What Drives Tax Policy? Political, Institutional, and Economic Determinants of State Tax Policy*

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Abstract

We examine the determinants of U.S. state tax policy using a comprehensive panel dataset on personal income, corporate income, sales, cigarette, gasoline, and alcohol tax rates spanning the past 70 years. Applying Shapley decomposition and machine learning methods, we find that commonly cited factors — such as economic conditions, political partisanship, institutional features, demographic trends, and tax competition among neighboring states — explain less than 20% of the observed variation in the timing and magnitude of tax changes. Furthermore, we demonstrate that state tax policies cannot be reliably classified into stable or interpretable categories over time. These findings suggest that state tax policies exhibit a high degree of idiosyncrasy and resist simple, systematic explanation.

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Economists have long sought to understand what drives changes in tax rates, both theoretically and empirically. Prior literature has identified a range of potential influences, including fiscal pressures, stabilization needs, preferences for redistribution, interjurisdictional competition, residential sorting based on preferences, electoral cycles, partisan control, institutional constraints, and more. Yet, it remains unclear how well these factors, taken together, can explain the patterns we observe in tax policy.

Empirical economic research typically emphasizes the identification of a causal relationship between one factor and the outcome of interest – a necessary approach for assessing the impacts of policy interventions or testing theoretical mechanisms. However, this focus has limits in contexts where understanding the full structure of the decision-making process is critical. Using all commonly studied factors, can we explain the outcomes we observe, or do researchers need to look for new explanations? Answering this question requires a fundamentally different approach, oriented around the overall predictability of outcomes.

In this paper, we conduct a comprehensive analysis of the determinants of U.S. state tax rate changes over time. Drawing on a broad set of factors identified in prior theoretical and empirical work, we first use a simple linear model and Shapley decomposition to investigate how much of the variation they can explain. We then use supervised and unsupervised machine learning to examine their predictive power. These tools allow for flexible functional forms and high-dimensional interactions that are not feasible to include in a regression analysis, and in the case of unsupervised approaches, they allow patterns to emerge from the data without pre-imposed structure. The fundamental nature of machine learning tools often makes them ill-suited for questions of inference, because they increase predictive power but provide less reliable information about the role of each individual factor compared to regression analysis (Mullainathan and Spiess, 2017). We avoid this drawback by focusing on the explanatory power of the full set of commonly studied factors, the exact setting where machine learning tools can reduce concerns about model misspecification.

Our findings are striking. Even with a rich set of predictors, the timing and magnitude of tax rate changes remain largely unpredictable. Across multiple specifications, the explained variation in tax rate changes does not exceed 20 percent, while out-of-sample prediction performance is consistently poor. Moreover, unsupervised methods fail to uncover stable or interpretable groupings of state tax policy behavior. These results point to two possibilities: either tax policy changes are driven by inherently unpredictable processes, or key determinants were not included in our analysis. Given that our analysis incorporates the most frequently cited factors in the literature – and implicitly accounts for any other correlated factors – our findings suggest that scholars may need to explore novel mechanisms or accept that tax policy is, to a substantial extent, idiosyncratic.

Our analysis examines changes from 1950 to 2020 in U.S. state-level top statutory tax rates including personal income, corporate income, sales, cigarette, gasoline, and alcohol taxes.[1] We focus on these six tax categories because they are predominantly determined at the state rather than local level, and together they account for approximately 80% of total state tax revenues (Robinson and Tazhitdinova, 2025).[2] By concentrating on top statutory rates, our analysis targets aspects of tax policy that are particularly salient to voters and highly relevant for assessing distributional consequences.

Our selection of potential tax determinants is guided by prior literature and encompasses five broad categories; the full list is presented in Table 1. First, we consider economic factors, such as cyclical changes in revenue needs due to economic downturns, as well as federal mandates. Second, we incorporate political variables, including election timing, the partisan composition of state governments, and shifts in political power. Third, we include institutional characteristics, such as legislature size, term limits, balanced budget requirements, and the presence of voter initiative mechanisms. Fourth, we

[1] Using unsupervised machine learning techniques in Section 3, we are able to consider tax changes starting in 1910.

[2] State governments collectively raise over $1 trillion annually, equivalent to roughly 5% of U.S. GDP, and finance a broad array of public services and welfare programs (Tax Policy Center, 2020).

examine demographic influences, including population size, labor force participation, poverty rates, and racial and age composition. Finally, we account for intergovernmental interactions, focusing on the relationship between federal and state tax policy, as well as interstate tax competition. These categories align closely with the motivations that policymakers often cite when enacting tax changes. For example, using presidential speeches and congressional documents, Romer and Romer (2010) document that federal tax policy decisions are typically justified by one of four motives: "offsetting a change in government spending; offsetting some factor other than spending likely to affect output in the near future; dealing with an inherited budget deficit; and achieving some long-run goal, such as higher normal growth, increased fairness, or a smaller role for government."

We begin by highlighting key empirical patterns in U.S. state tax rate changes. Tax rates exhibit substantial volatility, with few sustained periods of stability, and we observe pronounced heterogeneity in tax rates both across states and within individual states over time. Tax changes are numerous, with an average of 20 states changing at least one tax rate every year, though some states implement changes much more frequently than others. These stylized facts motivate our central question: what factors drive the highly dynamic nature of state-level tax legislation?

Next, we leverage variance decomposition and supervised machine learning techniques to assess the extent to which our chosen set of determinants can explain changes in state tax rates. We find that linear OLS models explain less than 20% of the variation in the timing and magnitude of tax rate changes. Incorporating machine learning methods that allow for flexible functional forms and interaction effects does not improve predictive performance. Across all algorithms, out-of-sample prediction accuracy remains low.

Our primary analysis examines changes in a given tax rate at the annual level. However, aggregating changes across time or across tax instruments yields similar results. In particular, when analyzing tax rate changes from one decade to the next, explanatory power increases only modestly. Given that decade-level analysis is less susceptible to measurement error, this pat-

tern further supports the robustness of our findings. Finally, we show that explanatory power remains limited when considering whether a state makes a change in any of the tax rates, and declines further when analyzing whether a state makes a change to more than one tax rate.

These findings are consistent with two broad interpretations. One possibility is that our analysis has omitted important determinants of tax policy variation. Some of these omitted variables — such as lobbying activities and political contributions — could plausibly exert direct influence on tax legislation.[3] Other omitted factors could be operating indirectly, for example by influencing how legislators interpret or prioritize the economic, political, and institutional variables we already consider. Whatever these unobserved drivers may be, they must be largely orthogonal to the variables considered in our models; with both OLS and machine learning techniques, any omitted variables correlated with our included variables will nonetheless contribute to explanatory power. An alternative interpretation is that tax policy is fundamentally idiosyncratic. The legislative process may be sufficiently complex and contingent that policy responses are shaped by unpredictable, state-specific factors, thus creating substantial randomness in the timing and nature of tax changes.[4]

To distinguish between these two explanations, we apply unsupervised machine learning techniques, which classify observations based on similarities across features of interest — in this case, state tax rates. If the resulting clusters are well-defined, this would indicate the presence of underlying structure in the data, even if the source of such latent patterns remains unidentified. Conversely, if clustering is unsuccessful, it suggests that the data lack clear structure and may be predominantly random or idiosyncratic.

[3]The existing political economy literature finds only limited evidence of systematic *quid pro quo* relationships. In the context of tax policy, Slattery et al. (2023) show that increases in independent corporate expenditures following the *Citizens United* decision did not lead to measurable changes in state tax policies. More broadly, Ansolabehere et al. (2003) argue that political donations are better understood as a form of consumption than as a means of buying policy influence.

[4]For instance, Mian et al. (2014) provide evidence that the degree of political polarization can delay fiscal responses to economic shocks by weakening governing coalitions.

Our efforts to systematically cluster tax rate data yield highly unstable results: the groupings are sensitive to both the choice of algorithm and the specification of implementation parameters. We find no evidence of consistent or robust typologies of state tax policy. This lack of stable clustering supports the interpretation that state tax policy is largely idiosyncratic.

Variation in tax rates contributes to revenue instability, amplifies macroeconomic fluctuations, and elevates policy uncertainty – developments that can ultimately hinder economic growth and reduce welfare (see, e.g., Seegert, 2015). Our findings are also relevant for empirical researchers who rely on tax variation as a source of identification. While our results do not imply that tax changes are outright "exogenous," they do suggest that the bias from omitting institutional, political, and economic factors is likely to be small in studies that exploit sharp variation in tax changes and focus on short-run outcomes. Simply put, the tax setting process appears to be sufficiently complex so that the exact timing of tax changes is quite random. However, longer-term estimates need to be interpreted with caution as most taxes follow a trend.

A caveat to our analysis is that, while we try to paint a comprehensive picture of state policies, these policies are very complex and hard to summarize. Because of this, we focus on explaining changes in specific features of tax policy – i.e., tax rates – instead of comparing effective tax burdens across states. We choose to focus on tax rates because these are most salient to voters, subject to extensive media coverage, and are changed frequently. While tax base rules altogether are key to understanding the amount of revenue generated by income and sales taxes (Suarez Serrato and Zidar, 2018), individual tax base rules are typically changed infrequently, resulting in little variation to explain. Furthermore, the excise taxes that we consider – gasoline, cigarette and alcohol taxes – have a uniform tax base and are robust to this issue. Relatedly, we do not consider property taxes, which are predominantly at the local level and heavily influenced by the tax base such that the statutory tax rate alone provides little information about the true tax burden. To account for trends over time in tax base rules, property taxes, or the small amount of non-property local taxes, our empirical analysis includes year or decade fixed

effects as well as quadratic time trends, and our machine learning models additionally allow for more flexible interactions with time.

This paper is related to two lines of prior work. First, this paper expands upon a small number of studies that document basic facts about state and local tax policies. Among these, Suarez Serrato and Zidar (2018) and Slattery and Zidar (2020) provide a comprehensive overview of state business tax policies, while Baker et al. (2020) and Robinson and Tazhitdinova (2025) document how state and local taxes have changed over time and the contemporaneous nature of tax changes. We extend the previous work by incorporating extensive data on political and institutional factors.

More importantly, our paper builds on the vast literatures that study the policy choices of the federal and local governments. This wide range of work explores fiscal competition (e.g., Besley and Rosen, 1998; Rork, 2003; Devereux et al., 2007), preference-based sorting (e.g., Tiebout, 1956; Rhode and Strumpf, 2003; Boadway and Tremblay, 2012), economic conditions (e.g., Robinson and Tazhitdinova, 2025), the importance of political cycles and structures (e.g., Alesina et al., 1997; Nelson, 2000; Alt and Lowry, 1994; Bernecker, 2016; Robinson and Tazhitdinova, 2024), federal mandates (Baicker et al., 2012), and various institutional features, such as balanced budget provisions (Poterba, 1994), size of legislatures (Gilligan and Matsusaka, 2001), term limits (Besley and Case, 1995a; Erler, 2007), and legislative initiative rules (Matsusaka, 1995, 2000; Asatryan et al., 2017a). Our work builds on these studies but differs in four dimensions: we focus on overall explanatory power instead of causal relationships, we take a comprehensive approach by considering numerous influences together instead of emphasizing a specific channel, we use machine learning techniques to allow for flexible modeling, and we focus on the timing of tax changes rather than tax levels in general.[5] Our focus on predictive power allows us to evaluate to what extent these models are able to explain the observed behavior. Consistent with previous work, we confirm that the competitive, political, and institutional forces highlighted in economic models

[5]Our work is thus related to Ferede et al. (2015), Kakpo (2019) and Gupta and Jalles (2020), but is more comprehensive both in our approach and in scope.

matter, but show that they explain a relatively small share of fluctuations in tax policy.

1 Data and Scope of Analysis

1.1 Tax Rate Data

We use data on U.S. state top personal income, top corporate income, sales, cigarette per pack, gasoline per gallon, and alcohol spirit per gallon taxes from Robinson and Tazhitdinova (2025). Tax rate data are available from 1910 to 2022. The data records the new tax rate in the year it becomes effective even if the change occurs at the end of the calendar year.

When studying tax changes, we disregard tax changes that are smaller than 0.1 percentage points for personal, corporate income tax and sales taxes. For excise taxes, we disregard tax changes that are smaller than \$0.005. The latter restriction allows us to disregard the frequent but small changes of gasoline taxes that arise from automatic adjustment rules implemented in some states. We consider all tax changes as independent observations, even when these changes were legislated as a set of reforms. We do so because legislative decisions are frequently overturned: temporary tax changes often do not expire as scheduled and instead turn into permanent changes, while scheduled tax changes are often canceled and/or changed in magnitude.

Finally, we inflation-adjust nominal rates of cigarette, gasoline, and alcohol excise taxes using the BLS CPI series.

1.2 Tax Rate Changes

Figures 1 and 2 summarize how U.S. state tax policy changed over time, and consequently, the tax policy variation we are trying to understand. Due to the availability of state-level political, institutional, and demographic data, our analysis in Section 2 is limited to years after 1950. As a result, we show the tax policy variation over the full period, but focus our discussion on the period from 1950 to 2020.

Figure 1 shows the number of states that changed a given tax rate in each year (left axis).[6] In addition, each figure also shows the average tax rate in that year (right axis). Across all tax rates since 1950, each year saw an average of 20 states changing at least one tax rate, ranging from 4 states in 1952 to 35 states in 1983. We see that alcohol taxes are adjusted the least frequently, by less than 2 states on average in each year. Gasoline taxes are changed the most frequently, by around 8 states in an average year. Both personal and corporate income taxes see an average of 5 changes per year since 1950.

Importantly, we see that while average tax rates vary dramatically over time, tax changes do not appear to follow a well-defined pattern. For example, we do not see a consistent clustering of tax increases or decreases, as one would expect if changes were driven by federal tax changes, economic conditions or by some models of state competition.

Next, Figure 2 shows how tax rates have varied over time within each state. For each tax type and each state, we show the minimum and maximum tax rate over the period 1950 to 2020 (left axis). In addition, the figure shows the number of tax changes each state implemented during the studied period (right axis).[7] We color each state based on its legislature's political affiliation in the most recent decade (2013 to 2022): blue if Democrats always had a majority in both chambers, red if Republicans always had a majority in both chambers, and gray for all other states. Figure 2 thus shows how much tax rate variation each state experienced during the studied period, and how that relates to the frequency of tax changes and state political leanings.

We see that states vary dramatically in their tax ranges. For some states, e.g., AL, LA, GA, and PA, we see minimal changes of the top income tax rate. For other states, we see significant swings: DE's top income tax rate has ranged from 3 to 19.8 percentage points. In contrast to income taxes, sales and excise taxes show less variability across states. We do not see an obvious pattern between states' tax histories and present political preferences.

[6] In C.1, we show the percent of states that change each tax, conditional on having a non-zero tax rate.

[7] See C.2 for changes as a percent of years with a non-zero tax, and C.3 for changes starting in 1910.

1.3 Political, Institutional, and Economic Data

In Section 2, we assess the extent to which the variation in tax changes can be explained by political, institutional, and economic factors. We follow the previous literature, summarized in Appendix Table A.1, to identify the features that are likely to have important effects on tax policy. Our choice of factors has been motivated both by political economy and fiscal federalism studies that directly explore tax setting processes, as well as by economic models in general. While we are not able to include all plausibly relevant factors, we consider a wide range of explanatory variables. In this section we briefly summarize the nature of our data, details are available in Appendix Section A. The complete list is available in Table 1. The data covers the years from 1950 to 2020.

We consider 11 groups of explanatory variables. First, we include a quadratic time trend to account for trends that may affect all states equally (e.g., secular demographic shifts, public good preferences, spending patterns, etc). Second, we consider variables related to federal tax policy: federal top income, top corporate, cigarette, and gasoline tax rates, both in levels and as changes. These variables are state-invariant and thus account for policy changes that occur across the states simultaneously, and help account for vertical tax competition.

Third, we account for economic influences: federal and state-level recessions, booms (periods of low unemployment), federal mandates, unemployment rates, inflation, prices of natural resources, and state's outstanding debt. We account for levels as well as lagging and leading changes. Fourth, we account for state demographics: population measures (total, labor force, employment to population, density), poverty rates, demographic composition of the state (share of black and non-white/non-black residents, age composition), and median household income, again both in levels and changes.

