NBER WORKING PAPER SERIES

POLICY DIFFUSION AND POLARIZATION ACROSS U.S. STATES

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Working Paper 30142
http://www.nber.org/papers/w30142

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2022

We thank Tim Besley, David Card, Janet Currie, Matthew Gentzkow, Bryan Graham, Jon Gruber, Jonas Hjort, Lawrence Katz, Pat Kline, Brian Knight, Sendhil Mullainathan, Angel O'Mahony, Giacomo Ponzetto, Gautam Rao, Jesse Shapiro, Francesco Trebbi, Brian Wheaton, David Yang and participants in seminars at NUS for helpful comments. We are grateful to a team of undergraduate research assistants—YeJin Ahn, Christian Alamos, Iden Azad, Emma Berman, Rupsha Debnath, Yifan Ding, AJ Grover, Rohan Jha, Chenxi Jiang, Chloe Liu, Matthew Liu, Junru Lu, Louis McKinnon, Akhalya Valluvan, Randol Yao, Owen Yeung, and Yi Yu—for exceptional research assistance. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 30142
June 2022
JEL No. D04,H3,J68

ABSTRACT

Economists have studied the impact of numerous state laws, from welfare rules to voting ID requirements. Yet for all this policy evaluation, what do we know about policy diffusion—how these policies spread from state to state? We present a series of facts based on a data set of over 700 U.S. state policies spanning the past 7 decades. First, 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 2000 is best predicted by proximity: a state is more likely to adopt a policy if nearby states have already done so. Third, instead since 2000, political alignment outperforms geographic proximity in predicting diffusion. Fourth, the diffusion of COVID state policies, as opposed to vaccination mandates since the 1970s, follows similar patterns of political polarization. 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, building on these results, we broadly classify the patterns of policy diffusion in a set of difference-in-differences papers.

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A data appendix is available at http://www.nber.org/data-appendix/w30142

1 Introduction

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

They have paid much less attention to the diffusion of policy innovations across government units, with the notable exceptions of the study of tax competition across U.S. states (Case, Rosen, and Hines, 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-differences studies such as these.

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

Our main data source is the State Policy Innovation and Diffusion (SPID) Database (Boehmke et al., 2020) which includes information on over 700 state law policies adopted in the last century 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 a limited coverage of the last decade. We thus extended its coverage through the 2010s for a subset of the policies 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 papers. From the 11,316 NBER working papers from April 2012 to September 2021, we

[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.

identify 169 papers with U.S. state-level policy variation. Out of this set, 91 papers meet our criteria, for a total of 57 policies (given that some policies are in multiple papers).

The combined data set covers 733 policies adopted from the 1950s onward, 676 from the SPID data set and 57 from the NBER data set. The laws are most often about the provision of public services, law and crime, economics, and civil rights. Figure 1 presents three examples. Anti-bullying laws (Figure 1a) spread from the initial adoptions in Louisiana, West Virginia and Colorado in 2001 in a fairly idiosyncratic way. In comparison, the Medicaid expansion from the Affordable Care Act (Figure 1b) followed political lines. Finally, the adoption of the initial prescription drug monitoring policy (Figure 1c) appears geographically clustered.

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

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

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

Which states innovate policies and originate new laws? One theory is that states with more resources, capacity, or "legislative professionalism" tend to innovate (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 (Mulligan and Shleifer, 2005). Nevertheless, we do not find clear differences in population or income per capita between the 10 states that have the most innovations and the 10 that have the fewest.

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 measure this both "statically" and "dynamically". For the static measure, we take the states that have adopted the policy at a particular cross-section (say, after the first 10 adoptions), and assess their degree of similarity in the different dimensions (e.g., geographic or political similarity). In the dynamic method, we use a logit hazard model outlining the dimensions along which policies tend to diffuse, given the observed adoption up to that period. The dimension of diffusion is informative about the underlying models. For example, diffusion along politically similar states would suggest the importance of ideological alignment.

We document that the patterns of policy diffusion have changed substantially over the last seven decades. Policy adoption from the 1950s to the 1990s is best predicted by geographic proximity. Another important predictor is demographic similarity: a state is more likely to adopt a policy if other states with similar demographics (such as income or urban percentage) have already done so. The adoption by politically aligned states is a weaker predictor.

In the 2000s and 2010s, geographic and demographic proximity remain similarly predictive, but by far the strongest predictor becomes adoption by politically aligned states, as measured by the Republican vote-share in recent elections. This effect is strong enough that the predictive accuracy of the model is higher in the latest periods.

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 since October 2019. 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 since 1975, and do not find evidence of political similarity driving the diffusion. Thus, these results are consistent with our general 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 flows, the extent of competition, and the correlation in preferences or environments across states may have shifted from mostly geographic to largely political. If this is the case, controlling for other inter-state flows that follow similar determinants, such as cross-state migration, should lower the explanatory power of political similarity across states. Migration flows are predictive of policy diffusion, and reduce the explanatory power of geography, but they do not affect at all the importance of the political variables. Furthermore, as a test of whether environments or local needs have become more politically correlated, we explore whether variables often used as outcomes for policy evaluations—such as the property crime rate, mortality, or poverty rate—have also become more correlated along politically similar states, but we do not find this to be the case. These two tests suggest that this first group of explanations is less likely to account for the recent patterns of policy diffusion.

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. To zero in on this explanation, we examine the impact of state party 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 divided state governments to unified state governments (that is, the governor and the majority in both state houses belong to the same party). We detect no impact in the earlier decades, but in the last two decades, this transition indeed raises the probability of passing laws associated with the governing state party, with no impact on bipartisan laws.

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. For each of the the 57 NBER policies, we estimate a measure of geographic correlation and a measure of political polarization and show that one can approximately classify the policy diffusion as either politically-clustered, both politically- and geographically-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 within economics, 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), state-level fair employment laws (Collins, 2003), and welfare reform (Bernecker, Boyer, and Gathmann, 2021). In political science, in line with our findings, Caughey, Warshaw, and Xu (2017), Grumbach (2018), and Mallinson (2021) also detect evidence of widening polarization in the adoption of state laws. Relative to these papers, 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; and (v) we 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. An important component of the Affordable Care Act was the expansion of the Medicaid health insurance to cover adults earning up to 138% of the Federal Poverty Line. The expansion comes at nearly no cost to the states, as the federal government pays 100% for newly eligible enrollees until 2016, and 90% thereafter (Gruber and Sommers, 2020). Despite this generous 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.

This suggests a large partisan impact on policy adoption, but it could be that the political preferences align with the underlying demand for the policy in the state: the Republican states that delay adoption may have fewer people who would benefit from Medicaid expansion. 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 the expense of the match quality between the policy and the state.

A possible explanation for these findings is that major benefit expansions have always had this partisan structure. We thus revisit the initial Medicare roll-out enacted in July 1965. Voluntarily participating states received federal funds from January 1966. In particular, initially there was 50-83% matching across states, though the states had to cover certain groups and provide required benefits, with some variation across states in the subsidy. This subsidy structure is thus not too dissimilar from the one for the ACA Medicaid expansion (though not as generous). Overall, 26 states enacted the Medicaid program within the first year, 37 within two, and nearly all within four years. 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 food stamp program. After county-level food stamp programs piloted in 1961, the Food Stamp Act was passed in 1964 and counties voluntarily set up their own food stamp programs, with the federal government paying for the benefits and the states setting their own eligibility criteria. As the bin scatter in Figure 2d shows, the voting patterns in the county have no predictive power for when the county approved its food stamp program. Demographics are predictive for the timing of adoption (i.e., counties with more vulnerable population) as Hoynes and Schanzenbach (2009) show, but not politics.

These case studies suggest that polarization may be playing a role in the current adoption of state 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, the source, its policy area, and the year of adoption in each state (if ever). The data set does not record if a law is rescinded, since it is a fairly rare event. Furthermore, the data set records only binary adoption, and not continuous variables such as the level of the minimum wage across states.

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 policy areas 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 make 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 extensive, there is no guarantee that it covers the type of state laws of interests to economists. We thus collected a similar, though smaller, sample of policy adoptions used in economics papers. From the 11,316 NBER working papers from April 2012 to September 2021, we manually checked and identified 169 papers with U.S. state-level policy variation, covering especially labor, public, and health economics (Column 2 in Table 1a). We then apply our sample restrictions, including the fact that we consider binary policy adoption, as opposed to state-level variation in tax rates for instance, resulting in a sample of 91 working papers (Column 3). For 81 out of these 91 papers we can extract the timing of state-level policy adoption, typically from a table in the paper, covering a total of 57 policies (given that, for example, multiple papers analyze the same policy of Medicaid expansion). In this sample, health economics is the most common field, followed by labor and public economics, and the share of published papers, 46 percent, is similar to the overall share for NBER papers of 48 percent (Column 1), and similarly for the share published in "Tier A" journals (following the categorization in Heckman and Moktan, 2020). The full list of these papers is in Table A.1b.

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 each policy. It also includes 57 policies from the NBER data set, with an average of 29 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 20 of the 57 policies in the NBER sample, we reconstruct the dependent variable studied in the papers, either through the replication files or public data sources. The papers typically evaluate the effect of the policies on these outcomes in a difference-in-differences design. Overall, we observe 10 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 supplement these dependent variables with 18 other state-level variables typically used in policy evaluations from the Correlates of State Policy Project (CSPP), such as the state-level poverty rate, per capita welfare expenditure, and Gini coefficient. 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 28 state policies regarding vaccination mandates enacted since 1975 from sources such as the CDC and 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 to be innovators or 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 larger and richer states should be more likely to generate new policies (Mulligan and Shleifer, 2005).

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 the number of times a state has been an innovator. In Figure 4a-b we present a color-coded map of the U.S. displaying how often a state was an innovator in the earlier years (1950-90, Figure 4a) and in the more recent years (1991-2020, Figure 4b).[2] The map does not show an obvious pattern. California, the largest U.S. state by population, tops the list of innovators, but other large states such as Florida and Texas are in the middle of the pack and a smaller state such as Connecticut is among the top states by this measure.

[2]Figure A.1 presents similar plots splitting by the data source, SPID or NBER.

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. We also do not see signs of polarization for innovations in recent decades; the differences between the most and least likely innovators in the absolute value of demeaned vote-share has not drastically increased. One consistent difference appears to be that innovative 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

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

Static Evidence. For each law, we consider the first 10 states that adopted (provided that this threshold of adoption was indeed reached), and compute the proximity of these first 10 adopters with respect to the relevant dimension—e.g., geography and politics.

