other states closest in:						
Demographic index				0.29	0.06	0.08
				(0.08)	(0.05)	(0.06)
Log(population)	0.05	0.04	-0.07			
	(0.07)	(0.05)	(0.04)			
Log(income per capita)	0.22	0.01	0.09			
	(0.07)	(0.05)	(0.05)			
Urban population %	0.12	0.03	0.17			
	(0.08)	(0.05)	(0.04)			
Non-white %		0.03	0.00			
		(0.03)	(0.06)			
Unemployed %		0.02	0.02			
		(0.03)	(0.05)			
Distance	0.22	0.19	0.14	0.16	0.20	0.12
	(0.10)	(0.08)	(0.07)	(0.10)	(0.08)	(0.07)
Republican vote-share	0.14	0.09	0.27	0.11	0.08	0.16
	(0.06)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)
State gvnt. partisanship	0.07	0.10	0.40	0.06	0.08	0.45
	(0.12)	(0.07)	(0.08)	(0.11)	(0.07)	(0.07)
State gvnt. partisanship×Divided gvnt.	-0.16	-0.03	-0.48	-0.16	0.01	-0.58
	(0.22)	(0.15)	(0.15)	(0.19)	(0.14)	(0.13)
Migration flows	0.14	0.01	0.12	0.14	0.02	0.15
	(0.14)	(0.10)	(0.09)	(0.14)	(0.09)	(0.08)
Voter preferences (ANES & GSS)	0.25	0.29	0.14	0.18	0.25	0.15
	(0.09)	(0.09)	(0.08)	(0.09)	(0.08)	(0.07)
Index of public opinion measures	0.19	0.17	0.19			
	(0.06)	(0.04)	(0.05)			
Citizen ideology (Berry et al., 1998)				0.36	0.05	0.17
				(0.06)	(0.03)	(0.05)
Public policy mood (Lagodny et al., 2022)				-0.07	-0.04	-0.04
				(0.06)	(0.04)	(0.04)
Mass social liberalism (Caughey and Warshaw, 2018)				0.07	0.19	0.22
				(0.06)	(0.05)	(0.05)
Mass economic liberalism (Caughey and Warshaw, 2018)				0.06	0.05	0.11
				(0.08)	(0.04)	(0.05)
Observations	53757	107999	66721	60453	116510	70341
Policies	227	414	359	227	414	350
Pseudo R^2	0.17	0.17	0.19	0.16	0.17	0.18

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

Table A.7b: Models of policy diffusion: Role of migration and voter preferences (expanded ANES & GSS voter preferences)

Dep. var.: Policy adoption (logit)	(1) 60-70s	(2) 80-90s	(3) 00-10s	(4) 60-70s	(5) 80-90s	(6) 00-10s
Proportion of states adopted	1.19	2.34	2.42	1.19	2.35	2.42
	(0.29)	(0.13)	(0.21)	(0.29)	(0.13)	(0.21)
Divided state government	0.01	0.02	-0.18	0.02	0.02	-0.18
	(0.11)	(0.05)	(0.07)	(0.11)	(0.05)	(0.07)
Measure of adoption among other states closest in:						
Demographic index	0.34	0.09	0.13	0.33	0.09	0.13
	(0.08)	(0.05)	(0.06)	(0.08)	(0.05)	(0.06)
Distance	0.23	0.19	0.11	0.23	0.18	0.11
	(0.10)	(0.08)	(0.06)	(0.10)	(0.08)	(0.06)
Republican vote-share	0.15	0.09	0.27	0.13	0.09	0.26
	(0.06)	(0.04)	(0.06)	(0.06)	(0.04)	(0.06)
State gvnt. partisanship	0.06	0.10	0.48	0.07	0.09	0.47
	(0.11)	(0.06)	(0.07)	(0.11)	(0.07)	(0.07)
State gvnt. partisanship×Divided gvnt.	-0.09	-0.00	-0.61	-0.11	0.00	-0.61
	(0.19)	(0.13)	(0.13)	(0.19)	(0.13)	(0.13)
Migration flows	0.14	0.02	0.15	0.11	0.03	0.14
	(0.14)	(0.09)	(0.08)	(0.13)	(0.09)	(0.08)
Voter preferences (ANES & GSS) in policy area	0.20	0.12	0.07			
	(0.09)	(0.05)	(0.05)			
Voter preferences in other policy areas	0.11	0.16	0.08			
	(0.09)	(0.08)	(0.06)			
Voter preferences and sentiment (ANES & GSS)				0.34	0.25	0.16
				(0.10)	(0.09)	(0.08)
Index of public opinion measures	0.22	0.14	0.21	0.20	0.14	0.21
	(0.07)	(0.04)	(0.05)	(0.07)	(0.04)	(0.05)
Observations	57932	108973	67435	57932	108973	67435
Policies	216	389	338	216	389	338
Pseudo R^2	0.16	0.17	0.18	0.16	0.17	0.18

