Policy Diffusion and Polarization across U.S. States*

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Abstract

Economists have studied the impact of numerous state laws, from welfare rules to voting ID requirements. Yet for all this policy evaluation, what do we know about policy diffusion -- how these policies spread from state to state? We present a series of facts based on a data set of over 700 US state policies spanning the past 7 decades. First, considering 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 1990 is best predicted by proximity: a state is more likely to adopt a policy if nearby states have already done so. Third, since 2000, instead, political alignment outperforms geographic proximity in predicting diffusion. Fourth, the diffusion of COVID state policies, as opposed to vaccination policies from the 1980s on, follows similar patterns. Models of learning and correlated preferences could account for these patterns, including the decreased role of geography over time, if ideas spread more easily and preference correlation has become more political than geographical. We document, however, a role for party control: similarity in state party control predicts policy adoption in the last two decades, even controlling for voter political preferences. We conclude that party polarization has emerged as a key factor recently for policy adoption. Finally, we apply our model to the policy evaluation setting, and broadly classify the patterns of policy diffusion in a set of difference-in-differences papers.

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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).

Economists 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 US states (Case, Rosen, and Hines, 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 on 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), of voter ID laws on turnout (Cantoni and Pons, 2021), of minimum-wage laws on worker earnings (Cengiz et al., 2019), and of monetary policy on macro outcomes (Richardson and Troost, 2009). A better understanding of the diffusion of such policies is not just of interest on its own, but could also inform our understanding of difference-in-difference studies such as the above.

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 US States has several advantages. The U.S. federalist system allows states to serve as "laboratories of democracy" (Callander and Harstad, 2015). 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 and was built combining several existing data sets. 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 limited coverage of the last decade. We thus extended its coverage through the 2010s for a subset of the policies so as to cover recent trends as well.

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

[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.

papers. From the 11,312 NBER working papers from April 2012 to September 2021, we identify 151 papers with U.S. state-level policy variation. Out of this set, 87 papers meet our criteria, for a total of 52 policies (given that some policies are in multiple papers).

The combined data set covers 722 policies adopted from the 1950s onward, 671 from the SPID data set and 52 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 2002 in a fairly idyosincratic way. In comparison, the well-known Medicaid expansion from the ACA (Figure 1b) followed political lines. Finally, the bicycle helmet regulation (Figure 1c) expanded largely along geographic lines.

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 we find that the share of population that would benefit from the policy is instead 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, and similarly for the food stamp introduction in the 1960s. 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 if this is a general feature, or the exact timing of the change. 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 important caveats. First, the findings are largely descriptive of patterns of policy diffusion, and do not reflect causal inferences. 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, making it impossible to 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 diff-in-diff study.

Which states innovate policies and originate new laws? One theory is that states with more resources, capacity, or "legislative professionalism" tend to innovate more (Walker, 1969; Besley and Persson, 2009). If innovative policies require a substantial fixed cost, then larger and richer states should be more likely to generate new policies. Nevertheless, we do not find clear differences in population or income per capita between the highest and lowest 10 states by the number of innovations. Furthermore, innovations source from both Republican and Democratic states. Overall, while there are specific states that consistently produce new policies (e.g., California) and those that do not (e.g., Georgia), 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, 1993; de Paula, Rasul, and Souza, 2020), learning (Wang and Yang, 2021), common preferences across states, and ideological alignment (Berry and Berry, 2007; Volden, Ting, and Carpenter, 2008). We provide evidence using a logit hazard model. Specifically, we estimate the dimensions (e.g., demographic features, geographic proximity, or political partisanship) along which policies tend to diffuse, given the observed adoption up to that period. The dimension of diffusion is informative of underlying models, e.g., diffusion along political dimensions 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: for each 10 percentage point increase in adoption of a policy among the closest third of states, the probability of adoption by a state goes up by around 20 percent (or, on average, 1 percentage point). Another important predictor is demographic similarity: adoption by states with similar demographics (such as income or racial composition) predicts adoption. The adoption by politically aligned states is a weaker predictor.

In the 2000s and 2010s, instead, geographic and demographic proximity become less predictive, and the strongest predictor becomes adoption by politically-aligned states, as measured by the Republican vote share in recent elections. For each 10 percentage point increase in adoption by politically similar states, the probability of adoption increases by roughly more than 25 percent. This effect is strong enough that the predictive accuracy of the model is higher in the latest periods, at 20% pseudo-R^2, compared to 12% in the 1970s.

These findings apply not just in the SPID data set, but also to the polices extracted from the NBER working papers, the types of policies that economists study.

Further, we consider the diffusion of 77 COVID-related state laws and rules adopted from October 2019 on. We estimate the same model, except at the weekly level, and find strong evidence of political similarity driving adoption. For comparison, we examine state vaccination policies from 1988 on, and do not find evidence of political similarity driving the diffusion. Thus, these results are consistent with our main findings.

Next, we relate these findings to leading models of policy diffusion. A set of explanations stresses the adoption of policies as reflecting *correlated preferences or environments*, or *learning* across states, or *competition* among states. These (distinct) explanations all naturally 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 and the extent of competition follow less geographic lines; further, the correlation in preferences or environments across states may have shifted from mostly geographical to largely political. If this is the case, other inter-state flows that follow similar determinants, such as cross-state migration, may exhibit similar patterns. Indeed, migration flows have quite strong predictive power of policy diffusion, and reduce the explanatory power of geography; they do not, however, affect much the importance of the political variables.

A separate explanation is that in the recent decades *party discipline* increasingly explains state policy, beyond the predictive power of local preferences or environments, learning, or competition. We thus examine the impact of state political control on policy diffusion, controlling for the state voting patterns. Indeed, similarity in state government, which did not predict policy up until the 1990s, is highly predictive in the last two decades. Further, we provide causal evidence through an event study of switches from split state government to unified state government (that is, governor and both state houses controlled by 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, consistent with the logit model results.

As a final piece of evidence, for the NBER papers with state policy variation, we consider the outcome variables, such as state-level BMI, mortality, income, and private insurance rate. If local environments and preferences are driving the increased impact of politics in policy adoption, we would expect the outcomes to have become more correlated over time among politically similar states, as opposed to among neighboring states. If instead party discipline is largely responsible for the polarization, we do not necessarily expect much change in the correlation of the outcomes. We find a high geographic correlation in outcomes, with no evidence of an increased correlation among states with similar party control. This is most consistent with the party discipline explanation for the findings for the last two decades.

We conclude that the changes in policy diffusion are most likely due to increased polarization of state politicians. We thus add to the growing 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, 2021), 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.

Finally, we return to the difference-in-differences policy papers in economics. We estimate a parsimonious model of policy diffusion for each of the the 52 NBER policies, and show that, while the estimates are noisier when done policy-by-policy, they approximately classify the policy diffusion as mostly geographically-clustered, politically-clustered, or neither. Identifying the type of diffusion raises potential implications for the policy evaluation.

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 may be 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 on policy diffusion, we provide evidence on broad patterns of diffusion for a wide range of policies, complementing the detailed evidence on specific policies, e.g., taxation in the pioneering contribution of Besley and Case (1995) or 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, our main contributions are that (i) we compare quantitatively the impact of polarization to the impact of geographic and demographic similarity; (ii) we document even stronger patterns for the policies studied by economists; (iii) we estimate similar polarization impacts for vaccination policies; (iv) we provide evidence on the models by testing additional predictions; (v) we use our model to classify policy changes in economics papers.

2 Case Study on Medicaid

Before we present the full analysis, we consider a case study outlining some of the key issues. As well known, the expansion of health insurance under the Affordable Care Act had as an important component the expansion of Medicaid 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 federal subsidy structure, 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 (if at all).

This suggests a large partisan impact on policy adoption, but it could be that the political preferences line up with the underlying demand for the policy in the state: the Republican states that delay adoption may have fewer people who would benefit from Medicaid. In fact, Figure 2b shows that 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 and thus from the subsidy. The political preference thus appears to come at a cost of a worse match quality of the policy to the state.

A possible explanation for these findings is that major benefit expansions always have this partisan structure. We thus revisit the initial Medicare roll-out enacted in July 1965. Voluntarily participating states received federal funds from January 1966. In particular, initially there was 50-83% matching 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) and it is thus interesting to compare the adoption. Overall, 26 states enacted the Medicaid program within the first year, 37 within two, and nearly all within four years. When we consider the timing, the state political leaning has no predictive power, as Figure 2c shows.

Another major public benefit expansion in the 1960s is the initial roll out of the food stamp program. After county-level food stamp programs started in 1961, in 1964 the Food Stamp Act was passed and counties voluntarily set up their own food stamp program, with the federal government paying for the benefits, but eligibility criteria set by the states. As the bin scatter in Figure 2d shows, the voting patterns in the country have no predictive power for when the county approved the food stamp program. Demographics are predictive 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 politics 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 on policy adoptions 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 was built combining several existing data sets on state-level adoptions with the purpose of providing a representative sample of typical state policy topics. The main sources of data 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) a number of other smaller sources. We present 50 randomly sampled examples of these laws in Table A.1a.

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 and the category it belongs to, 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.

An important question is whether these laws are representative, in some way, of state-level policy-making. While there was certainly selection by topic in some of the meta-analyses used to build the data set, the SPID PIs document that the categories of laws represented in the data set are representative of the categories of state laws (Figure 3a, reproduced from Boehmke et al., 2020). Another relevant question is the accuracy of the coding in the data set. We cross-checked a sample of the laws included in the data set and validated its information on adoption, with only a few corrections.

A significant limitation of the data set is that it provides limited coverage of the most recent decade. Figure 3b shows the number of policies covered by year, with a steep decrease in the second half of the 2010s. To allow us to make clear enough inferences also about the most recent years, we extended its coverage for a subset of the policies—the Uniform Law policies—beyond 2015 to 2020, as Figure 3b shows.

NBER Data Set. While the SPID data set is impressively comprehensive, there is no guarantee that it covers the type of state laws of interests to economists. We thus collected a similar, if smaller, sample of policy adoptions used in economics papers. From the 11,316 NBER working papers from April 2012 to September 2021, we pre-screen potentially relevant papers through keywords searches for terms such as "difference-in-differences", "U.S. states", and "policies". From this screened set, we identify 151 papers with U.S. state-level policy variation. As Column 2 in Table 1a documents, these papers are most commonly in labor, public, and health economics. We then apply our sample restrictions, including the fact that we consider binary policy adoption, as opposed to state-level variation in say tax rates. This results in a sample of 87 working papers (Column 3). We can extract the timing of state-level policy adoption for 77 out of these 87 papers, covering 52 policies (given that, for example, multiple papers analyze the same Medicaid expansion). The information on the policy diffusion typically comes from a table in the paper. Health economics is the most common field in this sample, followed by labor and public economics. The share of published papers in this sample, 44 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. The full list of these papers is in Table A.1b-c.

Main Sample. We pool the SPID and NBER data sources and apply a set of sample restrictions. First, we keep policies with the last adoption after 1950 since we do not have enough coverage to consider older historical patterns. Second, we consider only adoption in the contiguous 48 states, since coverage of adoptions by 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 level of the minimum wage).

As Table 1b shows, the data set includes 676 policies from the SPID data set, with an average of 23 states ultimately adopting per policy. It also includes 52 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).

Outcome Variables. For 24 of the 52 policies in the NBER sample, we reconstruct the dependent variable studied in the papers, either through the replication files or public data sources. The papers typically evaluate the effect of the policies on these outcomes in a difference-in-differences design. Overall, we observe 11 outcome variables at the state-year level, such as the private insurance coverage rate, voter turnout rate, and BMI, as summarized in Table A.2a. We use these variables in Section 5.1.

Covid and Vaccination Samples. As a separate sample, we collect 77 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). We record the policy adoption at the weekly level. We complement this data set with information on the introduction of 15 state policies regarding vaccination mandatesenacted from 1988 on from the Immunization Action Coalition. We summarize these data sets in Table A.2b and A.2c.

4 Evidence on Innovation and Diffusion

4.1 Innovation

We first consider whether there are states that are more likely than others to be innovators, that is, early adopters of state-level policies. One theory is that states with more resources, capacity, or "legislative professionalism" tend to innovate policies (Walker, 1969; Besley and Persson, 2009). If innovating policies requires a substantial fixed cost, then in line with this theory, larger and richer states should be more likely to generate new policies.

To measure innovation in policy-making, for each policy we consider the states that adopted a policy in its first year of adoption, and sum across policies how often a state has been an innovator from this perspective. In Figure 4a-b we present a color-coded map of the US displaying how often a state was an innovator in the earlier years (1961-90, Figure 4a) and in the more recent years (1991-2020, Figure 4b).[2] The map does not show an obvious pattern. California, the largest US 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 small state such as Connecticut is among the top states by this measure.

Table 2 presents a statistical comparison between states that are in the top 20% of this innovation measure, versus states that are in the bottom 20%.[3] We do not find much evidence that states that are larger in population are more likely to be innovators and only suggestive evidence that states with higher per-capita income are more likely to be in the top-innovators group. Furthermore, innovations source from both Republican and Democratic states, as measured by vote-share in presidential elections or by state government partisanship. One consistent difference appears to be that innovator states have a larger share of the population living in urban areas. Overall, while there are specific states that consistently produce new policies (e.g., California) and those that do not (e.g., Georgia), innovation appears to be mostly idiosyncratic on observable state characteristics.

4.2 Policy Diffusion

Set up. We turn to examining how policies diffuse, following the initial adoptions. We model the adoption with a hazard model at the yearly level. 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. Formally, we run

$$log\left(\frac{P(Y_{iqt}=1)}{1-P(Y_{iqt}=1)}\right) = \eta_q + \Pi X_{it} + \sum_k \beta_k \left(\sum_{j\neq i} w^k_{ijt} Y_{jqt}\right) + \varepsilon_{iqt}. \quad (1)$$

This specification, with the log odds on the left-hand side, has three right-hand-side variables. The first one, η_q, captures a policy-specific baseline hazard rate. In the baseline specification, we parametrize the policy-specific baseline hazard rate by including a policy fixed-effect for each decade, thus allowing for differences across policies in the overall probability of adoption. The second term, ΠX_{it}, is a vector of state-level characteristics such as the Republican vote share and the log population that captures the overall impact of state-level differences on adoption. This term, for example, captures a further test of the state-capacity hypothesis, not in terms of early adoption as in the previous section, but in terms of overall adoption.

The third, key term, $\sum_k \beta_k \left(\sum_{j\neq i} w^k_{ijt} Y_{jqt}\right)$, aims to capture the influence of adoption by other states that are similar along a particular factor k, such as geography, demographics, or

[2] Figure A.1 presents similar plots splitting by the data source, SPID or NBER.
[3] In Table A.3 we present parallel evidence for the policies from the NBER papers.

politics. Let's consider the case of geography, which we label as $k = g$. We are interested in whether adoption by neighboring states predicts faster adoption by a given state, compared to the case with the same rate of adoption, but by states that are not close. We assign weights w^g_{ijt} that are uniform for the third of states that are the closest geographic neighbors to state i (using the state centroid), and zero weight to states that are further distant. Thus, the term $\sum_{j \neq i} w^g_{ijt} Y_{jqt}$ measures the average adoption of policy q in year t by states neighboring state i. In contrast, setting uniform weights $w^u = 1/47$, the term $\sum_{j \neq i} Y_{jqt}/47$ captures the average adoption of the policy across all other 47 states. To the extent that the adoption hazard is better predicted by the adoption by geographic neighbors, we expect β_g to be positive.

In addition to the measure of geographic proximity which is constant over time, we also build measures of similarity along demographic and political lines in a parallel way, except that the weights are time-varying. To capture the demographic similarity, we consider state-level log population, share of urban residents, and log income per capita. We standardize these three variables, take the absolute difference in each dimension, and average across the three differences to create the index. For each state, we then assign weights that are uniform for the third of states with the smallest difference in the demographic index, and zero otherwise. We construct measures of similarity along political lines by taking the third of states that are closest in the Republican vote share for the latest Presidential election.

The three similarity parameters — β_g for geographic closeness, β_d for demographic closeness, and β_p for political closeness — are scaled to be comparable. So if β_g is larger than β_d, for example, it implies that on average adoption by geographically-similar states matters more than adoption by demographically-similar states to predict future adoption by a state.

