What Drives Tax Policy?

Political, Institutional and Economic Determinants of State Tax Policy in the Past 70 Years*

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Abstract

We study U.S. state tax rules over the past 70 years to shed light on the determinants of U.S. state tax policy, generating three key results. First, we show that long-term tax trends are not consistent with Tiebout sorting and race-to-the-bottom competition models. Second, we document evidence of increasing polarization of tax rates between Democratic and Republican states in the 1970s and from 2000 onward. Third, we use machine learning techniques to show that the timing and magnitude of tax changes are not driven by federal changes, economic needs, state politics, institutional rules, neighbor competition, or demographics. Altogether, these factors explain less than 20% of observed tax variation.

JEL Classification: D72, H20, H71, H73, H77
Keywords: state taxes, fiscal federalism, income tax, corporate tax, sales tax, cigarette tax, alcohol tax, gasoline tax, machine learning

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Taxation is at the heart of redistribution and can be a powerful tool for correcting market failures and smoothing business cycles. However, increasing political polarization and legislative gridlock in the U.S. has made it difficult to achieve these goals using fiscal policy.[1] While these issues have been studied on a national level, much less is known about the extent to which they pervade tax policy at the state level, despite its great importance – the U.S. states raise large tax revenues (over $1T or 5% of U.S. GDP each year) and provide a wide range of services and welfare benefits to their residents.

The goal of this paper is to provide a comprehensive analysis of the plausible determinants of U.S. state tax policy, focusing both on long-term trends and the actual timing of policy changes. We start by evaluating the degree of policy heterogeneity over the past 70 years, the direction of tax trends, and the growth of polarization, and compare these outcomes to the long-term predictions of fiscal federalism models. Next, we use permutation analysis, variance decomposition, and machine learning techniques to evaluate to what extent the *timing and magnitude* of tax changes are driven by economic, political, and institutional factors highlighted by the previous literature. This allows us to assess the degree to which tax changes and their timing are reactionary versus idiosyncratic in nature. We consider *economic influences*, such as competition and changing revenue requirements due to economic downturns or federal mandates; *political influences*, such as election cycles, composition and changes of political powers within the state; *institutional features*, such as the size of state legislatures, term limit requirements, balanced budget and voter initiative rules; and the relationship between federal and state tax policies.

The comprehensive nature of our approach and the flexibility of the machine learning algorithms we employ allow us to evaluate the extent to which existing studies of policy setting behavior, taken together, can explain the tax-setting processes. We formally show that in a broad set of policy setting models, tax policy should be highly predictable even if policymakers' pref-

[1] For evidence on political polarization see McCarty et al. (2016). For empirical evidence on policy uncertainty and legislative gridlock, see e.g. Binder (2004), Baker et al. (2014), Mian et al. (2014), Aizenman et al. (2021).

erences are somewhat idiosyncratic. Empirically, this implies that a flexible machine learning algorithm that incorporates relevant explanatory variables should have a high predictive power. Therefore, a low explanatory power – as we find – implies that either tax policy has a large idiosyncratic component, or that relevant explanatory factors have been omitted from the model. Our results do not imply that the factors we consider are not important, merely that other factors may have even larger influence on tax policy, suggesting a need for future work.

For our analysis, we have collected detailed information on state personal income, corporate, sales, cigarette, gasoline and alcohol taxes, from 1950 until 2020. We focus on these taxes because they are primarily controlled by state, rather than local, governments, and combined represent approximately 80% of state tax revenues. Since tax policies are multi-dimensional, in our analysis we focus on six key parameters – top personal income tax rate, top corporate tax rate, standard sales tax rate, cigarette tax per pack, gasoline tax per gallon, spirit tax per gallon. By focusing on (top) statutory rates, our analysis centers on tax features that are important for inequality considerations and, due to their salience, provide the best test of fiscal federalism models.