The fifth, sixth, and seventh groups consider state institutional features which cover both time-invariant rules such as the size of legislatures and balanced budget provisions, as well as time-variant rules such as the existence of rainy day funds, term limits, whether states require supermajorities and type for tax increases, and whether the state is a right-to-work state.

Our eighth group accounts for political influences: party of legislatures' majorities and governorship, the strength of majority, the number of party switches, whether this is the first year of new party in charge, state and federal government shutdowns, outcomes of presidential elections, and DW-NOMINATE scores of state representatives/senators.[8] For indicators of party control, we account for levels and changes.

Ninth, we include variables that measure neighboring states' tax policies: average neighbor tax rates (top income, top corporate, sales, cigarette, gasoline and alcohol) in levels and changes, as well as indicators for tax changes. Tenth, we control for other tax rates in the state, in levels and changes. Finally, our eleventh group of explanatory variables includes values of top income, top corporate, sales, cigarette, alcohol and gasoline tax rates in 1995 as well as revenue shares of these six types of taxes in 1995. Including these variables allows us to control for the structure of the tax system in the state, e.g., the importance of each tax type or lack of such.[9]

In addition to the levels of explanatory variables, we also include changes to account for possibly dynamic relationships. This also ensures that our specifications are econometrically consistent i.e., tax policy outcomes measured as changes are regressed on the changes in economic conditions (as well as the levels). We restrict our attention to changes occurring at most two years ago, noting that events typically necessitate a speedy response – e.g., enacting tax reforms three years after a recession is unlikely to be useful. We include changes for economic conditions, demographics, party control, and tax rates (federal, neighbor, and own). We do not include changes for institutional factors as these mostly have little to no variation over time.

One may worry about endogeneity issues in our specifications since some explanatory variables are likely to be chosen simultaneously with our outcome variables. Given that we are not estimating causal effects, and that the resulting predictive powers are low for all specifications we have considered, we

[8]DW-NOMINATE scores were developed by Keith T. Poole and Howard Rosenthal to describe the political ideology of political actors, political parties and political institutions.

[9]Year 1995 was chosen as the first round-year after which no major tax types were adopted.

generally err on the side of being too generous when choosing which variables to include. However, we choose to exclude two potentially important but likely highly endogenous variables from the set of explanatory variables – expenditures and tax revenues. Changes in expenditures could be driven by either changing preferences or changing economic conditions. For example, state governments may choose to adjust expenditures instead of tax rates in order to balance budgets, or may need to increase tax rates due to increased demand for public goods. Similarly, state governments may be pressured to increase tax rates in order to maintain steady levels of tax revenue despite changing demographics and spending patterns. Instead of including expenditures and tax revenues as explanatory variables, we attempt to control for the *underlying* factors that may affect expenditures and/or revenues. For example, we account for economic conditions (e.g., recessions or booms) and demographics. Since expenditures and revenues are omitted from the set of explanatory variables, our preferred interpretation of the results is that taxes may not be very responsive to economic/demographic conditions in part because state governments adjust via other margins, e.g., by changing spending levels.

In addition to the 172 variables in Table 1, we account for remaining time-invariant state characteristics using state fixed effects, and for state-invariant time trends using year or decade fixed effects. Alongside the quadratic time trends, these fixed effects flexibly account for unobserved broader secular trends such as increased spending on non-taxable services or growth in local sales taxes. Finally, our enriched models allow for even more interactions and functional forms.

2 Do Tax Rates Respond to Political, Institutional, and Economic Influences?

In this section we explore the extent to which the substantial heterogeneity in tax rates and tax changes can be explained by the economic and political causes or institutional rules listed in Table 1. We ask how much of the tax

policy variation can be explained by these factors using two complementary approaches.

First, we estimate a simple linear model to assess how much of the variation in tax changes can be explained overall and to evaluate the explanatory power of individual factors. Second, we turn to a more flexible set of machine learning models – specifically LASSO and random forest methods – which allow us to enrich the specification by incorporating non-linear and interaction terms.

2.1 Simple Linear Model and Variance Decomposition

We start with a simple linear regression model estimated using the variables listed in Table 1. This approach allows us to quantify the extent to which these factors can jointly explain the observed variation in tax policy, as well as the relative importance of each factor when controlling for the others. Because our explanatory variables are not orthogonal, most covariates contribute to the explanatory power in a non-unique way. For this reason, we use the Shapley decomposition method to assign each group of variables' contribution to the overall explanatory power, measured by the R^2.[10] Since several explanatory variables are time-invariant and would be omitted if state and year fixed effects were included, we conduct the Shapley decomposition using a specification without these fixed effects. We then quantify the contribution of the fixed effects as the change in R^2 between a model without state and year fixed effects (but including all variables listed in Table 1) and a model with these fixed effects (and all the variables).

Variance decomposition results are summarized in Figure 3, which shows the shares of total variation attributed to the above-mentioned groups of ex-

[10] Another potential approach would be to use a Kitagawa-Oaxaca-Blinder decomposition method to understand the extent to which various factors can explain a gap in tax rates or changes between two groups. For example, Seegert (2016) documents a clear break in tax revenue volatility pre- and post-2000 and uses this approach to explain the gap between the two time periods. However, we do not observe a clear break in tax rates or changes across time or across states. As a result, we prefer a decomposition approach that seeks to explain the variation overall, rather than separating similar states and years into two arbitrary groups.

planatory variables. Since the number of observations varies across tax rates, we show the adjusted R^2. Figure 3(a) summarizes the decomposition of tax rate levels, in percentage points for income and sales taxes and in $2020 for the excise taxes. Figure 3(b) shows the decomposition of tax changes, in percentage points or dollars. Figures 3(c) and (d) focus on the timing of tax changes, and thus perform decomposition of indicators of tax rate increases and decreases respectively.

We find that nearly all of the *tax rate level* variation can be explained with our chosen variables. However, most of the explanatory power comes from other tax rates and lagged tax rates, alongside 1995 tax rates and revenues, the quadratic time trend, and federal rates. Put simply, past tax rates do well at predicting future tax rates, because tax rates are somewhat persistent. Since this decomposition includes both within-state variation and across-state variation, it exaggerates our ability to predict taxes. For this reason, we next turn to explain the magnitude and timing of tax changes.

Our ability to explain the *magnitude of tax changes* is significantly weaker – the explanatory power decreases to under 20%. Unsurprisingly, past tax rates play a less important role. Instead, federal tax rates as well as political and demographic factors increase in relative importance. We see some variation in the relative importance of factors for different tax rates, but the overall ranking is generally consistent across tax types.

Our ability to explain the *timing of tax changes* is equally weak – under 30%. Interestingly, the tax increases and decreases appear to be influenced by different factors. For example, tax increases are more consistently influenced by federal tax policy than tax decreases. Similarly, economic factors (recessions and mandates), neighboring tax rates, and other tax rate levels are more important for tax increases. Political factors are important for both and yet account for less than one quarter of overall explanatory power. In general, tax rate increases are easier to predict than tax decreases. A potential explanation for this would be if tax increases are more likely to be driven by economic needs, while tax decreases are more likely to be ideologically motivated. Since the former are more time-sensitive than the latter, the timing of increases

should be more predictable.

Our analysis of the timing of tax changes does not distinguish between small and large changes in rates. If large changes are explained by the factors we consider, but small changes are more idiosyncratic, grouping them together would mask this heterogeneity. However, Figure 4 shows that focusing on the largest 50% of tax changes does not improve our predictive powers. A possible explanation is that the magnitude of tax changes is more idiosyncratic than whether the tax change is legislated in the first place. This explanation is consistent with the fact that explanatory powers are generally higher when focusing on the timing only, and when focusing on all changes rather than the largest ones.

One may worry that while predicting yearly changes may be difficult, predicting long-term changes could be easy. We test this possibility by conducting an equivalent analysis but using decade changes in Figure 5. One caveat to this comparison is that the adjusted R^2 does not perfectly account for changes in the relative number of observations and explanatory variables, making comparison of Figures 3 and 5 imperfect. With this caveat in mind, we see that the overall conclusion remains: tax changes are hard to predict, even in the long run. However, relative to yearly changes, the predictive power indeed increases. This increase is not driven by one particular group of covariates – most groups explain a larger share of variation with the exception of own other tax rates.

There are two plausible explanations for why decade changes are more predictable. One, is that tax changes are costly to implement and therefore not every change in economic or political conditions results in action, e.g., similarly to investment decisions of firms. However, if this were the case, large tax changes should arguably be more predictable, since these are driven by stronger needs. This explanation is not consistent with the evidence in Figure 4. Alternatively, our preferred explanation is that the increased explanatory power across all groups is consistent with the possibility of gridlock: economic, political, and demographic influences matter, but the timing of tax changes is volatile due to stalemate frictions. Over time, however, changes in these factors

do lead to changes in tax policy, making decade changes more predictable.

One may also be concerned that changes in any tax rate, or changes in more than one tax rate, are easier to predict than changes to a specific type of tax. Policymakers might desire to increase tax revenue overall, but view changes in the different tax rates as substitutes. And as documented by Robinson and Tazhitdinova (2025), many tax changes occur simultaneously – it could be the case that these broader bundles of tax reform are more responsive to economic, political, and institutional factors than changes in only one tax rate. Thus in Figure 6, we consider a change in at least one tax rate, and a change in two or more tax rates. However, we do not find bundles of tax reform to be easier to predict. We are still only able to explain about 20% of the variation in whether any tax change occurs, and our ability to explain bundles of two or more tax changes is actually lower. The decision to change tax policy *in general* is difficult to predict, not just changes in a particular tax.

Overall, we conclude that a simple linear model does a poor job of predicting the timing and magnitude of tax changes, especially year-to-year fluctuations.

2.2 Enriched Models Using LASSO and Random Forest

The above model allowed only for the simplest relationships between the explanatory variables and tax policy. It is possible and likely, however, that the relationship between economic, institutional and political factors and state tax policies is more nuanced than that model would permit. For this reason, we then turn to a richer set of models, LASSO and random forest, which allow for nonlinear and interactive terms.

Because it is neither possible nor desirable to include all possible nonlinear and interactive terms in a regression analysis, we employ LASSO techniques to select a subset of variables in a data-driven way. The LASSO model is a regression estimated on variables that have been selected to minimize prediction error while including a penalty parameter for additional terms. In our setting, we found that LASSO and elastic net approaches work equally well, and the

best results are achieved when the model is selected by cross-validation or using an adaptive approach; linear, probit and logit regressions yield similar qualitative results.

Random forest is a machine learning technique that allows for more flexible modeling. To make predictions, the algorithm builds multiple decision trees using a different random subset of the variables provided and a different bootstrapped sample of the data. The final predictions are then obtained by averaging individual predictions from the randomly built trees. The randomness of the sample variables and the dataset used to build a given tree ensure that individual trees are not correlated. This gives random forest its high predictive power and partially shields it from overfitting.

Table 2 summarizes our results. As our baseline comparison we take the models from Section 2.1 which included 172 "core" variables. Next, we use LASSO to select the best model using these variables plus decade fixed effects and the full set of interactions – a total of 27,794 variables. Finally, the random forest algorithm uses all 172 core variables plus decade fixed effects and quadratic and cubic terms – a total of 404 variables. (Note that the random forest algorithm implicitly allows for all potential fixed effects and variable interactions via its "tree" structure). The results summarized in Table 2 are based on 100 random splits of the data into a training sample (80%) and a test sample. The algorithms search for the best model using the training sample, and that model is then used to make predictions on the test sample. Thus, the final predictions shown in Table 2 present a true and independent test of model performance, by evaluating predictions on the 20% of the data that was not used to select a model.

Table 2 shows that while machine learning algorithms improve the predictions, the improvement is modest. The random forest algorithm does an outstanding job making predictions in the training sample but out-of-sample predictions are still poor and typically fall well below 20%. Moreover, many predictions are negative, suggesting that the models selected by machine learning perform worse than a simple sample mean. We must note that while both LASSO and random forest algorithms require a number of choices made by

a researcher, Table 2 presents the results from the "most promising" specifications. While the quantitative results vary depending on specification, the qualitative results do not.

2.3 Discussion

What are the possible explanations for the low predictive power? One possibility is that our explanatory variables suffer from measurement error, biasing our results towards zero. While we cannot address this issue directly, our decade analysis should be less prone to measurement error, yet it leads to similar results. Empirically, the quality of our data is comparable to that used in the broader literature, suggesting that tax changes simply cannot be predicted with the types of data researchers are able to collect. Second, our analysis may have omitted potentially important drivers of tax policy, for example, lobbying and political contributions. Whatever these omitted factors are, they appear to play a more important role than the economic, political, and institutional influences we have considered. Furthermore, these factors must be sufficiently orthogonal to the included variables, because both regression and machine learning models inadvertently account for any other missing factors that are correlated with included ones.

Third, policymakers may be evenly split in their preferences, making policy decisions highly unpredictable. Since most states have strong Democratic or Republican majorities in the state legislatures, this would imply that policymakers are not as split on taxes as their speeches suggest (Gentzkow et al., 2019). In general, we expect tax policy – and any other legislative decisions – to be more predictable than individual taxpayer decisions because these are based on aggregate preferences. For example, if tax policy decisions were driven by median voter preferences, then tax policy outcomes would be fully predictable as long as median voter's preferences can be observed or sufficiently well deduced.[11]

Finally, the legislative process for tax policy may be so complex that

[11] In Appendix B, we discuss models of policy setting in more detail, and the conditions under which we would and would not expect tax policy to be predictable.

idiosyncratic factors create substantial randomness in the timing and nature of policy response. If the variance of idiosyncratic factors is very large relative to the variance of other decision-making factors, policy decisions would be hard to predict. In this case, the economic, political and institutional factors indeed matter, but in a nuanced rather than systematic, stable, and predictable way.

3 Clustering Analysis

Our analysis so far demonstrates that commonly examined explanatory variables perform poorly in predicting changes in tax policy. This could arise either because the models rely on an incorrect or incomplete set of predictors, or because tax policy is inherently unpredictable. In this section, we provide evidence consistent with the latter interpretation by showing that U.S. state tax policies do not exhibit stable or easily classifiable patterns.

We do so by applying clustering machine learning algorithms to our tax rate data. Such algorithms sort observations into groups based on the characteristics of interest (i.e., characteristics of state tax policy). Since this approach organizes the data based on the similarity of these variables only, the algorithm is agnostic as to what causes the formation of such groups. These techniques are considered to be "unsupervised" machine learning, as their goal is to discover hidden patterns in the data without researcher involvement, thus letting the data speak for itself. If we were considering only two dimensions of state tax policy, this approach would be analogous to creating a scatterplot and visually identifying groups of observations that are close to one another. Clustering algorithms allow us to extend this approach to more dimensions of tax policy.

We cluster states based on bundles of tax rates. While Section 2 was limited to years with economic, political, and institutional data, for our clustering analysis we are able to take advantage of the full time series of tax rates from 1910 to 2022. To ensure comparability across tax types and avoid distortions due to differences in scale or variance, we standardize each tax rate by subtracting its mean and dividing by its standard deviation. We implement this

normalization both with and without detrending. In the detrended version, tax rates are standardized using year-specific means and standard deviations; in the non-detrended version, the means and standard deviations are computed over the entire sample period.

We consider two bundles of tax rates. The first is a three-rate bundle, consisting of the top marginal personal income tax rate, the top marginal corporate income tax rate, and the general sales tax rate. Income and sales taxes are especially important for states, today accounting for more than two-thirds of state tax revenues. The second is a six-rate bundle that includes the above three rates along with taxes on cigarettes, gasoline, and spirits, which together account for 80% of state tax revenues (Robinson and Tazhitdinova, 2025). We conduct clustering analyses both at the state level – where each state is grouped based on its entire historical profile of tax rates – and at the state-year level, where a state may belong to different clusters in different years.

We consider a variety of clustering algorithms (k-means, CLARA, and hierarchical clustering), and a variety of distance measures (complete or Ward's linkage, and for state-level clustering, a variety of time warping algorithms as well). Each combination of algorithm and distance metric carries specific advantages and limitations, and there is no *a priori* reason to prefer one over another, as their performance depends on the data structure under investigation, which is unknown. For this reason, we implement a variety of algorithms/distance measures and then explore the sensitivity of our results.

Our primary objective is to determine whether U.S. state tax rate data exhibits any consistent and discernible structure. If such structure exists, we would expect a reasonably stable clustering pattern across algorithms and distance metrics. Conversely, substantial variation in clustering results would suggest a lack of systematic patterns, thereby supporting the hypothesis that tax policy is largely idiosyncratic.