We estimate specification (1) separately for each decade in the sample, to allow for a time-varying impact of the coefficients, though we pool the 1950s and 1960s given the more limited coverage for the earlier years. In each year t, only states that have not yet adopted policy q remain in the sample. For each policy, we start the hazard model in the first year of adoption and end it in the last year of adoption in the sample. 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). 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 among the most likely nature of common shocks and circulation of ideas. Further, 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-difference design. Below, we provide estimates with a causal interpretation from an event study design for a specific variable, the change in state government control.

Estimates. Table 3 reports the estimates. Considering first the set of demographics X, we do not find any reliable pattern that state-level demographics predict faster adoption of state laws. In particular, consistent with the results on innovation, we do not find any consistent evidence that states with higher income or with larger populations adopt state policies faster. Unlike for the innovation results, the urban share is not a reliable predictor.

We thus turn to the estimates of the similarity predictors β_k, starting from similarity in the index of demographic features of the states, as one would expect demographically similar states to be more likely to share contexts and preferences (with the caveat that our demographic measures may only capture this to a limited extent). We find that demographic similarity is indeed predictive of adoption: for example in the 1980s we estimate a coefficient of 1.27 (s.e.=0.34), that is, for each 10 percentage point higher adoption in demographically similar states, the probability of adoption increases by approximately 13 percent, or 0.4 percentage points from a baseline yearly probability of adoption of 3 percent.[4]. In the most recent decades, the impact of demographic similarity is estimated to be somewhat lower, at 0.84 (s.e.=0.38) in the 2000s and 1.07 (s.e.=0.41) in the 2010s. The impact of demographic similarity is certainly consistent with the model of adoption by similarity of context and preferences, but can also be interpreted in light of models of competition and learning, if demographic similarity affects these margins.[5]

Next, we consider the impact of geographic closeness, which we would expect to capture the impact of competition across neighboring states, of learning about states policies and, to an extent, similarity in contexts and preferences. We find strong evidence that adoption by geographic neighbors matters: in the 1950-60s we estimate a coefficient of 2.52 (s.e.=0.36), indicating that for each 10 percentage point higher adoption in the nearest states, the probability of adoption increased by approximately 25 percent. The estimate is similar in the 1970s, and then still highly significant but lower in the 1980 and 1990s, and in the 2000s and 2010s (1.49 and 1.71). Overall, thus, geographic similarity is highly predictive, though with a decreasing importance over time.

Third, we consider the role of politics, and specifically similarity in the Republican vote

[4]Given that the baseline probability of adoption is fairly lower, the log odds is approximated with the log of the probability of adoption.

[5]Table A.4 shows the results for diffusion along each of the demographic variables separately, with the population and income per capita variables having the more consistent weights, especially in the earliest decades.

share at the state level. This captures similarity in political preferences and, to an extent, in the political control of the state (we return to this distinction in Section 5.2). For the first five decades, political similarity impacts adoption, but the effect size is about one half the size, or smaller, compared to the impact of geographic similarity: 0.40 (s.e.=0.41) in the 1950s-60s and 1.21 (s.e.=0.34) in the 1990s. In the last two decades, instead, the impact of political similarity doubles, with estimates of 2.66 (s.e.=0.28) in the 2000s and of 2.77 (s.e.=0.32) in the 2010s. Thus the recent decrease in importance of geographic similarity is more than compensated by the increase in importance of political similarity.

Figure 5 summarizes the estimates: demographic and especially geographic similarity remain important over time, but with declining weight, while the impact of political similarity skyrockets recently.

The bottom of the table highlights a final noteworthy finding: over time, the predictability of policy adoption has generally increased. If we exclude the first time period, the pseudo R-squared has increased nearly monotonically from 0.12 in the 1970s, to 0.14 in the 1980s, 0.18 in the 1990s and 2000s, and 0.20 in the 2010s. Thus, not only has the role of political similarity increased over the role of geographic similarity, but this increase is sizable enough that it makes the process of adoption more predictable.

Simulated Diffusion. To clarify the magnitudes of the estimated policy diffusion coefficients in the different decades, in Figure 6 we present two different counterfactuals, one corresponding to the estimated policy diffusion for the 1970s (Figure 6a), one for the estimated diffusion for the 2010s (Figure 6b). Namely, we take a hypothetical policy that is introduced by California in 2009, and then we trace out the probability of adoption over the next years by the different states, stopping once the predicted diffusion reached 10 states.[6] We assume the same political and demographic variables from the relevant years (2009 onwards) across the two plots, and only vary the estimated diffusion coefficients from the model. The policy with the estimated 1970s coefficients (Figure 6a) diffuses geographically, spreading in the West. In contrast, in the simulation with the estimated 2010s coefficients (Figure 6b), the policy spreads geographically only to the states with similar political leanings (Oregon and Washington), but then is predicted to spread to the North East, where the majority of the Democratic-controlled states are.

We present further simulations in Figures A.2a-f: (i) the simulated adoption in Connecticut, a state that is reliably Democratic like California but is smaller and on the other coast (Figure A.2a-b); (ii) the simulated adoption by Texas, a large, Republican state (Figure

[6]The simulation uses the model estimated in Table 3, and takes the coefficients on the proportions of other states adopting (all other states, as well as the thirds closest in the demographic index, Republican vote-share, and distance). In each simulated year, the policy diffuses to the next state with the highest predicted likelihood of adopting among the states yet to adopt.

A.2c-d); and (iii) the simulated adoption by a Republican-leaning Midwestern state (Ohio, Figure A.2e-f). In all cases, there is a sizable difference in the largely geographic, versus largely political, spread of policies.

Robustness. In Table A.5 we explore the robustness of the results in Table 3 to a range of alternative specifications. We run the models for the decades 1950-70s, 1980-90s and 2000-20s and report the coefficients on geographic similarity and political similarity.

First, we replicate the benchmark model estimate (except for the different year grouping). In the next row we present the results from a linear probability model instead of a logit specification, with parallel findings. The estimates from this model also provide further evidence on the magnitude of the findings. For example, in the most recent decade, if hypothetically the adoption by politically similar states were to increase by 10 percentage points, the probability of adoption by one state would increase by 1.4 percentage points.

In the third row we return to the logit specification, and estimate the model including a fuller set of controls, with very similar findings. Conversely, we present next a parsimonious specification which drops the levels of state characteristics X (e.g., the level of urban %) which are typically not significant. The patterns of the results are similar to the benchmark ones, and the pseudo-R^2 is nearly the same. We adopt this specification in the panels to follow.

In the final two specifications we adopt alternative weighting schemes for the adoption of other states. In the fifth row, we replicate the benchmark specification, but consider adoption by other states up to year $t-1$, instead of considering adoptions up to year t. In the next row, we use different weights w_k to capture similarity, using inverse rank weights instead of splitting the sample in thirds, as in the benchmark specification. The results are very similar to the benchmark.

Heterogeneity. In Table 4 we replicate the parsimonious specification featured in Table A.5 for different subsamples. In Panel A we present separate estimates for the SPID sample versus for the NBER sample, to test whether the patterns above are similar for the policies studied by economists. Interestingly, in the NBER sample the increase in polarization is even larger than in the SPID sample, with a coefficient on political similarity for the 2010s as high as 3.08 (s.e.=0.53), compared to a coefficient of 2.53 (s.e.=0.24) in the SPID sample. The pseudo-R^2 is also higher for the NBER sample for the last decade (0.22 versus 0.17), suggesting a rather strong predictability of policy expansions along political lines; we find a similar decrease in the impact of geographic similarity over time. In the third row, we study the Interstate Compacts. These are intended to be policies on which states can cooperate to address a common problem, such as the Interstate Wildlife Violator Compact, which facilitates the sharing of information among states on those violate fishing and hunting laws.

We find similar patterns even on this sample, suggesting a wide reach of the polarizing forces at play.

In Panel B we split the area of policy. We focus on the economics-related policies, to measure whether the results are different when mostly economic values, as opposed to social ones, are at play. We find a strong decrease in the role of geography and demographics over time, with a smaller increase in the role of politics. The strong decrease in the role for geography would seem to run counter to a strong role for competition across states, as one presumably would expect such competition to be strongest among neighboring states.

In Panel C we split the estimates along a few dimensions for the states. First, we separately estimate the results for Republican-voting states, Democratic-voting states, and "battleground" states, splitting the states into thirds. We find evidence of a decrease in the importance of geography in all three samples, but the increased importance of politics is largely driven by the Republican-voting states and especially the Democratic-voting states, not by the battleground states.

Finally, we study whether the patterns differ by state size. Returning to the "state capacity" model, we examine whether larger states, which likely have larger state capacity, display different patterns. To the extent that state capacity, for example, enables states to learn from a broader range of other states, we may expect a smaller impact of geographical closeness. We do not find any 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 US states of, e.g., Besley and Case (1995) and de Paula, Rasul, and Souza (2020) and in the political science literature with results as early as Walker (1969) and, reviewing the papers since then, in Mallinson (2020). 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.

4.3 Diffusion of Vaccination Policies

While the main focus of the analysis is on the diffusion of state level policies over the years, a natural question is whether the patterns identified for the last two decades apply also to the diffusion of COVID-related policies adopted since October 2019 by the US states, such as masking policies and school closures. Given the shorter time frame, we estimate the model (1) at the weekly level. Column 1 of Table 5 presents the estimates of the model. We estimate a significant impact of demographic and geographic similarity, with political similarity also playing a strong role, findings consistent with the estimated patterns in the recent decades for the main sample. In Column 2 we add additional similarity variables, described below. Cui et al. (2021) also provides consistent evidence of partisan spread of Covid policies.

For comparison, we present evidence on the adoption of vaccination policies for the period from 1988 on, covering laws such as on the required immunizations for school. As Column 3 in Table 5 shows, in this sample the adoption of policies is predictable based on demographic similarity and, to come extent, geographic similarity, while instead political similarity has no impact. This makes the politically polarized patterns for the adoption of COVID policies stand out even more.

5 Evidence Relating to Models of Policy Diffusion

We now aim to 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 adoption of policies as reflecting *correlated preferences or environments*, or *learning* across states, or *competition* among states. While these explanations are distinct, they share the prediction about the importance of 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 fits neatly with these models.

The patterns for the 2000s and 2010s are a less obvious fit, with the declining weight on geography and the increased weight on political voting patterns. It is plausible, though, that recently both the diffusion of information and the extent of competition follow less geographic lines. This would make the recent findings consistent with learning or competition. It is also possible that the correlation in preferences or environments across states may have shifted from mostly geographical to largely political. That is, the relevant context for policy adoption may be better captured by political voter preferences than by geography. In this case, the shift in the policy adoption estimates may still reflect correlated preference or environments, with a change in the weights of correlation.

Evidence using Migration Flows. If these changes have indeed happened, other inter-state flows that follow similar determinants, such as cross-state migration, may exhibit similar patterns. We thus construct measures of similarity across states identifying the top third of other states with the most inflow-outflow migration from a given state. In Table 6 we first replicate the result of Table 3 pooling decades in Column 1-3, and then add migration-based similarity in Columns 4-6. As the table shows, migration-based familiarity has quite strong predictive power of policy diffusion both in the earlier period and in the later period. Further, it reduces the explanatory power of geography. It does not, however, affect much the importance of the voting variable (or of demographic similarity). We can revisit in this light also the specifications on Covid and vaccination policies by adding the migration-based similarity measure in Table 6. We estimate an impact of migration-based similarity especially for the vaccination laws (Column 4).

Evidence from Outcome Variables. As a further piece of evidence, for the NBER papers with state policy variation, we consider the outcome variables, such as state-level BMI, mortality, income, and private insurance 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 over time among politically similar states, as opposed to among neighboring states. This is thus a fairly direct test of whether a change in the economic environments across states has been driving the change policy adoption patterns. If, instead, other factors are at play, the correlation between the outcome variables may not change over time.

We adopt a specification as parallel as possible to the one in (1) but with the outcomes as variables. Denote by Z_{iyt} the outcome variable y for state i in year t. The index y keeps track of the various dependent variables, e.g., BMI, opioid mortality, etc. Each of the outcome variables Z_{iyt} is standardized. We include in the regression each state and outcome for each year t. We then run

$$Z_{iyt} = \sum_k \beta_k \left(\sum_{j \neq i} w_{ijt}^k Z_{jyt} \right) + \varepsilon_{iyt} \tag{2}$$

This specification allows for a parallel interpretation of the coefficient β_k as in equation (1). For example, if β_g is positive, it indicates that the states are correlated along geographical lines. We run the specification both in levels, to check how the outcome variables are correlated across states, and with state-outcome fixed effects, to test how the changes over time in the variables are correlated across states.

Columns 1 to 3 of Table 7 show the results of the estimation of equation (1). We find a sizable correlation in outcome variables among states that are demographically or geographically similar, as we would expect. This pattern of geographic correlation is fairly constant over time, while the demographic one decreases. We find instead less evidence of a correlation in outcomes among politically-similar states up to the 1990s. Political similarity does become a positive, if small, predictor of outcomes in the 2000s.

In Columns 4 to 6 we estimate the same specification with state-outcome fixed effect, which allows us to consider the correlation in changes in outcomes over time. Geographic and demographic proximity are somewhat predictive in this case, with no explanatory power from political correlation.

Overall, this suggests that the increased weight of political variables on policy adoption may not be due to a change in the correlation across states in the environment, but rather to other factors. We discuss a major one in the next section.

5.2 Party Discipline

A separate explanation is that in the recent decades *party discipline* increasingly explains state policy, beyond the predictive power of local preferences or environments, learning, or competition. The evidence thus far does not allow us to tell this explanation apart, as the political variable may just capture preferences of voters, and thus correlation in preferences across states.

We thus examine the impact of state political control on policy diffusion, controlling for the state voting patterns. We construct a measure of similarity in state government control which gives uniform weight to states with similar state control, and zero otherwise; for state government control, we consider three possibilities: unified Democratic state control (governor party and both state houses), Republic state control, and split-party state control. In Columns 7 to 9 of Table 6, we add this variable to the logit model.

This measure yields evidence of an even more striking change over times. In the decades up to the 1990s, we do not find any statistically significant evidence that similarity in state politics control matters, with an estimate for the 1980-90s of 0.37 (s.e.=0.21). In contrast, we estimate a large and precisely estimated impact of 1.49 (s.e.=0.22) in the last two decades. The increase in importance of politics is even more striking when measured by political control, as opposed to political preferences of the electorate.

We also revisit the Covid and vaccination sample in Table 5 with this additional political similarity variable. We find that the state government similarity is the strongest predictor of the adoption of Covid policies (Column 2), while it plays no role for the earlier vaccination policies (Column 4). This pattern also points to the politicization of state policies in the recent years.

Event Study. This result provides descriptive evidence that party control matters for the diffusion of policies. We now use an event study to provide causal evidence on the impact of political control. We focus on the switch to unified party control at the state level, since the political science literature suggests is likely the most critical threshold.

We estimate the model

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

where e_i^s indexes a year of switch in party control in state i, and the key parameter of interest δ_d is allowed to depend on the type of state law. We control for the baseline probability of adopting different policies with α_i, for state government election years with X_{it} , and for the different level of adoption of policies over the years with policy-year fixed effects γ_{qt}. We include all state-year-policy observations as in Table 3 (not just the years before and after a switch), to identify the baseline parameters, such as the policy-year fixed effects γ_{qt}.

The key missing ingredient is to code policies as being in line with the state government control, or not. We split policy laws depending on the political leaning of the states that adopted the law up to that point. More precisely, we take the average 2-party (residualized) Republican vote share for the states that have adopted the law up to year $t-1$. If a policy is adopted by states with on average a 1 percentage point, or higher, advantage for Republicans in the vote share, we categorize the policy as Republican leaning, and conversely we categorize policies as Democratic leaning. If the average vote share of states adopting a policy is at some point within the 2 points buffer, we code the policy as neutral leaning.

Figure 7a displays the event study coefficients with confidence intervals for the period 1991-2020. To start with, 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 in general. Next, we consider the impact on the probability of adopting a policy that is leaning in the same direction of the unified state government switch, compared to the adoption of policies aligned in the opposite direction. We detect a statistically significant increase of about 2 percentage points in the 4 years following they switch, compared to the previous year. The increase arises already in year $t+1$, as one would expect, and appears to be persistent. The data does not suggest any obvious pre-trends.

In Figure 7b we consider the same event study for the earlier 1950-1990 time period. In this earlier period we do not detect any change from a switch in party control in the probability of passing laws aligned to that party. Thus, the results from the event study confirm the findings from the hazard analysis: partisan support of laws is a relatively recent phenomenon in the US states.