As a measure of clustering along a particular dimension, we use the Geary's C statistic, which is typically used to measure geographic correlation (Geary, 1954; Barrios et al., 2012). The statistic is a ratio of average pairwise squared differences. The denominator is an unweighted average of the squared differences between all pairs, and the numerator is a weighted average where the weight for each pair increases in their proximity along the specified dimension. Hence, if the states that are closer in the dimension are similar in policy adoptions, then the weighted average of the differences in the numerator should be smaller than the unweighted average of the differences between all pairs in the denominator. Consequently, values of this measure below 1 indicate clustering, values above 1 suggest the

[3] In Table A.3 we present parallel evidence for the policies from the NBER papers.

opposite, and a value of 1 is the null hypothesis. Specifically, the ratio can be written as:

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

where $x_i \in \{0,1\}$ is an indicator for whether state i has adopted the policy, n is the total number of states in the sample, w_{ij} is the weight for the pair ij, and W is the sum of weights.[4]

To gain intuition on this measure, consider the simple case of 5 states on a line, A, B, C, D, E, with each state contiguous to the nearby ones, and assume that we compute Geary's C with respect to contiguity, that is, A is contiguous to B, B is contiguous to A and C, etc. Consider first the case in which the adoption of a particular policy is (1,1,1,0,0), that is, A, B, and C adopted, but D and E did not. The pairs used to compute the variance measure in the numerator are (1,1), (1,1), (1,0), and (0,0), each repeated twice. We take the difference between each pair, square it, sum all the squared differences, and finally average, yielding a numerator of 1/4. The denominator has the average of squared differences between all pairs, which can be shown to yield 12/20=3/5. This results in a C of $\frac{1/4}{3/5} = 5/12 < 1$, indicating substantial correlation among contiguous neighbors. Consider instead the case in which adoption is (1,0,1,0,1); this has the same number of adoptions, but none of the adoptions are contiguous. In this case, the numerator is 1 given that all contiguous pairs are of the type (0,1), while the denominator is the same; the overall C is $1/(3/5) = 5/3 > 1$, indicating a negative degree of contiguous clustering in adoptions.

This measure can be computed for clustering along any dimension, as one only needs to specify the rule applied in the numerator of the C statistic. In our case, along each dimension of interest—say, geography or politics—for each state we find the third of other states that are most similar with respect to that dimension. For instance, we take the third of states that are closest in geographic distance for the measure of geographic clustering. To make the comparison more intuitive, we display 1-C, so that higher values correspond to higher similarity and 0 corresponds to no clustering. We compare the observed clustering to a counterfactual of adoption by 10 random states, from 1000 simulations.

In Figure 5a we compare to this counterfactual the geographic clustering of policies that reach the tenth state adoption in the 1950s-70s (112 policies), in the 1980s-90s (233 policies), and in the 2000-10s (171 policies). The figure shows a clear pattern of geographic clustering across all three time periods, to a comparable degree over time. For example, the median policy in the 1950s-70s has an extent of geographic clustering that corresponds to the 80th

[4] The weights need not be symmetric, so the weight for pair ij may not equal the weight for the pair ji. For example, Michigan is in the closest third of states for Maine, but Maine is not in the closest third of states for Michigan.

percentile in the distribution of random policies. The degree of geographic clustering thus is both substantial and persistent over time.

We then consider the extent of political clustering in Figure 5b. Unlike the degree of geographic clustering, the figure shows clear changes over time. For the 1950s-70s and 1980s-90s, the evidence of political clustering is quite muted, and the median policy has a 1-C statistic that is very close to 0, implying no measurable political clustering. We observe instead a quite dramatic shift in the last two decades, at all quantiles of the distribution, including a thick tail of policies that are heavily politically clustered. For example, at the 90th percentile, the average $1 - C$ for the 2000-20s is 0.2, indicating substantial correlation, compared to 0.08 for the earlier decades.

This evidence suggests both geographic and political clustering in policy diffusion, with political correlation increasing over time. This finding is robust to alternative measurement. For example, in Figure A.2, we find the same results if we measure the adoption of the first 16 (a third of the contiguous states) and 24 (a half) states, instead of the first 10 adopters.

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

Hazard Model of Diffusion. 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

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

This specification, with the log odds on the left-hand side, has three types of right-hand-side variables. The first one, η_q, is a policy-specific baseline hazard rate, which we model as 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 features on adoption. The coefficient on the log population term, for example, captures a further test of the state-capacity hypothesis in terms of overall adoption of policies.

The third, key term, $\sum_k \beta_k p\left(A^k_{-iqt}, A_{-iqt}\right)$, aims to capture the influence of adoption by other states that are similar along a particular factor k, such as geography, demographics, or politics. We explain here the functional form we adopt, focusing on the case of geography, which we label as $k = g$. We summarize the adoption with a 2-sided likelihood $p\left(A^g_{-iqt}, A_{-iqt}\right)$ that the number of adoptions by geographically close states (A^g_{-iqt}) is proportional to the number of adoption by all states (A_{-iqt}). Denoting the realized number of adopters within the closest set of states as a^g_{-iqt}, we take the probability of having fewer adopters in the closest set of states $P(A^g_{-iqt} < a^g_{-iqt}|A_{-iqt})$ minus the probability of having more adopters in the closest set of states $P(A^g_{-iqt} > a^g_{-iqt}|A_{-iqt})$, assuming that each state has an equal, independent probability of adopting.

Specifically, for each state i, we rank the other 47 contiguous states in terms of distance between their own state centroid and the centroid of state i, and then take the 16 states in the closest third.[5] The probability of $a^g_{-iqt} \in \{0, ..., 16\}$ adopters within the closest third given the total number of adopters $A_{-iqt} \in \{1, ..., 47\}$ under the null of uniformly random adoption is:

$$P(a^g_{-iqt}|A_{-iqt}) = \begin{pmatrix} A_{-iqt} \\ a^g_{-iqt} \end{pmatrix} \frac{\left(\frac{16!}{(16-a^g_{-iqt})!}\right)\left(\frac{31!}{(31-(A_{-iqt}-a^g_{-iqt}))!}\right)}{\left(\frac{47!}{(47-A_{-iqt})!}\right)}$$

We use this probability mass function to calculate the measure defined as:

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

Consider a state i that has yet to adopt a policy that has been adopted by $A_{-iqt} = 15$ states so far, of which $a^g_{-iqt} = 5$ are in the closest third geographically. Under the null that each state has an equal chance of adopting, the probability of seeing fewer adoptions in the closest third of 16 states is 0.35, and the probability of more adoptions in the closest third is 0.39. Hence, the measure is $p\left(a^g_{-iqt}, A_{-iqt},\right)$=$0.35 - 0.39 = -0.04$, which is close to 0: the adoption by nearby states is in line with the adoption nationwide. Suppose instead that out of the 15 total adoptions, 9 of them had been in the closest third of states. In this case, under the null, the probability of seeing fewer adoptions in the closest third is 0.99, and the probability of seeing more is just 0.002, and the measure is $p\left(a^g_{-iqt}, A_{-iqt}\right) = 0.99 - 0.002 = 0.99$, indicating high diffusion among the neighboring states.

This measure ranges from -1 (states similar to state i statistically have been unlikely to adopt a policy) to +1 (states similar to state i have proven quite likely to adopt). Later, we consider alternative measures, such as the proportion of the states in the closest third that have adopted. While the results are similar with alternative measures, this benchmark measure performs best on specification checks (discussed in Online Appendix Section A).

We build measures of demographic and political similarity in a parallel way, except that the set of the most similar states is time-varying. To capture demographic similarity, we standardize the state-level log population, share of urban residents, and log income per

[5] In the robustness checks, we find that the results are similar regardless of the exact threshold.

capita, take the absolute difference in each dimension, average across the three differences to create the index, and identify the third of states with the smallest difference in this index. For the measure of similarity along political lines, we take the third of states with the smallest absolute difference in the Republican vote-share from the most recent Presidential election for each year.

A positive coefficient β_k on the similarity variable indicates that more adoptions by similar states increase the chances of state i adopting as well. 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, to estimate time-varying coefficients, though we pool the 1950s and 1960s as well as the 2010 and 2020s given the more limited coverage for the earliest and latest years. In each year t, only states that have not yet adopted policy q are in the sample. For each policy, we start the model in the first year of adoption and end it in the last year of adoption in the sample, and exclude policies that end with fewer than 5 adopters or span less than 3 years. We cluster the standard errors at the state level to capture autocorrelation, as well as correlations across policies.

We stress that we do not place a causal interpretation on the estimates in (1) (Manski, 1993). For example, the adoption of a policy by a state may be predicted by the adoption of geographic neighbors because of learning and diffusion of information (Banerjee, 1992; Bikhchandani, Hirshleifer, and Welch, 1992), or alternatively because of common demand for a policy or a common shock (e.g., a shared lobbyist). With this in mind, it is still useful to examine which dimensions predict adoption, as they inform us about the most likely nature of common shocks and circulation of ideas. Furthermore, even viewing the results as purely descriptive, they enable one to make predictions about future adoptions, which can be useful, for example, in the econometric evaluation of a difference-in-differences design. In Section 5.2, we provide estimates with a causal interpretation from an event study design for a specific variable, the change in state government control.

Hazard Estimates. Table 3 reports the estimates. Considering first the set of demographics X_{it}, 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 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 demographic similarity, 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). Demographic similarity is indeed predictive of adoption: in the 1980s we estimate a coefficient of 0.20 (s.e.=0.06), which remains about constant up to the most recent decades, at 0.22 (s.e.=0.07). These estimates are certainly consistent with a 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 reflects these margins.[6]

Next, we consider the impact of geographic closeness, which we would expect to capture the impact of competition across neighboring states, 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 1970s we estimate a coefficient of 0.34 (s.e.=0.06), which remains about constant until the most recent decade, at 0.33 (s.e.=0.08). Thus, geographic similarity is highly predictive, with a somewhat larger impact than demographic similarity, and with consistent importance over time.

Third, we consider the role of similarity in the Republican vote-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 is a modest predictor of adoption, with an effect size mostly between a third to a half of the magnitude for geographic similarity: 0.14 (s.e.=0.05) in the 1970s and 0.17 (s.e.=0.05) in the 1990s. In the last two decades, however, the impact *triples*, with estimates of 0.46 (s.e.=0.05) in the 2000s and of 0.52 (s.e.=0.07) in the 2010-20s. Thus in the last two decades, political similarity has become the most important predictor of policy adoption.

Figure 6 summarizes the estimates: demographic and especially geographic similarity have fairly constant predictive power for adoption over time, while the impact of political similarity, which used to modest, has skyrocketed recently.

The bottom of the table highlights that the predictability of policy adoption has generally increased. If we exclude the first time period, the pseudo R-squared has increased nearly monotonically from 0.13 in the 1970s, to 0.19 in the 2010s. Thus, not only has the role of political similarity increased over the role of geographic similarity, but this increase has also been sizable enough to make the process of adoption more predictable.