Our analysis generates three key insights. First, focusing on the long-term trends, we show that tax rates exhibited a period of rapid convergence in 1950-1980s, which was primarily fueled by the adoption of new taxes by states. In the most recent 30 year period, however, all six tax rates exhibited stable levels of tax rate variance, and have neither been converging nor diverging over time.[2] Our results are consistent with and complementary to the findings of Rhode and Strumpf (2003) who document a substantial convergence in state policies (mainly tax expenditures) over the 20th century but show similar level of policy heterogeneity during the last 30 years of the century. The observed trends are thus inconsistent both with Tiebout-sorting models (which predict divergence of tax rates) and race-to-the-bottom competition models (which

[2] Our results are robust to using various measures of convergence, e.g. coefficient of variation (CV) defined as the ratio of the standard deviation to the mean or simple standard deviation.

predict convergence), suggesting that these were not the primary drivers of tax policy changes during the most recent period.

Second, we explore to what degree polarization permeates state tax policies. To do so, we compare tax policies in states that have only voted for a Democratic presidential candidate since 2000 elections to states that have only voted for a Republican candidate. We find that states that lean Democratic tend to have higher tax rates on average, and that the difference between average taxes in Democratic and Republican states was particularly large during the 1970s and from approximately 2000 onward. Importantly, the higher tax rates in Democratic states are not driven by a few outliers – tax rates are generally higher across all percentiles. At the same time, we note a substantial overlap in tax rates between Democratic- and Republican-leaning states, implying that political leanings explain only a small share of the overall variation in state tax policy. Furthermore, we see little evidence of convergence among states with the same party in control.

Our findings of increasing polarization between states with Democratic and Republican majorities suggest that the observed polarization in political discourse indeed translates into polarization in tangible tax policy, resulting in approximately 20% higher taxes in Democratic states as compared to Republican states. However, while polarization in public preferences has been observed since the 1970s (McCarty et al. (2016)), tax policies polarized during the 1970s, followed by convergence during the 1990s and increased polarization from 2000 onward.

Third, we show that the timing and magnitude of tax changes are difficult to predict, suggesting that either taxes are not legislated "in response to" economic and political events, or that the response is often untimely, perhaps, due to legislative gridlock. We use two approaches to show this. We start by using permutation techniques to investigate what share of tax changes follow an event of interest: a recession, the introduction of an unfunded federal mandate, neighboring state's tax change, or a change of majority party. We compare observed co-occurrences to a simulated benchmark that assumes the timing of tax changes is random. Our analysis shows that the rates of co-occurrences are not dramatically different from the simulated benchmark, suggesting that economic and political events have a limited influence on the timing of tax changes.

Next, we turn to a variance decomposition approach and machine learning techniques. Overall, we find that federal changes, economic needs, neighborly competition, institutional features, political factors and demographics explain less than 20% of variation in the timing and magnitude of tax changes, even when employing machine learning techniques that allow for various interactions and flexible functional forms. Interestingly, variance decomposition suggests that tax increases and tax decreases may be influenced by different factors. For example, tax increases are substantially more influenced by federal tax policy than tax decreases. Similarly, economic factors (recessions and mandates), neighbors' and own other tax rate levels are more important for tax increases, while size of legislatures, balanced budget provisions, demographics and historical rates are more important for decreases.

While low explanatory power is rarely of concern in economics because of researchers' focus on identifying causal relationships, it is of great interest in the setting of state tax policies. For this reason, tax policy choice process has been the focus of a large number of empirical and theoretical studies, discussed below. Our inability to explain a large share of tax fluctuations thus suggests that a wide range of existing models, even when combined, do not explain the observed policy outcomes. One possibility is that our analysis omitted important drivers of tax policy, for example, lobbying and political contributions, that play a substantially more important role than the economic, political and institutional influences the literature has focused on. Alternatively, the legislative process for tax policy may be so complex that idiosyncratic factors create substantial randomness in the timing of policy response.[3] This implies that tax policy is unnecessarily volatile, resulting in excess state tax revenue volatility, business cycle volatility, and policy uncertainty that can have detrimental

[3] For example, Mian et al. (2014), provide evidence of delayed government interventions in response to financial crises due to increasing polarization and resulting weakening of the ruling coalition.

effects on growth and the welfare of state residents.[4]

Our results bring some good news to empirical researchers who rely on tax variation as a source of identification – the timing of tax changes indeed appears to be largely exogenous to many observable state characteristics and does not coincide with major economic or political changes. Having said that, tax changes often coincide with other changes within the state, and in many states, tax changes follow a trend. This is concerning because many empirical studies do not control for changes in other tax rates and do not account for taxes' path dependence.