In Table A.6 we present the separate components contributing to these event study Figures, reproduced in Column 1. In Column 2 we present the impact on the passage of Republican-associated policies (as per the coding above) for the case of switched to Republican unified government, and in Column 3 the impact for Democratic-associated policies for the same switch, with the difference in Column 4. In Column 5 we present the impact on neutral policies. In Columns 6-9 we replicate the same specifications, but for the cases of switches to unified Democratic state government. The findings generally follow the patterns one would expect, with the largest impacts from switches to Democratic state governments for Democratic-leaning policies. In Column 10 we examine the impact of switches away from unified state governments, which yield smaller impacts.

6 Policy Diffusion in Economics Papers

Above, we analyzed the patterns of policy diffusion in the sample of NBER working papers with state-level policy variation, documenting both geographic spread and, more recently, a partisan component in the spread. While this analysis aimed to capture the overall pattern of policy spread, it is possible, to a first approximation, to estimate the type of spread of policy diffusion policy-by-policy, provided there is enough statistical power (that is, enough states take up over enough different years).

In this Section, we provide evidence in this direction by estimating the model of diffusion individually for each policy. Specifically, we estimate a version of equation (1):

$$log\left(\frac{P(Y_{iqt}=1)}{1-P(Y_{iqt}=1)}\right)=\eta_q+\beta_{g,q}\left(\sum_{j\neq i}w^g_{ijt}Y_{jqt}\right)+\beta_{p,q}\left(\sum_{j\neq i}w^p_{ijt}Y_{jqt}\right)+\varepsilon_{iqt}. \tag{3}$$

That is, we estimate a parsimonious version of the main model which does not include the overall controls X and include only the diffusion terms with respect to geography and politics. The key coefficients $\beta_{g,q}$ and $\beta_{p,q}$ are estimated policy-by-policy.

Figure 8a plots the estimated coefficients from the above regressions for the set of policies in the NBER working papers in the sample. To a first approximation, the policies fall into three category. One group of policies has diffusion that is largely predicted by politics, such as the Medicaid Expansion. A second group of policies has diffusion that instead is predicted by a combination of geography and politics. Finally, a third group appears to be fairly idiosyncratic, at least given the (parsimonious) model above.

We envision that it can be useful for authors of papers that rely on policy changes to identify where their policy variation falls relative to the average difference-in-difference paper of this kind. For example, the presence of geographic versus political diffusion suggests possible concerns for identification which differ depending on the extent of correlation in the diffusion. We discuss the econometric implication of this correlation in separate work.

7 Discussion and Conclusion

We documented a series of facts about the diffusion of state-level policies in the US, and aimed to relate them to different models of policy diffusion. As we discussed, the estimated impact of geographic and demographic similarity resonates with models put forward in the literature of competition across states, learning from state to state, and underlying similarity of voter preferences or economic context. It is more difficult to tell apart these three models, given that they share several key predictions. We document directly the similarity of economic contexts along geographic lines by considering measures of outcomes evaluated in the relevant economic papers.

We also showed that the pattern for the most recent two decades points to the increasing importance of another factor: the party influence on state policy adoption. We find in the last two decades a significant increase in the importance of political similarly, and especially similarity in the state party control. These results suggest that it is not just a question of voter preferences, but a party-line impact.

This result implies a parallel with the polarization results which have been a key focus of the recent political science and political economy literature. A key finding in this literature is that politicians in the US Congress have started polarizing, that is, voting more more for the party line, from the 1950s. Indeed, Figure 9 reproduces the pattern using the DW-NOMINATE data, one of the commonly-used data sets in the literature. Our results indicate that the polarization of state policies has not started until later, in the 2000s. Still, its path is rapidly rising and the results for the Covid vaccination policies imply that it has quickly affected even topics for which we do not find evidence of polarization in previous years. This evidence on state polarization is consistent with the evidence on roll-call state data in Shor and McCarty (2011).

This trend is important because it suggests, at least, that state policy adoption appear to respond to forces other than the preferences of voters and the demands of the local economic situation.

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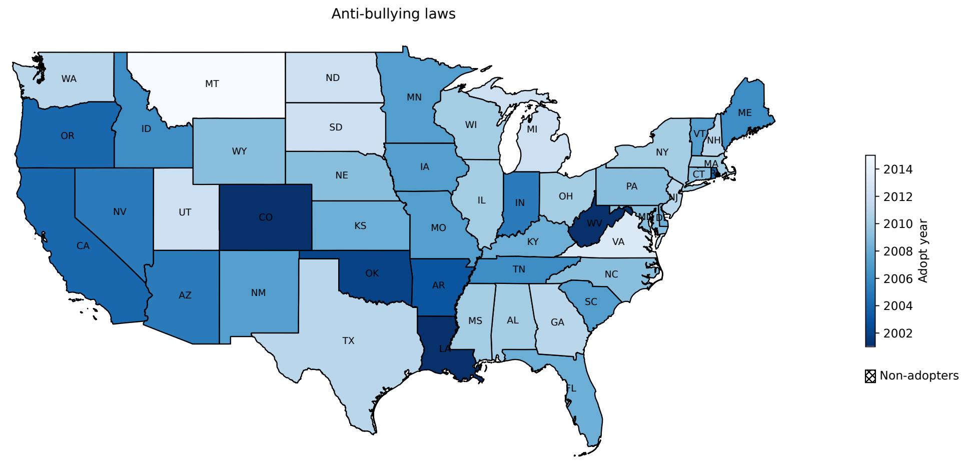
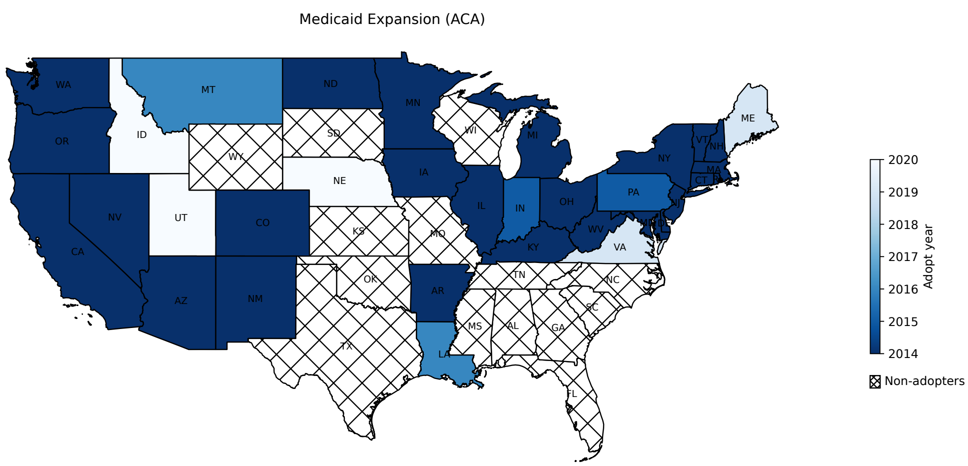
Figure 1: Three policy examples

(a) Anti-bullying laws



(b) 2014 Medicaid expansion (Affordable Care Act)



(c) Bicycle helmet regulation

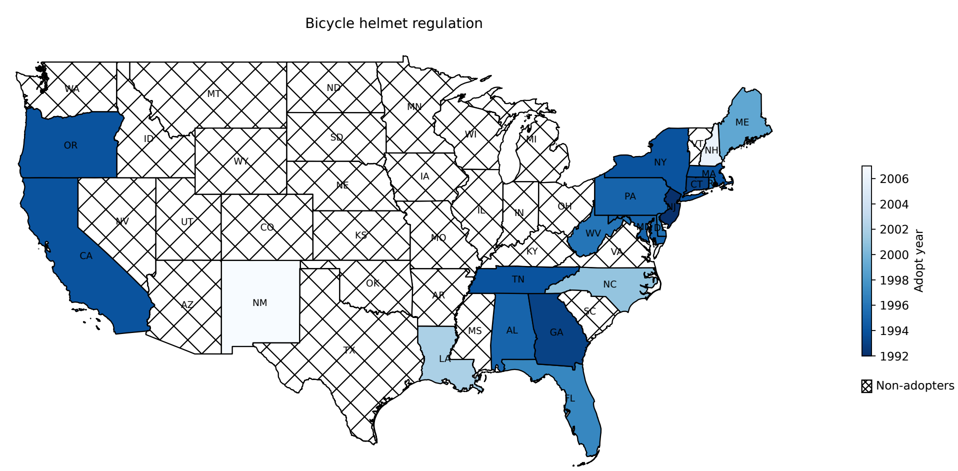


Figure 2: Case studies of welfare programs

(a) 2014 Medicaid expansion (ACA)

(b) 2014 Medicaid expansion coverage

(c) 1960s Initial Medicaid adoption

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

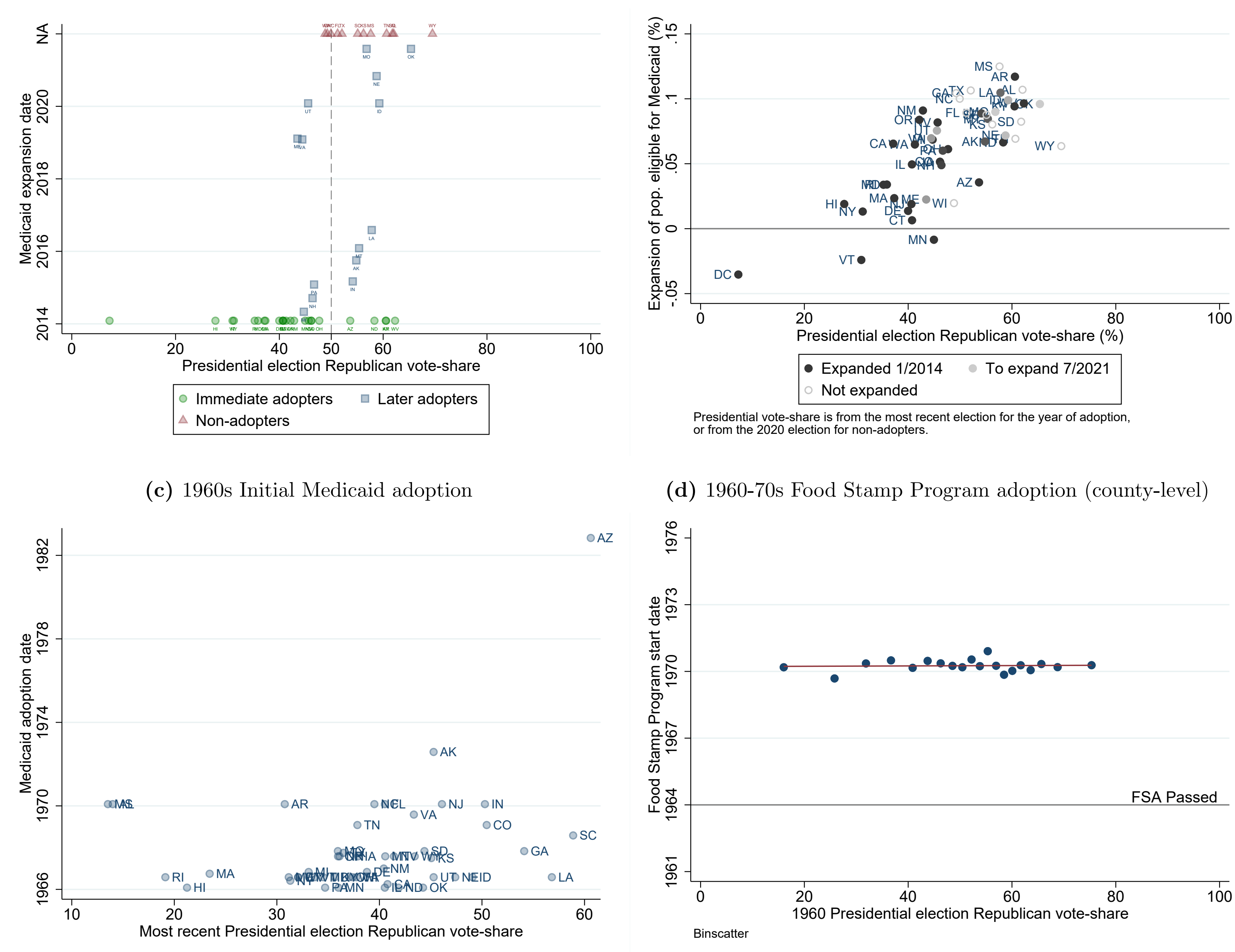
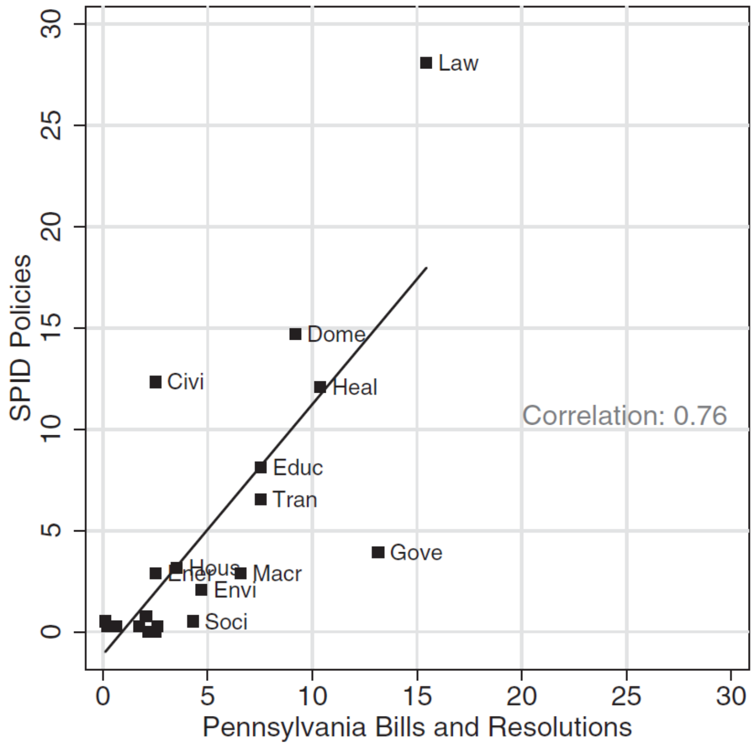


Figure 3: Policy sources and representativeness

(a) Comparison with PA laws (Fig. 3, Boehmke et al., 2020)



(b) Sources

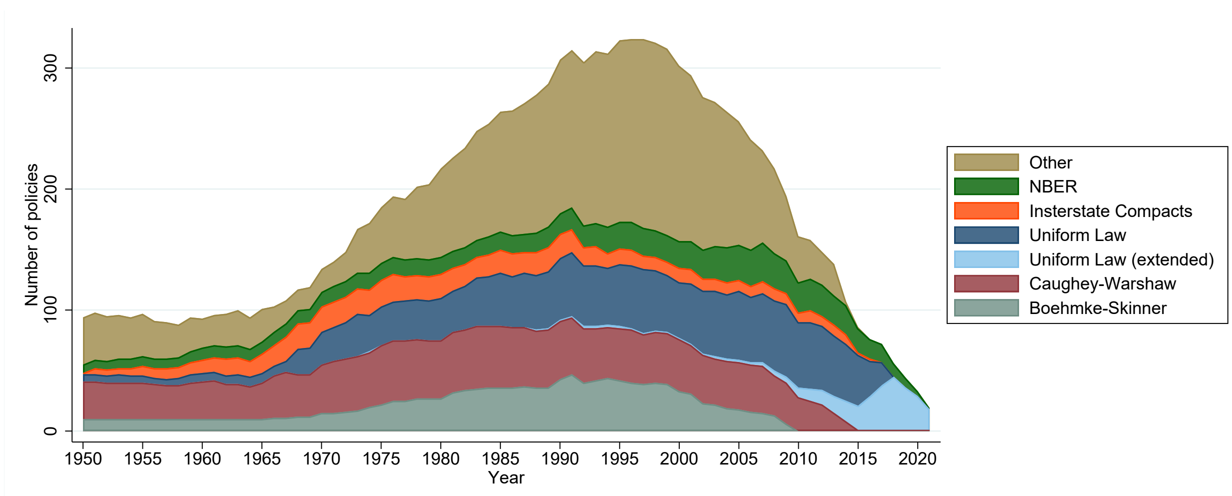
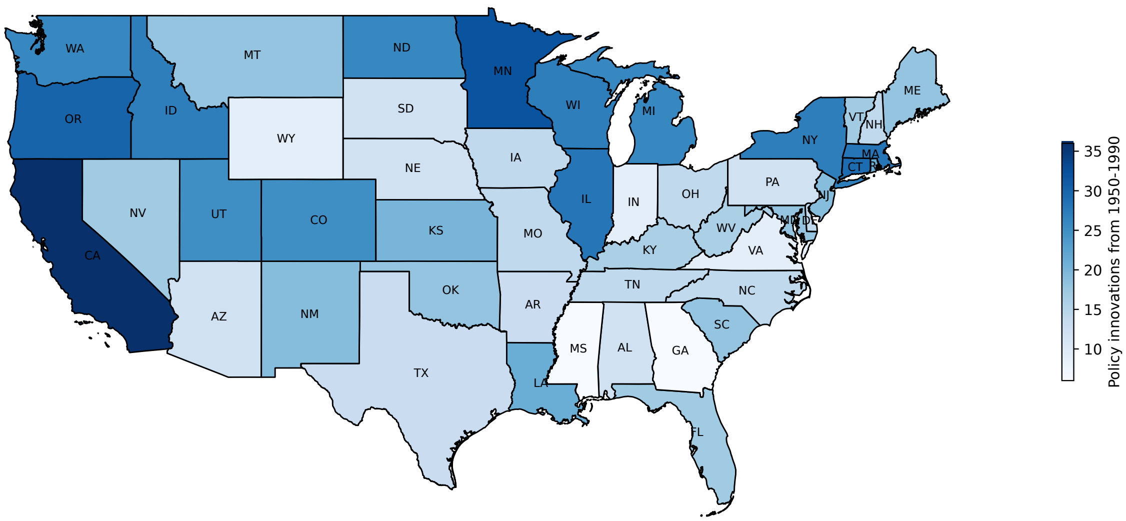


Figure 3a is reproduced from Boehmke et al. (2020) and shows the correlation of policy areas between the policies in the SPID dataset and in the Pennsylvania Policy Database Project (McLaughlin et al., 2010). The Pennsylvania Policy Database is used as an example of policies in a typical state.
Figure 3b 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 "Uniform Law (extended)" subgroup refers to policy adoption data from the Uniform Law Commission source that this paper extended for more coverage in recent decades.