Simulated Diffusion. To clarify the magnitudes of the estimated coefficients, in Figure 7 we present two different counterfactuals, one corresponding to the estimated policy diffusion for the 1990s (Figure 7a), one for the estimated diffusion for the 2010s (Figure 7b). Namely, we take a hypothetical policy introduced by California in 2000, and we use the estimated

[6]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.

model in Table 3 to simulate the diffusion of the policy over 20 years or until 10 adopters. For every state that has yet to adopt in each year, we calculate its probability of adopting, and based on that probability, we randomly draw whether it adopts in that year. We assume the same political and demographic variables from the relevant years (2000 onward) across the two plots, and only vary the estimated diffusion coefficients from the model. In the figures, we plot the probability that each state would be among the first ten adopters, as obtained across 1,000 simulations.

The policy with the estimated 1990s coefficients (Figure 7a) diffuses geographically, spreading in the West, as well as in the Northeast among some demographically and politically similar states. Meanwhile, in the simulation with the estimated 2010s coefficients (Figure 7b), the policy is most likely to spread to the states with similar political leaning; geographically close but politically distanced states such as Nevada, Utah, and Arizona become less likely to adopt than before, while the politically similar but furthest states in the Northeast become more likely to do so.

In Figures A.3a-f, we present further simulation diffusion patterns following an innovation in: (i) Connecticut, a state that is reliably Democratic like California but is smaller and on the other coast (Figure A.3a-b); (ii) Texas, a large, Republican state (Figure A.3c-d); and (iii) Ohio, a Republican-leaning Midwestern state (Figure A.3e-f). In all cases, the spread of policies has become more predictable along political lines in recent decades.

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 demographic, geographic, and political similarity.

First, we replicate the benchmark model estimates (except for the expanded grouping of decades). In the next row we present the results from a linear probability model instead of a logit specification, with parallel findings. In the third row we return to the logit specification, but include a fuller set of controls, also with very similar findings.[7] Conversely, we next present a parsimonious specification which drops the levels of state characteristics X_{it} (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. For comparability, we adopt this specification in the panels to follow.

In the next five specifications, we adopt alternative forms for the measure of adoptions

[7] The full set of controls include the percent of non-white population, the unemployment rate; quadratic terms for the proportion of all other states adopted, Republican vote-share, log population, income per capita, urban percentage, non-white percentage, and the unemployment rate; adoption measures among the closest third of states in migration flows, non-white percentage, and the unemployment rate; a more flexible policy-specific baseline hazard parametrized as a step function that varies every five years; and state fixed-effects.

among similar states. In the fifth row, we consider adoption by other states up to year $t-1$, instead of considering adoptions up to year t when computing the measure $p\left(a^k_{-iqt}, A_{-iqt}\right)$. In the next row, we use a weighted average of the binary adoption status of all other 47 states, where the weights are proportional to the other state's rank in similarity. Under this weighting scheme, the most distal state carries 1/47th of the weight of the most similar state. The results are very similar to the benchmark.

In rows 7-9, we present further alternative measures, such as the proportion of adoption among states in the closest thirds, that are simpler parametrizations than our benchmark two-sided likelihood measure, but suffer from mis-specification issues detailed in Online Appendix Section A. Nevertheless, all measures find the same patterns of policy diffusion over time, in the increasing role of politics relative to geographic distance and demographics.

Finally, we ensure that the results are not an artifact of setting the threshold of closest states to be the third. In Figure A.4, we show that the coefficients for each dimension are remarkably comparable whether we use a threshold of the closest fifth, fourth, third, or half.

Heterogeneity. In Table 4 we replicate the parsimonious specification featured in row 4 of 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 most recent two decades as high as 0.66 (s.e.=0.09), compared to a coefficient of 0.42 (s.e.=0.04) in the SPID sample. The impact on geography is fairly constant since the 1970s in both samples, with higher coefficients in the NBER sample than in the SPID sample. In the third row, we study a special set of policies, the Interstate Compacts on which states 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 observe a pattern of party polarization even in this sample, though with smaller magnitudes, suggesting a wide reach of the polarizing forces at play.

In Panel B we split the sample by policy area based on whether the policy deals primarily with economic, or social issues. For economic policies, we find a decrease in the role of geography and demographics over time, with a smaller increase in the role of politics. The 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. By comparison, for non-economic policies the role of geography is about constant, and we observe an especially strong impact of political polarization, as one would expect given the more polarizing nature of social issues.

In Panel C we separately estimate the results for Republican-voting states, Democratic-voting states, and "battleground" states, by splitting the states into thirds based on their vote-share. The increased importance of politics is driven by the Republican-voting states and especially the Democratic-voting states, and less so by the battleground states. This fits with a party-driven model for the polarization. In the battleground states, the party in control varies from Democratic to Republican, so battleground states do not specifically adopt policies from one another, as opposed to states at the polar opposites that do.

Finally, 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 U.S. states in Besley and Case (1995) and de Paula, Rasul, and Souza (2020), for example, and with findings in the political science literature as early as Walker (1969) and in Mallinson (2020) who reviews the papers since then. More recently, Caughey, Warshaw, and Xu (2017), Grumbach (2018), and Mallinson (2021) find evidence, as we do, for the increasing importance of political alignment for policy diffusion. Relative to these papers, we compare quantitatively the impact of polarization to the impact of geographic and demographic similarity, we present results for the most recent years, and we document even stronger patterns for the policies studied by economists.

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 arising from recent events 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 U.S. 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, geographic, and political similarity, which is consistent with the estimated patterns in the recent decades for the main sample. In Column 2 we add additional similarity variables that we describe in the following section.

For comparison, we present evidence on the adoption of vaccination policies since 1975, covering laws such as immunizations requirements for schools and in hospitals. As Column 3 in Table 5 shows, the adoption of policies in this sample is predicted by demographic similarity and, to some extent, geographic similarity. Political similarity, however, has no impact whatsoever. This makes the politically polarized patterns for the adoption of COVID policies stand out even more so as a recent phenomenon.[8]

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 with a strong impact of both demographic and geographic similarity fits neatly with these models.

The patterns for the 2000-20s are a less obvious fit, with an 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 and more political 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 recently by political voter preferences than by geography. In this case, the shift in the policy adoption estimates may still reflect correlated preferences or environments. We present two pieces of evidence in this regard.

Evidence using Migration Flows. First, if these changes have 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 similarity has strong predictive power both in the earlier period and in the later period. Further, it reduces the explanatory power of geography. It does not, however, affect at all the importance of the similarity in vote-share (nor of demographic similarity). The lack of a change in the

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

contribution of political similarity suggests that its growing role is likely driven by alternative factors, which we examine in Section 5.2.

We can also revisit the specifications on COVID and vaccination policies in this light by adding the migration-based similarity measure in Table 5. We estimate an impact of migration-based similarity especially for the vaccination laws (which reduces the coefficient on geographic similarity), but less so for the COVID policies (Column 4).

Evidence from Outcome Variables. As a second piece of evidence, we consider variables that are typical policy outcomes, such as the state-level opioid mortality rate, income, and poverty rate. If changes in local preferences or environments are driving the increased impact of politics in policy adoption, we would expect these outcomes to have become more correlated among politically similar states. If, instead, other factors are at play, the correlation between the outcome variables and politics may not have changed over time.

We compute the same measure of Geary's C statistic using again the closest third of states by vote-share for these dependent variables, first for the period 1980-85 and then for the period 2005-10. Figure 8 plots the two measures of correlation expressed as $1 - C$ at different time periods for each of these outcome variables. The figure provides no evidence that these variables have become more politically correlated.[9]

Overall, this suggests that the increased weight of political variables on policy adoption largely is not due to a change in the correlation across states in the environment or local needs, but rather due to other factors. We discuss a prominent one in the next section.

5.2 Party Discipline

A separate explanation is that in the recent decades *party discipline* increasingly explains the diffusion of state policy, beyond the predictive power of local preferences or environments, learning, or competition. The evidence thus far does not allow us to distinguish this explanation, as the similarity in vote-share may just be capturing 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 which defines the "closest" states in this dimension to be those with the same partisan control of the state government. We categorize three types of state governments: unified Democratic (i.e., the governor is Democratic and both state houses have a Democratic majority), unified Republican, and

[9]Figure A.5 shows the trends in geographic correlation for the outcomes and finds that outcomes have become less geographically correlated in recent times.

divided state control (which encompasses all the non-unified cases).[10] In Columns 7 to 9 of Table 6, we add this variable to the logit model, considering separately the case of unified control (Republican or Democrat) and the case of divided split-party governments.

This measure yields evidence of an even more striking change over time. In the decades up to the 1990s, we do not find any evidence that similarity in state political control matters: the point estimate is zero. In contrast, for the 2000-20s period, we estimate that for states under a unified state government, the strongest predictor of adoption is previous adoption by other governments with the same state party control (estimate of 0.42, s.e.=0.06). In contrast, for states with split governments, there is no predictive power of adoption by other states with split governments, which further underscores the role of party control. Thus, the increase in importance of politics is even more striking when measured by partisan control, as opposed to political preferences of the electorate.

We also revisit the COVID and vaccination policies in Table 5 with this additional dimension of political similarity. We similarly find that the similarity in state government is the strongest predictor of the adoption of COVID policies (Column 2), while it plays no role for the earlier vaccination policies (Column 4).

Event Study. The previous 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, a distinction that the political science literature has found to be a 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 is the year of switch s to unified party control in state i, and the key parameter of interest δ_d is allowed to depend on the ideology (defined below) of the policy q. We control for each state's baseline probability of adopting 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 the ideology of the policies to distinguish those that align with, or run counter to, the party in control of the state government. We categorize policies using the vote-share of the states that have adopted the law so far. More precisely, we take the average 2-party Republican vote-share (demeaned by year) in the latest Presidential

[10] We assign Nebraska, which has a unicameral nonpartisan state legislature, to the party of its governor.

election among the states that have adopted the policy by year $t-1$.[11] If a policy has been adopted on average by states with a 1 percentage point or higher advantage in the vote-share for the Republican side, we define the policy as Republican-leaning, and conversely for Democratic-leaning policies. If the average vote-share of states adopting a policy is within the 2 percentage-point buffer, we code the policy as neutral-leaning. Policies can be classified as neutral in one year but then ideologically aligned with one party in another year when new adoptions occur, but we drop a small fraction of policies that switch from left- to right-leaning or vice versa at some point in its life-cycle.[12]

Figure 9a displays the event study coefficients with 95% confidence intervals for the period 1991-2020. A switch to a unified state government does not lead to any increase in the passage of neutral-leaning state laws; it does not appear that unified government reduces gridlock in general. Next, we consider the impact on the probability of adopting a policy that aligns ideologically with the inaugurated unified state government, compared to the adoption of policies leaning in the opposite direction. We detect a statistically significant increase of about 2 percentage points in the 4 years following the switch, compared to the year before the switch. The increase arises already in year $t+1$, as one would expect, and appears to be persistent. The data does not indicate any obvious pre-trends.

In Figure 9b we consider the same event study for the earlier 1950-1990 time period. In this earlier period we do not uncover any change from a switch in party control in the probability of passing laws aligned with 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 at the level of U.S. states.