3.1 State-Level Clustering

As a starting point, we explore whether states can be clustered into groups based on their entire histories of tax rates, using a hierarchical clustering algorithm. This algorithm begins by assigning each observation to its own cluster, thus "partitioning" all 48 states into 48 clusters.[12] The algorithm then merges the two closest clusters to form 47 clusters, and then the next two closest to form 46 clusters, etc. A key advantage of this approach is that it is particularly insensitive to the number of clusters chosen, as the result for n clusters is identical to the result for $n-1$ clusters until the very last step. Furthermore, the entire clustering hierarchy can be conveniently summarized using a dendogram.

We evaluate a range of potential specifications using silhouette scores, which measure how similar observations are to their own clusters versus other clusters. Consequently, higher scores are desirable as they reflect more distinct clustering. We find that the silhouette score remains mostly constant between nine clusters and four clusters, as shown in Appendix Figure D.4. We focus on the results for six clusters, in the middle of this range. Appendix Figure D.4 also shows the silhouette scores for various measures of distance and ways of accounting for the time series nature of the data. We focus on those with the best performance: minimizing the sum of squared distances within each cluster (Ward's minimum variance linkage), and using soft dynamic time warping.

Figure 7(a) shows the results from grouping states into six clusters based on their income and sales taxes. The smallest cluster contains three states, while the largest cluster contains 14 states. We can also see that six clusters is the first point at which every state belongs to a non-trivial group; at seven, NH is in a cluster by itself.

We plot the average tax rates in each cluster in Figures 7(b) and (c). We see that some of the groupings are intuitive: the furthest left group includes states that never adopted a sales tax, and the furthest right group includes states without personal or corporate income taxes. However, the other four

[12] We omit AK and HI because of their shorter time series.

groupings are less obviously distinguishable from one another.

To test the sensitivity of this process, in Figure 7(d) we compare this cluster assignment to clustering based on all six tax rates. We see that cluster assignment is quite sensitive to the choice of tax types; many of the clusters change significantly when using six instead of three tax rates. To assess similarity more formally, we measure the overlap in cluster-mates across two algorithms. We find that, on average, states retain 46% of their cluster-mates in the transition from using three-rate bundles to six-rate bundles.[13] This suggests that states choose each type of tax at least somewhat independently. In other words, knowing a state's income and sales tax rates does not allow one to accurately predict its excise tax rates, and vice versa.

We further explore the sensitivity of our results to other clustering choices in Panel A of Table 3; corresponding graphical evidence is presented in Appendix D. We consider differences in cluster formation when using non-detrended versus detrended time series. The cluster assignment overlap is 59%-65% for assignments based on three rates and 83% for assignments based on six rates. Next, we study how clustering assignment depends on the choice of distance measure used. Here, instead of minimizing the sum of distance squares within each cluster (i.e., Ward's linkage), we minimize the distance between the two elements (one from each cluster) that are farthest away from each other (i.e., complete linkage). The cluster assignment overlap is 60%-72% and 76%-77% for three-rate and six-rate assignments, respectively. Finally, we compare cluster assignments arising from hierarchical algorithms to those obtained using other clustering algorithms: DTW Barrycenter Averaging (DBA, akin to k-means) and Partition Around Medoids (PAM, akin to CLARA). The overlap between hierarchical and DBA is 56%-72% for three-rate and 57%-70% for six-rate assignments, between hierarchical and PAM is 56%-72% and 57%-70%, respectively, and between k-means and CLARA is 77-81% and 64-67%.

Overall, Table 3 shows that the assignment is sensitive to every choice

[13] We calculate these shares as following: for each state i, we identify cluster-mates under assignment A. We then calculate what share of these states are in the same cluster as state i under assignment B. We then report the average of these shares. For the transition from 6-rate to 3-rate bundles, the analogous statistic is 43%.

clustering entails: choice of algorithm, distance measure, etc. On average, the resulting cluster structures overlap by only 60%, with a large share of this overlap consisting of states with zero rates (see examples in Appendix D). These results suggest that the clustering assignment is not very stable.

In conclusion, our analysis indicates that it is challenging to robustly and systematically partition *states* into distinct clusters based on the full time series of tax rates. A plausible explanation for this difficulty is the temporal instability of state tax policies, driven by evolving political preferences and other time-varying factors. If tax policy is indeed characterized by such instability, it may be more appropriate to treat each state-year as a distinct observational unit. We adopt this approach next.

3.2 State-Year Clustering

To allow states to change the style of their tax policy over time, we now consider a more flexible assignment approach: we allow states to belong to different clusters in different years. Once again we consider a variety of algorithms and distance measures, and then explore the robustness of our results.

Figure 8 describes the cluster structure based on three tax rates, using a CLARA algorithm and Ward's linkage. For convenience, clusters are labeled based on the average year of their observations. Figure 8(a) shows that, when grouping non-detrended series, observations are largely grouped by time period: all states start in Cluster 1, while Cluster 6 only includes observations from 2000-2022. This suggests that tax policy overall has changed over time, and that the policy bundles that existed in the first half of the 20th century are no longer observed in the 21st century. Figure 8(c) shows the cluster assignment history for each state, and the number of times each state switched clusters. We see that, with the exception of a handful of states, most states join at least three clusters, with the majority appearing in four or five clusters, again consistent with states transitioning through period-specific clusters. The cluster assignments demonstrate a reasonable amount of persistence, in the sense that states rarely jump through multiple clusters in consecutive years.

In other words, states change their policy over time, but do so gradually.

This overarching pattern of tax rates over time is likely driven, at least in part, by national forces and trends. Thus, in Figures 8(b) and (d) we cluster detrended series, so that states are grouped based on their deviations from this overarching trend. We now see a more even distribution of clusters across years. Nonetheless, Figure 8(d) again shows that nearly all states appear in at least three clusters, and many states in four or five clusters. These results suggest that states' tax policies change over time, even after accounting for the overarching trend.

Panel B of Table 3 explores the sensitivity of these cluster assignments to the choice of specification; Appendix D provides graphical evidence. First, we see that the assignments vary substantially depending on the number of clusters chosen. Because partitioning algorithms do not cluster sequentially, the cluster-mates in a 6-cluster assignment need not belong to the same cluster in a 5-cluster assignment. The overlap between assignments using five, six, or seven clusters is around 66-79% for CLARA for non-detrended series and 46-71% for detrended series.[14] Next, cluster assignments using three-rate bundles versus six-rate bundles show between 44-55% overlap both for non-detrended and detrended series. Finally, we explore how cluster assignment varies with the algorithm used. For non-detrended series, 72% of states that are CLARA cluster-mates are also k-means cluster-mates, and only 58% are cluster-mates under hierarchical assignment. For detrended series, the overlap is lower: 46% of states that are CLARA cluster-mates are also k-means cluster-mates, and 48% are also cluster-mates under hierarchical assignment.

Thus we see that allowing states to belong to different clusters in different years still does not lead to meaningful and systematic groupings. Table 3 shows that the groupings are sensitive to the choice of algorithm, cluster size, cluster variables, and other implementation factors.

We conclude that state tax policies – as proxied by their tax rates – do

[14]These overlap shares for k-means are similar, suggesting that this issue is not inherent to the CLARA algorithm. The overlap shares for the hierarchical algorithm are much higher, by construction.

not appear to exhibit any consistent and discernible structure. This suggests that the tax policy is largely idiosyncratic.

4 Conclusion

This paper investigates the determinants and dynamics of U.S. state tax rates over the past 70 years. We document that, while tax rates exhibit a considerable degree of persistence, they also display substantial variation – both across states and within individual states over time.

To better understand the drivers of state tax policy, we adopt two methodological approaches. First, we use Shapley variance decomposition and supervised machine learning techniques to predict tax rate changes using a wide array of explanatory variables identified in the existing literature, including economic, political, and institutional factors. Despite the use of flexible predictive models and a comprehensive set of covariates, our best specifications explain less than 20% of the observed variation and perform poorly in out-of-sample prediction. These findings suggest that most tax policy changes are inherently difficult to predict.

Second, we apply unsupervised machine learning algorithms to uncover latent structure in the data. We find that clustering methods struggle to consistently group states into meaningful categories, implying that state tax policies lack stable and interpretable patterns. This evidence supports the view that tax policy decisions are largely idiosyncratic.

Further research is needed to identify potentially omitted explanatory variables and to understand the nature of the idiosyncratic shocks driving tax policy. Given that tax policy directly affects state revenues, business cycle dynamics, and policy uncertainty, excessive tax volatility may have adverse implications for economic growth and the welfare of state residents.

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Table 1: 172 Core Explanatory Variables

Group (N of var)		Variable	Level in t	Change $[t-1,t]$	Change $[t-2,t-1]$	Change $[t,t+1]$
1	Time trend (2)	Year	1			
		Year squared	1			
2	Federal rates (10)	Federal tax rates (separately by tax; no federal sales)	5	5		
3	Recessions and	Unemployment rate	1	1	1	1
	mandates (28)	1 if state recession	1	1	1	1
		1 if federal recession	1	1		1
		National inflation rate	1	1		1
		1 if unemployment rate is less than or equal to 4%	1	1		
		1 if federal mandate: welfare-program related	1			
		1 if federal mandate: minimum wage change (changes excluded due to frequency of mandates)	1			
		1 if other federal mandate	1			
		National price for crude oil	1	1		
		National price for natural gas	1	1		
		National price for coal	1	1		
		Long-term debt	1	1		
		1 if change in debt is greater than 25% of previous year	1			
4	Demographics (20)	Population	1	1		
		Population density	1	1		
		Labor force participation rate	1	1		
		Employment to population ratio	1	1		
		Poverty rate	1	1		
		Black percent of population	1	1		
		Non-Black and non-white percent of population	1	1		
		Children (age 0-17) percent of population	1	1		
		Senior (age 65+) percent of population	1	1		
		Median household income	1	1		
5	State legislatures (11)	Number of seats in the lower chamber	1			
		Number of seats in the upper chamber	1			
		Average legislative session duration in calendar days	1			
		Average salary in 2019/20	1			
		Average per diem expenses in 2019/20	1			
		Indicator of right-to-work state	1			
		1 if state had tax by 1950 (separately by tax; gasoline = 1 for all states and thus excluded)	5			
6	Term limits (9)	1 if there is governorship term limit	1			
		1 if there is a legislature term limit	1			
		1 if governor's last term	1			
		1 if Republican governor's last term	1			
		1 if Democratic governor's last term	1			
		1 if voter initiatives are allowed	1			
		Indicators for 60%, 67%, or 75% supermajority requirements	3			
7	Balanced budget	1 if budget deficits are allowed	1			
	rules (3)	1 if capital expenditures are part of the budget	1			
		1 if rainy day fund exists	1			

Continues on next page

Table 1: 172 Core Explanatory Variables (continued)

Group (N of var)		Variable	Level in t	Change $[t-1,t]$	Change $[t-2,t-1]$	Change $[t,t+1]$
8	Political factors (44)	Number of times governor party switched	1			
		Number of times majority in house switched	1			
		Number of times majority in senate switched	1			
		Number of times both house and senate switched	1			
		Republican share of senate	1			
		Democratic share of senate	1			
		Republican share of house	1			
		Democratic share of house	1			
		1 if majority Republican legislature	1	1		1
		1 if majority Democratic legislature	1	1		1
		1 if Republican governor	1	1		1
		1 if Democratic governor	1	1		1
		1 if Southern Democratic governor	1			
		1 if majority Southern Democratic legislature	1			
		1 if divided government (party of house, senate, and governor is not the same)	1			
		1 if first term after governor party change	1			
		1 if first term after senate party change	1			
		1 if first term after house party change	1			
		1 if federal government shutdown	1			
		1 if state government shutdown	1			
		1 if Democratic president	1	1		1
		1 if state's preferred presidential candidate lost	1			
		1 if legislative majority matches state's preferred presidential candidate	1			
		Indicators for each year in the presidential election cycle	3			
		Indicators for each year in the gubernatorial election cycle	3			
		1 if divided government and deficit not allowed	1			
		DW-NOMINATE dimension 1 for US house representatives	1			
		DW-NOMINATE dimension 2 for US house representatives	1			
		DW-NOMINATE dimension 1 for US senate representatives	1			
		DW-NOMINATE dimension 2 for US senate representatives	1			
9	Neighbor's taxes (22)	Average tax rate in neighboring states (separately by tax)	6	6		
		1 if tax rate increase in neighboring state (separately by tax)	6			
		1 if tax rate decrease in neighboring state (separately by tax, cigarette and spirit excluded)	4			
10	Own other taxes (11-19)	For tax level outcomes: tax rates For change in tax rate outcomes: tax rate changes For tax rate increase/decrease outcomes: indicators for increases and decreases (all separately by tax, decreases for cigarette and spirit excluded)	5-9	6-10		
11	1995 tax rates and revenue shares (12)	Tax rates in 1995 (separately by tax)	6			
		Tax revenue shares in 1995 (separately by tax)	6			

Notes: This table summarizes the 172 variables used in Sections 2.1 and 2.2. See Appendix Section A for details. The simple linear analysis adds state and year fixed effects (total of 291 variables). The LASSO analysis adds decade fixed effects and the full set of interactions (total of 27,794 variables). The random forest algorithm adds decade fixed effects and the full set of quadratic and cubic terms (total of 404 variables), and the methodology implicitly allows for all potential fixed effects and interaction terms.

Table 2: Machine Learning Results

Outcome	Basic Regressions		LASSO		Random Forest	
	Training R^2	Out-of-Sample R^2	Training R^2	Out-of-Sample R^2	Training R^2	Out-of-Sample R^2
Income tax change (pp)	0.2	0.00	0.27	-0.1	0.65	0.03
Corporate tax change (pp)	0.22	-0.49	0.09	-0.05	0.63	0
Sales tax change (pp)	0.2	-7.73	0.17	-0.1	0.64	0
Cigarette change ($)	0.15	-0.78	0.21	-0.04	0.66	0.04
Gasoline change ($)	0.18	-0.48	0.15	-0.17	0.66	0.01
Alcohol spirit change ($)	0.14	-0.25	0	-0.01	0.57	-0.06
Income tax decrease	0.25	0.10	0.31	0.09	0.69	0.1
Corporate tax decrease	0.26	-0.40	0.36	0.07	0.71	0.16
Sales tax decrease	0.12	-3.75	0.09	-0.11	0.61	-0.02
Gasoline decrease	0.17	-0.21	0.06	-0.03	0.64	0.07
Income tax increase	0.32	0.18	0.39	0.17	0.68	0.1
Corporate tax increase	0.31	-1.07	0.34	0.13	0.67	0.06
Sales tax increase	0.23	-24.53	0.22	0.01	0.66	0.02
Cigarette increase	0.22	-1.03	0.31	0.02	0.69	0.06
Gasoline increase	0.21	0.01	0.3	0	0.7	0.08
Alcohol spirit increase	0.21	-0.05	0.25	-0.03	0.64	0

Notes: This table compares the results of linear regression models with LASSO selection models and random forest algorithms. The table reports the average R^2 obtained when estimating the model on the training sample (80% of the data) and when making predictions on the remaining 20% test sample. The average is calculated over 100 random splits of the data. The linear regression is estimated on the explanatory variables summarized in Table 1 plus state and year fixed effects (total of 291 variables). The LASSO model is a linear regression estimated on a subset of variables selected to minimize prediction error. The pool of variables includes those in Table 1 plus decade fixed effects and the full set of interactions (total of 27,794 variables). The random forest algorithm randomly selects subsets of variables to build decision trees, and then averages over the predictions from many trees. The pool of variables includes those in Table 1 plus decade fixed effects and the full set of quadratic and cubic terms (total of 404 variables), and the methodology implicitly allows for all potential fixed effects and interaction terms. Throughout, cigarette and alcohol tax decreases are omitted due to lack of events.