Figure 4: Innovating states

(a) Policies innovated 1950-1990



(b) Policies innovated 1991-2020

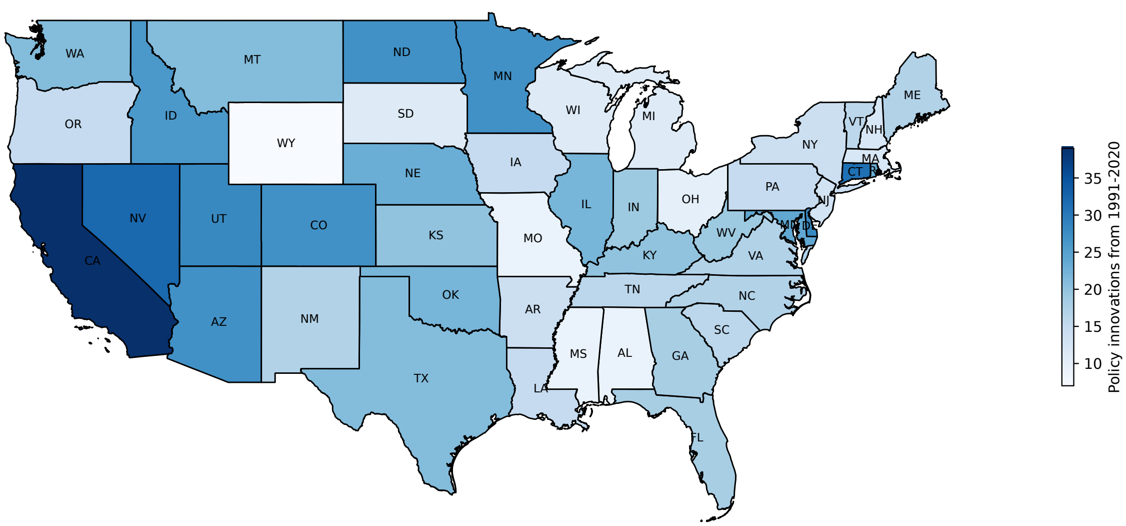
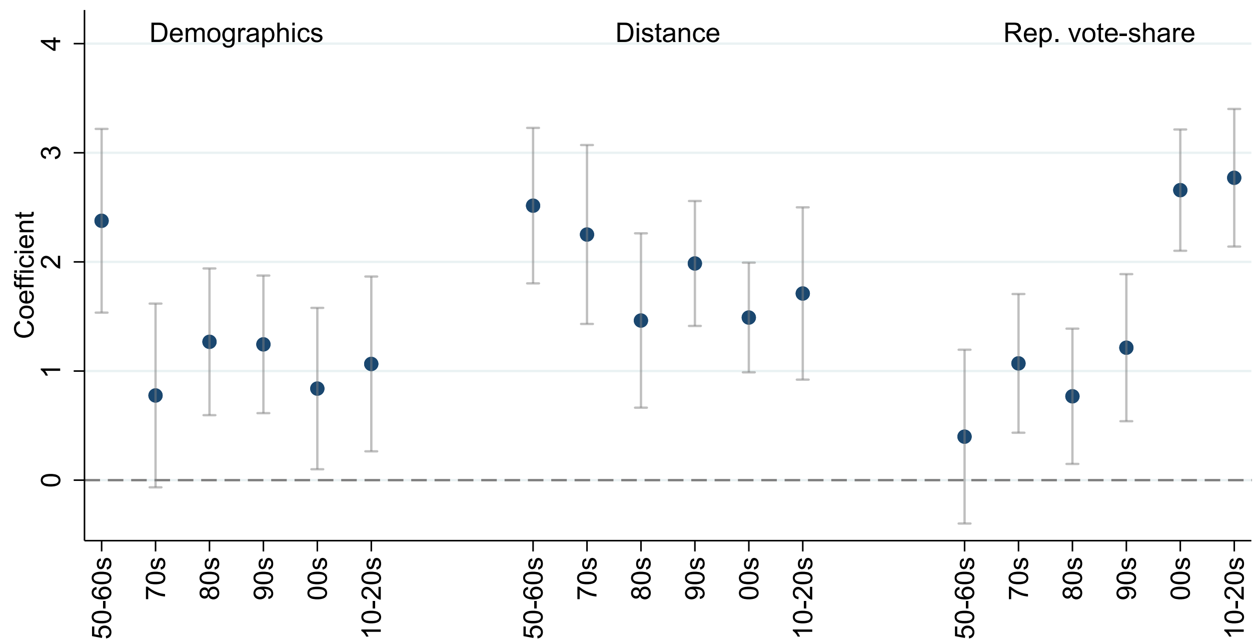


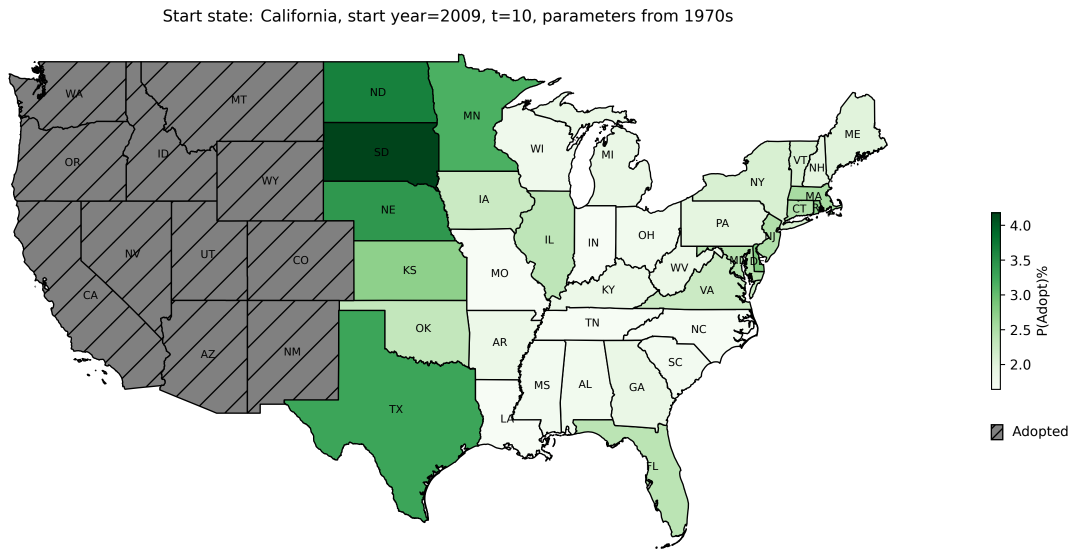
Figure 5: Dynamics of policy adoption predictors



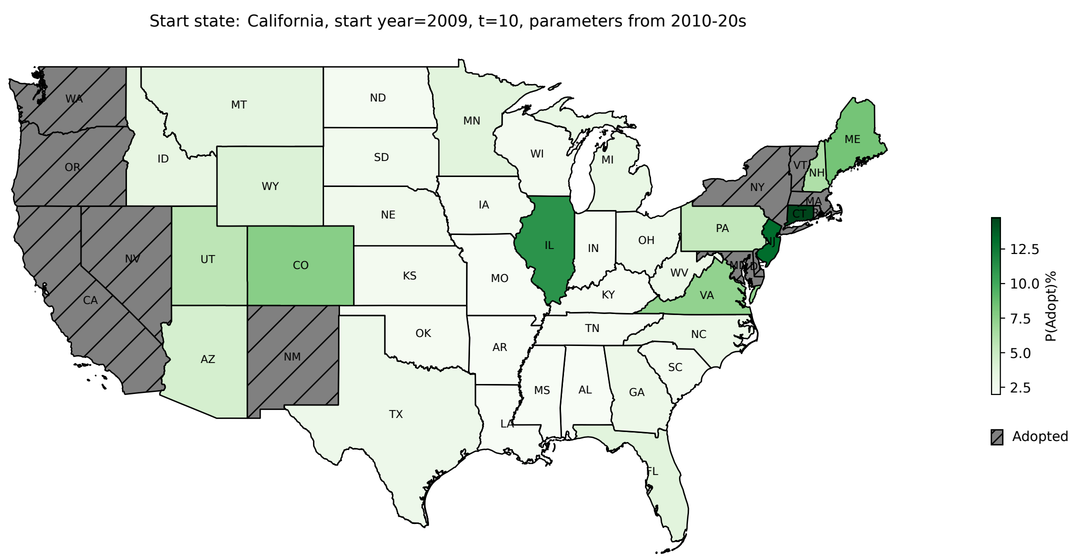
This figure plots the coefficient estimates from the logit regressions of policy adoption on the proportion of adoptions within the third of other states that are closest in each characteristic. 95% confidence intervals are shown with standard errors clustered by state.

Figure 6: Simulated policy diffusion

(a) Coefficients from 1970s



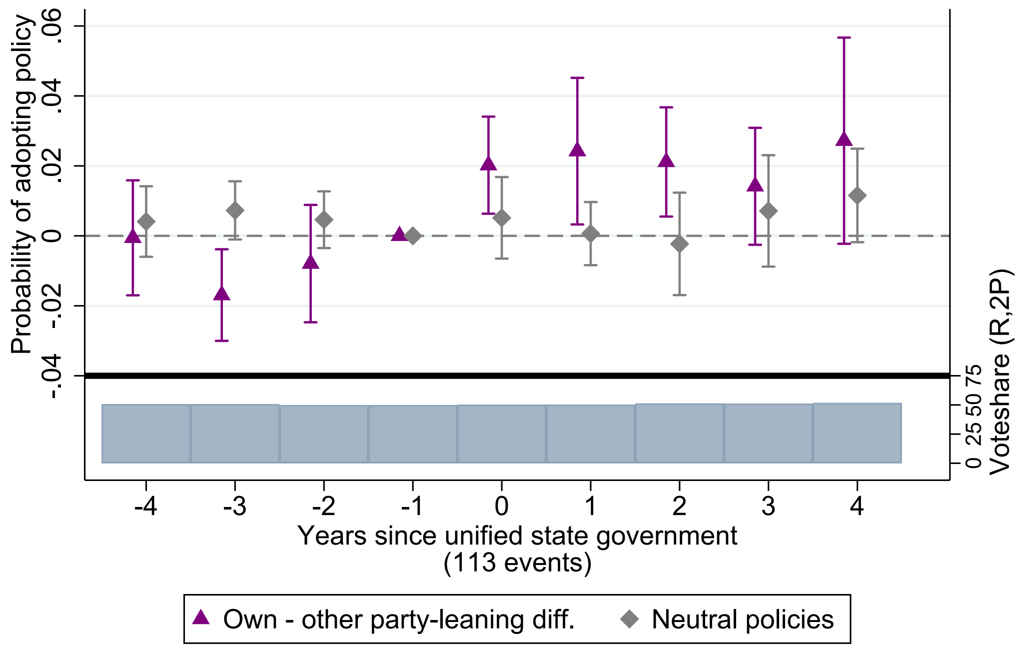
(b) Coefficients from 2010-20s



These maps show the simulated diffusion of a policy innovated by California in 2009 after 10 years based on the model estimated in Table 3. The simulation does not include the coefficients on the levels of state characteristics and only uses the coefficients on the proportions of other states adopting (all other states and the thirds closest in demographic index, Republican vote-share, and distance). The baseline probability of adopting is set to 0.03. Figure 6a uses estimated coefficients from the 1970s decade, and Figure 6b from the 2010-20s decade. In each simulated year, the policy diffuses to the next state with the highest predicted likelihood of adopting among the states yet to adopt.

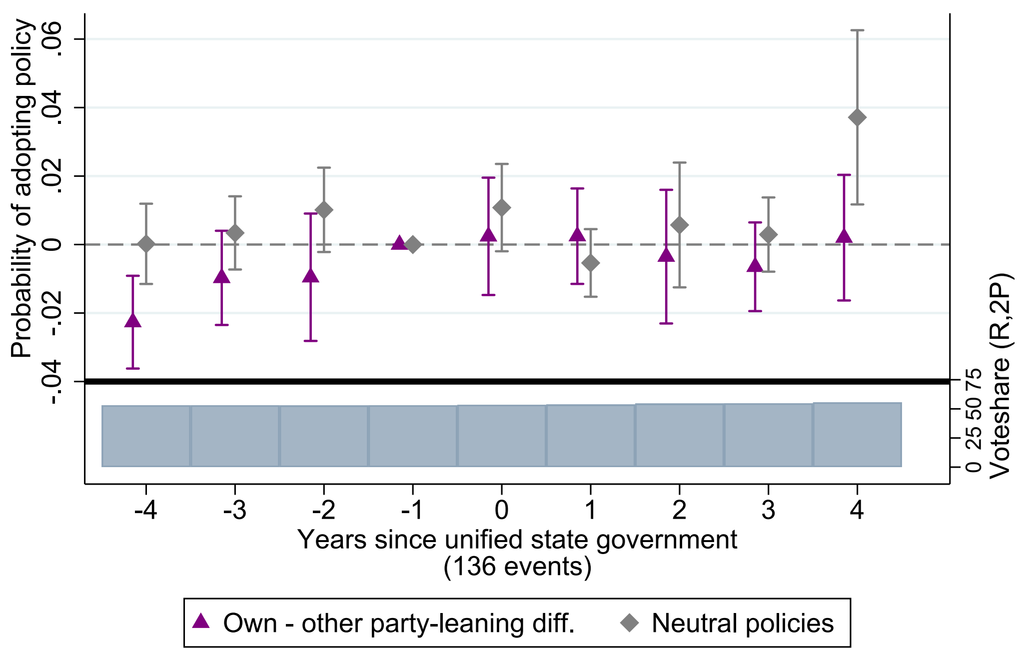
Figure 7: Event study from switches in state government party control

(a) Events during 1991-2020



This regression includes state and policy-year fixed effects and events occuring between 1991-2020.
Policies are added after 5 adoptions and exclude those that switch ideology.
95% CIs shown with standard errors clustered by state.