In Table A.6 we present the separate components contributing to these event study estimates, reproduced in Column 1. In Column 2 we present the impact on the passage of Republican-leaning policies (as per the coding above) for the case of switching to a Republican unified government, and in Column 3 the impact for Democratic-leaning 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

[11] In the average among the adopters, we record the vote-share at the time of adoption. For example, if California adopts the policy in 2001 and Oregon in 2005, the average would be calculated using California's vote-share in the 2000 election and Oregon's vote-share in the 2004 election.

[12] Figure A.6a shows the distribution of average demeaned 2-party Republican vote-share among adopters for the policies over the last 30 years. Figure A.6b follows the ideological evolution of the three most left-, right-, and neutral-leaning policies in 1990 until 2020. Figure A.6c summarizes the number of policies under each ideological classification depending on the threshold used. (The event-study uses a threshold of 1 pp.).

unified state governments, which yield smaller impacts.

6 Policy Diffusion in Economics Papers

In the heterogeneity analysis of Section 4.2, we analyzed the patterns of policy diffusion in the sample of NBER working papers that feature state-level policy variation, documenting both geographic spread and the recent rise of a strong partisan role in the diffusion.

In this section, we instead provide a first approximation of the diffusion patterns for each policy in the NBER sample individually. We use the same measure of policy clustering as before, the Geary's C, computed for every policy both along the geographic dimension and along the political dimension.

Figure 10a plots a scatter of the $1 - C$ measure of political and geographic clustering for each policy in the sample of NBER working papers, compared to the SPID policies. The shaded light blue regions show the 5th to 95th percentile of the $1 - C$ statistic for placebo policies, or what we would expect to see under the null of diffusion at random. Generally, the actual policies fall into three categories. One group has a pattern of diffusion that is largely predicted by politics, such as the Medicaid Expansion. A second group of policies has diffusion that is predicted by a combination of geography and politics, such as the ban on employers asking about a prospective employee's past salary. Finally, a third group, which includes Anti-Bullying Laws, appears to be fairly idiosyncratic, at least based on these parsimonious measures.

We envision that 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-differences 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 U.S., 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 these three models apart, given that they share several key predictions.

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 similarity, and especially similarity in the state party control. These results suggest that it is not just a question of voter preferences, but also of party discipline emerging at the state level.

This result runs parallel with other studies on polarization, which have been a focal topic in the recent political science and political economy literature. A key finding in this literature is that politicians in the U.S. Congress have shown polarizing voting patterns since the 1950s. Indeed, Figure 11 reproduces the trends in the House and the Senate using DW-NOMINATE, one of the commonly-used data sets in the literature. Our results indicate that the polarization of state-level policies did not start until later, in the 2000s. Still, its role is rapidly rising and 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.[13]

One of the most touted advantages of the U.S. federalist system is the ability of independent states to tailor their policies swiftly and optimally to voter preferences and state-specific needs. Yet the current trends suggest that the adoption of state policies is becoming less focused on local economic demands, and instead responding more so to partisan forces.

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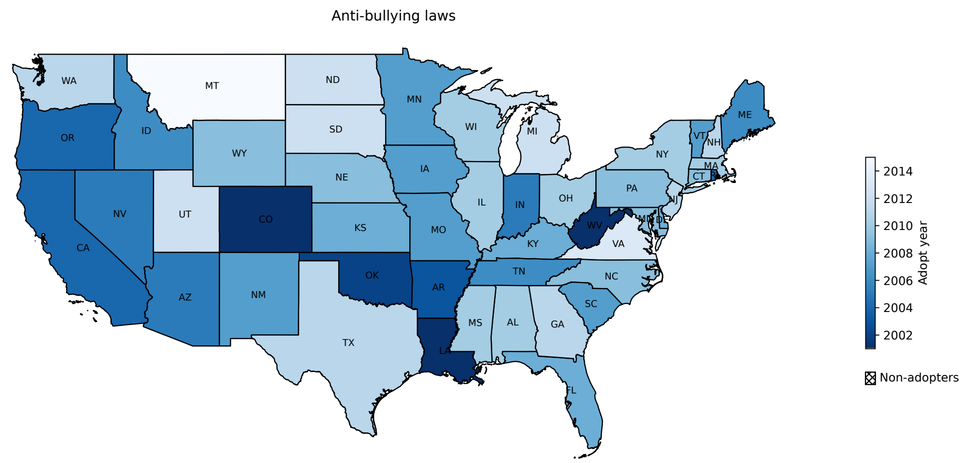
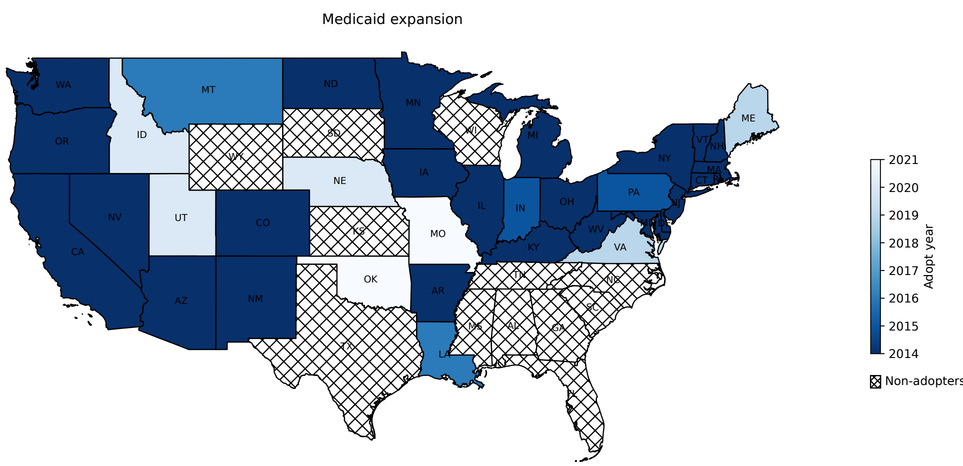
Figure 1: Three policy examples

(a) Anti-bullying laws



(b) 2014 Medicaid expansion (Affordable Care Act)



(c) Initial prescription drug monitoring program

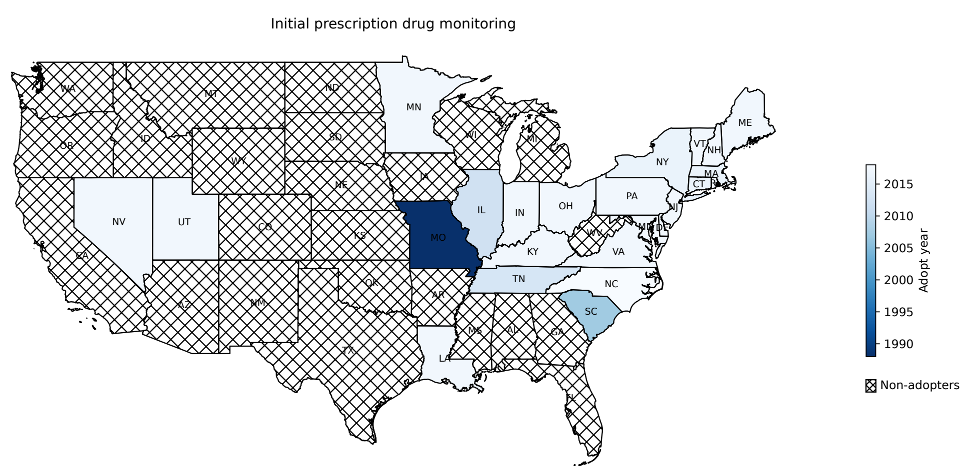
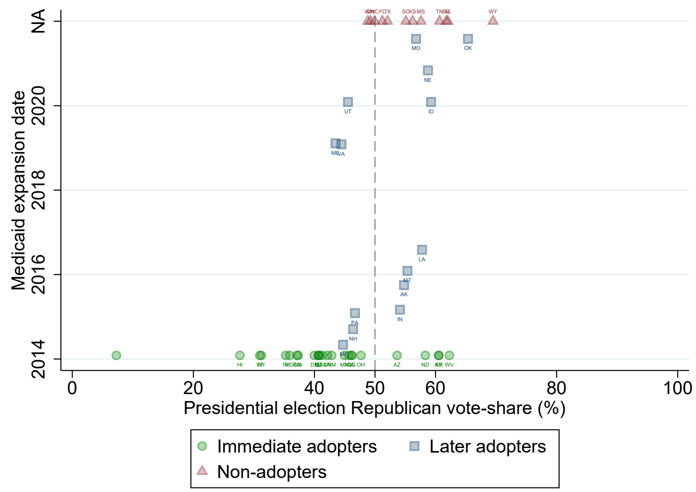
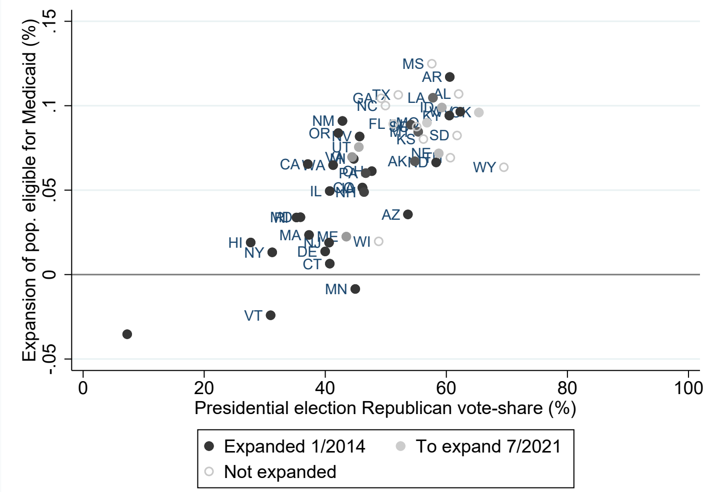


Figure 2: Case studies of welfare programs

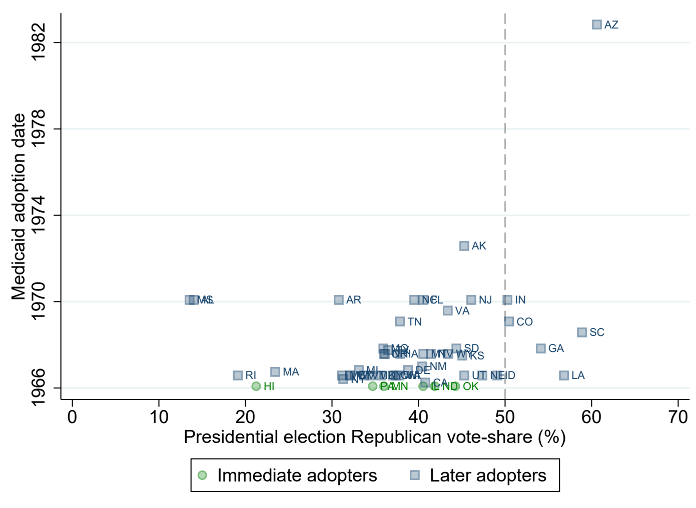
(a) 2014 Medicaid expansion (ACA)