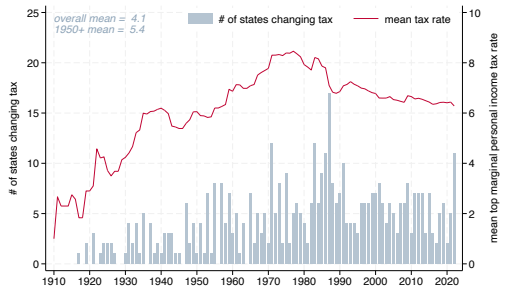
Table 3: Clustering Assignment Overlap

Panel A: State Clustering		
	3-rate 6-cluster non-detrended Ward hierarchical	6-rate 6-cluster non-detrended Ward hierarchical
3-rate 6-cluster non-detrended Ward hierarchical	100%	43-46%
6-rate 6-cluster non-detrended Ward hierarchical	43-46%	100%
3-rate/6-rate (resp.) 6-cluster detrended Ward hierarchical	59%-65%	83%
3-rate/6-rate (resp.) 6-cluster non-detrended complete hierarchical	60%-72%	76%-77%
3-rate/6-rate (resp.) 6-cluster non-detrended Ward DBA	56%-72%	57%-70%
3-rate/6-rate (resp.) 6-cluster non-detrended Ward PAM	62%-76%	63%-69%
Panel B: State-Year Clustering		
	3-rate 6-cluster non-detrended Ward CLARA	3-rate 6-cluster detrended Ward CLARA
3-rate 5/7-cluster non-detrended/detrended (resp.) Ward CLARA	66-79%	46-71%
6-rate 6-cluster non-detrended/detrended (resp.) Ward CLARA	44-55%	44-55%
3-rate 6-cluster non-detrended/detrended (resp.) Ward K-means	72%	46%
3-rate 6-cluster non-detrended/detrended (resp.) Ward Hierarchical	58%	48%

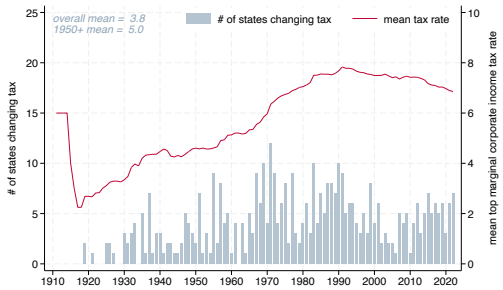
Notes: This table shows the overlap in cluster composition between the assignment listed at the top of column 2 or 3 and the alternative listed in column 1. We calculate overlap shares as following: for each state i, we identify cluster-mates under assignment X. We then calculate what share of these states are in the same cluster as state i under assignment Y. We then report the average of these shares. We then repeat the procedure, but swapping assignments X and Y. We report the two resulting shares in the table (as a single number when equivalent).

Figure 1: Timing of State Tax Changes

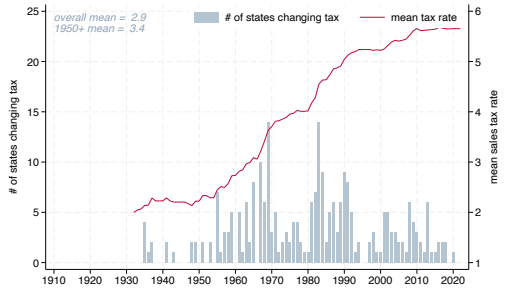
(a) Top Personal Income Tax



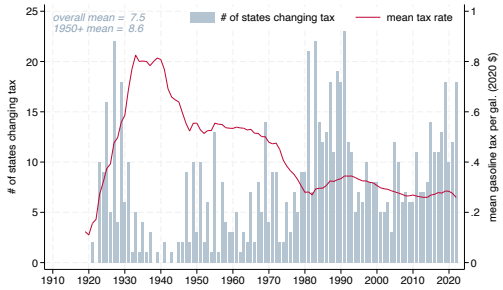
(b) Top Corporate Income Tax



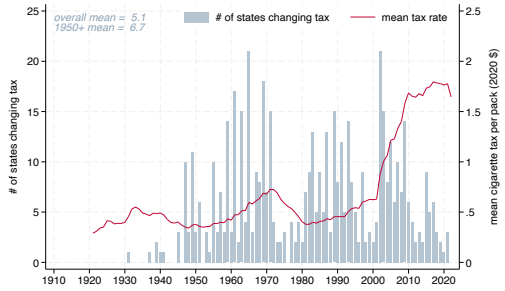
(c) Sales Tax



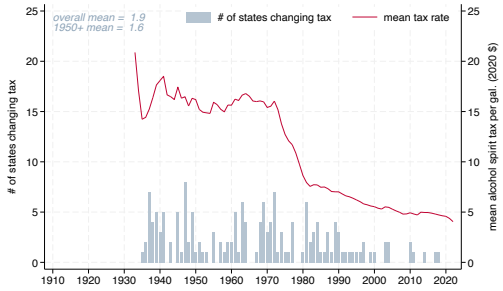
(d) Gasoline Tax



(e) Cigarette Tax



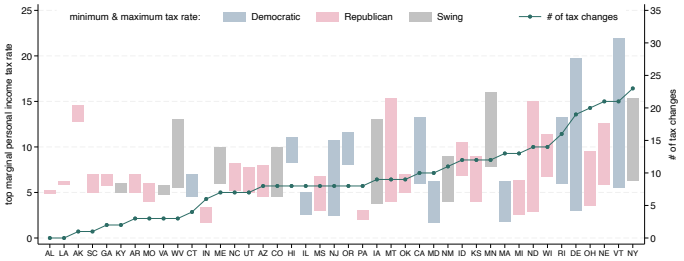
(f) Alcohol Spirit Tax



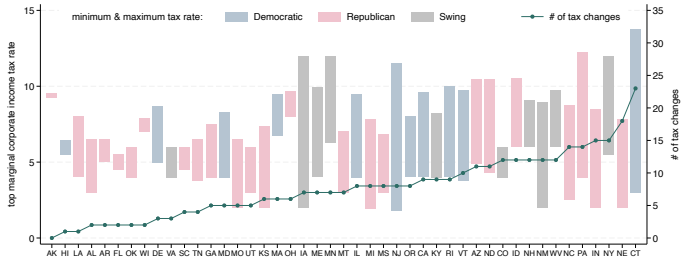
Notes: These figures show the number of states that change a given tax rate in a given year (blue bars), as well as the average tax rate in that year (red line). Only intensive margin tax changes are included (tax adoptions and cancellations are excluded), and the average tax rate is calculated using only non-zero tax rates. These statistics are shown for (a) top personal income tax rates, (b) top corporate income tax rates, (c) standard sales tax rates, (d) gasoline excise tax rates, (e) cigarette excise tax rates, and (f) alcohol spirit excise tax rates. See Appendix Figure C.1 for tax changes expressed as a percent of states collecting the tax.

Figure 2: Tax Changes by State (1950-2020)

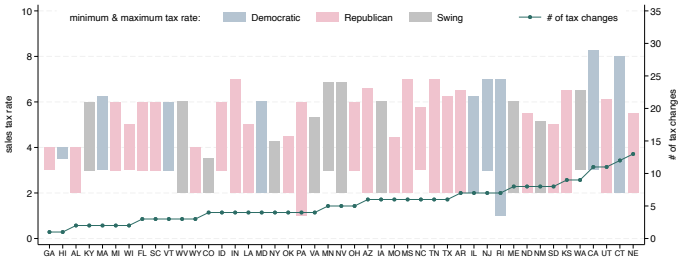
(a) Top Personal Income Tax



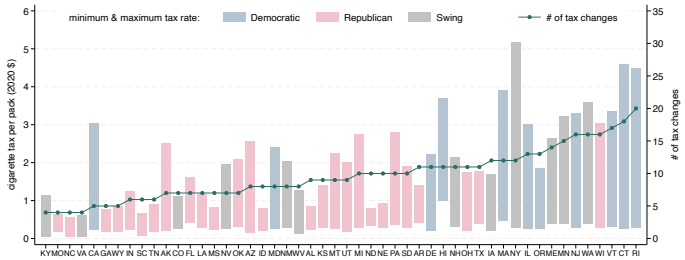
(b) Top Corporate Tax



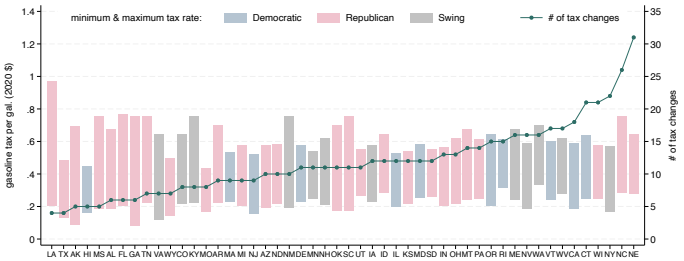
(c) Sales Tax



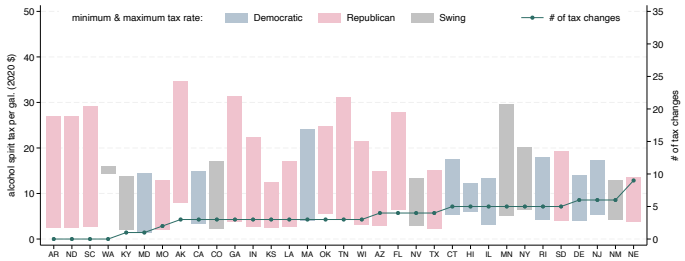
(d) Cigarette Tax



(e) Gasoline Tax



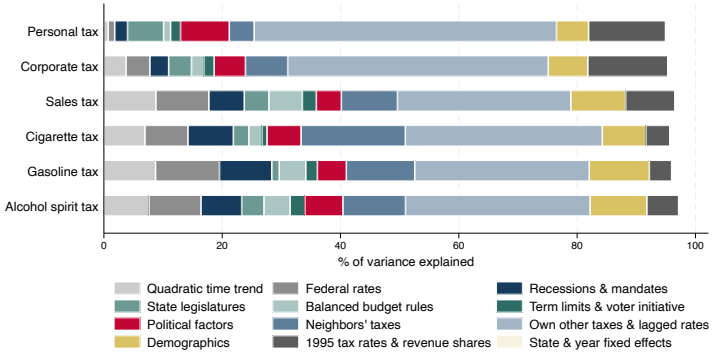
(f) Alcohol Spirit Tax



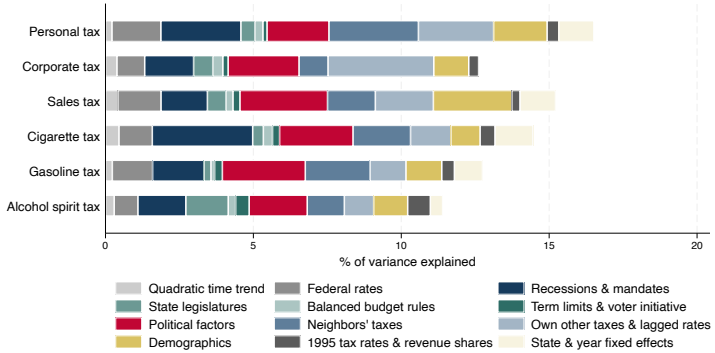
Notes: This figure shows for each state the minimum and maximum tax rate (bars), as well as the number of times the state has changed the tax rate (line) between 1950 and 2020. Only non-zero tax rates are included. The range for each state is colored by the majority party in both chambers of the state legislature from 2013+. These statistics are shown for (a) top personal income tax rates, (b) top corporate income tax rates, (c) standard sales tax rates, (d) gasoline excise tax rates, (e) cigarette excise tax rates, and (f) alcohol spirit excise tax rates. See Appendix Figure C.2 for tax changes expressed as a percent of years with a non-zero tax rate, and C.3 for statistics over the entire 1910-2022 period.

Figure 3: Variance Decomposition

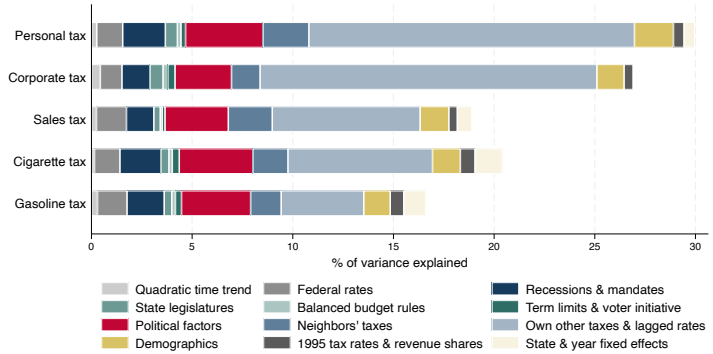
(a) Tax Rate Levels



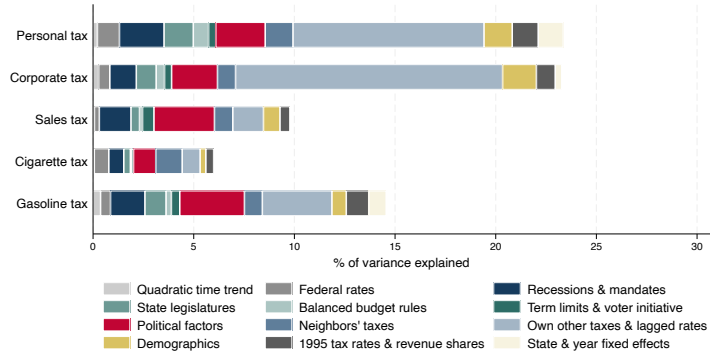
(b) Tax Changes in $ or %



(c) Tax Rate Increase



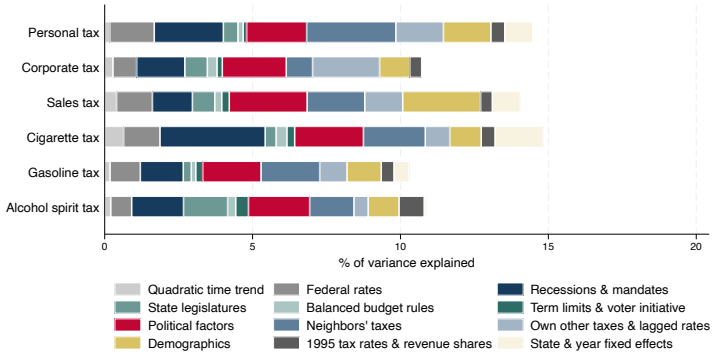
(d) Tax Rate Decrease



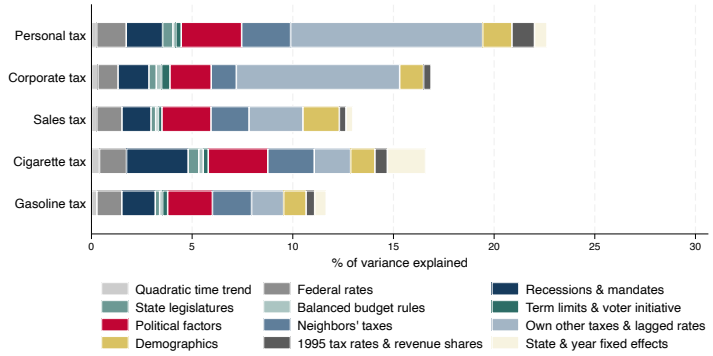
Notes: This figure shows the Shapley variance decomposition of adjusted R^2 for (a) all tax rates in percentage points or in 2020 dollars; (b) all tax rate changes relative to the previous year in percentage points or in 2020 dollars; (c) indicators when a tax increase occurs; and (d) indicators for when a tax decrease occurs. All decompositions use the variables summarized in Table 1, plus any additional variation explained by state and year fixed effects.