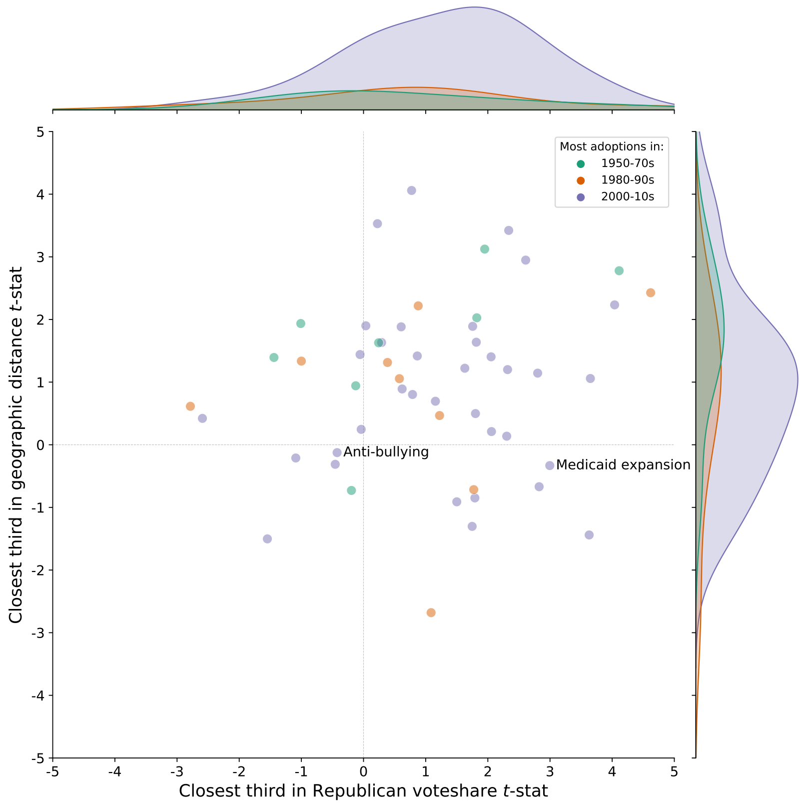
(b) Events during 1950-1990



This regression includes state and policy-year fixed effects and events occuring between 1950-1990.
Policies are added after 5 adoptions and exclude those that switch ideology.
95% CIs shown with standard errors clustered by state.

Figure 8: NBER policy-by-policy diffusion patterns

(a) t-stats



(b) Coefficients

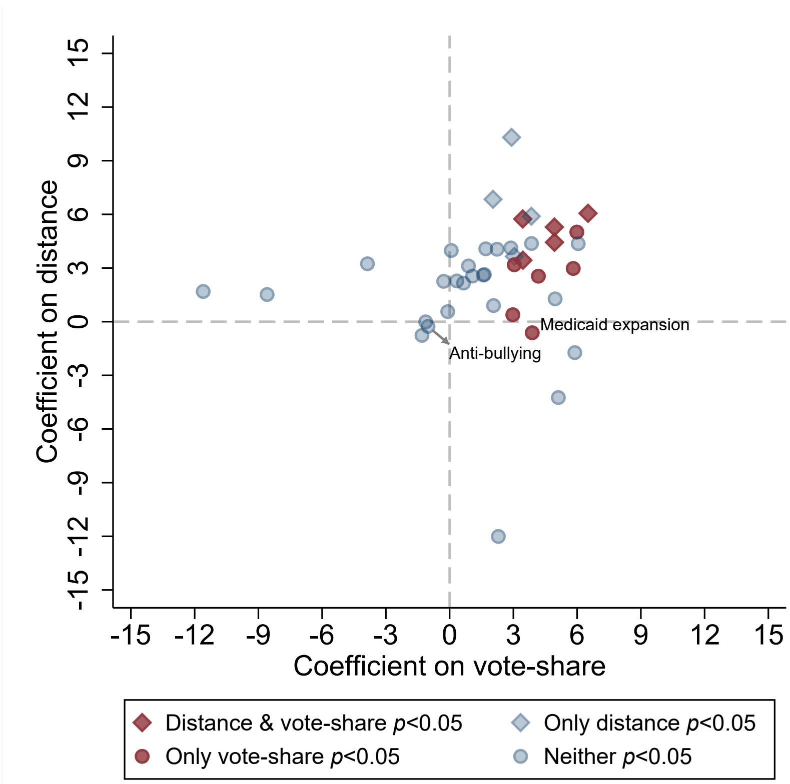


Figure 9: Comparison to polarization in DW-NOMINATE

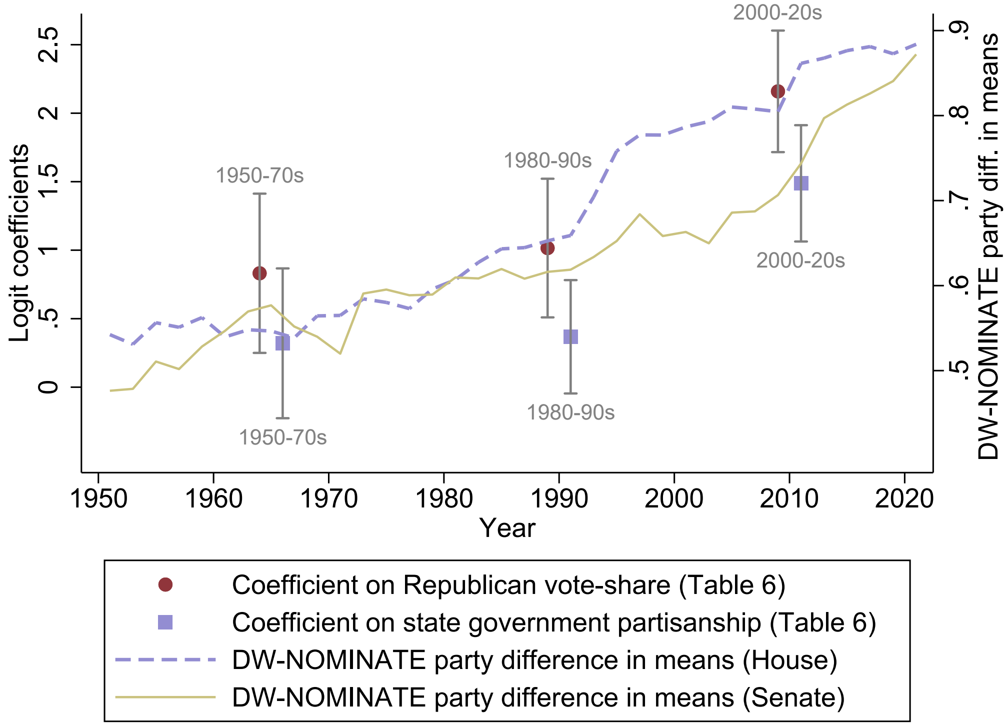


Table 1a: Summary of NBER dataset

	(1) All (4/12 - 9/21)	(2) Cross-state policy	(3) Meets criteria*	(4) Sample
Total	11316	151	87	77
Issue date	2017.3 [2.7]	2017.5 [2.7]	2017.4 [2.7]	2017.7 [2.6]
Field				
% in Labor Studies	23	33	30	29
% in Public Economics	23	38	32	31
% in Economic Fluctuations and Growth	22	7	0	0
% in Health Economics	12	50	61	66
Other	41	16	10	9
Publication				
% Published	48	48	48	44
% Published in Top 5	9	3	1	0
% Published in Tier A	14	17	18	19
Year published	2017.3 [2.4]	2017.1 [2.3]	2016.7 [2.5]	2016.9 [2.6]
% Policy adoption data available	–	–	89	100
% Replication data available	–	–	–	9

Working papers numbered 18000-29318 included. Means and standard deviations in brackets are reported for dates. Working papers can be listed under multiple fields. Papers that cover the same policy are 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 datasets

	SPID				NBER			
	Mean (SD)	Min	Median	Max	Mean (SD)	Min	Median	Max
Number of policies	676	–	–	–	52	–	–	–
First year of adoption	1977.27 (29.33)	1804	1983	2017	1987.48 (26.75)	1911	1997.5	2017
Last year of adoption	1998.10 (17.13)	1949	2002	2021	2010.69 (9.55)	1971	2014	2021
Number of states adopted	23.18 (15.07)	1	21	48	28.15 (15.42)	5	28	48

Policies with the last adoption before 1949 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	181 (27%)	27 (51%)
Law & Crime	Law & Crime	Gun open carry laws	193 (29%)	4 (8%)
Economics	Domestic Commerce, Labor	Bankrupcy laws	117 (17%)	17 (32%)
Civil Rights	Civil Rights, Immigration	Gender discrimination laws	111 (17%)	2 (4%)
Environment & Energy	Energy, Environment	Renewable energy standards	36 (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 voteshare %	52.55	55.97	51.84	52.12	-3.43	-0.27
	[8.56]	[12.99]	[9.93]	[8.91]	(2.14)	(3.89)
|Demeaned two-party voteshare|	4.94	8.36	8.00	6.64	-3.42	1.36
	[4.16]	[9.43]	[5.46]	[5.27]	(1.80)	(2.08)
Unified Dem. state gvt.	0.21	0.45	0.16	0.11	-0.25	0.05
	[0.40]	[0.50]	[0.37]	[0.31]	(0.15)	(0.07)
Unified Rep. state gvt.	0.21	0.24	0.36	0.43	-0.03	-0.07
	[0.41]	[0.43]	[0.48]	[0.50]	(0.10)	(0.16)
Log(population)	15.24	14.70	14.93	15.01	0.54	-0.08
	[1.05]	[0.99]	[1.09]	[1.01]	(0.44)	(0.48)
Income per capita	6957.12	5975.40	36593.14	35089.26	981.72	1503.88
	[5703.98]	[4992.64]	[12523.16]	[11958.60]	(327.84)	(2577.51)
Log(income per cap.)	8.53	8.34	10.45	10.41	0.18	0.04
	[0.80]	[0.85]	[0.35]	[0.35]	(0.06)	(0.07)
Urban pop. %	69.66	57.09	80.51	65.92	12.57	14.59
	[14.91]	[12.19]	[12.06]	[11.85]	(5.39)	(5.35)
Minority %	10.66	16.57	26.24	18.94	-5.91	7.31
	[8.54]	[10.85]	[14.44]	[9.81]	(3.94)	(5.36)
Unemployed %	6.99	6.51	5.20	5.33	0.49	-0.13
	[2.25]	[2.37]	[2.09]	[1.90]	(0.68)	(0.49)
States	12	10	10	10		

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

Dep. var.: Policy adoption (logit)	(1) 50-60s	(2) 70s	(3) 80s	(4) 90s	(5) 00s	(6) 10-20s
Prop. of states adopted	-2.81	-3.62	-1.39	-1.28	-2.59	-2.11
	(0.67)	(0.76)	(0.59)	(0.49)	(0.56)	(0.60)
Republican vote-share	-0.31	-0.07	-0.59	0.09	0.64	-1.10
	(0.32)	(0.29)	(0.55)	(0.39)	(0.56)	(0.72)
Log(population)	0.05	0.03	0.02	0.04	0.01	0.02
	(0.07)	(0.06)	(0.03)	(0.05)	(0.04)	(0.06)
Income per capita ($10,000s)	2.55	-0.45	-0.14	-0.10	-0.12	-0.15
	(1.12)	(0.42)	(0.14)	(0.14)	(0.07)	(0.10)
Urban pop. %	0.01	0.00	0.01	0.01	0.01	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Average adoption among other states closest in:						
Demographic index	2.38	0.78	1.27	1.24	0.84	1.07
	(0.43)	(0.43)	(0.34)	(0.32)	(0.38)	(0.41)
Distance	2.52	2.25	1.46	1.99	1.49	1.71
	(0.36)	(0.42)	(0.41)	(0.29)	(0.26)	(0.40)
Republican vote-share	0.40	1.07	0.77	1.21	2.66	2.77
	(0.41)	(0.32)	(0.32)	(0.34)	(0.28)	(0.32)
Baseline P(Adopt)	0.03	0.03	0.03	0.05	0.05	0.06
Observations	59667	54830	78973	93407	70833	27658
Policies	162	203	282	392	344	179
Pseudo R^2	0.21	0.12	0.14	0.18	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 by 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 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. Alaska, Hawaii, and Washington D.C. are excluded from the analyses. Only policies spanning at least 3 years with at least 5 adopters are included.

Table 4: Heterogeneity in policy diffusion

Demographic index			Distance			Republican vote-share		
1950-70s	1980-90s	2000-20s	1950-70s	1980-90s	2000-20s	1950-70s	1980-90s	2000-20s
Dep. var.: Policy adoption (logit)								
Panel A. Source of policy								
NBER (R^2: $0.14, 0.17, 0.22$; $N_{\text{pol.}}$: $13, 24, 42$)								
2.15	1.99	1.72	3.89	2.09	2.40	0.37	1.80	3.08
(0.96)	(0.71)	(0.54)	(0.75)	(1.03)	(0.50)	(0.70)	(0.95)	(0.53)
SPID (R^2: $0.16, 0.16, 0.17$; $N_{\text{pol.}}$: $260, 408, 343$)								
2.10	1.51	1.00	2.31	1.76	1.36	0.92	1.00	2.53
(0.38)	(0.30)	(0.33)	(0.30)	(0.29)	(0.32)	(0.30)	(0.27)	(0.24)
Interstate Compacts (within SPID) (R^2: $0.14, 0.12, 0.20$; $N_{\text{pol.}}$: $22, 26, 15$)								
1.00	0.85	0.94	2.86	3.98	0.16	0.53	-0.18	2.16
(0.84)	(0.97)	(1.02)	(0.61)	(0.73)	(0.74)	(0.61)	(0.99)	(0.69)
Panel B. Policy area								
Economics (R^2: $0.10, 0.18, 0.19$; $N_{\text{pol.}}$: $48, 59, 70$)								
2.14	1.47	1.40	3.28	2.07	0.78	0.87	1.03	1.38
(0.63)	(0.49)	(0.49)	(0.49)	(0.37)	(0.44)	(0.56)	(0.57)	(0.47)
Panel C. By state characteristics								
Third of states with highest Republican vote-share (R^2: $0.16, 0.16, 0.17$; $N_{\text{pol.}}$: $273, 432, 385$)								
1.73	1.50	1.55	1.92	1.77	1.52	0.53	0.93	2.15
(0.51)	(0.41)	(0.43)	(0.42)	(0.34)	(0.52)	(0.59)	(0.52)	(0.48)
Third of states with most neutral vote-share (R^2: $0.16, 0.16, 0.17$; $N_{\text{pol.}}$: $273, 432, 385$)								
2.47	1.63	0.45	2.26	1.70	1.52	0.63	0.00	0.98
(0.59)	(0.42)	(0.38)	(0.46)	(0.34)	(0.40)	(0.48)	(0.47)	(0.37)
Third of states with highest Democratic vote-share (R^2: $0.16, 0.16, 0.17$; $N_{\text{pol.}}$: $273, 432, 385$)								
2.03	1.40	1.08	2.97	1.78	1.50	1.40	1.98	3.91
(0.54)	(0.44)	(0.63)	(0.50)	(0.57)	(0.45)	(0.45)	(0.52)	(0.51)
Third of states with highest population (R^2: $0.16, 0.16, 0.17$; $N_{\text{pol.}}$: $273, 432, 385$)								
3.17	2.35	1.99	2.54	1.21	1.40	0.63	0.50	2.16
(0.64)	(0.56)	(0.65)	(0.49)	(0.55)	(0.55)	(0.41)	(0.36)	(0.46)
Third of states with lowest population (R^2: $0.16, 0.16, 0.17$; $N_{\text{pol.}}$: $273, 432, 385$)								
1.36	1.13	0.37	2.80	2.26	1.96	0.43	1.04	2.74
(0.49)	(0.42)	(0.35)	(0.45)	(0.39)	(0.50)	(0.53)	(0.34)	(0.42)

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 2000-20s), a parsimonious diffusion model is estimated, which includes only (i) policy fixed effects and the proportion of adopters among (ii) all other states, (iii) the closest third of other states in a demographic index combining population, income per capita, and urban % (see notes in Table 3 for details), (iv) the closest third of other states in geography, and (v) the closest third of other states in Republican vote-share in the most recent presidential election. The table shows coefficients on (iii), (iv), and (v) 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 for only policies in the "Economics" policy area.

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: COVID-19 policies and vaccine laws

	COVID policies		Vaccine laws	
Dep. var.: Policy adoption (logit)	(1)	(2)	(3)	(4)
Proportion of states adopted	-2.13	-3.14	-1.72	-2.50
	(0.69)	(0.62)	(1.35)	(1.41)
Average adoption among other states closest in:				
Demographic index	1.49	1.35	2.47	2.17
	(0.48)	(0.47)	(0.66)	(0.65)
Distance	2.04	1.55	1.14	0.04
	(0.33)	(0.45)	(0.51)	(0.75)
Republican vote-share	1.93	0.52	-0.18	-0.27
	(0.40)	(0.47)	(0.76)	(0.76)
Migration flows		1.05		2.21
		(0.63)		(0.93)
State gvnt. partisanship		2.08		-0.08
		(0.38)		(0.59)
Observations	27935	27935	9365	9365
Policies	77	77	15	15
Pseudo R^2	0.32	0.33	0.17	0.17
Time unit	Weeks (Mo-Su)	Weeks (Mo-Su)	Years	Years
Time range	10/2019-8/2021	10/2019-8/2021	1988-2021	1988-2021

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 6 for the definition of closest states in each characteristic. Alaska, Hawaii, and Washington D.C. are excluded from the analyses. Only policies spanning at least 3 time periods with at least 5 adopters are included.