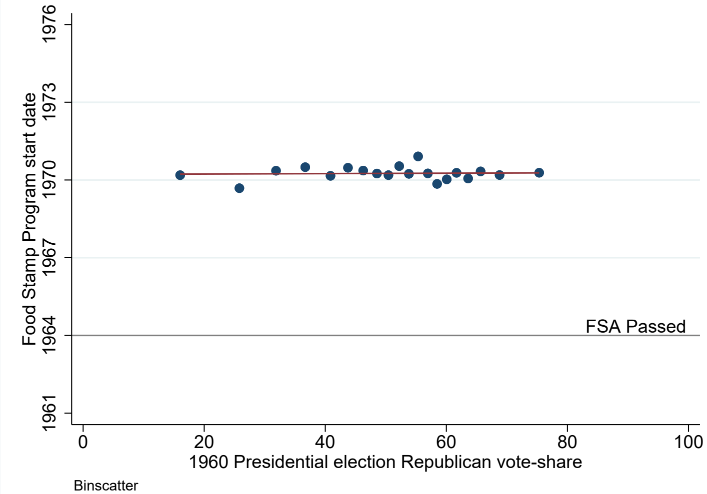
(b) 2014 Medicaid expansion coverage



(c) 1960s Initial Medicaid adoption



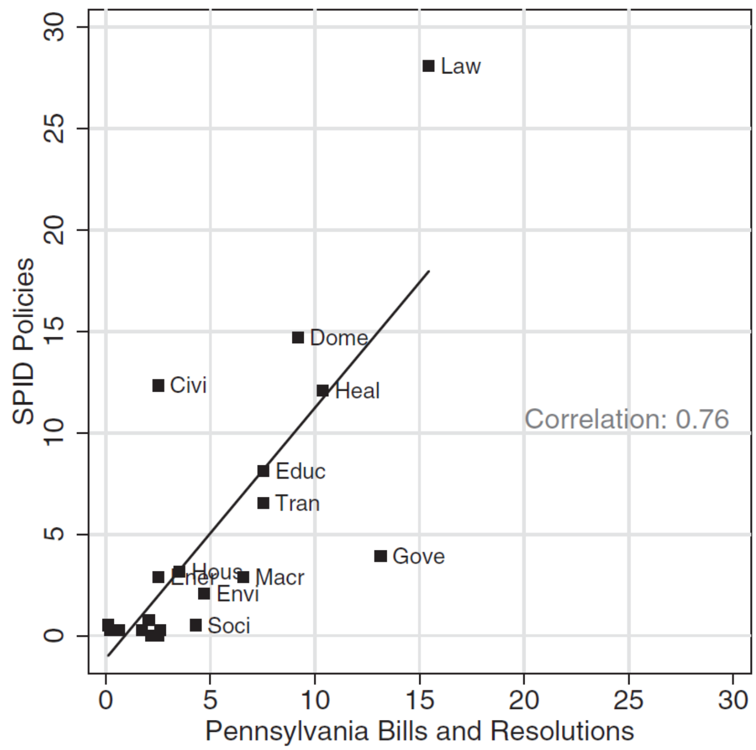
(d) 1960-70s Food Stamp Program adoption (county-level)



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

Figure 3: Policy sources and representativeness

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



(b) Sources

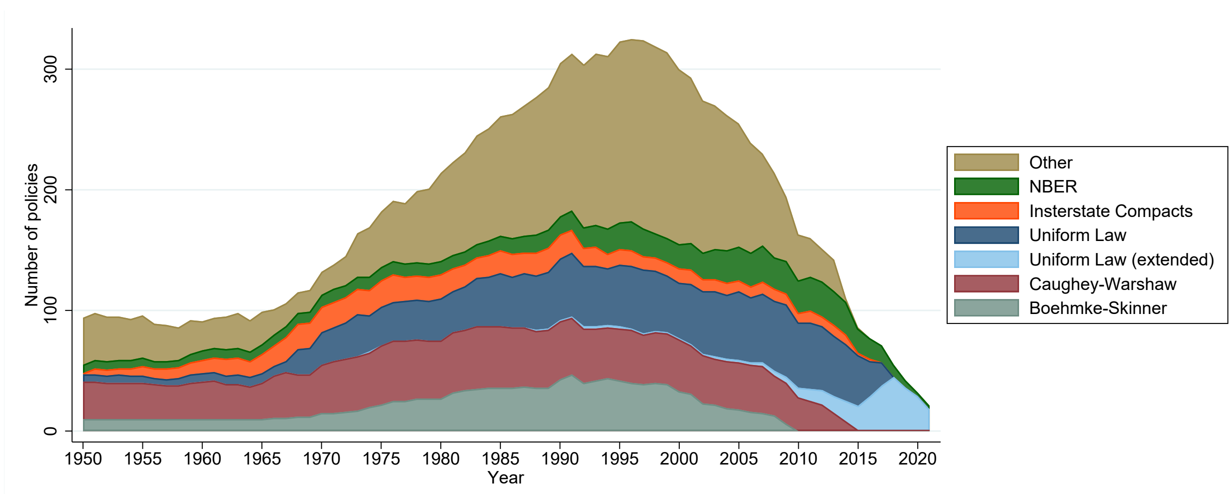
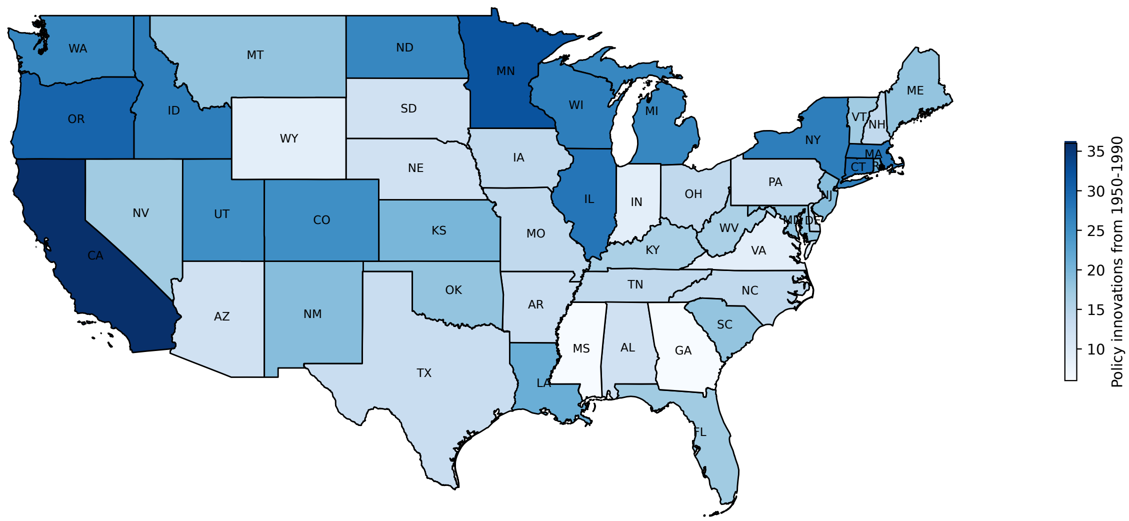


Figure 3a is reproduced from Boehmke et al. (2020) and shows the correlation of policy areas between the policies in the SPID dataset and in the Pennsylvania Policy Database Project (McLaughlin et al., 2010). The Pennsylvania Policy Database is used as an example of policies in a typical state.
Figure 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

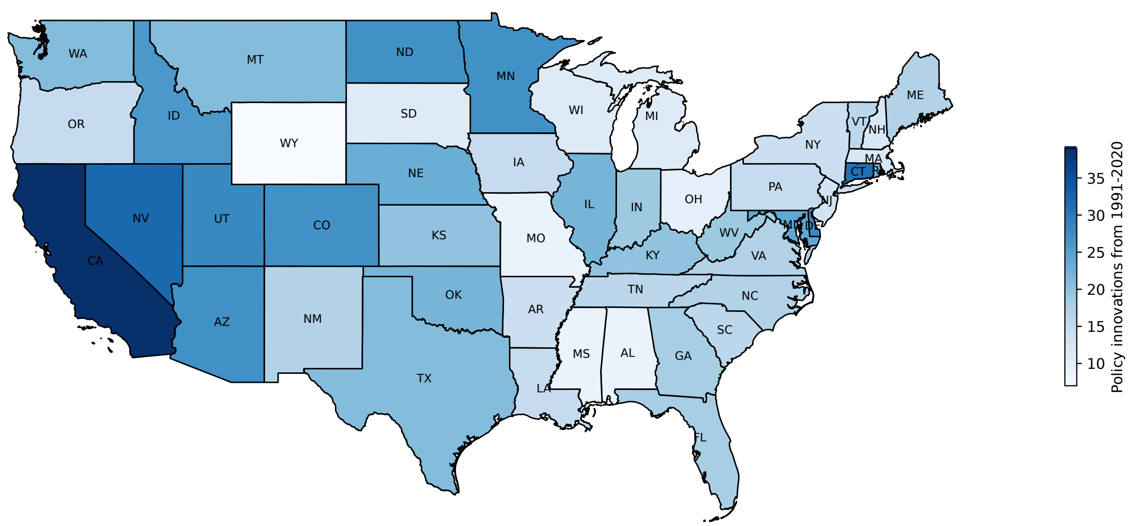
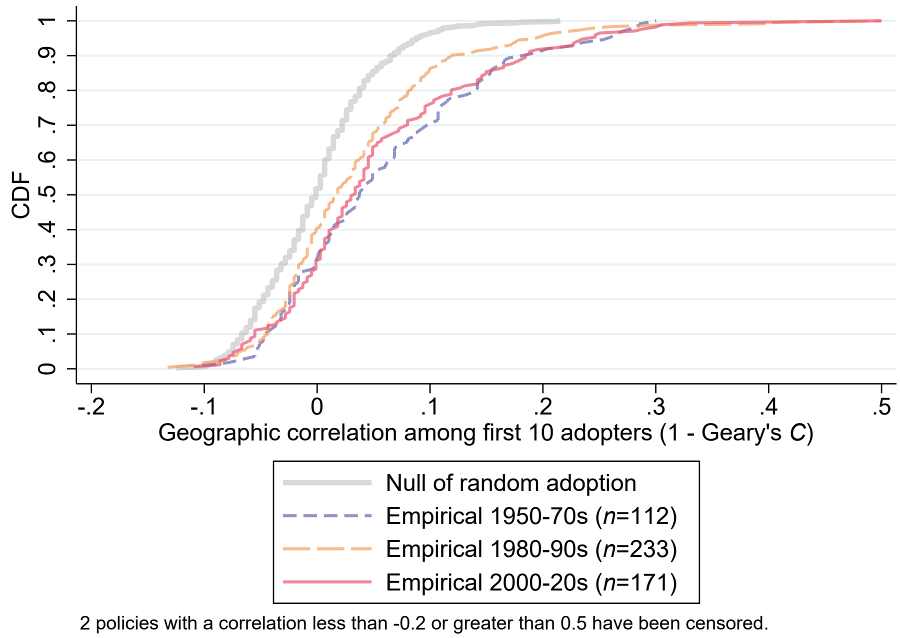
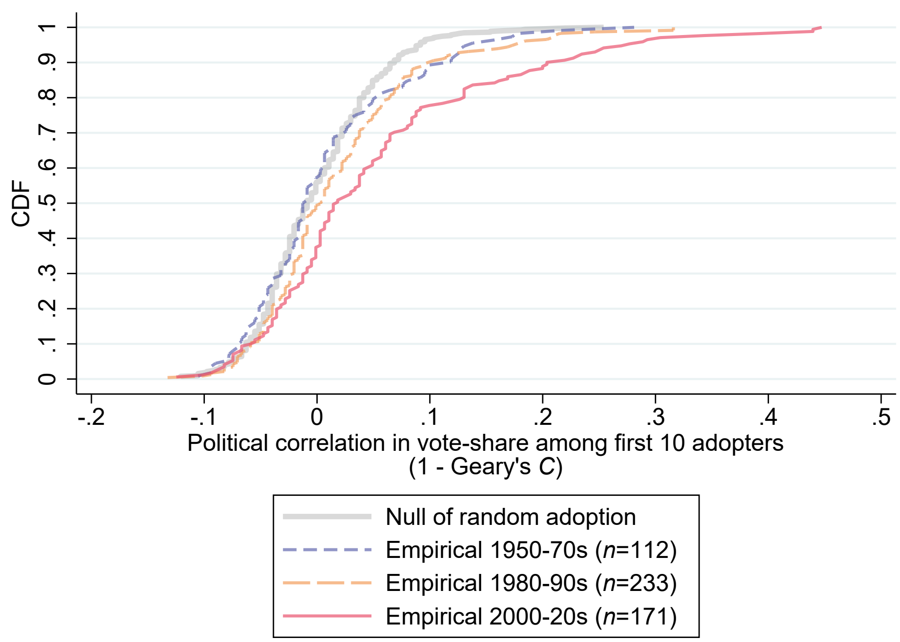