Figure 4: Variance Decomposition – Largest 50% of Changes

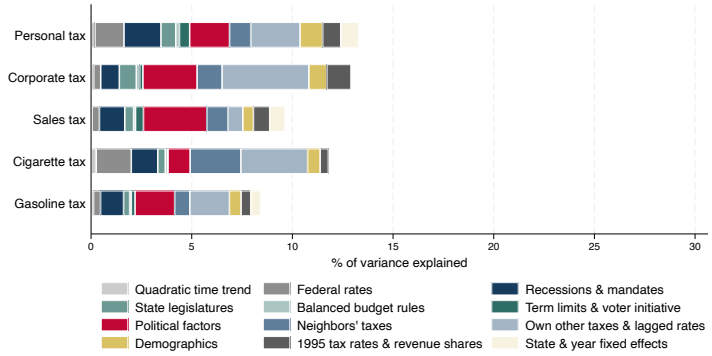
(a) Tax Changes in $ or %



(b) Tax Rate Increase



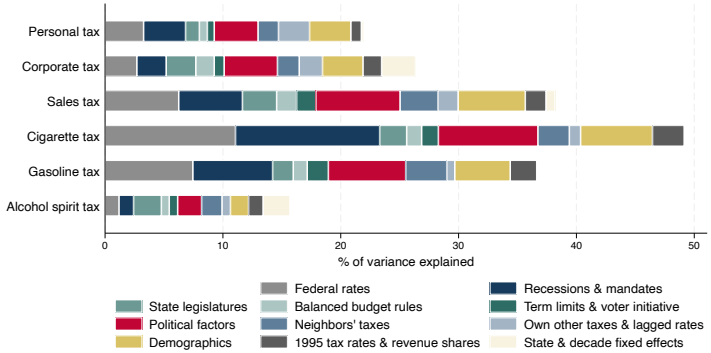
(c) Tax Rate Decrease



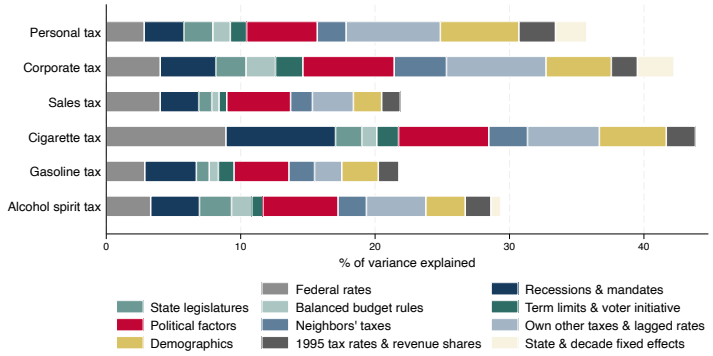
Notes: This figure shows the Shapley variance decomposition of adjusted R^2 for (a) all tax rate changes relative to the previous year in percentage points or in 2020 dollars; (b) indicators when a tax increase occurs; and (c) indicators for when a tax decrease occurs. Only the 50% largest tax changes are included. All decompositions use the variables summarized in Table 1, plus any additional variation explained by state and year fixed effects.

Figure 5: Variance Decomposition – Decade Changes

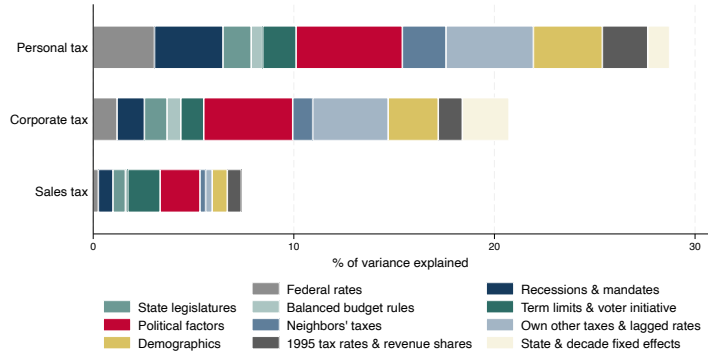
(a) Tax Rate Changes



(b) Tax Rate Increase



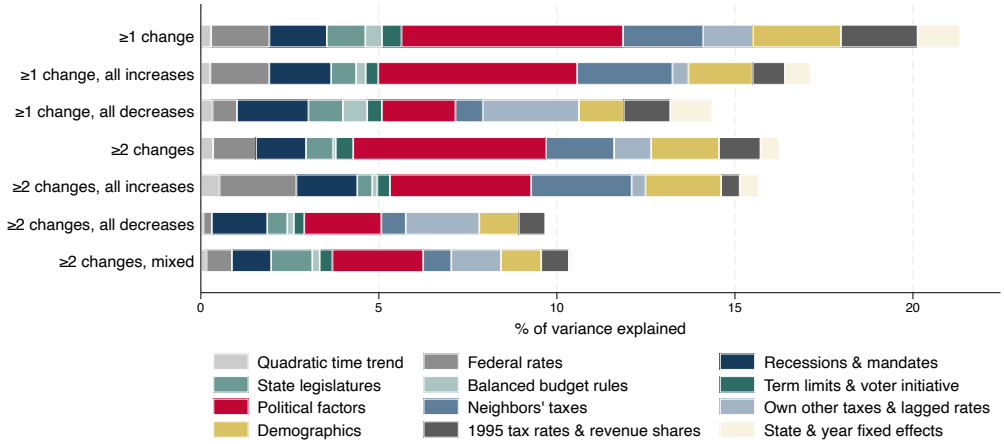
(c) Tax Rate Decrease



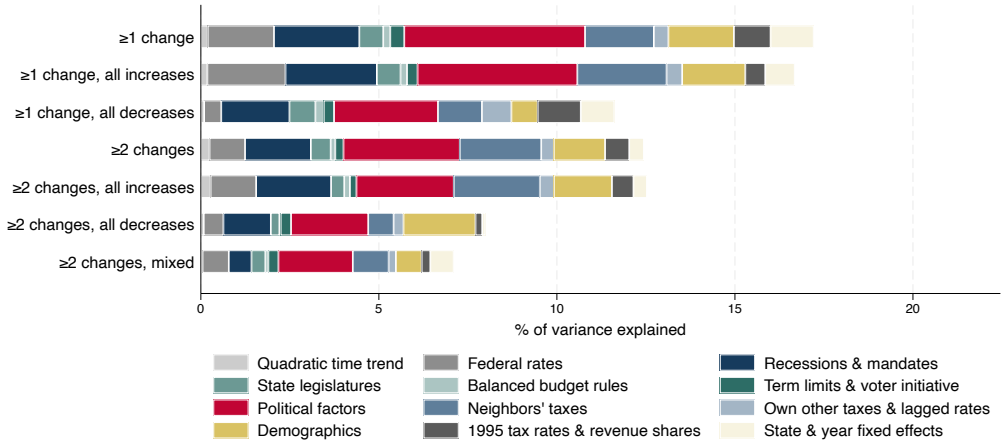
Notes: This figure shows the Shapley variance decomposition of adjusted R^2 for (a) all tax rate changes from one decade to the next in percentage points or \$2020, (b) all tax rate increases (indicators that tax rate increased over the decade), (c) all tax rate decreases (indicators tax rate decreased over the decade). The quadratic time trends are omitted due to multicollinearity; the decompositions use all other variables summarized in Table 1, plus any additional variation explained by state and decade fixed effects. For decreases, excise taxes are omitted because they are very infrequent.

Figure 6: Variance Decomposition – Bundle Changes

(a) Tax Rate Changes



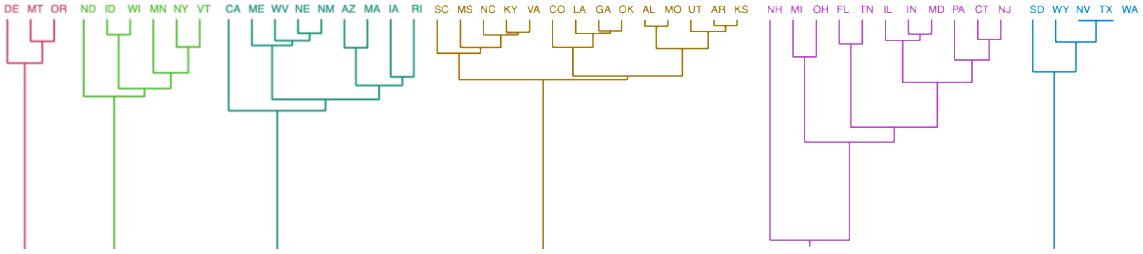
(b) Tax Rate Changes (Largest 50%)



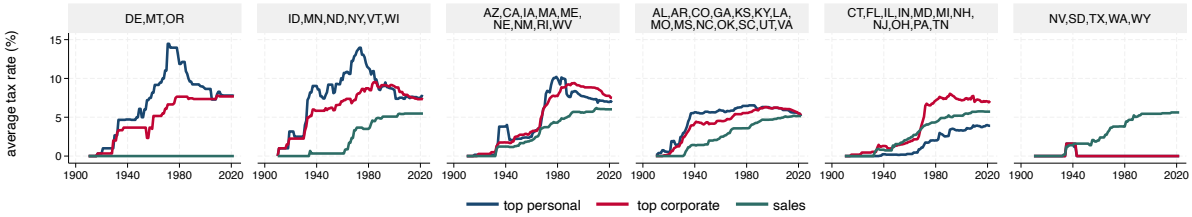
Notes: This figure shows the Shapley variance decomposition of adjusted R^2 for all (a) bundles of tax changes, and bundles of (b) 50% largest tax changes. All decompositions use the variables summarized in Table 1, plus any additional variation explained by state and year fixed effects. For decreases, excise taxes are omitted because they are very infrequent.

Figure 7: Clustering States Using Three-Rate Bundles

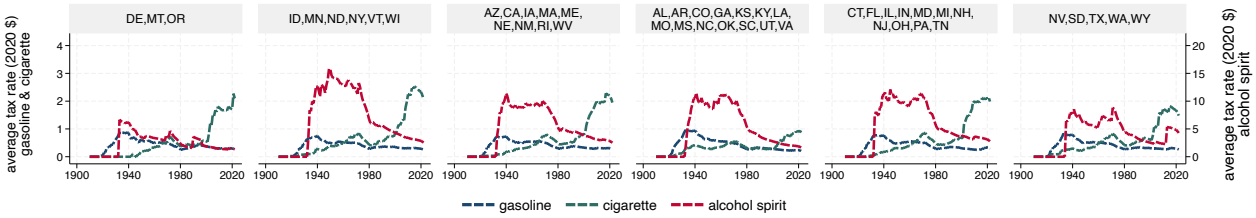
(a) Cluster Structure



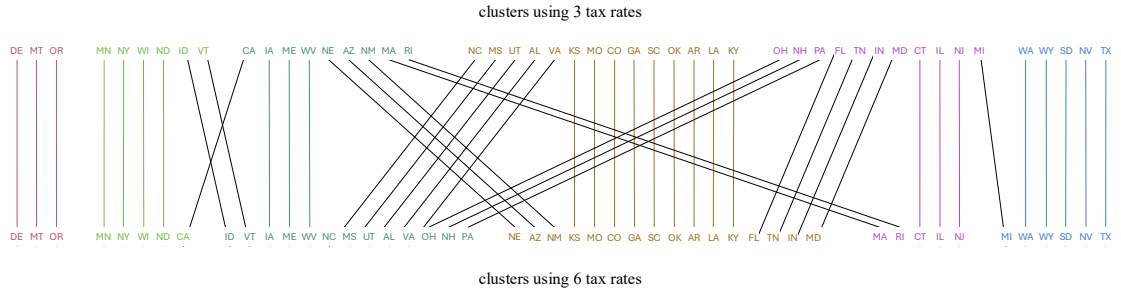
(b) Average Income & Sales Tax Rates



(c) Average Excise Tax Rates

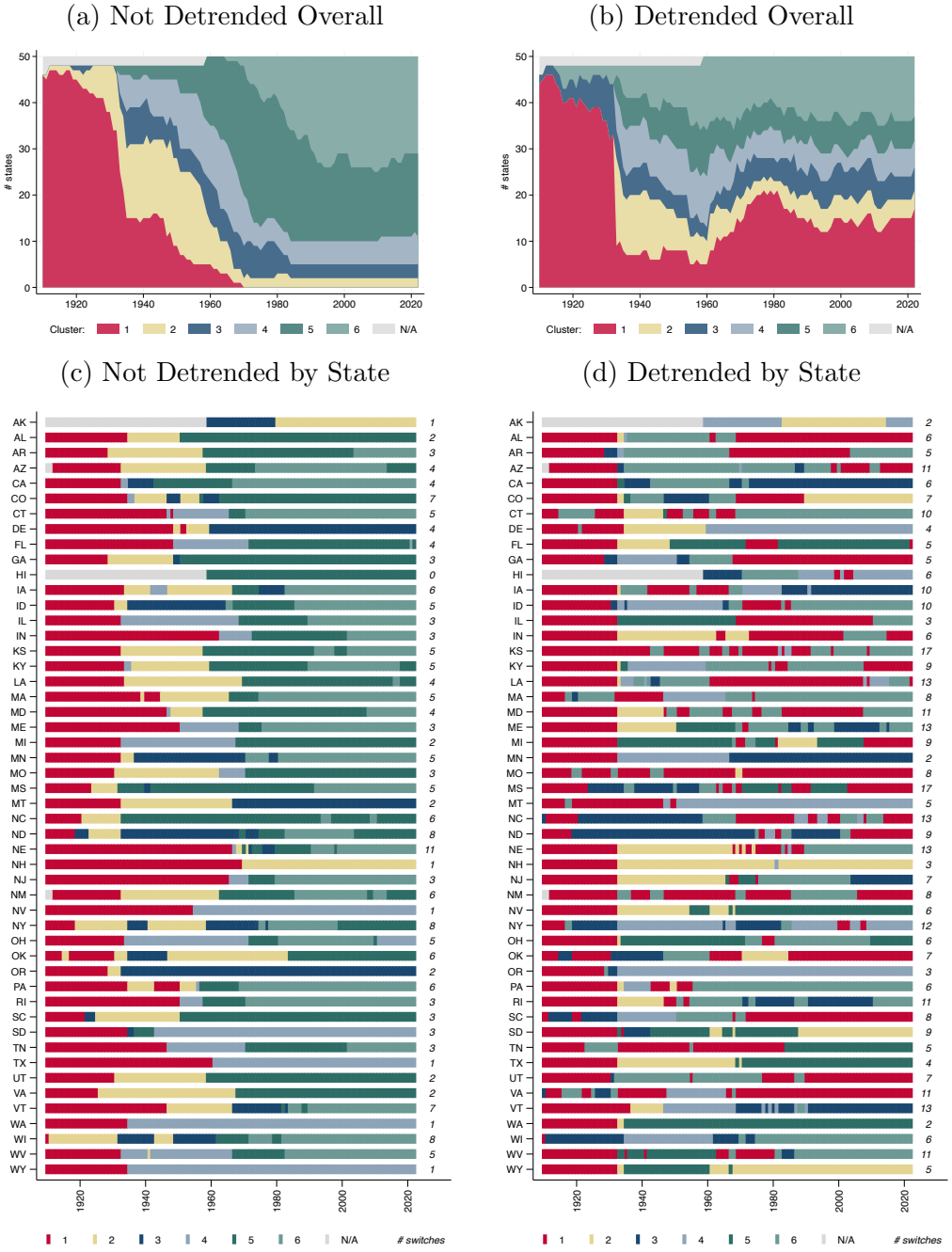


(d) Comparison to Using Six-Rate Bundles



Notes: We organize states into clusters using hierarchical clustering, with soft dynamic time warping and Ward's distance measures, applied to the entire time series of tax rates from 1910 until 2022. Each state is assigned to one cluster. In (a), (b), and (c), we cluster states using top personal, top corporate, and sales tax rates. Figure (a) shows the sequence (the dendrogram) in which the individual states are merged into six clusters. Figure (b) shows average income and sales tax rates in each cluster, and Figure (c) shows average excise tax rates in each cluster. In Figure (d), we compare these cluster assignments using 3 rates (personal, corporate, and sales) to an alternative clustering assignment using 6 rates (the above three plus gasoline, cigarette, and alcohol spirit tax rates). HI and AK are omitted. Alternative specifications available in Appendix D.

Figure 8: Clustering State-Years Using Three-Rate Bundles



Notes: We use CLARA clustering algorithm (Ward's linkage) to organize state-year observations into clusters based on 3 tax rates (personal, corporate, sales). Figures (a) and (b) show the number of states belonging to each cluster in a given year. For convenience of exposition, clusters are ordered by average year in the cluster. Figures (c) and (d) show what share of years (not necessarily consecutively) each state appears in each cluster. Note that state-year observations in which excise taxes were measured as percent of prices rather than in dollars are omitted from the analysis. Figures (a) and (c) use non-detrended series of tax rates, while figures (b) and (d) use detrended series.

APPENDIX FOR ONLINE PUBLICATION

A Data Notes

We rely on the previous literature, summarized in Table A.1 to identify the set of relevant economic, political and institutional variables that we use in our analysis. The resulting set of explanatory variables is available in Table 1. In this section, we describe how we construct these explanatory variables.