Table 6: Models of policy diffusion: Migration and state party control

Dep. var.: Policy adoption (logit)	(1) 1950-70s	(2) 1980-90s	(3) 2000-20s	(4) 1950-70s	(5) 1980-90s	(6) 2000-20s	(7) 1950-70s	(8) 1980-90s	(9) 2000-20s
Proportion of states adopted	-3.25	-1.76	-2.91	-3.83	-2.12	-3.41	-4.06	-2.45	-4.56
	(0.64)	(0.49)	(0.43)	(0.66)	(0.52)	(0.45)	(0.70)	(0.56)	(0.42)
Average adoption among other states closest in:									
Demographic index	2.10	1.53	1.10	2.13	1.50	1.01	2.10	1.51	1.07
	(0.37)	(0.30)	(0.31)	(0.37)	(0.30)	(0.30)	(0.37)	(0.30)	(0.29)
Distance	2.40	1.77	1.58	1.42	1.02	0.82	1.41	1.01	0.80
	(0.30)	(0.29)	(0.29)	(0.39)	(0.34)	(0.34)	(0.39)	(0.34)	(0.32)
Republican vote-share	0.88	1.03	2.62	0.86	1.02	2.56	0.83	1.02	2.16
	(0.30)	(0.26)	(0.25)	(0.30)	(0.26)	(0.24)	(0.30)	(0.26)	(0.23)
Migration flows				1.57	1.13	1.44	1.54	1.11	1.48
				(0.46)	(0.48)	(0.40)	(0.46)	(0.48)	(0.39)
State government partisanship							0.32	0.37	1.49
							(0.28)	(0.21)	(0.22)
Observations	121717	182510	102289	121717	182510	102289	121396	182510	102289
Policies	273	432	385	273	432	385	273	432	385
Pseudo R^2	0.15	0.16	0.17	0.16	0.16	0.17	0.16	0.16	0.18

This table explores the correlation in policy adoption among states that are closer in demographics, distance, Republican vote-share in the most recent presidential election, migration flows, and state government partisanship. See Table 3 for the definition of the states closest in demographics, distance, and Republican vote-share. For migration flows, the closest states are defined as the third with the highest sum of in- and out-migration normalized by the originating state's population. 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). Each column reports a separate logit regression within the time period indicated in the header. The baseline hazard for each policy is parametrized by policy fixed effects within each time period. Standard errors clustered by states in parentheses below.

Table 7: Models of policy diffusion: Correlation of outcomes

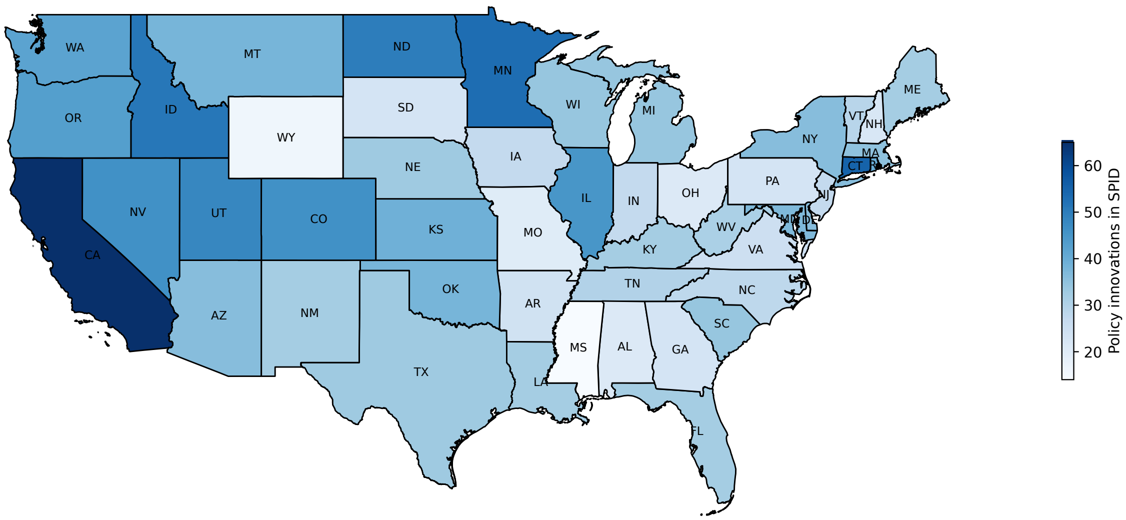
Dep. var.: Std. outcomes (OLS)	(1) 1950-70s	(2) 1980-90s	(3) 2000-20s	(4) 1950-70s	(5) 1980-90s	(6) 2000-20s
Average standardized outcome among other states closest in:						
Demographic index	0.89	0.60	0.48	0.20	0.11	0.26
	(0.13)	(0.12)	(0.14)	(0.14)	(0.07)	(0.09)
Distance	0.85	0.94	0.74	0.54	0.42	0.27
	(0.18)	(0.11)	(0.10)	(0.16)	(0.10)	(0.09)
Republican vote-share	0.25	0.02	0.39	0.03	-0.03	0.06
	(0.10)	(0.12)	(0.11)	(0.03)	(0.03)	(0.05)
Migration flows	-0.01	0.18	0.33	0.23	0.13	0.04
	(0.19)	(0.14)	(0.12)	(0.15)	(0.11)	(0.06)
State government partisanship	0.05	0.06	0.03	-0.09	-0.03	-0.01
	(0.08)	(0.08)	(0.06)	(0.04)	(0.02)	(0.02)
State-outcome FE				✓	✓	✓
Observations	5712	9473	8927	5712	9473	8927
Policies	7	11	11	7	11	11
Pseudo R^2	0.38	0.29	0.28	0.33	0.27	0.27

This table shows the correlation in outcomes among states that are closer in demographics, distance, Republican vote-share in the most recent presidential election, migration flows, and state government partisanship. See Table 3 for the definition of the states closest in demographics, distance, and Republican vote-share. Since log income per capita is one of the outcomes, it is not used in constructing the demographic index. For migration flows, the closest states are defined as the third with the highest sum of in- and out-migration normalized by the originating state's population. 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). The outcomes are taken from the sample of NBER working papers that evaluate a state policy. The outcomes are standardized to have a mean of 0 and standard deviation of 1 within each year. Examples of outcomes include the voter turnout rate, log state revenue, and the private health insurance coverage rate. Each column reports a separate linear regression within the time period indicated in the header. Coefficients are reported with standard errors clustered by states in parentheses below.

Online Appendix

Figure A.1: Innovating states

(a) SPID policies



(b) NBER policies

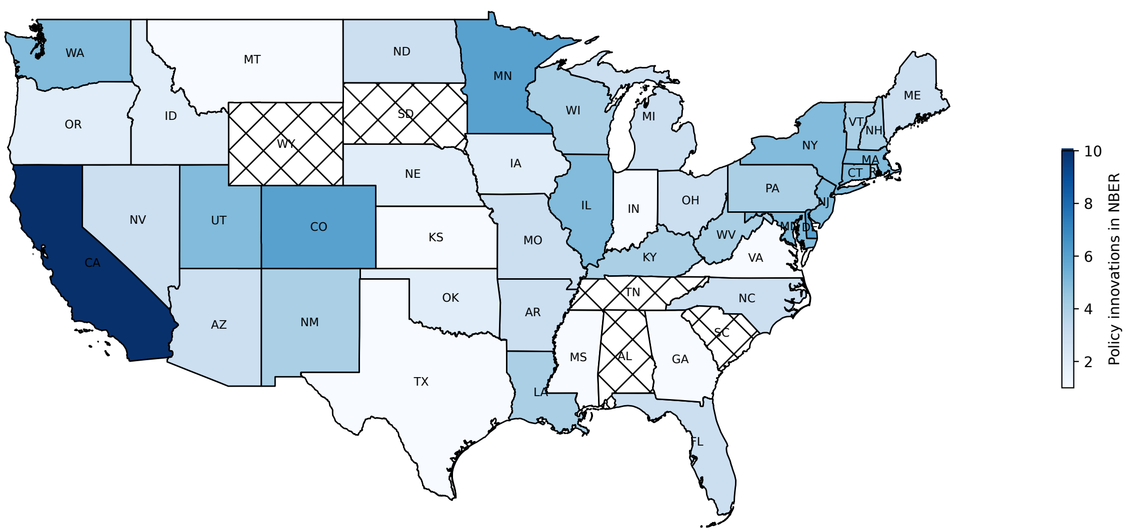
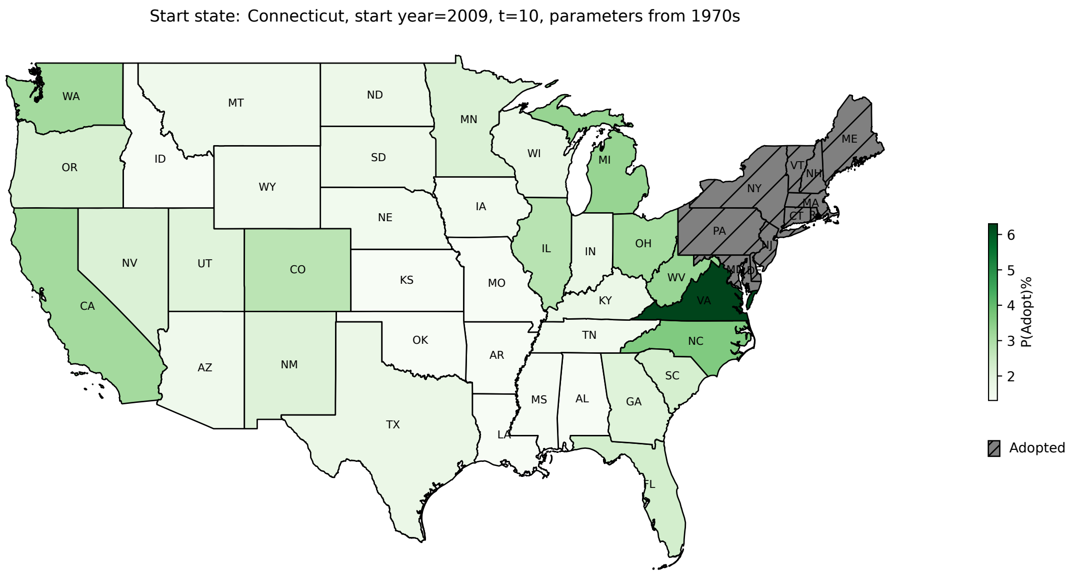
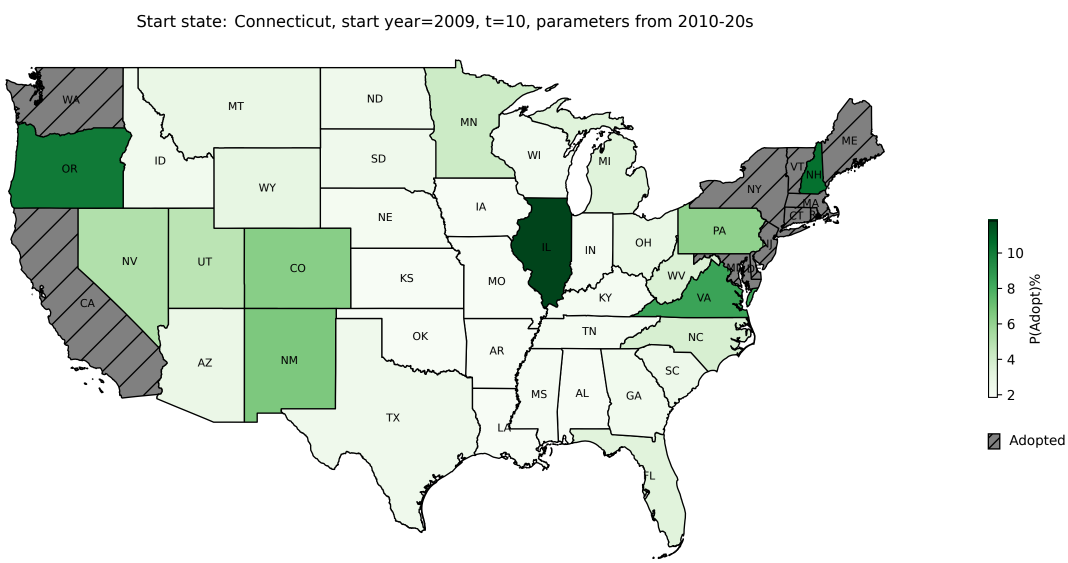


Figure A.2: Simulated policy diffusion

(a) Coefficients from 1970s (Connecticut)



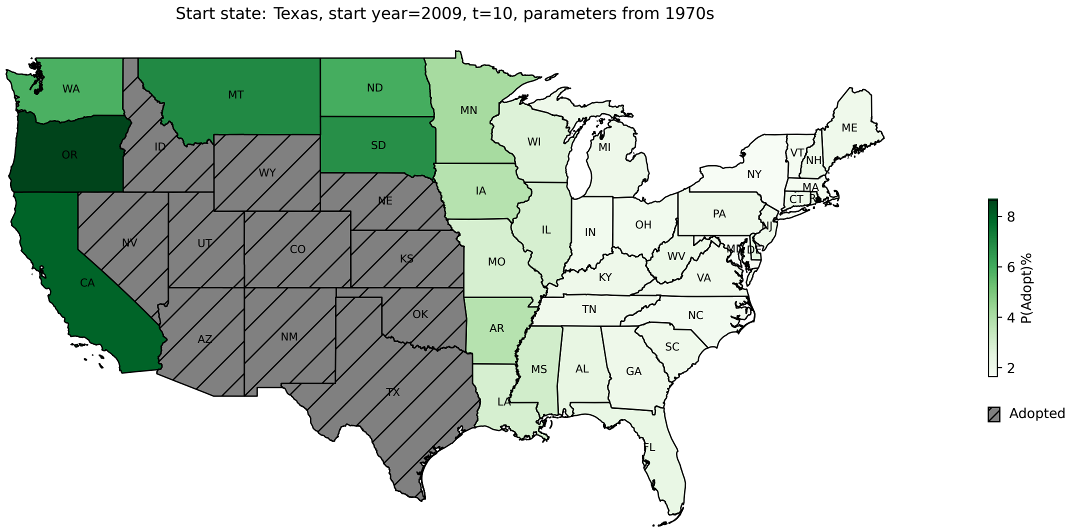
(b) Coefficients from 2010-20s (Connecticut)



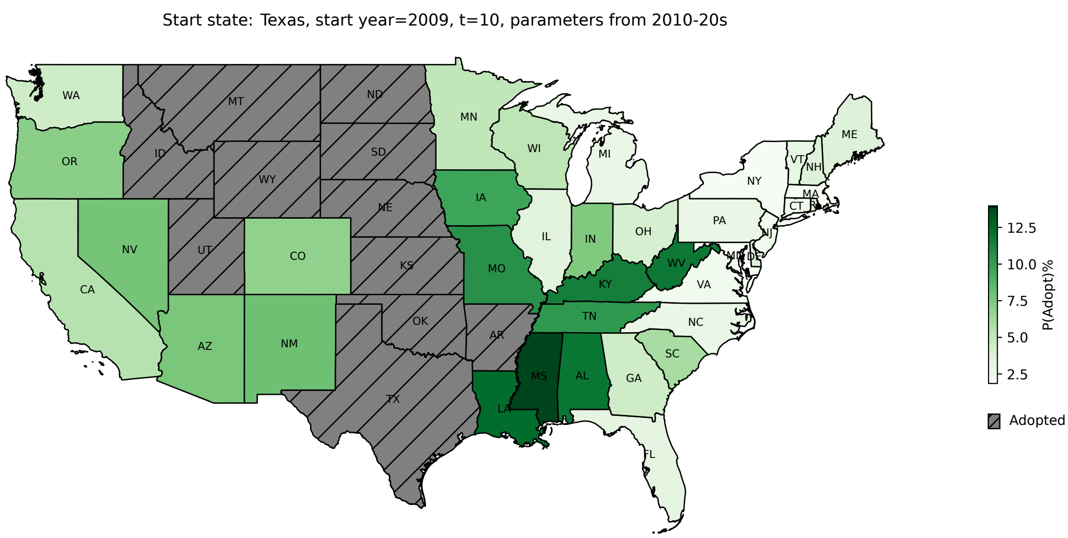
These maps show the simulated diffusion of a policy innovated by Connecticut in 2009 after 10 years based on the model estimated in Table 3. The simulation does not include the coefficients on the levels of state characteristics and only uses the coefficients on the proportions of other states adopting (all other states and thirds closest in demographic index, Republican vote-share, and distance). The baseline probability of adopting is set to 0.03. Figure A.2a uses estimated coefficients from the 1970s decade, and Figure A.2b from the 2010s decade. In each simulated year, the policy diffuses to the next state with the highest predicted likelihood of adopting among the states yet to adopt.