Figure 5: Correlation in geography and politics among adopters (random and observed)

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

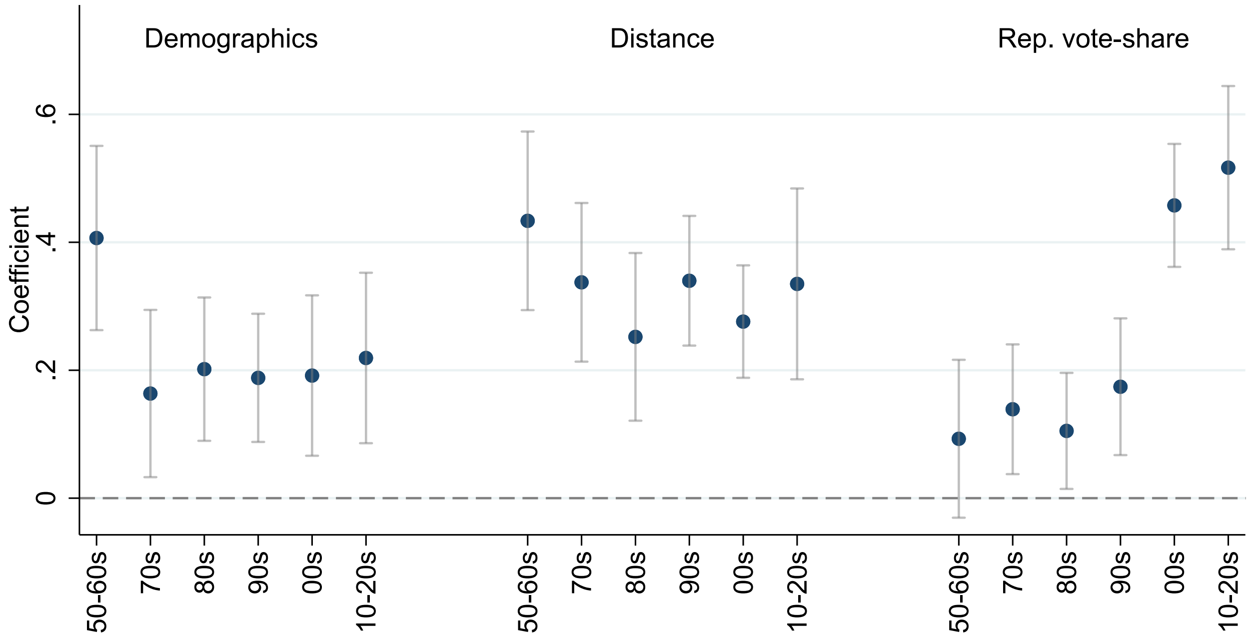


(b) Correlation in Republican vote-share (first 10 adopters)



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

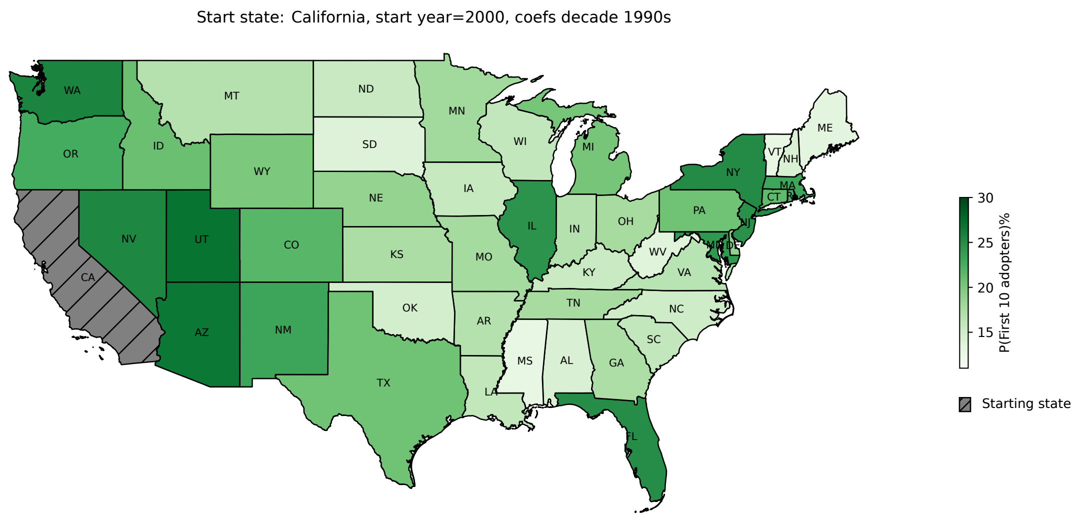
Figure 6: Dynamics of policy diffusion among similar states



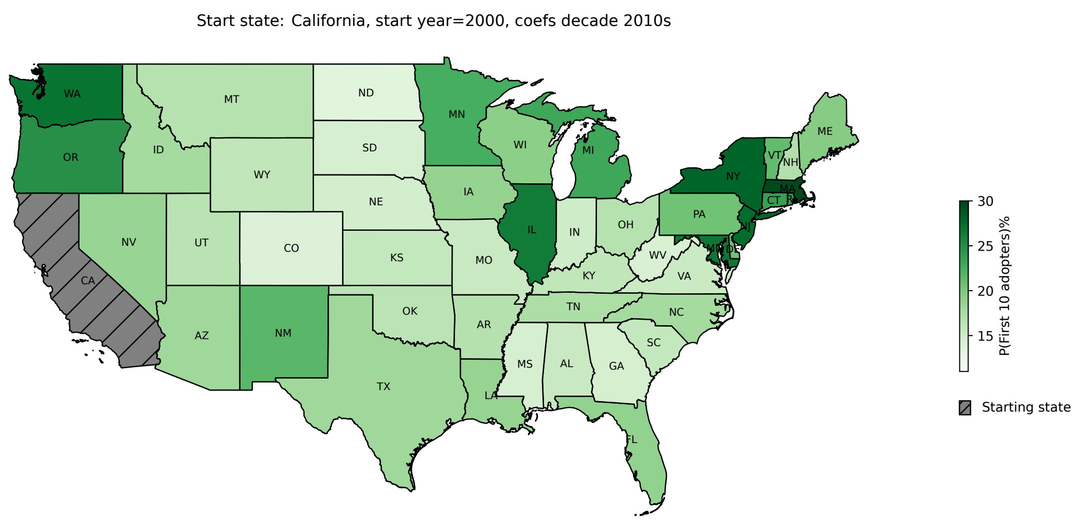
This figure plots the estimates from Table 3 for the coefficients on the measure of adoption among the closest states in each dimension. 95% confidence intervals are shown with standard errors clustered by state.

Figure 7: Simulated policy diffusion

(a) Coefficients from 1990s



(b) Coefficients from 2010-20s



These maps show the probability of the diffusion of a policy innovated by California in 2009 for each of the other states based on the model estimated in Table 3. Figure 7a uses estimated coefficients from the 1990s decade, and Figure 7b from the 2010-20s decade.