A caveat to our analysis is that we do not explore changes in tax base rules, yet these may have sizable implications on tax revenue. To the extent that tax base rules are less salient to voters and are more complex, they are likely to be more driven by idiosyncratic factors and thus be even less predictable than (top) tax rates. Relatedly, our analysis does not account for differences in cost of living across states, which are likely to result in differences in tax bases. This is of particular concern for property taxes, since the property tax burden is heavily influenced by its tax base. For this reason, we do not include property taxes in our analysis, despite their nontrivial contribution to states' tax revenues.[5] On the other hand, the excise taxes that we consider – gasoline, cigarette and alcohol taxes – have a uniform tax base and are robust to this issue.

This paper is related to several lines of prior work. 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)), the importance of political cycles and structures (e.g. Alesina et al. (1997); Nelson (2000) and Alt and Lowry (1994); Bernecker (2016)), federal mandates (Baicker et al. (2012)), and various institutional features, such as

[4] Seegert (2016) explores the nature of state tax revenue volatility and shows that it is largely driven by state tax policy.

[5] Furthermore, property taxes vary across the localities within the state, to a much larger extent than other types of taxes.

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); Matsusaka (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.[6] 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 competitive, political and institutional forces matter, but show that they explain a relatively small share of the overall tax policy fluctuations.

Our paper also contributes to the literature that studies the policy consequences of polarization (McCarty (2007); Bjrnskov and Potrafke (2013); Grumbach (2018); Rigby and Wright (2015); McCarty et al. (2016)) by focusing on state tax policy. The closest study by Grumbach (2018) also finds an increase in tax policy polarization after 2000, measured as the difference between the number of liberal and conservative tax policies. In our analysis, we focus on tax rate levels directly, thus avoiding the need for subjective classifications.

Finally, this paper builds upon a small number of studies that document basic facts about state and local tax policies. The closest study, Baker et al. (2020), document how state and local taxes have changed over time, while Surez Serrato and Zidar (2018) and Slattery and Zidar (2020) provide a comprehensive overview of state business tax policies. We extend the previous work by collecting extensive data on state tax policies, as well as on political and institutional factors.

[6] 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.

1 Conceptual Framework

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 explanatory variables identified in the previous literature. 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 such model used 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. In this case, tax changes should be fully determined by changes in economic fundamentals, such as elasticities, population shares, and other relevant parameters. 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. In these frameworks, tax policy should still be highly predictable, even if the policymakers who cast the votes experience idiosyncratic shocks, 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 gets 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 the majority rule, as is common in U.S. state legislatures, then policy prediction implies predicting whether the share of yes votes, $\frac{1}{n}\sum_i Vote_{it}$, exceeds 0.5. 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 idiosyncratic 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 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, that individual idiosyncratic shocks dominate policymakers' preferences and decision-making factors, or that policymakers are evenly split in their preferences.

2 Data

2.1 Tax Rate Data

We collect data on top personal income, top corporate income, sales, cigarette per pack, gasoline per gallon and alcohol spirit per gallon taxes from the Council of State Governments Book of the States from 1949 until 2020.[7] Whenever possible, we cross-validate tax data with other sources, such as Tax Foundation, Tax Policy Center, OTPR's World Tax Database, CDC, and the Federation of Tax Administrators. We complement this information with corresponding federal tax rates.

Since we are interested in understanding the timing of tax changes, we record the new tax rate in the year it becomes effective even if the change occurs at the end of the calendar year. When focusing on tax changes, for excise taxes, we include all tax decreases but only include tax increases that result in higher rates in real terms relative to the previous change. We do

[7] Our analysis can be extended to include some tax base features: e.g. minimum personal and corporate tax rates, income thresholds for minimum and top tax rates, personal income tax exemptions, whether federal tax liabilities are deductible, state EITC availability, and whether food and prescriptions are exempt from sales taxes.

so to abstract away from tax changes that are legislated to keep up with inflation. Our results, however, are robust to including all tax changes. 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 cancelled and/or changed in magnitude. Finally, we inflation-adjust nominal rates of cigarette, gasoline and alcohol excise taxes using the BLS CPI series.