Figure A.2: Simulated policy diffusion

(c) Coefficients from 1970s (Texas)



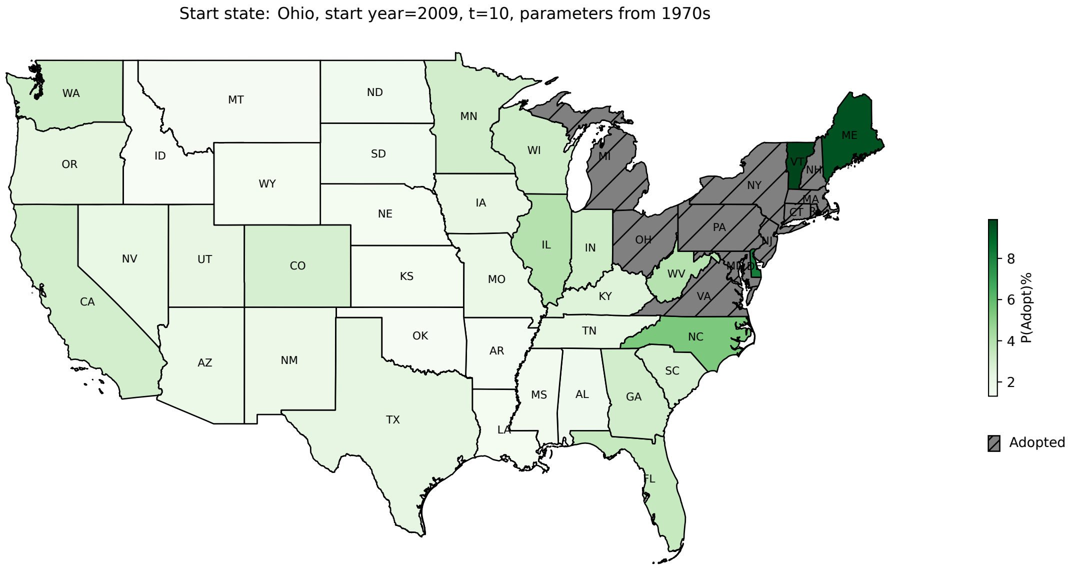
(d) Coefficients from 2010-20s (Texas)



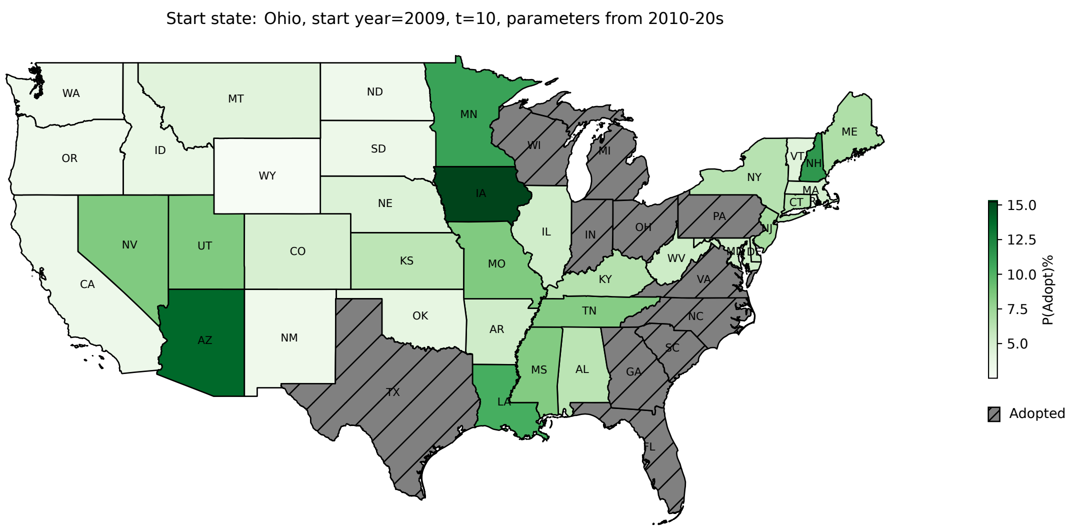
These maps show the simulated diffusion of a policy innovated by Texas in 2009 after 10 years based on the model estimated in Table 3. The simulation does not include the coefficients on the levels of state characteristics and only uses the coefficients on the proportions of other states adopting (all other states and thirds closest in demographic index, Republican vote-share, and distance). The baseline probability of adopting is set to 0.03. Figure A.2c uses estimated coefficients from the 1970s decade, and Figure A.2d from the 2010-20s decade. In each simulated year, the policy diffuses to the next state with the highest predicted likelihood of adopting among the states yet to adopt.

Figure A.2: Simulated policy diffusion

(e) Coefficients from 1970s (Ohio)



(f) Coefficients from 2010-20s (Ohio)



These maps show the simulated diffusion of a policy innovated by Ohio in 2009 after 10 years based on the model estimated in Table 3. The simulation does not include the coefficients on the levels of state characteristics and only uses the coefficients on the proportions of other states adopting (all other states and thirds closest in demographic index, Republican vote-share, and distance). The baseline probability of adopting is set to 0.03. Figure A.2e uses estimated coefficients from the 1970s decade, and Figure A.2f from the 2010s decade. In each simulated year, the policy diffuses to the next state with the highest predicted likelihood of adopting among the states yet to adopt.

Table A.1a: SPID sample examples

Number	Source	Description	Area	Adoptions	First year	Last year
4	Boehmke-Skinner	Abortion Pre-Roe	Civil Rights	16	1966	1972
44	Biggers	Request Any Id For Voting	Civil Rights	32	1972	2013
49	Uniform Law	Provides Judicial Facilitation Of Private Dispute Resolution	Law and Crime	19	2001	2018
61	Walker	Automobile Safety Compact	Public Services	43	1962	1965
64	Sheprd	Full Smoking Ban In Bars	Public Services	24	1980	2010
68	Walker	Aid To The Blind (Social Security)	Public Services	48	1936	1953
71	Boushey	Short-Term Programs For Incarcerated Youth (Similar To Military School)	Law and Crime	22	1982	1999
79	Karch	System For Bus Fleet Owners To Pro-Rate Mileage In Multiple States	Public Services	5	1965	1983
103	Kreitzer	No-Protest Zone Around Abortion Clinic	Civil Rights	16	1973	2005
118	Karch	Provides All The Benefit Of Adoption Subsidy Agreement, Regardless Of State	Law and Crime	21	1984	2002
158	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
162	Lacy	Comprehensive Remediation Reform	Public Services	17	1988	2009
167	Lacy	Placement Policies (Placement Examination, Changes To Placement Criteria	Public Services	3	1997	2008
177	Other	Notification Of Sex Offenders Is At Authority'S Discretion	Law and Crime	8	1995	2006
187	Caughey-Warshaw	Is It Legal To Use Marijuana For Medical Purposes?	Public Services	19	1996	2021
213	Uniform Law	Allows State Governments During A Declared Emergency To Give Reciprocity To Other States Licenses On Emergency Service Providers	Economics	17	2007	2018
219	Boehmke-Skinner	State Enterprise Zones	Public Services	37	1981	1992
225	Caughey-Warshaw	Does The State Have A Recycling Program For Electronic Waste?	Environment and Energy	28	2000	2012
231	Walker	Equal Pay For Females	Civil Rights	27	1919	1966
284	Caughey-Warshaw	Has The State Passed A State-Level Equivalent To The Equal Rights Amendment?	Civil Rights	20	1971	1999
291	Caughey-Warshaw	Does The State Require Background Checks For Private Rifle Sales?	Law and Crime	9	1966	2014
324	Caughey-Warshaw	Does The State Allow In-State Tuition For Illegal Immigrants?	Civil Rights	18	2001	2014
337	Uniform Law	Provides Cognitive Test For Determining Insanity	Law and Crime	1	1985	1985
382	Caughey-Warshaw	Does The State Have Collective Bargaining Rights For Local Teachers?	Economics	31	1960	1987
418	Uniform Law	It Minimizes The Number Of Prohibited Marriages, And Includes The Concept Of No-Fault Divorce.	Law and Crime	6	1973	1978
433	Uniform Law	Provides That A Student Loan Is Enforceable Against Debtor	Public Services	6	1970	1973
482	Walker	Parolees And Probationers Supervision	Law and Crime	48	1935	1951
522	Uniform Law	Articulate And Confirm The Role Of The State Attorney General In Protecting Charitable Assets.	Economics	1	2014	2014
524	Uniform Law	Requires Prudent And Diverse Investments Of State Funds	Government Operations	47	2007	2012
556	Caughey-Warshaw	Does The State Have A Law Permitting Individuals Control Over The Use Of Heroic Medical Treatment In The Event Of A Terminal Illness?	Public Services	48	1976	1992
560	Caughey-Warshaw	Enables Cities To Adopt A Home Rule Charter That Acts As The City'S Basic Governing Document Over Local Issues.	Government Operations	29	1875	1960
569	Caughey-Warshaw	Does The State Have Anti-Sedition Laws?	Civil Rights	30	1935	1955
598	Uniform Law	Regulates Offer And Sale Of Securities	Economics	18	2003	2016
632	Boushey	Laws Establishing State Exchanges For Used Needles	Public Services	13	1987	2004
659	Uniform Law	Attempts To Standardize Negotiable Instruments In States	Economics	47	1991	2008
678	Uniform Law	Governs All Unincorporated Nonprofit Associations That Are Formed Or Operate In A State	Economics	12	1993	2008
687	Uniform Law	Protect The Purchaser Of Real Estate Where There Is A Binding Contract Of Sale	Economics	12	1937	1997
694	Uniform Law	Regulating Satisfaction Of Losses Suffered From Victims Of Crime	Law and Crime	1	1995	1995
704	Caughey-Warshaw	Does The State Approve For A Local Tax Credit For Residential Solar Installations?	Environment and Energy	8	1975	2007
726	Sheprd	Law That Establishes Legal Bac Limit Of .02 For Underage Drivers	Public Services	48	1983	1998

Table A.1b: 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	2008
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
19294	Biotech tax incentives	State Incentives for Innovation, Star Scientists and Jobs: Evidence from Biotech	Economics	11	1984	2013
19904	Community rating regulations	Regulatory Redistribution in the Market for Health Insurance	Public Services	7	1993	2006
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 'Cheeseburger Bills' Work? Effects of Tort Reform for Fast Food	Economics	25	2003	2012
21345	Medical marijuana laws	Do Medical Marijuana Laws Reduce Addictions and Deaths Related to Pain Killers?	Public Services	21	1996	2015
21373	Corporate income tax	Broadening State Capacity	Economics	43	1911	2008
21373	Individual income tax	Broadening State Capacity	Economics	42	1911	2008
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 minumum age	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	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	Smokefree provision	Impact of Comprehensive Smoking Bans on the Health of Infants and Children	Public Services	34	1994	2012
24153	Interstate tax audit info share	Intergovernmental Cooperation and Tax Enforcement	Government Operations	41	1950	1971
24259	Union contracts cover non-unionized workers	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	48	2004	2015
24662	Merit Aid Programs	State Merit Aid Programs and Youth Labor Market Attachment	Public Services	19	1988	2011
24782	Duty-to-bargain laws	The Long-run Effects of Teacher Collective Bargaining	Economics	31	1960	1987
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	2009
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

Table A.1c: NBER working paper sample

Number	Policy	Title	Area	Adoptions	First year	Last year
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
25600	School finance equilization	School Finance Equalization Increases Intergenerational Mobility: Evidence from a Simulated-Instruments Approach	Public Services	34	1983	2003
25758	Minor abortion parental consent	The Impact of Parental Involvement Laws on Minor Abortion	Public Services	39	1953	2000
25974	Initial prescription drug monitoring	Can Policy Affect Initiation of Addictive Substance Use? Evidence from Opioid Prescribing	Public Services	24	1988	2019
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	9	2004	2018
26416	Partial paid leave for pregnancy	The Long-Term Effects of Californias 2004 Paid Family Leave Act on Womens Careers: Evidence from U.S. Tax Data	Economics	5	2004	2020
26500	Triplicate prescription	Origins of the Opioid Crisis and Its Enduring Impacts	Public Services	5	1939	2004
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
26980	Workers compensation	Rising Burdens of Proofs and The Grand Bargain of Workers Compensation Laws	Economics	14	2003	2016
27054	Salary history ban	Information and the Persistence of the Gender Wage Gap: Early Evidence from California's Salary History Ban	Economics	8	2017	2020
27306	Medicaid expansion	Medicaid Expansion and the Mental Health of College Students	Public Services	34	2014	2020
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	Standard certificate of live birth	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
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.2a: Summary statistics: Policy outcomes

Outcome	Coverage	Example NBER policy	NBER WP numbers
Log(income per capita)	1950-2020	Partial paid leave for pregnancy	26416, 19294
Poverty rate	1980-2017		
Voter turnout rate	1980-2019	Strict voter ID	26206, 24259
Log(opioid mortality rate)	1968-2014	Naloxone Access Law	23171, 23171, 25974, 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.2b: COIVD-19 policies

Example policy	Coverage (MM/DD/YYYY)	Num. adopted states
SNAP Waiver - Temporary Suspension of Claims Collection	4/2/2020-5/13/2020	24
SNAP Waiver - Pandemic EBT during school year 2019-2020	4/9/2020-8/13/2020	48
CDC moratorium start	9/4/2020-12/15/2020	15
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 legal visitation in state prisons	3/7/2020-6/25/2020	18
Date adults ages 55+ became eligible for COVID-19 vaccination	3/1/2021-4/19/2021	48
Utilities reconnection start	3/4/2020-4/13/2020	8
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 - Pandemic EBT during school year 2020-2021	12/15/2020-3/23/2021	25
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
Average (all 77 policies)	29/6/2020-25/9/2020	30.56

This table shows 15 randomly selected COVID-19 policies in the dataset as well as the overall average. Policies are kept in dataset until the first repeal. Source: COVID-19 US State Policies (CUSP)

Table A.2c: Vaccine regulations

Policy	Coverage	Num. adopted states
Hepatitis A Vaccine Mandates for Child Care	1998-2020	20
Hepatitis A Vaccine Mandates for K-12	1988-2021	15
Hepatitis B Vaccine Mandates for Child Care	1993-2018	40
Hepatitis B Vaccine Mandates for Colleges and Universities	1992-2011	15
Hepatitis B Vaccine Mandates for elementary	1994-2008	43
Hepatitis B Vaccine Mandates for secondary	1997-2009	35
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	2001-2020	40
Rotavirus Vaccine Mandates for Child Care and Pre-K	1999-2021	8
Tdap Vaccine Mandates for Elementary and Secondary Schools	2006-2020	48
Varicella Vaccine Mandates for Child Care	1991-2015	46
Varicella Vaccine Mandates for Elementary School	1997-2015	48
Varicella Vaccine Mandates for Middle/junior/senior high	1997-2015	37
Average (15 policies)	1997-2017	30.53

This table lists all 15 policies in the vaccine regulations data set. Source: Immunization Action Coalition

Table A.3: Highest and lowest innovators of NBER policies (20%)

	1991-2020		Difference (SE)
	(1) Top 20%	(2) Bottom 20%	(1)-(2)
Rep. two-party voteshare %	45.40	57.07	-11.67
	[8.56]	[5.53]	(2.32)
|Demeaned two-party voteshare|	8.64	6.44	2.20
	[5.06]	[4.23]	(1.42)
Unified Dem. state gvt.	0.31	0.10	0.21
	[0.46]	[0.30]	(0.06)
Unified Rep. state gvt.	0.14	0.46	-0.32
	[0.35]	[0.50]	(0.09)
Log(population)	15.59	15.07	0.53
	[0.86]	[1.06]	(0.39)
Income per capita	39630.17	32954.06	6676.11
	[13051.79]	[10714.06]	(1834.36)
Log(income per cap.)	10.53	10.35	0.18
	[0.34]	[0.33]	(0.05)
Minority %	29.06	26.31	2.75
	[12.28]	[12.98]	(4.84)
Unemployed %	5.51	5.32	0.19
	[1.81]	[1.77]	(0.35)
States	14	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.4: Policy diffusion predictors by decade (expanded)