Figure 8: Correlation of policy outcomes with vote-share: 1980-85 vs. 2005-10

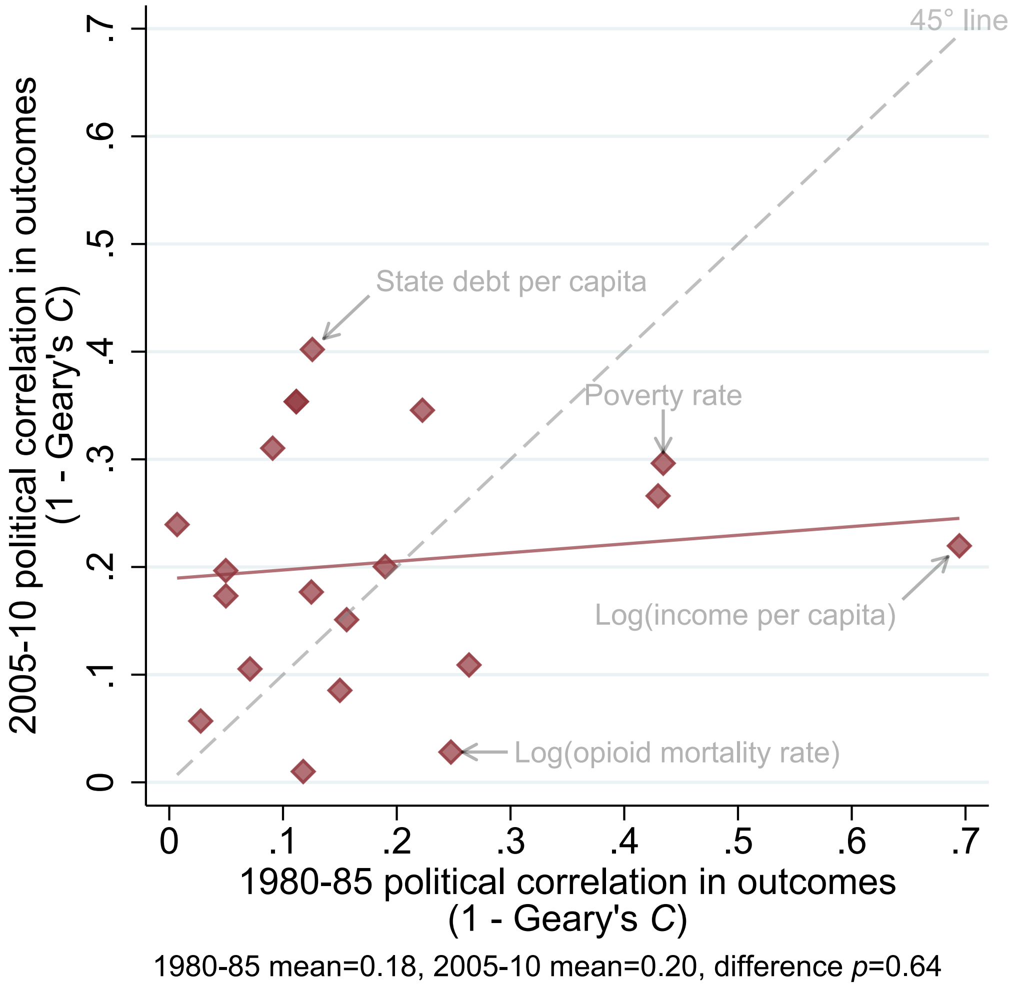
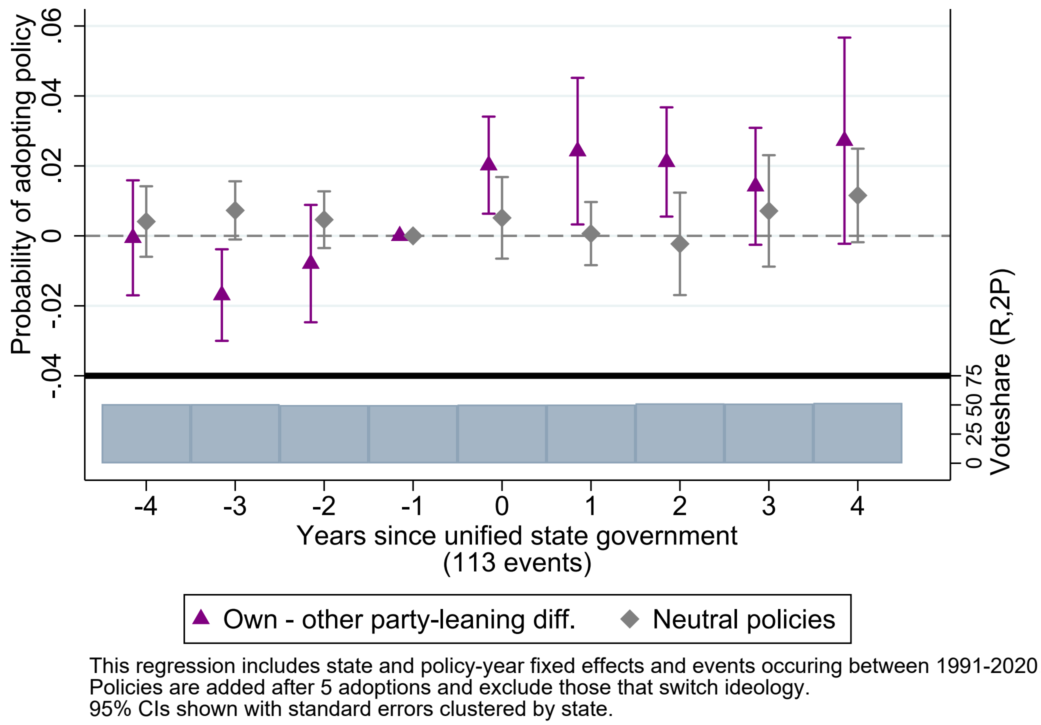


Figure 9: Event study from switches in state government party control

(a) Events during 1991-2020



(b) Events during 1950-1990

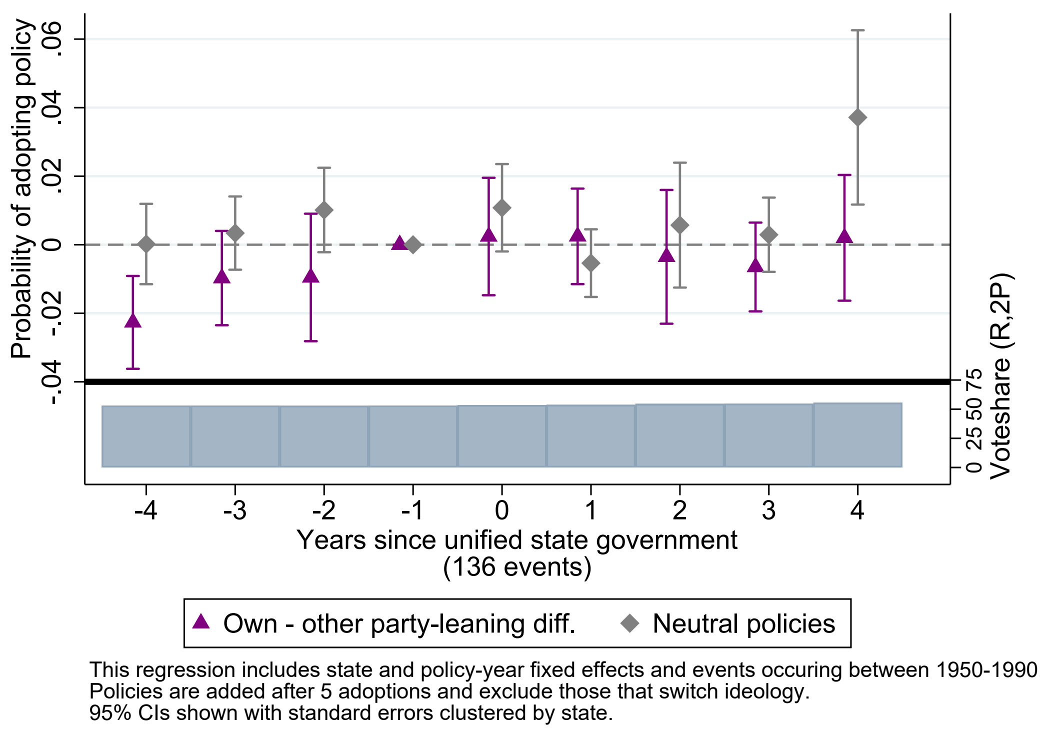
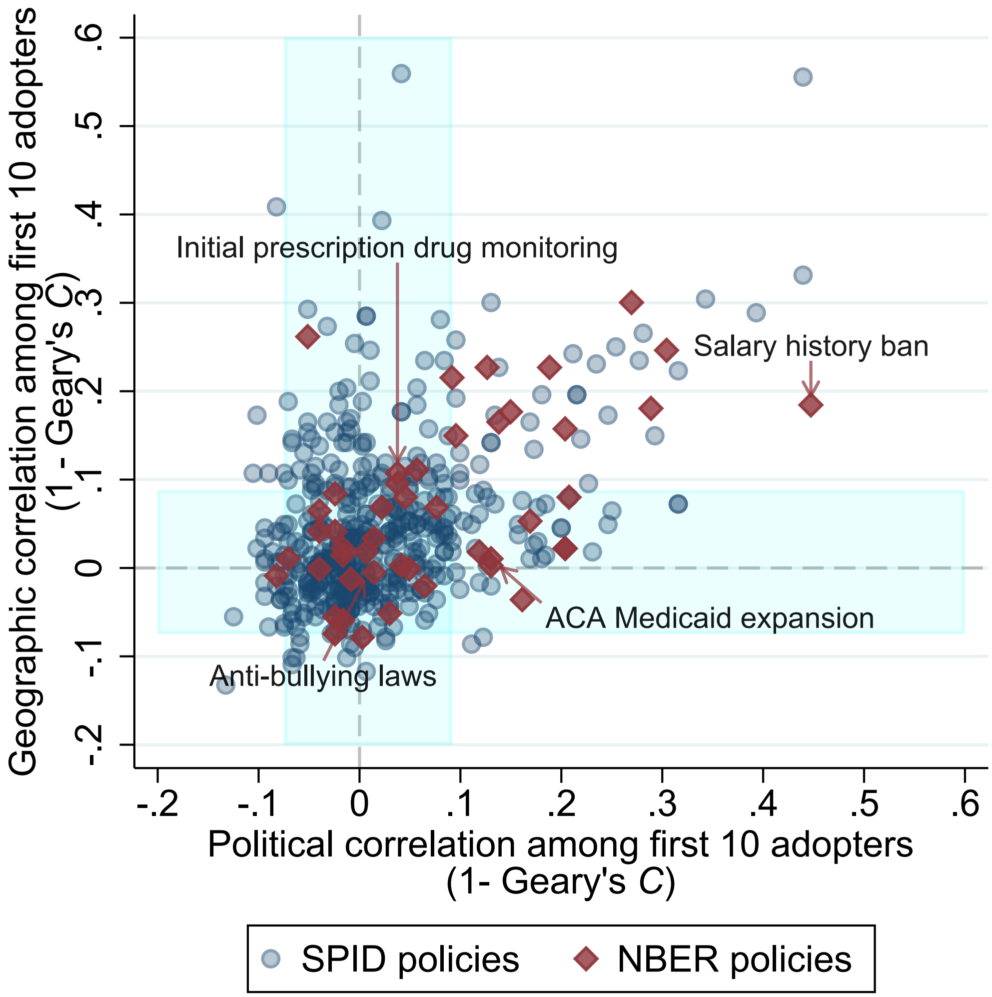


Figure 10: Policy-by-policy diffusion patterns



Geographic correlation mean: SPID=0.04, NBER=0.07, diff. *p*=0.10
Political correlation mean: SPID=0.02, NBER=0.08, diff. *p*=0.00
Shaded region indicate 5-95th percentiles for placebo policies