2.2 Political, Institutional and Demographic Data

We follow the previous literature, summarized in Appendix Table A.1, to identify economic, political, institutional and demographic features that are likely to have importance effects on tax policy. The resulting set of explanatory variables is available in Appendix Table A.2. In this section we briefly summarize the nature of our data, details are available in Appendix Section A.

First, 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 the control of legislatures or 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.

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.[8] 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.

To investigate whether states change their tax rates in response to competition, we identify tax rates in the neighboring states. We considered three approaches to defining neighbors. First, we consider states as neighbors if they share a geographical border. Second, we break down states into nine Census regions and then consider tax changes within each region. Finally, our third and preferred approach is to use migration flows as measure of neighborliness,

[8] 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.

following Baicker (2005). Since tax competition is primarily concerned with out-migration, for each state, we identify five "neighbor" states that accept the largest number of migrants from that state, using 2010 state-to-state migration data from the IRS.

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.

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 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 outstanding debt from Census Annual Survey of State Governments.

The resulting set of economic, political and institutional explanatory variables is summarized in Appendix Table A.2; further data details are described in Appendix Section A.

2.3 Federal 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.[9]

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 1 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.[10]

[9] 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.

[10] 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.

3 Long-Term Trends: Are Tax Rates Converging or Polarizing?

Figures 1 (a) and (b) show average tax rates across 50 states and, when applicable, corresponding federal rates. Two observations stand out. First, the six tax rates considered do not show similar patterns: while the sales tax rate steadily increased over the 70 year period, corporate and income tax rates both increased and decreased, while gasoline and alcohol taxes generally decreased. Cigarette taxes showed the most dramatic growth, tripling between 2000 and 2020. Second, with the exception of cigarette taxes, the most dramatic changes to tax rates happened during 1950-1990. Since approximately 1990, however, average tax rates have remained substantially more stable. The large increases in average rates were both due to adoptions of tax rates by various states and due to actual rate increases – Figures 1 (e) and (f) show similar patterns despite including only states with nonzero tax rates. These figures also show the tax levels of the newly adopted taxes and years when they were introduced. Most adoptions happened before 1970, and in most cases – though not always – taxes are first adopted at rates lower than the prevailing average at the time.

The average tax rates mask substantial heterogeneity in rates across states. Figures 1 (c) and (d) plot the coefficient of variation (CV) – the ratio of the standard deviation to the mean for all 50 states.[11] Figures 1 (c) and (d) show two distinct patterns. For income and sales taxes, we see a dramatic decrease in variation during 1950-1990 and little convergence in rates since then. In contrast, for excise taxes, the coefficient of variation remains relatively stable. Among the six tax rates, alcohol spirit taxes exhibit the largest heterogeneity, followed by personal income and cigarette taxes, then corporate income and sales taxes. Gasoline taxes are most homogenous. The large decrease in heterogeneity of income and sales taxes could either be due to adoptions of these taxes by the states or due to changes of existing rates. Figures 1 (g) and (h) plot the coefficient of variation (CV) for states with nonzero rates only, thus shutting down the extensive margin effect due to adoptions. Figures 1 (g) and

[11] Results are robust to using other measures of convergence, e.g. standard deviation.

(h) show that the 1950-1990 convergence was primarily due to a large number of new tax adoptions rather than convergence of rates. In fact, personal income taxes exhibited increasing heterogeneity through the 1970s. For excise taxes, adoptions played a smaller role.

Our results are consistent and complementary to findings of Rhode and Strumpf (2003) who document a substantial convergence in state policies over the 20th century, but find similar levels of heterogeneity during the 1970-90s. The lack of substantial convergence or divergence in presence of reduced mobility costs is inconsistent both with Tiebout-sorting and race-to-the-bottom competition model predictions, suggesting that these are not the primary drivers of tax policy changes.