Political Affiliations. We collect detailed information on the political affiliation of state legislators, both in the upper and lower chambers of legislatures, and that of the governor. Our data also allows us to identify years in which control of legislative chambers or the governorship has changed, as well as episodes of divided governments. Previous work has shown these to be important determinants of state policy (e.g. McCubbins (1991); Alt and Lowry (1994); Bernecker (2016)). We complement party control data with information on election cycles for state upper and lower chambers, governorship, and federal presidential elections (e.g. Alesina et al. (1997)). In addition, we collect information on states' pledges in presidential elections, and DW-NOMINATE scores for state representatives and senators. We also control for potential differences between Southern and non-Southern Democratic parties. We identify the following states as Southern Democratic states: AL, AR, FL, GA, KY, LA, MS, NC, OK, SC, TN, TX, VA, WV, for all years before 2015.

Institutional Rules. Previous work has also shown that state policy is influenced by institutional features, such as the number of legislators in the legislatures (Gilligan and Matsusaka (2001), Egger and Koethenbuerger (2010)), term limits (Erler (2007); Besley and Case (1995a)), balanced budget provisions (e.g. Poterba (1994)), and legislative initiative rules (Matsusaka (1995), Matsusaka (2000), Asatryan et al. (2017a), Asatryan et al. (2017b)). Therefore, in addition to the political affiliation of the state legislators and governors in each year, we collect information on institutional features of the state. The size of the legislatures – number of seats in each legislative chamber

– has been obtained from Ballotpedia.[15] Information on the applicable term limits in state legislatures and when they were introduced has been obtained from the National Conference on State Legislatures (NCSL), while information on governor term limits was obtained from the Council of State Governments. We have identified all state-year observations during which an incumbent governor could no longer seek re-election because of the binding term limit. We also collect information on average durations of legislative sessions, as well as salaries and per-diem rates in 2019/2020 from NCSL. In contrast to the federal government, states are not allowed to carry budgetary deficits for prolonged periods of time. We collect information on the stringency of balanced budget rules as of 2010: whether the governor must submit a balanced budget, whether legislatures must enact a balanced budget, and whether deficit carry-forwards are allowed, all from NCSL (2010). We also identify states with separate capital budgets in addition to operating budgets using 2014 data from NASBO (2014). We also collect information as to whether states have a rainy day fund and the year it was adopted.

States differ in who can propose new laws. We obtain information on voter initiatives from Matsusaka (1995): a number of states allow citizens to initiate and approve laws by popular vote, while other states only allow state legislators to do so. These rules remain unchanged during the studied period. We also identify states that require supermajorities in order to pass tax increases, and whether the state is a right-to-work state in a given year.

Neighbors. To investigate whether states change their tax rates in response to competition, we identify tax rates in the neighboring states. We use two approaches to defining neighbors. First, we consider states as neighbors if they share a geographical border. We believe this is the best approach for excise taxes since individuals can purchase goods by driving to a neighboring state. Second, we use migration flows as measure of neighborliness, following Baicker (2005). Since tax competition is primarily concerned with out-migration, for each state, we identify five "neighbor" states that accept

[15]For Nebraska, we utilize the total number of seats as our measurement for both the number of upper chamber seats and the number of lower chamber seats.

the largest number of migrants from that state, using 2010 state-to-state migration data from the IRS. While migration flows vary from year to year, the ranking of states, especially at the very top, appears to be fairly stable. For this reason – and due to the lack of consistent yearly data throughout the 70-year period – we use 2010 neighbors for all years. We calculate average tax rates in these five neighboring states, and we consider neighbors to change taxes if at least one of five states changed their tax rate. We use this approach to identify neighbors for all other tax types.

Recessions. We identify state recessions by applying the Bry-Boschan Method to Federal Reserve Bank of Philadelphia State Coincident Index. Since the Index is available from 1979 onward, we supplement our measure with equivalent calculations based on yearly state GDP values for years 1963-1979, and with federal recessions using NBER datings for years 1949-1962. Method identifies the peaks and troughs in the level of a time series, thus marking the beginning and ends of expansions and contractions. Our specification uses a window of 12 month, with a phase of at least 6 months and a complete cycle of 24 months. For 1949-1962, we rely on federal recessions using NBER datings. We also obtained information on natural resource prices (oil, natural gas and coal). We include inflation in our set of explanatory variables.

Mandates. Many federal policy changes impose substantial fiscal costs on state and local governments, as well as on the private sector. These federal mandates come in many different forms: from federal statutes that "order" costly changes (e.g. minimum wage mandates, or improving accessibility for the disabled), to federal policies that influence state spending by offering matching grants or other forms of incentives. Importantly, many of these mandates are unfunded and thus require states to raise more tax revenue or cut other expenditures in order to balance their budgets.

We use three sources to identify the federal mandate changes that are likely to have important economic consequences for state budgets. First, we use Congressional Budget Office (CBO) reports to identify mandates that exceed the "UMRA" threshold. A rapid increase in federal unfunded mandates led to the introduction of the Unfunded Mandates Reform Act of 1995 (UMRA), which

required the CBO to estimate the costs of mandates to state and local governments, as well as the private sector, for new legislative proposals. While UMRA applies to most legislation that can impose enforceable duties, it typically does not apply to existing programs, Social Security, and legislation that cover national security and constitutional rights. Since UMRA's introduction in 1996, 15 laws have been enacted that have costs estimated exceed the 50 million 1996$ threshold (Congressional Research Service (2020)). Second, because UMRA did not apply before 1996, we look for costly mandates in the U.S. Advisory Commission on Intergovernmental Relations (ACIR) reports and National Conference of State Legislatures Mandate Monitor. Finally, we supplement these sources by hand-collecting information on historical changes to existing social welfare programs that are jointly funded by federal and state governments: AFDC/TANF, Food Stamp Program /SNAP, and Medicaid.[16]

Since our goal is to identify federal changes that may influence state tax policy, we focus on mandates that are large (i.e. likely to exceed the UMRA threshold) and are persistent in nature (i.e. affect state expenditures in all future years rather than impose a one-time burden). With these requirements in mind, we have identified 27 mandates summarized in Table A.2 that were enacted in 1950 or later. For each mandate, we record the year of mandate enactment and the year it became effective, as well as the list of states the mandate affected. While federal mandates apply to all states, they are not binding if a state had already satisfied the mandate prior to enactment.[17]

Demographics. We augment the political and institutional data with information on the demographics of each state. We obtain the poverty rate for 1980-2019 and population measures along with race and ethnicity breakdowns for 1969-2019 from the Census Bureau. We collect the unemployment rate, employment to population ratio, and labor force participation rate for

[16]We do not include SSI, SSDI, and Medicare in our collection process because these programs are fully federally funded. Food Stamp / SNAP benefits are funded by the federal government, but administrative costs are shared with the states.

[17]For example, according to CBO calculations, federal minimum wage increases impose a substantial burden on state budgets through their direct effect on state employee salaries. However, any state with state minimum wage above the new federal wage was unaffected by this mandate.

1976-2020 from the Bureau of Labor Statistics. Earlier year observations are collected from the Statistical Abstracts of the United States. Finally, we obtain information on state tax revenues, expenditures and total outstanding debt from Census Annual Survey of State Governments.

We obtain population measures along with race and age breakdowns for 1969-2019 from the Surveillance, Epidemiology, and End Results (SEER) Program of the National Cancer Institute. Population totals for 1949-1969 are obtained from the Statistical Abstracts of the United States. Breakdowns by race and age were obtained from the Statistical Abstracts of the United States for years 1950, 1960 and 1968. These values are then used in place of missing years, i.e 1950 value for years 1949-1955, 1960 value for years 1956-1963, and 1968 value for 1964-1968.

We obtain the poverty rate for 1980-2019 from Census and for years 1959, 1969 and 1975 from the Statistical Abstracts of the United States. These values are then used in place of missing years, 1959 for years 1949-1963, 1969 for years 1964-1972, and 1975 for years 1973-1979. Median household income values are available from Census for years 1979-2019, and are supplemented with values for 1950, 1959, 1969 and 1975 from the Statistical Abstracts of the United States. Again, the latter values (but inflation-adjusted) are used in place of missing data: i.e 1950 value for years 1949-1955, 1959 value for years 1956-1963, 1969 value for 1964-1972, 1975 value for 1973-1978.

We collect the unemployment rate, employment to population ratio, and labor force participation rate for 1976-2020 from the Bureau of Labor Statistics. The unemployment rate and total unemployment for 1957-1975 were obtained from the Manpower Report of the President and the Employment and Training Report of the President. For 1957-1970, the employment to population ratio is estimated as the number of employed individuals (obtained by multiplying one-minus the unemployment rate by the size of the labor force, i.e., unemployment divided by the unemployment rate) divided by the number of prime age-adults (i.e., age 19-65). The labor force participation rate is estimated as the number unemployed divided by the unemployment rate and divided by the number of prime age-adults (i.e., age 19-65). Values for earlier

years (1949-1956) are filled with values from 1957.

Oil, gas and coal prices. Crude oil prices are represented by the historical free market (stripper) oil prices of Illinois Crude from Illinois Oil and Gas Association and Plains All American Oil. Natural gas price is based on Wellhead price until 2012, after which it is Citygate price minus 2.07; both from U.S. Energy Information Administration. Coal prices were obtained from U.S. Bureau of Labor Statistics, Producer Price Index by Commodity: Fuels and Related Products and Power: Bituminous Coal and Lignite (WPS0512) (averaged over a year), retrieved from FRED, Federal Reserve Bank of St. Louis.

Table A.1: Plausible Explanatory Variables Based on Previous Literature

Studies	Suggested explanatory variables
Election Cycles:	
Mikesell (1978), Rosenberg (1992), Foremny and Riedel (2014), Katsimi and Sarantides (2012), Nelson (2000), Chang et al. (2020)	election cycle year indicators
Ashworth et al. (2006)	election cycle year indicators, neighbors' tax rates, coalition vs single-party in control indicator
Veiga and Veiga (2007)	election cycle year indicators, salience of tax instrument
Rose (2006)	election cycle year indicators, election cycle year indicators x deficit not allowed indicator
Political Structures:	
Alt and Lowry (1994)	divided government indicator, divided government indicator x deficit not allowed indicator
McCubbins (1991)	divided government indicator, party of the president
Bernecker (2016)	divided government indicator, governor election cycle year indicator, percent of female legislators in the legislature
Castanheira et al. (2012)	size of majority, election cycle year indicators, recession indicator, tax reform the year prior indicator
Roubini and Sachs (1989)	government tenure, coalition vs single party in control indicator
Institutional Rules:	
Erler (2007)	legislator term limit indicator
Besley and Case (1995a)	governor term-limited, governor term-limited x Democrat, governor term-limited x Republican
Gilligan and Matsusaka (2001), Egger and Koethenbuerger (2010)	size of senate, size of house
Matsusaka (1995), Matsusaka (2000), Asatryan et al. (2017a), Asatryan et al. (2017b)	voter initiative indicator, voter initiative indicator x complexity of voter initiative requirements
Poterba (1994)	deficit not allowed indicator, tax limitations, general fund balance, divided government x deficit not allowed, governor election cycle year indicators

Table continues on next page.

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Table A.1: Plausible Explanatory Variables Based on Previous Literature (continued)

Studies	Suggested explanatory variables
Competition:	
Besley and Case (1995b), Chirinko and Wilson (2017), Deskins and Hill (2010), Rork (2003)	neighbors' tax rates
Buettner (2003)	neighbors' tax rates, neighbors' tax rates x size of state
Case et al. (1993)	neighbors' spending, as defined based on economic and geographic similarities
Besley and Rosen (1998), Goodspeed (2000), Goodspeed (2002), Devereux et al. (2007),	neighbors' tax rates, federal tax rates
Geys (2006)	neighbors' ratio of the cost of public goods provision to the level of public goods actually provided by the government, also interacted with coalition vs single-party in control indicator
Baicker (2005)	neighbors' tax rates, defined based on degree of mobility between states
Bordignon et al. (2003)	neighbors' tax rates x mayor term-limited, election year indicators, demographics: unemployment, elderly and young shares of population
Other:	
Inman and Fitts (1990)	income level, unemployment level, demands from special interest groups, share of young people in population, strength of party control
Bozzano et al. (2021)	gender equality level

Notes: This table summarizes variables that are likely to explain variation in state tax policies based on the previous studies.

Table A.2: Federal Mandates

Mandate	Enacted	Effective	States affected
Medicaid: Mandatory preventative services for children	1967	1973	All states except AL, AK, AZ, AR, CO, FL, IN, MS, NJ, NC, SC, TN, VA
FSP/SNAP: Mandatory expansion	1973	1974	All states
FSP/SNAP: Expanded eligibility	1977	1979	All states
Medicaid: Mandatory coverage for pregnant women and infants up to 100% FPL	1988	1989	CO, ID, IN, MT, ND, NH, NV, NY, WI
AFDC: Mandatory coverage for 2-parent families w/ unemployed primary earner	1988	1990	AK, AL, AR, AZ, CO, FL, GA, ID, IN, KY, LA, MS, ND, NH, NM, NV, OK, SD, TN, TX, UT, VA
Medicaid: Requirement to cover pregnant women and young children up to 133% FPL	1989	1990	All states except: CA, CT, IA, ME, MA, MI, MN, MS, RI, VT, WV
AFDC: AFDC ended; replaced by Temporary Assistance for Needy Families (TANF) w/ looser spending restrictions	1996	1997	All states
FSP/SNAP: Reduced reimbursement of state administration costs	1998	1998	All states
Min wage increase	1950	1950	All states except: AK not affected
Min wage increase	1956	1956	All states except: AK not affected
Min wage increase	1961	1961	All states except: AK not affected
Min wage increase	1963	1963	All states except: AK not affected
Min wage increase	1967	1967-1968	All states except: AK, CA not affected
Min wage increase	1974	1974-1976	All states except: AK, HI not affected
Min wage increase	1977	1979-1981	All states except: AK, CT not affected
Min wage increase	1990	1990-1991	All states in 1990, except: HI, IA, ME, MN, VT, WA in 1991; AK, CA, CT, OR, RI not affected
Min wage increase	1996	1996-97	All states in 1996, except: NJ and WA in 1997; AK and HI not affected.
Min wage increase	2007	2007-09	All states in 2007 except: AR, MN, NV in 2008; AK, AZ, DE, FL, NJ, NY in 2009; CA, CT, HI, IL, ME, MA, MI, OR, RI, VT, WA, WV not affected.
Clean Air Act	1963, 1967, 1970, 1977, 1990	1963, 1967, 1970, 1977, 1990	All states
Occupational Safety and Health Act	1970	1970	All states
Federal Water Pollution Control Act	1972, 1977, 1987	1972, 1977, 1987	All states
Marine Protection Research and Sanctuaries Act	1972	1972	All states
Endangered Species Act	1973	1973	All states
Safe Drinking Water Act	1974, 1986, 1996	1974, 1986, 1996	All states
Surface Mining Control and Reclamation Act	1977	1977	All states
Internet Tax Freedom Act	1998	2020	HI, NM, ND, OH, SD, TX, and WI.
Healthy, Hunger-Free Kids Act	2010	2012	All states

Notes: This table summarizes federal mandates enacted in 1950 or later that are likely to impose a substantial burden on state budgets, i.e. have projected costs that exceed the UMRA threshold ($50 million 1996 dollars). See Appendix Section A for details.

B Should Tax Policy be Predictable?

In this paper we evaluate the extent to which the timing and magnitude of tax changes are driven by economic, political, and institutional factors. To do so, we measure the share of observed variation in tax changes that can be explained by the variables that the previous literature identified as explanatory. Our approach thus raises a natural question: should tax policy be predictable, and if it is not, what does that imply? In this section, we argue that in a broad set of policy setting models, tax policy should be highly predictable even if the individual behavior of policymakers is not. As a consequence, if a sufficiently flexible econometric model has limited predictive power, then the explanatory variables included in the model are unlikely to be drivers of the policies we analyze. This implies that either other factors are at play, or the policy setting process is truly idiosyncratic.

Consider two broad categories of policy setting models. In the first set of models, tax policies represent implementations of "optimal" policies as defined by the optimal tax literatures. States may use state taxes to fine-tune federal tax policies to better match their constituents' preferences. In this case, tax changes should be fully determined by changes in economic fundamentals, such as elasticities, population shares, and other relevant parameters. State To the extent that these fundamentals (or their proxies – e.g. demographic and economic indicators) are observable to policymakers, they should also be observable to researchers, making tax policy highly predictable.