Figure 11: Comparison to polarization in DW-NOMINATE

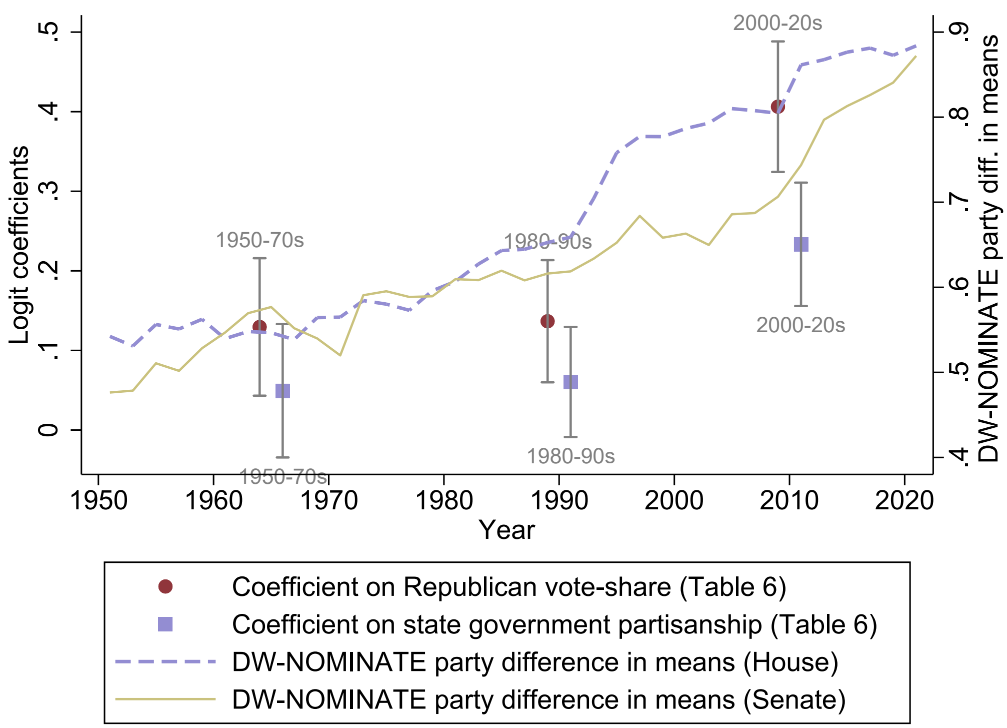


Table 1a: Summary of NBER data set

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

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

Table 1b: Summary statistics of policy data sets

	SPID				NBER			
	Mean (SD)	Min	Median	Max	Mean (SD)	Min	Median	Max
Number of policies	676	–	–	–	57	–	–	–
First year of adoption	1977.27 (29.33)	1804	1983	2017	1987.81 (25.34)	1911	1995	2017
Last year of adoption	1998.10 (17.13)	1949	2002	2021	2007.30 (13.82)	1955	2014	2021
Number of states adopted	23.18 (15.07)	1	21	48	29.21 (14.68)	6	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	183 (27%)	28 (49%)
Law & Crime	Law & Crime	Gun open carry laws	193 (29%)	4 (7%)
Economics	Domestic Commerce, Labor	Bankrupcy laws	120 (18%)	20 (35%)
Civil Rights	Civil Rights, Immigration	Gender discrimination laws	111 (16%)	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

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.: Policy adoption (logit)	50-60s	70s	80s	90s	00s	10-20s
Prop. of states adopted	2.44	0.39	2.09	3.21	2.39	3.27
	(0.26)	(0.42)	(0.26)	(0.20)	(0.24)	(0.29)
Republican vote-share	-0.47	-0.15	-0.59	0.14	0.57	-1.16
	(0.32)	(0.30)	(0.55)	(0.37)	(0.56)	(0.72)
Log(population)	0.04	0.03	0.02	0.04	0.01	0.05
	(0.07)	(0.06)	(0.04)	(0.05)	(0.04)	(0.06)
Income per capita ($10,000s)	2.79	-0.36	-0.13	-0.09	-0.11	-0.12
	(1.13)	(0.41)	(0.14)	(0.14)	(0.07)	(0.09)
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)
Measure of adoption among other states closest in:						
Demographic index	0.41	0.16	0.20	0.19	0.19	0.22
	(0.07)	(0.07)	(0.06)	(0.05)	(0.06)	(0.07)
Distance	0.43	0.34	0.25	0.34	0.28	0.33
	(0.07)	(0.06)	(0.07)	(0.05)	(0.04)	(0.08)
Republican vote-share	0.09	0.14	0.11	0.17	0.46	0.52
	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)
Baseline P(Adopt)	0.03	0.03	0.03	0.05	0.05	0.06
Observations	58552	54643	79132	94437	70892	28393
Policies	162	203	284	397	345	182
Pseudo R^2	0.22	0.13	0.14	0.19	0.17	0.19

This table shows the coefficients from a logit regression. Standard errors are clustered by state. The baseline hazard for each policy is parametrized by policy fixed effects for each decade. The closest states are defined as the third of all the states with the smallest absolute value difference in each characteristic. The difference in the demographic index is calculated by first standardizing 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: 0.21, 0.25, 0.19; $N_{\text{pol.}}$: 14, 30, 43)								
0.27	0.28	0.32	0.62	0.32	0.43	0.07	0.26	0.66
(0.18)	(0.11)	(0.08)	(0.17)	(0.11)	(0.09)	(0.15)	(0.12)	(0.09)
SPID (R^2: 0.15, 0.16, 0.16; $N_{\text{pol.}}$: 260, 408, 343)								
0.35	0.23	0.21	0.38	0.30	0.26	0.15	0.13	0.42
(0.06)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
Interstate Compacts (within SPID) (R^2: 0.14, 0.12, 0.20; $N_{\text{pol.}}$: 22, 26, 15)								
0.17	0.15	0.15	0.47	0.71	-0.05	0.19	-0.05	0.32
(0.12)	(0.15)	(0.17)	(0.10)	(0.13)	(0.13)	(0.09)	(0.16)	(0.11)
Panel B. Policy area								
Economics (R^2: 0.10, 0.21, 0.18; $N_{\text{pol.}}$: 48, 63, 70)								
0.34	0.21	0.27	0.62	0.37	0.19	0.17	0.14	0.22
(0.10)	(0.07)	(0.08)	(0.09)	(0.06)	(0.07)	(0.09)	(0.08)	(0.08)
Non-Economics (R^2: 0.17, 0.16, 0.16; $N_{\text{pol.}}$: 226, 375, 316)								
0.34	0.24	0.22	0.34	0.28	0.32	0.14	0.14	0.51
(0.07)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)
Panel C. By state characteristics								
Third of states with highest Republican vote-share (R^2: 0.16, 0.17, 0.17; $N_{\text{pol.}}$: 274, 438, 386)								
0.28	0.23	0.29	0.32	0.32	0.27	0.10	0.16	0.45
(0.08)	(0.06)	(0.07)	(0.07)	(0.06)	(0.09)	(0.10)	(0.08)	(0.09)
Third of states with most neutral vote-share (R^2: 0.16, 0.17, 0.17; $N_{\text{pol.}}$: 274, 438, 386)								
0.37	0.26	0.10	0.33	0.29	0.28	0.08	-0.01	0.18
(0.09)	(0.07)	(0.05)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)	(0.05)
Third of states with highest Democratic vote-share (R^2: 0.16, 0.17, 0.17; $N_{\text{pol.}}$: 274, 438, 386)								
0.37	0.21	0.24	0.51	0.29	0.30	0.22	0.26	0.69
(0.09)	(0.07)	(0.11)	(0.08)	(0.09)	(0.08)	(0.07)	(0.08)	(0.09)
Third of states with highest population (R^2: 0.16, 0.17, 0.17; $N_{\text{pol.}}$: 274, 438, 386)								
0.49	0.34	0.37	0.40	0.21	0.24	0.13	0.08	0.38
(0.11)	(0.09)	(0.11)	(0.10)	(0.08)	(0.10)	(0.06)	(0.05)	(0.08)
Third of states with lowest population (R^2: 0.16, 0.17, 0.17; $N_{\text{pol.}}$: 274, 438, 386)								
0.22	0.19	0.12	0.45	0.36	0.37	0.07	0.16	0.48
(0.08)	(0.07)	(0.06)	(0.08)	(0.07)	(0.09)	(0.07)	(0.05)	(0.07)

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, (ii) the proportion of adopters in all states, and the measure of adoption among the closest third of states in (iii) a demographic index combining population, income per capita, and urban % (see notes in Table 3 for details), (iv) geography, and (v) 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 separately for only policies in the "Economics" policy area and all other policies.
In Panel C, the states are first partitioned into thirds each year based on a characteristic (e.g., Republican vote-share in the most recent presidential election). The coefficients are then allowed to differ and reported separately for each third. The exercise is implemented for two characteristics: Republican vote-share and population.

Table 5: Vaccine regulations and COVID-19 policies

	COVID		Vaccine laws	
Dep. var.: Policy adoption (logit)	(1)	(2)	(3)	(4)
Proportion of states adopted	3.34	3.45	1.44	1.37
	(0.23)	(0.23)	(0.48)	(0.48)
Measure of adoption among other states closest in:				
Demographic index	0.24	0.22	0.40	0.38
	(0.08)	(0.08)	(0.11)	(0.11)
Distance	0.35	0.28	0.19	0.06
	(0.06)	(0.07)	(0.09)	(0.12)
Republican vote-share	0.37	0.15	-0.01	-0.02
	(0.07)	(0.08)	(0.10)	(0.10)
Migration flows		0.12		0.28
		(0.10)		(0.15)
State gvnt. partisanship		0.40		-0.04
		(0.07)		(0.08)
Observations	27935	27935	25482	25478
Policies	77	77	28	28
Pseudo R^2	0.32	0.33	0.19	0.19
Time unit	Weeks (Mo-Su)	Weeks (Mo-Su)	Years	Years
Time range	10/2019-8/2021	10/2019-8/2021	1975-2021	1975-2021

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: Tests for 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	2.05	2.61	2.32	2.08	2.62	2.36	2.07	2.62	2.33
	(0.18)	(0.12)	(0.15)	(0.18)	(0.12)	(0.16)	(0.18)	(0.12)	(0.16)
Divided state government							0.05	0.04	-0.10
							(0.08)	(0.04)	(0.06)
Measure of adoption among other states closest in:									
Demographic index	0.34	0.24	0.23	0.32	0.22	0.19	0.31	0.22	0.20
	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)
Distance	0.39	0.30	0.29	0.21	0.18	0.16	0.21	0.18	0.15
	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)	(0.04)
Republican vote-share	0.15	0.14	0.46	0.13	0.14	0.46	0.13	0.14	0.39
	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Migration flows				0.37	0.24	0.31	0.36	0.23	0.31
				(0.07)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)
State government partisanship							0.00	0.03	0.42
							(0.06)	(0.06)	(0.06)
Divided gvnt.×State gvnt. partisanship							0.09	0.05	-0.46
							(0.12)	(0.09)	(0.08)
Observations	120415	183269	102906	120415	183269	102906	120094	183269	102906
Policies	274	438	386	274	438	386	274	438	386
Pseudo R^2	0.16	0.17	0.17	0.16	0.17	0.17	0.16	0.17	0.17

This table shows 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.