Next, to understand the importance of political leanings, we explore how taxes differ across states that predominantly align with Democratic versus Republican party. To do so, we break down states into three groups based on states' pledges in presidential elections. We consider a state a "safe" Republican ("safe" Democratic) state if the state voted for a Republican (Democratic) presidential candidate in every election since 2000 (see Table A.3). All other states are considered swing states. Figure 2 shows mean, median, the 25th and 75th percentiles as well as the minimum and maximum of (a) top personal income tax rates, (b) top corporate tax rates, (c) standard sales tax rates, and inflation-adjusted (d) cigarette excise tax rates, (e) gasoline excise tax rates, and (f) alcohol spirit tax rates over time. Episodes of zero tax rates are omitted. Years of federal recessions are marked by vertical grey bars, and years of respective federal changes are marked by vertical gray lines.

Figure 2 provides several insights. First, most tax rates exhibit a time trend that is largely consistent across Democratic and Republican states. For example, over the 70 year period studied, sales and cigarette taxes generally increased, while gasoline and spirit taxes decreased. Second, Democratic-learning states tend to have higher taxes than Republican-leaning states. This tendency generally applies to the overall distribution of tax rates within these states, and not just to the mean or median. At the same time, states exhibit substantial variation in tax rate levels within a year, even after controlling for their political leanings. Finally, Figure 2 provides little evidence of convergence: we do not see much evidence of convergence between Democratic and Republican states, nor do we see a reduction in variance within each group. Appendix Figure B.1 shows this more formally by plotting the coefficient of variation for each tax series separately for safe Democratic and safe Republican states.

Continuing to focus on states with nonzero rates, Figure 3 plots the difference between Democratic and Republican means. Figure 3 reveals several patterns. For personal, corporate and sales taxes we see an increasing difference in tax rates during the 1970-1980 period, followed by a decrease in heterogeneity during the 1990s. In recent years – since approximately 2000 onward – once again we see an increasing difference between safe Democratic and safe Republican states. Since 2010, top personal and corporate rates are 1.5-2 percentage points higher in Democratic than in Republican states, implying an approximately 30-50% difference in average rates. Appendix Figure B.4 provides additional graphical evidence by showing overlapping distributions of tax rates.

The pattern observed in Figure 3 is generally robust to alternative specifications. Appendix Figure B.2 shows very similar patterns when states with zero tax rates are included, thus allowing for extensive margin effects due to tax adoptions. Figure B.3 considers a different break down of states: instead of using a fixed breakdown, it assigns states to Republican/Democratic group each year depending on the majority of the legislature in that year. Unsurprisingly, the results are more noisy, and the difference between means is smaller but the pattern is similar. Again, we see an increasing polarization in recent years, but less of a difference in 1950-70s, possibly due to the fact that Northern and Southern Democratic states are combined in one group.

Overall, our findings of increasing polarization between Democratic and Republican states suggest that the observed polarization in political discourse indeed translates into polarization in tangible tax policy, resulting in approximately 20% higher taxes in Democratic states as compared to Republican states and shifting of the tax distributions to the extremes. However, the timing of the divergence does not perfectly align with the onset of polarization in public preferences in the 1970s (McCarty et al. (2016)). Divergence appears to start from prior to 1960s and increased in the most recent decade. Furthermore, we see no evidence of convergence within Republican/Democratic states.

Figure 2 does not allow us to see which states are driving the observed trends or whether states tend to change tax rates gradually over time versus allow tax rates to fluctuate within a certain range. To explore this, we compare average tax rates in 1950-1970 to tax rates in 1971-1999 and in 2000-2020. We then identify three categories of states: (1) those whose tax rates increased over the three periods by more than 2 percentage points total, (2) those whose tax rates decreased by more than 2 pp total, (3) those whose tax rates fluctuated, meaning the 1971-1999 average rate was either above or below both 1950-1970 and 2000-2020 averages. We ignore tax adoptions and only consider nonzero tax rates. Groupings are summarized in Table 2 for top personal income tax rate, top corporate rate and sales tax rates.[12] Several observations are notable. First, during the 70 year period, roughly half of the states kept their tax rates within 2pp range. Second, for sales and corporate taxes, we mostly observe an increasing trend, while for personal income tax there a number of large fluctuations. Third, there does not appear to be any relationship between tax trends: different states change different tax rates, and states do not appear to substitute one tax with another, or on the opposite, increase or cut tax rates across all types. Finally, consistently with evidence in Figure 2, there does not appear a strong relationship between the trend and the state's political tendency.