Dep. var.: Policy adoption (logit)	(1) 50-60s	(2) 70s	(3) 80s	(4) 90s	(5) 00s	(6) 10s
Prop. of states adopted	-4.76	-3.63	-3.75	-2.85	-5.32	-4.39
	(0.84)	(0.93)	(0.87)	(0.67)	(0.79)	(0.76)
Republican vote-share	-0.24	-0.04	-0.22	0.13	0.79	-1.02
	(0.35)	(0.30)	(0.45)	(0.41)	(0.62)	(0.85)
Unified Dem. state gvnt.	-0.10	0.23	0.01	0.06	0.27	0.07
	(0.13)	(0.11)	(0.06)	(0.06)	(0.08)	(0.10)
Unified Rep. state gvnt.	-0.16	0.20	-0.20	-0.07	-0.03	0.06
	(0.11)	(0.12)	(0.11)	(0.06)	(0.07)	(0.11)
Log(population)	0.09	0.11	0.03	0.03	0.01	0.05
	(0.07)	(0.07)	(0.04)	(0.05)	(0.04)	(0.07)
Income per capita ($10,000s)	2.27	-0.56	0.03	-0.10	-0.15	-0.15
	(1.13)	(0.40)	(0.15)	(0.15)	(0.08)	(0.15)
Urban pop. %	0.00	0.00	0.01	0.01	0.01	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Non-white %		-0.02	-0.01	0.00	-0.00	-0.01
		(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Unemployed %			0.04	-0.00	-0.03	0.03
			(0.02)	(0.02)	(0.02)	(0.04)
Avg. adoption among other states closest in:						
Geography						
Distance	1.37	1.33	0.62	1.18	0.68	1.20
	(0.54)	(0.51)	(0.47)	(0.35)	(0.27)	(0.35)
Ideology						
Republican vote-share	0.24	0.93	0.74	1.19	2.37	1.72
	(0.39)	(0.31)	(0.32)	(0.34)	(0.25)	(0.32)
State gvnt. partisanship	0.71	-0.67	0.63	0.10	1.17	1.72
	(0.32)	(0.45)	(0.28)	(0.28)	(0.26)	(0.31)
Demographics						
Log(population)	0.61	0.41	0.96	0.90	0.75	0.14
	(0.40)	(0.48)	(0.34)	(0.23)	(0.31)	(0.32)
Income per capita	1.16	0.64	0.07	0.82	0.55	0.51
	(0.42)	(0.49)	(0.34)	(0.29)	(0.27)	(0.32)
Urban pop. %	0.53	-0.32	0.20	0.32	0.34	1.15
	(0.48)	(0.42)	(0.31)	(0.32)	(0.30)	(0.30)
Migration flows	2.62	1.57	1.36	1.41	1.72	1.30
	(0.60)	(0.66)	(0.57)	(0.52)	(0.50)	(0.45)
Non-white %		0.31	0.74	0.32	-0.07	0.13
		(0.46)	(0.32)	(0.27)	(0.28)	(0.34)
Unemployed %			0.52	-0.22	0.23	0.14
			(0.34)	(0.25)	(0.25)	(0.34)
Observations	59609	54586	78973	93407	70833	27658
Policies	162	203	282	392	344	179
Pseudo R^2	0.22	0.13	0.15	0.19	0.18	0.21

This table shows the coefficients from a logit regression. Standard errors are clustered by state. The baseline hazard for each policy is assumed to be constant within a decade and is captured by policy fixed effects. The closest states are defined as the third of all the states with the smallest absolute value difference in each characteristic. The states closest in State gvnt. partisanship are those with the same party in control of the state government (either unified Democratic, unified Republican, or divided). Alaska, Hawaii, and Washington D.C. are excluded from the analyses. Only policies spanning at least 3 years with at least 5 adopters are included.

Table A.5: Robustness checks

Demographic index			Distance			Republican vote-share		
1950-70s	1980-90s	2000-20s	1950-70s	1980-90s	2000-20s	1950-70s	1980-90s	2000-20s
Dep. var.: Policy adoption (all logit except (2))								
(1) Baseline (R^2: 0.16, 0.16, 0.17; $N_{\text{pol.}}$: 273, 432, 385)								
1.76	1.33	0.94	2.50	1.81	1.57	0.87	1.03	2.71
(0.35)	(0.29)	(0.31)	(0.29)	(0.28)	(0.28)	(0.30)	(0.26)	(0.26)
(2) Baseline linear probability model (R^2: 0.07, 0.08, 0.10; $N_{\text{pol.}}$: 276, 438, 393)								
0.07	0.06	0.05	0.09	0.07	0.08	0.03	0.04	0.14
(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
(3) Full controls (R^2: 0.15, 0.18, 0.20; $N_{\text{pol.}}$: 168, 432, 385)								
0.78	1.12	0.83	1.42	1.23	1.04	-0.08	1.12	2.29
(0.65)	(0.29)	(0.27)	(0.66)	(0.32)	(0.25)	(0.51)	(0.24)	(0.23)
(4) Parsimonious model (R^2: 0.15, 0.16, 0.17; $N_{\text{pol.}}$: 273, 432, 385)								
2.10	1.53	1.10	2.40	1.77	1.58	0.88	1.03	2.62
(0.37)	(0.30)	(0.31)	(0.30)	(0.29)	(0.29)	(0.30)	(0.26)	(0.25)
(5) Closest third (lagged adoptions) (R^2: 0.14, 0.15, 0.16; $N_{\text{pol.}}$: 244, 403, 385)								
1.84	1.50	0.86	2.06	1.49	1.16	0.41	0.87	2.26
(0.38)	(0.30)	(0.33)	(0.33)	(0.26)	(0.31)	(0.33)	(0.29)	(0.28)
(6) Rank-inverse weighted (R^2: 0.15, 0.16, 0.17; $N_{\text{pol.}}$: 273, 432, 385)								
1.68	1.24	1.14	2.56	1.81	1.73	0.31	0.86	2.09
(0.30)	(0.21)	(0.24)	(0.26)	(0.23)	(0.31)	(0.25)	(0.19)	(0.22)

This table presents results from alternate specifications of the policy diffusion model. The table shows coefficients on the proportion of adopters among the "closest" states (i.e., the closest third unless otherwise noted) in terms of an index for demographic characteristics (see notes in Table 3 for details), distance, and Republication vote-share in the most recent presidential election. Standard errors clustered by state are in parentheses. Each model is estimated over three separate time periods (1950-70s, 1980-90s, and 2000-20s). 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.

Full 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 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 closest third of other states in geography, Republican vote-share in the most recent presidential election, and the demographic index. (This specification is used in Table 4 and Columns 1-3 of Table 6.)

Closest third (lagged adoptions): uses the Parsimonious model but takes the proportion of adoptions among other states up to the *prior* (not current) year.

Rank-inverse weighted: instead of defining the "closest" states as the third with smallest absolute difference, 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.

Table A.6: 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 1990										
4 years pre-event	-0.023 (0.007)	-0.009 (0.006)	0.011 (0.007)	-0.020 (0.010)	0.005 (0.010)	-0.009 (0.006)	0.015 (0.007)	-0.024 (0.010)	-0.004 (0.007)	0.001 (0.006)
3 years pre-event	-0.010 (0.007)	-0.001 (0.006)	-0.003 (0.008)	0.002 (0.012)	0.020 (0.007)	-0.012 (0.004)	0.005 (0.006)	-0.017 (0.008)	-0.008 (0.006)	-0.000 (0.007)
2 years pre-event	-0.010 (0.009)	-0.003 (0.008)	0.007 (0.010)	-0.010 (0.017)	0.016 (0.011)	-0.003 (0.007)	0.007 (0.005)	-0.010 (0.009)	0.004 (0.008)	0.006 (0.007)
1 year pre-event	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)
Year of event	0.002 (0.009)	-0.004 (0.009)	-0.001 (0.012)	-0.003 (0.019)	0.005 (0.012)	0.012 (0.006)	0.009 (0.006)	0.003 (0.009)	0.011 (0.008)	0.002 (0.009)
1 year post-event	0.002 (0.007)	0.003 (0.008)	-0.000 (0.007)	0.004 (0.014)	0.002 (0.006)	-0.000 (0.006)	-0.002 (0.004)	0.001 (0.008)	-0.009 (0.007)	0.003 (0.005)
2 years post-event	-0.004 (0.010)	0.001 (0.008)	0.001 (0.015)	-0.000 (0.019)	-0.000 (0.014)	0.005 (0.007)	0.011 (0.008)	-0.006 (0.012)	0.005 (0.012)	-0.003 (0.009)
3 years post-event	-0.006 (0.006)	-0.008 (0.007)	-0.002 (0.011)	-0.005 (0.015)	0.000 (0.009)	-0.006 (0.006)	0.001 (0.005)	-0.007 (0.007)	0.004 (0.007)	-0.011 (0.007)
4 years post-event	0.002 (0.009)	0.002 (0.008)	0.002 (0.008)	0.000 (0.011)	0.016 (0.020)	0.004 (0.009)	0.003 (0.009)	0.002 (0.013)	0.046 (0.018)	0.000 (0.011)
Observations	104048	104048	104048	104048	104048	104048	104048	104048	104048	104663
Policies	315	315	315	315	315	315	315	315	315	315
Events	136	54	54	54	54	82	82	82	82	150
Events during years 1991 to 2020										
4 years pre-event	-0.001 (0.008)	0.001 (0.010)	-0.005 (0.009)	0.006 (0.017)	-0.000 (0.009)	0.000 (0.005)	0.003 (0.005)	-0.003 (0.008)	0.005 (0.006)	0.017 (0.008)
3 years pre-event	-0.017 (0.007)	-0.005 (0.007)	0.004 (0.008)	-0.009 (0.012)	0.015 (0.007)	-0.011 (0.006)	0.009 (0.006)	-0.020 (0.007)	0.000 (0.005)	0.010 (0.008)
2 years pre-event	-0.008 (0.008)	-0.006 (0.008)	0.018 (0.009)	-0.024 (0.015)	0.019 (0.008)	0.003 (0.006)	-0.006 (0.006)	0.009 (0.010)	-0.008 (0.006)	0.014 (0.007)
1 year pre-event	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)	– (–)
Year of event	0.020 (0.007)	0.012 (0.007)	0.000 (0.006)	0.012 (0.010)	0.010 (0.011)	0.023 (0.008)	-0.004 (0.006)	0.026 (0.009)	0.001 (0.007)	0.000 (0.010)
1 year post-event	0.024 (0.010)	0.012 (0.010)	-0.002 (0.006)	0.014 (0.013)	0.009 (0.008)	0.021 (0.010)	-0.010 (0.006)	0.031 (0.014)	-0.007 (0.005)	0.010 (0.008)
2 years post-event	0.021 (0.008)	0.003 (0.009)	-0.012 (0.006)	0.014 (0.012)	-0.013 (0.013)	0.021 (0.009)	-0.003 (0.008)	0.024 (0.012)	0.003 (0.007)	0.008 (0.009)
3 years post-event	0.014 (0.008)	0.008 (0.011)	-0.005 (0.007)	0.013 (0.015)	0.004 (0.013)	0.011 (0.008)	-0.005 (0.006)	0.015 (0.011)	0.008 (0.010)	0.001 (0.007)
4 years post-event	0.027 (0.015)	-0.007 (0.009)	-0.014 (0.010)	0.007 (0.014)	0.006 (0.010)	0.031 (0.020)	-0.021 (0.009)	0.052 (0.024)	0.017 (0.010)	0.001 (0.010)
Observations	129265	129265	129265	129265	129265	129265	129265	129265	129265	129265
Policies	456	456	456	456	456	456	456	456	456	456
Events	113	49	49	49	49	64	64	64	64	99

Table A.7: Migration flows over time

Dep. var.: Log(migration+1) (OLS)	(1) 1955-60, 1965-70	(2) 1975-80, 1985-90	(3) 1995-2019	(4) 1955-60, 1965-70	(5) 1975-80, 1985-90	(6) 1995-2019
Log($\text{pop}_{it} \times \text{pop}_{jt}$)	0.52	0.68	0.86	0.53	0.68	0.85
	(0.017)	(0.024)	(0.028)	(0.017)	(0.024)	(0.028)
Log(miles of distance_{ij})	-0.28	-0.46	-0.55	-0.27	-0.46	-0.51
	(0.026)	(0.034)	(0.043)	(0.026)	(0.035)	(0.043)
Contiguous states	0.72	0.92	1.12	0.70	0.90	1.09
	(0.068)	(0.078)	(0.10)	(0.069)	(0.078)	(0.10)
Log(1950 migration+1_{ij})	0.48	0.17	0.17	0.47	0.16	0.16
	(0.0072)	(0.010)	(0.014)	(0.0075)	(0.010)	(0.014)
Same state gvt. party control	0.14	0.032	0.12	0.11	0.030	0.071
	(0.047)	(0.026)	(0.030)	(0.047)	(0.026)	(0.030)
Log(income per cap._{it}/income per cap._{jt})	0.51	-0.055	-0.10			
	(0.13)	(0.13)	(0.16)			
Log(urban $\%_{it}$/urban $\%_{jt}$)	-0.34	0.033	0.026			
	(0.10)	(0.089)	(0.10)			
Log(Rep. vote-share_{it}/Rep. vote-share_{jt})	-0.35	-0.030	0.013			
	(0.092)	(0.11)	(0.13)			
$\lvert z_{it}^{\text{log(inc. per cap.)}} - z_{jt}^{\text{log(inc. per cap.)}}\rvert$				-0.0082	-0.071	-0.11
				(0.030)	(0.025)	(0.031)
$\lvert z_{it}^{\text{urban }\%} - z_{jt}^{\text{urban }\%}\rvert$				-0.017	-0.025	-0.026
				(0.034)	(0.028)	(0.033)
$\lvert z_{it}^{\text{Rep. vote-share}} - z_{jt}^{\text{Rep. vote-share}}\rvert$				-0.090	-0.0040	-0.18
				(0.028)	(0.018)	(0.031)
Constant	-9.17	-9.90	-15.9	-9.16	-9.88	-15.4
	(0.53)	(0.69)	(0.83)	(0.53)	(0.69)	(0.82)
Observations	13536	13536	28200	13536	13536	28200
State pairs	1128	1128	1128	1128	1128	1128
R^2	0.54	0.76	0.54	0.54	0.76	0.55

This table estimates a gravity model of migration. The dependent variable is the natural logarithm of the sum of in- and out-migration between state pairs. Observations are at the state-pair-year level. There are $48 \times 47/2 = 1128$ state pairs each year. (Alaska, Hawaii, and Washington D.C. are excluded.) i, j index states where $i \neq j$ and t indexes years. Columns 1-3 explore the direction of migration following income per capita, urban %, and Republican vote-share. Columns 4-6 show the flow of migration according to similarities in these variables, measured by the absolute difference in the standardized values. (The variable z represents the standardized variable.) Each column covers the time period indicated in the header. Migration statistics are from IPUMS decennial census data up to 2000 and from the ACS thereafter. In the 1960, 1970, 1980, 1990, and 2000 IPUMS data, the variable for migration is taken from a survey question that asked respondents where they lived 5 years ago (MIGPLAC5); hence, for these decades, only the following years are included: 1955-60, 1965-70, 1975-80, 1985-90, and 1995-2000. In the annual ACS data from 2001 to 2019, the variable for migration reflects where respondents were a year ago (MIGPLAC1). Log(1950 migration+1_{ij}) controls for the initial "stock" of migration in 1950. Coefficients are estimated by linear regression, and standard errors shown in parentheses are clustered by state-pair.

Table A.8: Medicaid case study

	Medicaid ACA	Initial Medicaid
Prop. of states adopted	-24.3	-7.72
	(7.15)	(2.75)
Prop. adopt among closest third in:		
Distance	-0.22	3.60
	(1.85)	(2.34)
Republican vote-share	3.74	1.83
	(1.31)	(2.38)
Constant	10.8	1.39
	(3.91)	(1.06)
Observations	166	114
Year range	2014-2020	1966-1982
Pseudo R^2	0.34	0.09

Standard errors clustered by state.