The second set of models treats policy makers as potentially self-interested utility-maximizing agents who may or may not take voter preferences into account. The most well-known of these models, the median voter framework, is fully deterministic – thus as long as the median voter's preferences are observed to policymakers, they should be observable to researchers. This intuition, however, can be extended to settings with idiosyncratic shocks, where policymakers (or voters) "tremble" when making choices. In these frameworks, tax policy should still be highly predictable, as long as the appropriate measures of aggregate policymakers' preferences and relevant decision-making

factors can be observed. To build intuition, consider the outcome of a 70-30 weighted coin flip. If we were to predict the outcome of an individual flip, we would fail approximately 30% of the time. However, if our goal is to predict whether 100 coin flips will result in a majority heads outcome, we are likely to succeed with nearly a 100% probability. Note, however, that the majority heads outcome becomes harder to predict as the coin gets closer to the 50-50 unweighted case.

Turning back to policy setting, suppose a policymaker's decision to vote yes on a given policy at time t is driven by a time-varying individual preference α_{it}, a vector of observable factors X_{it}, and a random shock ε_{it}. Furthermore, assume policymaker i votes yes if the policy results in positive utility, and no otherwise:

$$Vote_{it} = \begin{cases} 1 & \text{if } U(\alpha_{it} + \beta X_{it} + \varepsilon_{it}) \geq 0, \\ 0 & \text{otherwise.} \end{cases}$$

If we were to predict individual policymakers votes using observable factors X_{it}, then the explanatory power would depend on the variance of the idiosyncratic factors ε_{it}. For example, some policy votes are easily predictable because they strictly follow party lines, while others appear to be driven by unobservable factors.

However, if policy adoption is determined by majority rule, as is common in U.S. state legislatures, then predicting policy outcomes is equivalent to predicting whether the share of yes votes, $\frac{1}{n}\sum_i Vote_{it}$, exceeds 0.5 (or another cutoff in case of supermajority rules). By the law of large numbers, for a sufficiently large number of voters n, the share of yes votes is approximated by the expected value:

$$\frac{1}{n}\sum_i Vote_{it} \to \mathbb{E}[Vote_{it}] = Prob[U(\alpha_{it} + \beta X_{it} + \varepsilon_{it}) \geq 0].$$

Therefore, in contrast to individual policymakers' votes that are idiosyncratic to some degree, policy decisions are effectively deterministic and are driven by the joint distribution of policymakers' preferences, observable factors and id-

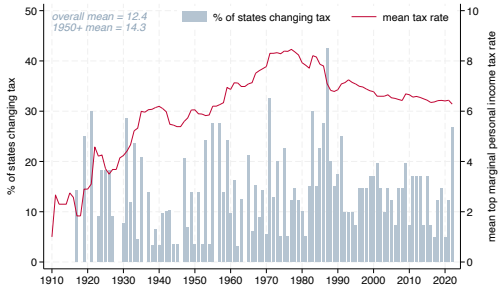
iosyncratic shocks. One exception to this rule is circumstances where $\mathbb{E}[Vote_{it}]$ is close to 0.5. In these situations, the policymakers are evenly split thus making policy outcomes potentially as difficult to predict as individual votes.

Two practical considerations are worthy of a discussion. First, state legislatures are not very large, ranging from 20 to 67 members in the upper chamber and from 40 and 400 members in the lower chamber, with the averages of 40 and 110 members, respectively. Due to legislatures' size, the law of large numbers will not hold perfectly, resulting in some uncertainty. This uncertainty should be smaller for larger state legislatures and when the variance of $Vote_{it}$ is small. Second, the joint distribution of policymakers' preferences, observable factors and idiosyncratic shocks is not known. For this reason, an econometric model employed to predict policy outcomes ought to be sufficiently flexible, in order to allow for unknown relationships and functional forms. Since machine learning techniques such as LASSO and Random Forest allow for such flexibility, lack of predictive power in such models would imply that either relevant explanatory factors have been omitted, individual idiosyncratic shocks dominate policymakers' preferences and decision-making factors, or policymakers are evenly split in their preferences.

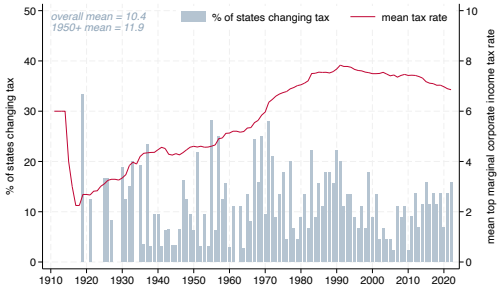
C Additional Descriptive Graphs

Figure C.1: Tax Changes by Year as a Percent of States with Non-Zero Tax

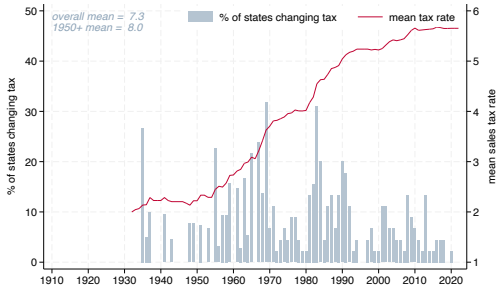
(a) Top Personal Income Tax



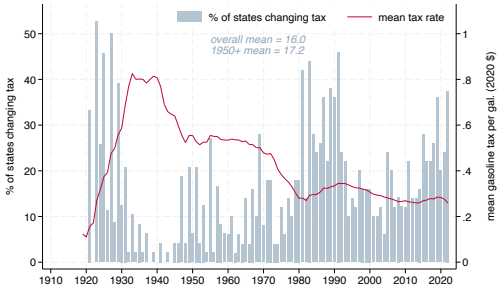
(b) Top Corporate Income Tax



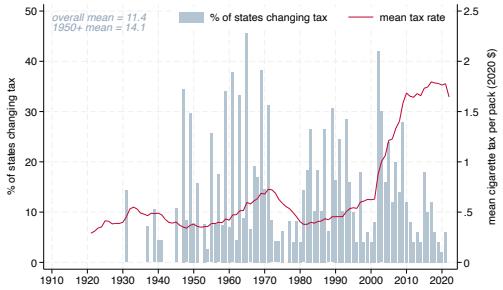
(c) Sales Tax



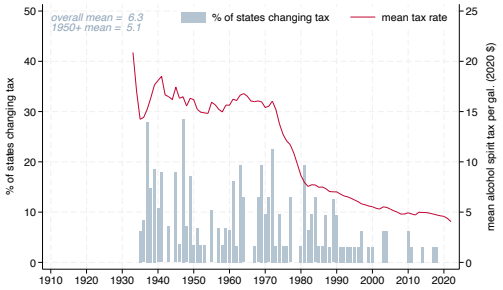
(d) Gasoline Tax



(e) Cigarette Tax



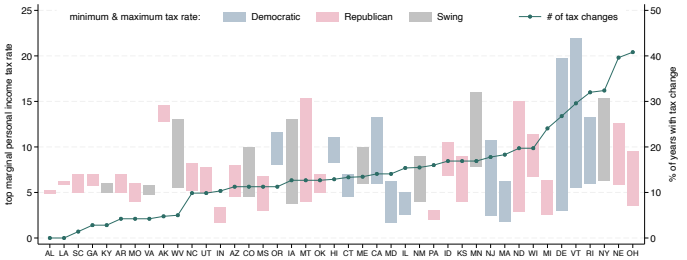
(f) Alcohol Spirit Tax



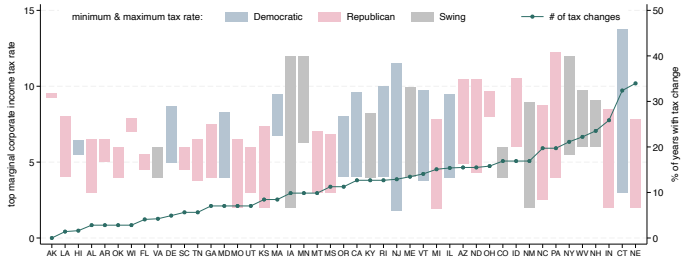
Notes: These figures show the percent of states that change a given tax rate in a given year (blue bars), as well as the average tax rate in that year (red line). All statistics are calculated using only non-zero tax rates, and only intensive margin tax changes are included (tax adoptions and cancellations are excluded). These statistics are shown for (a) top personal income tax rates, (b) top corporate income tax rates, (c) standard sales tax rates, (d) gasoline excise tax rates, (e) cigarette excise tax rates, and (f) alcohol spirit excise tax rates.

Figure C.2: Tax Changes by State as a Percent of Years with Non-Zero Tax (1950-2020)

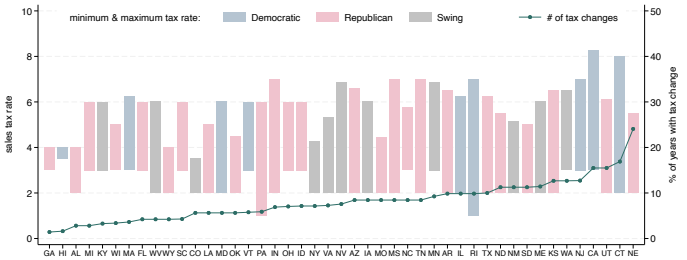
(a) Top Personal Income Tax



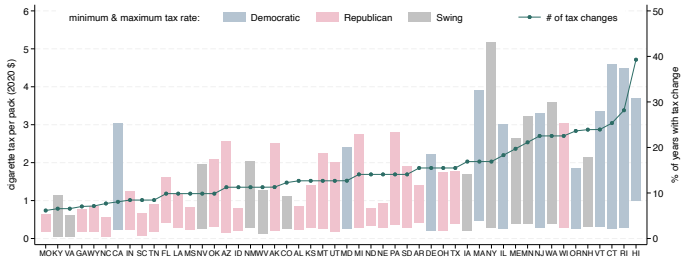
(b) Top Corporate Tax



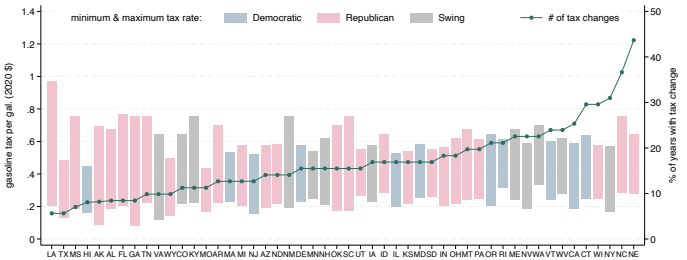
(c) Sales Tax



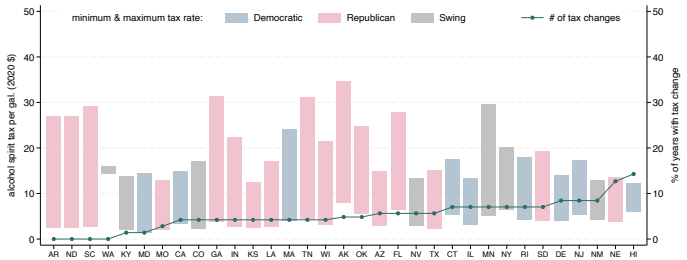
(d) Cigarette Tax



(e) Gasoline Tax



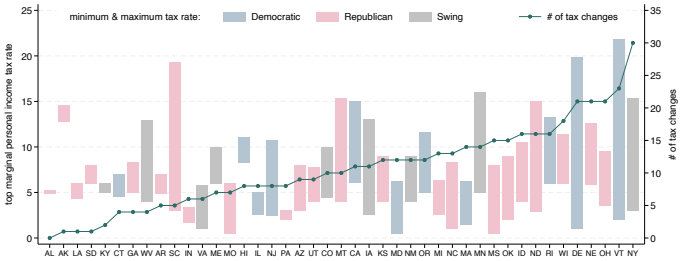
(f) Alcohol Spirit Tax



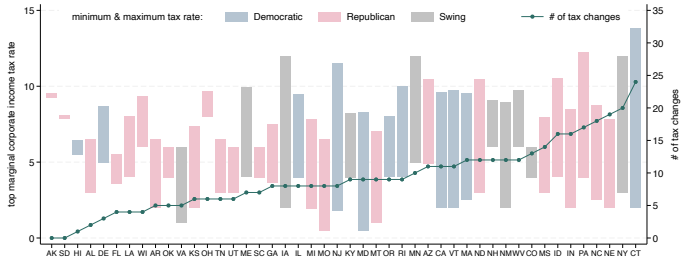
Notes: This figure shows for each state the minimum and maximum tax rate (bars), as well as the percent of years each state changed the tax rate (line) between 1950 and 2020. Only years with non-zero tax rates are included. The range for each state is colored by the majority party in both chambers of the state legislature from 2013+. These statistics are shown for (a) top personal income tax rates, (b) top corporate income tax rates, (c) standard sales tax rates, (d) gasoline excise tax rates, (e) cigarette excise tax rates, and (f) alcohol spirit excise tax rates.

Figure C.3: Tax Changes by State (1910-2022)

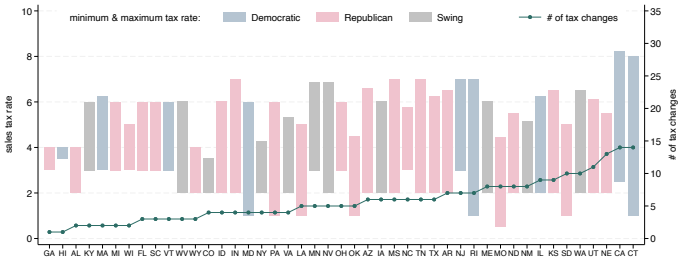
(a) Top Personal Income Tax



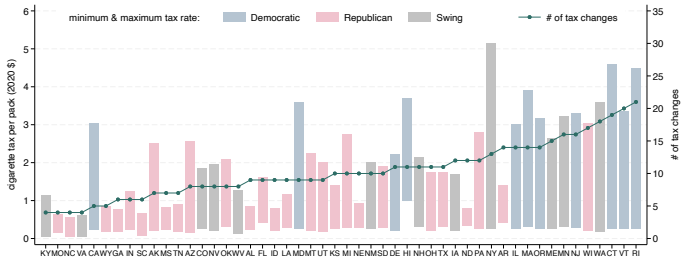
(b) Top Corporate Tax



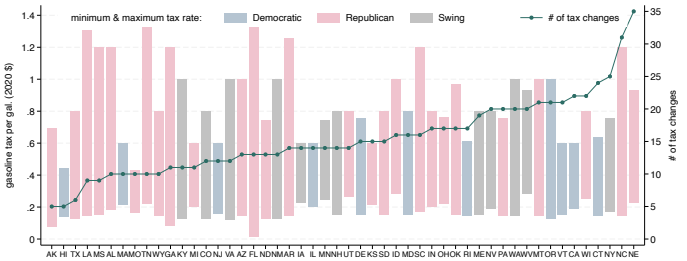
(c) Sales Tax



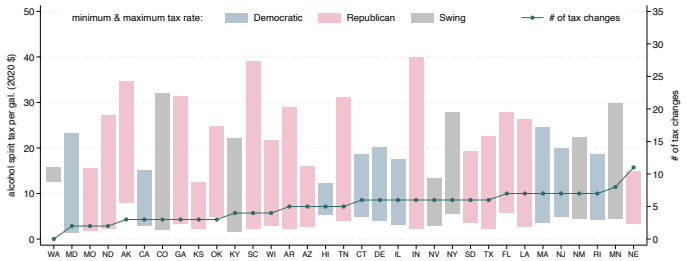
(d) Cigarette Tax



(e) Gasoline Tax



(f) Alcohol Spirit Tax



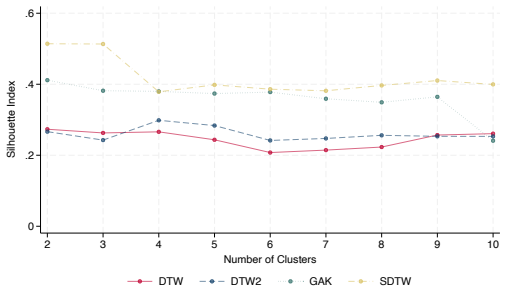
Notes: This figure shows for each state the minimum and maximum tax rate (bars), as well as the number of times the state has changed the tax rate (line) between 1910 and 2022. Only non-zero tax rates are included. The range for each state is colored by the majority party in both chambers of the state legislature from 2013+. These statistics are shown for (a) top personal income tax rates, (b) top corporate income tax rates, (c) standard sales tax rates, (d) gasoline excise tax rates, (e) cigarette excise tax rates, and (f) alcohol spirit excise tax rates.