Figure 4 explores to what extent states differ in how often they change tax rates and how. Figure 4(a) orders states by total number of personal, corporate, sales, cigarette, gasoline, and spirit tax changes. For excise taxes, we include all tax decreases but only include tax increases that result in higher rates in real terms relative to the previous change. We do so to abstract away from tax changes that are legislated to keep up with inflation, but we find that

[12] Appendix Figure B.5 shows the actual time series for each state.

this restriction does not affect our results qualitatively. The number of changes vary dramatically: over the 70 year period studied, the five least active states – AL, AK, LA, WY and VA – changed the six tax rates less than 15 times. On the other hand, most active states – CT, RI, NC, NE and NY changed their taxes more than 50 times, i.e. in 80% of years. Since personal income tax changes account for the bulk of changes, states that do not have personal income taxes (AK, FL, NH, NV, SD, TN, TX, WA, WY) appear to be less active than others. In general, states that do not have certain taxes – sales taxes (AK, DE, MT, NH, OR) or corporate taxes (NV, OH, SD, TX, WA, WY) – appear to be less likely to change tax rates than states that have all five types of taxes.

Figure 4(b) explores whether tax increases and decreases tend to happen in different states or in different time periods. For most states, we see a roughly equal number of tax increases before 1985 and after 1985, however tax decreases are substantially more common since 1985 than prior to 1985. Three states – AL, TX and TN never cut the six tax rates considered in this paper, while also raising the tax rates much less than average. Finally, Figure 4(c) explores whether states that change their tax rates frequently tend to make smaller changes when compared to states that change their taxes infrequently. This may happen if some states prefer to adjust their rates gradually instead of making large occasional adjustments. Figure 4(c) shows no relationship between the frequency of tax changes and tax change magnitude, thus implying that states differ in the levels of tax policy volatility, rather their implementation of tax changes.

Finally, focusing on the timing of tax changes, Figure 5 shows the percent of states that increase (resp. decrease) the tax rate in a given year, and the average magnitude of tax increase (resp. decrease) in percentage points.[13] The key insight from these graphs is that there appears to be no well-defined pattern for tax changes. For example, we do not see a consistent clustering of tax increases or decreases in years of federal recessions or around federal tax

[13] The percent of states that change the tax rate is conditional on already having the tax. The average magnitude is further conditional on a change occurring.

changes, nor do we see clustering of tax changes in general, as would happen in the case of fierce state competition. Second, we see that income tax rates and sales tax rates change much more frequently than excise tax rates. While Democratic-leaning states tend to increase taxes more often than Republican ones, both groups increase and decrease their taxes over time. Appendix Figure B.7 further shows that our conclusions remain unchanged if we focus on 50% largest tax changes instead of including all changes, large and small.

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

In this section we explore to what extent the substantial heterogeneity in tax rates over time documented in Section 3 can be explained by economic and political causes or is driven by institutional rules discussed in the previous literature. We consider three types of influences on tax changes: economic needs, such as interstate tax competition, economic downturns and federal mandates; political incentives, such as election cycles, and changes of governing parties; and institutional rules, such as balanced budget provisions, terms limits, legislature size, session duration, and voter initiative rules. In this section, we omit alcohol spirit taxes from our analysis because tax changes are very infrequent.

4.1 Competition, Recessions, Mandates

To understand whether taxes respond to economic needs, we explore to what extent tax changes occur simultaneously or following economic changes. Of course, such co-occurrences need not be causal in nature, and may occur by pure chance, especially, if tax changes are numerous as is the case for top personal income taxes. For this reason, we supplement the observed coincidence rates with simulated ones, which are calculated as follows: we keep the number of tax changes fixed but randomize their timing. We then calculate the number of random matches. We repeat this procedure 100 times and then show the average number of simulated coincidences, as well as the 5th and 95th percentiles. For excise tax changes, we include all tax decreases but only include tax increases that result in higher rates in real terms relative to the previous change. We do so to abstract away from tax changes that are legislated to keep up with inflation. Our results, however, are robust to including all tax changes.