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

Table A.8: Event studies

	Uni. st. gvnt.	Unified Republican state government				Unified Democratic state government				Loss of uni.
	(1) Diff.	(2) Right-lean. policy	(3) Left-lean. policy	(4) Diff. (2-3)	(5) Neutral policy	(6) Left-lean. policy	(7) Right-lean. policy	(8) Diff. (6-7)	(9) Neutral policy	(10) Diff.
Events during years 1950 to 1989										
4 years pre-event	-0.024 (0.009)	-0.023 (0.012)	0.024 (0.013)	-0.047 (0.023)	0.019 (0.017)	-0.006 (0.007)	0.019 (0.011)	-0.025 (0.014)	-0.008 (0.008)	-0.001 (0.008)
3 years pre-event	-0.014 (0.007)	-0.012 (0.008)	0.014 (0.011)	-0.026 (0.014)	0.026 (0.014)	-0.012 (0.005)	0.001 (0.006)	-0.013 (0.008)	-0.008 (0.007)	-0.003 (0.008)
2 years pre-event	-0.013 (0.011)	-0.011 (0.019)	0.029 (0.015)	-0.039 (0.032)	0.026 (0.019)	-0.005 (0.007)	0.005 (0.006)	-0.010 (0.010)	0.004 (0.010)	0.002 (0.008)
1 year pre-event	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)
Year of event	0.009 (0.010)	-0.001 (0.014)	-0.006 (0.010)	0.005 (0.018)	0.028 (0.020)	0.005 (0.006)	-0.006 (0.008)	0.011 (0.012)	0.007 (0.009)	0.000 (0.011)
1 year post-event	0.001 (0.008)	0.009 (0.010)	0.006 (0.009)	0.003 (0.017)	0.005 (0.011)	-0.002 (0.006)	-0.006 (0.005)	0.003 (0.008)	-0.012 (0.009)	0.007 (0.007)
2 years post-event	-0.006 (0.012)	0.002 (0.015)	0.011 (0.016)	-0.009 (0.025)	-0.014 (0.019)	0.003 (0.008)	0.010 (0.010)	-0.006 (0.014)	0.003 (0.011)	-0.003 (0.010)
3 years post-event	-0.003 (0.009)	0.004 (0.013)	-0.002 (0.013)	0.006 (0.022)	-0.002 (0.013)	-0.008 (0.007)	-0.004 (0.006)	-0.004 (0.008)	0.008 (0.009)	-0.009 (0.008)
4 years post-event	0.003 (0.010)	-0.012 (0.011)	0.005 (0.010)	-0.018 (0.014)	0.029 (0.025)	0.005 (0.009)	-0.006 (0.011)	0.011 (0.014)	0.049 (0.017)	-0.008 (0.010)
Observations	72118	57439	57439	57439	57439	72049	72049	72049	72049	73639
Policies	233	191	191	191	191	233	233	233	233	241
Events	135	52	52	52	52	82	82	82	82	148
Events during years 1990 to 2020										
4 years pre-event	0.000 (0.007)	-0.002 (0.009)	-0.002 (0.008)	-0.001 (0.014)	0.005 (0.010)	0.003 (0.005)	0.002 (0.005)	0.002 (0.007)	0.005 (0.006)	0.019 (0.008)
3 years pre-event	-0.013 (0.007)	-0.006 (0.008)	0.004 (0.008)	-0.010 (0.014)	0.017 (0.007)	-0.005 (0.007)	0.009 (0.005)	-0.014 (0.007)	-0.001 (0.005)	0.013 (0.007)
2 years pre-event	-0.007 (0.008)	-0.006 (0.008)	0.019 (0.008)	-0.024 (0.012)	0.026 (0.008)	0.003 (0.006)	-0.007 (0.006)	0.010 (0.010)	-0.009 (0.007)	0.017 (0.008)
1 year pre-event	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)
Year of event	0.022 (0.007)	0.012 (0.008)	0.003 (0.006)	0.008 (0.010)	0.015 (0.011)	0.028 (0.008)	-0.005 (0.006)	0.033 (0.010)	0.001 (0.008)	0.001 (0.010)
1 year post-event	0.022 (0.009)	0.011 (0.009)	-0.003 (0.006)	0.014 (0.011)	0.012 (0.009)	0.020 (0.009)	-0.011 (0.006)	0.031 (0.012)	-0.006 (0.005)	0.016 (0.009)
2 years post-event	0.026 (0.009)	0.008 (0.010)	-0.006 (0.008)	0.014 (0.014)	-0.001 (0.015)	0.026 (0.010)	-0.009 (0.007)	0.035 (0.013)	-0.007 (0.007)	0.009 (0.010)
3 years post-event	0.018 (0.007)	0.007 (0.010)	-0.010 (0.007)	0.017 (0.013)	0.013 (0.014)	0.014 (0.007)	-0.007 (0.006)	0.021 (0.010)	0.002 (0.009)	0.005 (0.008)
4 years post-event	0.028 (0.015)	-0.014 (0.008)	-0.010 (0.010)	-0.005 (0.014)	0.005 (0.011)	0.041 (0.022)	-0.023 (0.009)	0.064 (0.027)	0.013 (0.009)	-0.002 (0.009)
Observations	124482	112437	112437	112437	112437	123679	123679	123679	123679	122133
Policies	427	417	417	417	417	426	426	426	426	426
Events	115	49	49	49	49	64	64	64	64	99