D Additional Clustering Results

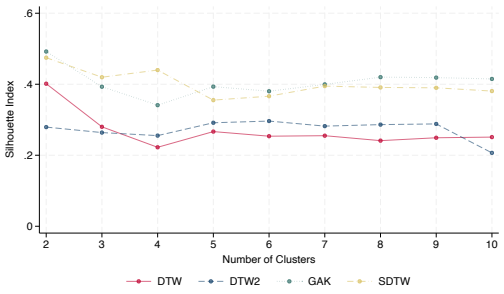
Figure D.4: Time Series Clustering: Silhouette Scores

Panel A: Clustering Using 3-Rate Bundles

(a) Complete Linkage

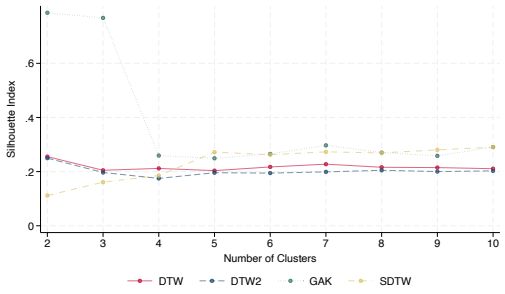


(b) Ward Linkage

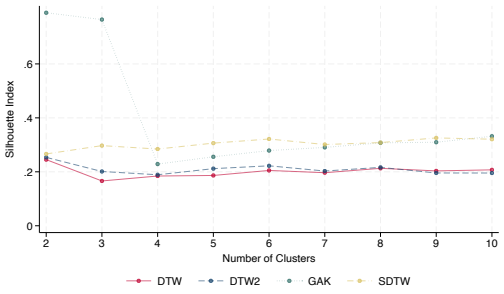


Panel B: Clustering Using 6-Rate Bundles

(c) Complete Linkage



(d) Ward Linkage

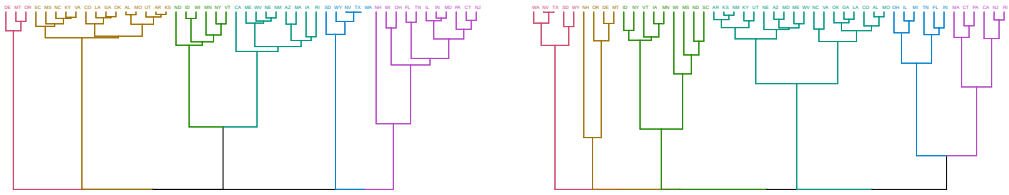


Notes: These figures show the silhouette scores for different number of clusters, different time warping algorithms, and different linkage choices when organizing states into clusters using hierarchical clustering approach applied to the entire time series of tax rates from 1910 until 2022. Each state is assigned to one cluster. In Panel A, we clusters states using three variables: top personal, top corporate and sales tax rates. In Panel B, we use the same three rates plus gasoline, cigarette and alcohol spirit taxes. Figures (a) and (c) show the silhouette scores when clustering non-detrended time series using complete linkage, while figures (b) and (d) show the silhouette scores when using Ward's linkage.

Figure D.5: Time Series Clustering: Detrended vs Not

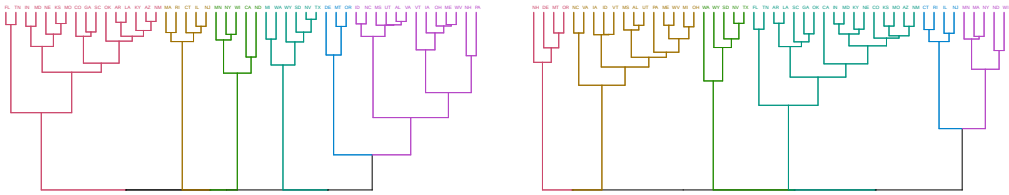
Panel A: Clustering Using 3-Rate Bundles

(a) Non Detrended (b) Detrended



Panel B: Clustering Using 6-Rate Bundles

(c) Non Detrended (d) Detrended

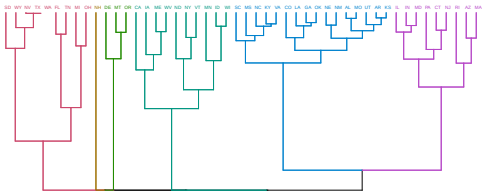


Notes: We organize states into clusters using hierarchical clustering (with soft dynamic time warping and Ward's distance measures) approach applied to the entire time series of tax rates from 1910 until 2022. Each state is assigned to one cluster. In Panel A, we clusters states using three variables: top personal, top corporate and sales tax rates. In Panel B, we use the same three rates plus gasoline, cigarette and alcohol spirit taxes. Figures (a) and (c) show the cluster structures when clustering non-detrended time series, figures (b) and (d) show the cluster structures when clustering detrended time series.

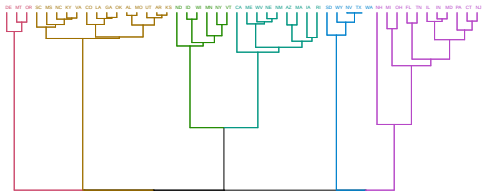
Figure D.6: Time Series Clustering: Alternative Distance Measures

Panel A: Clustering Using 3-Rate Bundles

(a) Complete Linkage

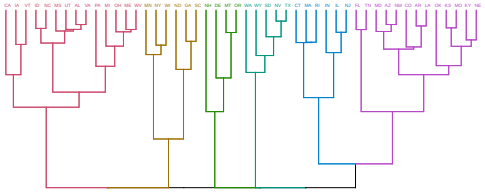


(b) Ward linkage

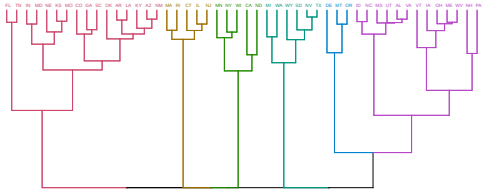


Panel B: Clustering Using 6-Rate Bundles

(c) Complete Linkage



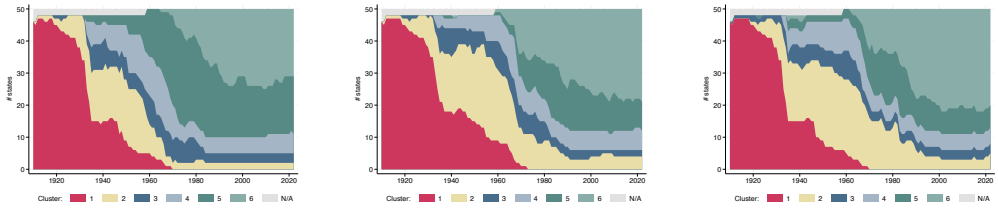
(d) Ward linkage



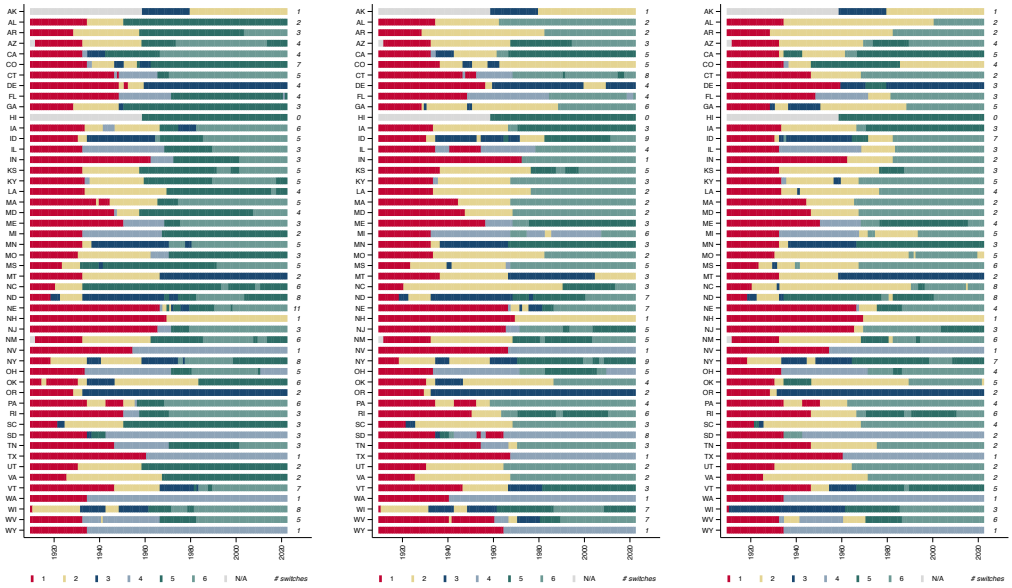
Notes: We organize states into clusters using hierarchical clustering (with soft dynamic time warping) approach applied to the entire time series of tax rates from 1910 until 2022. Each state is assigned to one cluster. In Panel A, we clusters states using three variables: top personal, top corporate and sales tax rates. In Panel B, we use the same three rates plus gasoline, cigarette and alcohol spirit taxes. Figures (a) and (c) show the cluster structures when clustering non-detrended time series using complete linkage, while figures (b) and (d) show the cluster structures when using Ward's linkage.

Figure D.7: Organizing State-Years into Clusters: Non-Detrended Series

(a) CLARA (b) K-Means (c) Hierarchical



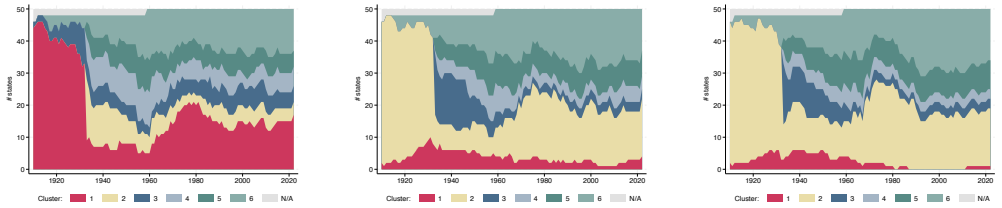
(d) CLARA (e) K-Means (f) Hierarchical



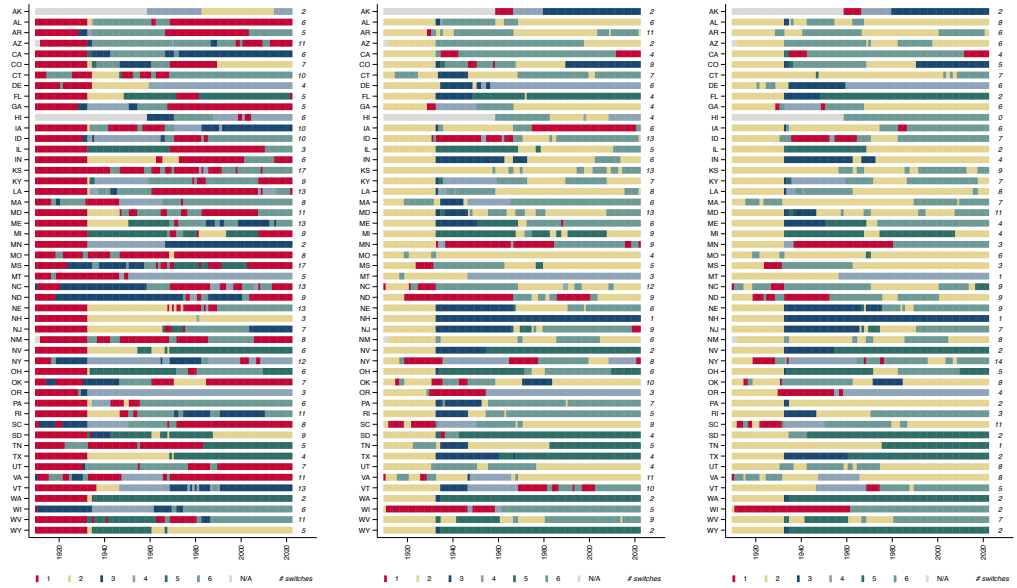
Notes: We use various clustering algorithms to organize state-year observations into clusters based on 3 tax rates (personal, corporate and sales). Figures (a), (b) and (c) show the number of states belonging to each cluster in a given year. For convenience of exposition, clusters are ordered by average year in the cluster. Figures (d), (e) and (f) show what years each state appears in each cluster. Note that state-year observations in which excise taxes were measured as percent of prices rather than in dollars are omitted from the analysis. All figures uses non-detrended series of tax rates.

Figure D.8: Organizing State-Years into Clusters: Detrended Series

(a) CLARA (b) K-Means (c) Hierarchical

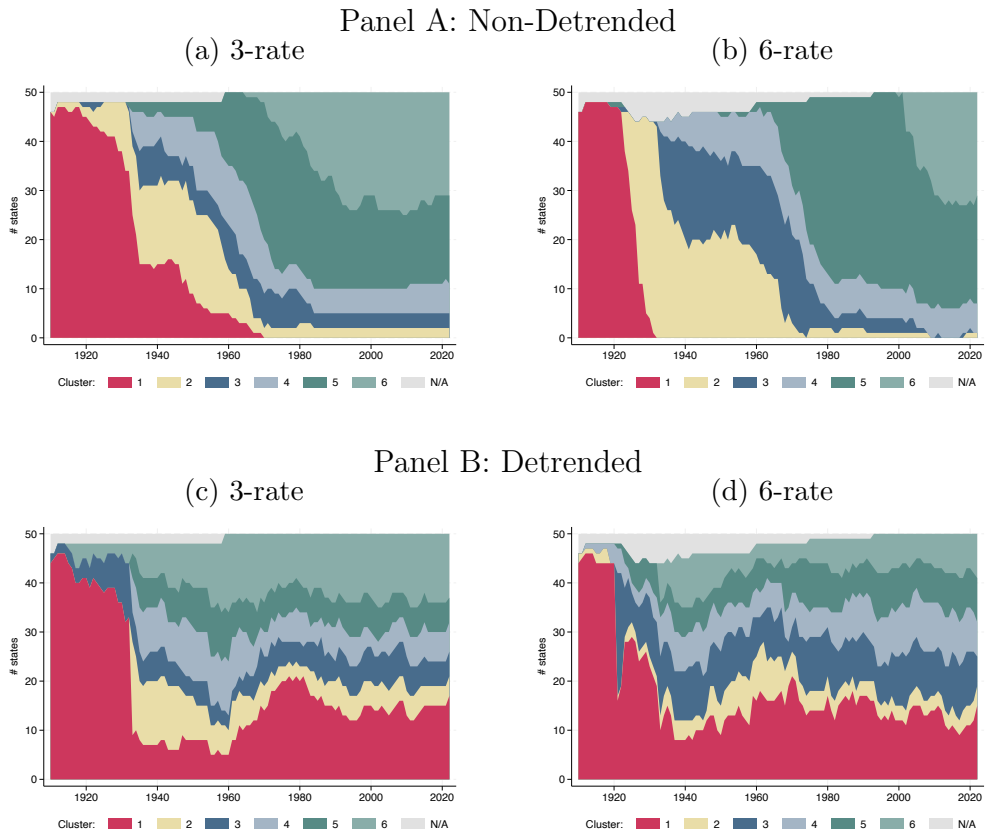


(d) CLARA (e) K-Means (f) Hierarchical



Notes: We use various clustering algorithms to organize state-year observations into clusters based on 6 tax rates (income, sales, excise). Figures (a), (b) and (c) show the number of states belonging to each cluster in a given year. For convenience of exposition, clusters are ordered by average year in the cluster. Figures (d), (e) and (f) show what years each state appears in each cluster. Note that state-year observations in which excise taxes were measured as percent of prices rather than in dollars are omitted from the analysis. All figures use detrended series of tax rates.

Figure D.9: Organizing State-Years into Clusters: 3-Rate vs 6-Rate Bundles



Notes: We use CLARA clustering algorithm to organize state-year observations into clusters based on 3 (income and sales) or 6 (income, sales, exciste) tax rates. Figures (a) and (b) show the number of states belonging to each cluster in a given year when using non-detrended tax series. Figures (c) and (d) show the number of states belonging to each cluster in a given year when using detrended tax series. For convenience of exposition, clusters are ordered by average year in the cluster. Note that state-year observations in which excise taxes were measured as percent of prices rather than in dollars are omitted from the analysis.