The above exercise does not prove the existence of causal responses when the observed co-occurrences greatly exceed simulated rates. However, it provides evidence against such causal relationship in cases where the observed co-occurrence matches the simulated rate, which is what we find in many cases. We now describe how we measure co-occurrences in the data.

Tax Competition. Tax competition has long been seen as a likely force behind state tax changes. While tax competition could in principle be responsible for both tax increases and tax decreases, it is typically predicted to drive tax rates down. To investigate whether states change their tax rates in response to competition, we identify tax changes in the neighboring states. Our preferred approach to define neighbors relies on migration flows, following Baicker (2005). Since tax competition is primarily concerned with out-migration, for each state, we identify five "neighbor" states that accept the largest number of migrants from that state, and use those states' tax changes in our analysis. Tax changes that were motivated by tax competition are likely to *follow* neighbors' tax changes. However, because legislative process is slow yet observable, we focus on tax changes that occur simultaneously and/or follow neighbors' tax changes; or occur within a set number of years of neighbors' tax changes. We find that our results are qualitatively robust to the choice and type of time-window studied and the measure of neighborliness.

Our approach thus differs from the previous literature that generally focused on identifying a causal relationship between neighboring states' tax rate levels (e.g. Devereux et al. (2007)). Instead, we focus on the timing of tax changes, as we believe this presents a stronger test of competition-driven responses, since similarity in tax rates levels may represent similarity in preferences in nearby jurisdictions.

Recessions. Economic downturns may force states to increase or decrease taxes in order to collect more revenue or to stimulate state economy. To the extent that states are generally required to balance their budgets on the yearly basis, tax rate increases are more likely. The extent of responses, however, is likely to depend on the nature of the balanced budget rules of a given state. An average state recession episode lasts 2.2 years. Since revenue needs and stimulus incentives are time-sensitive, we expect economic-downturn-driven tax changes to occur during the recession years. As a further robustness check, we also allow tax changes to occur during or 1 year after the recession.

Federal Mandates. Unfunded federal mandates may impose significant revenue burdens, requiring states to raise more tax revenue – and thus increase their tax rates – in order to finance mandate-related expenditures. We consider federal mandates summarized in Table 1. Most mandates became effective within two years of their enactment. For this reason, we focus on tax changes that occur in the year of enactment or in the year of becoming effective, as well as on tax changes that occur during the enacted-effective window for mandates that became effective within three years of enactment.

Figure 6 shows the percent of all tax changes that occur (a) following neighbors' tax change, (b) during a state recession, and (c) upon implementation of a federal mandate. In each figure and for each tax type, the top bar shows the actual percent of tax changes that coincide with the studied event, while the bottom (gray) bar shows the simulated mean. Since Democratic and Republican states may differ in their responses, we calculate all statistics separately for "safe" Democratic and "safe" Republican states, as previously defined (Table A.3). Appendix Figure B.8 shows that our results are robust to the choice of window, while Figure B.9 shows that results are similar when focusing on largest 50% of tax changes.

Figures 6(a) and (b) show some support to the notion that competition may affect tax policy – for a number of tax types, we see that taxes are more likely to be implemented following a change in neighbors' taxes. For sales as well as gasoline and cigarette taxes, we see that tax changes are more common after a neighbors' tax change than a pure coincidence would predict.

However, the changes in personal and corporate income taxes appear to be purely coincidental. One possibility is that purchases of goods are perceived by state legislatures to be more responsive, due to temporary travel across borders, than the location of personal or corporate income.

Figures 6(c) and (d) explore what share of tax changes occur during recessions: between 7% and 27% of tax changes occur during the years of recessions. Interestingly, Democratic states appear to be more active during recession episodes. Nonetheless, most of these occurrences appear to be coincidental: the observed shares are very similar in magnitude to simulated shares. While Figures 6(c) and (d) tell us what share of tax changes could in principle be explained by recessions, they do not provide us a clear answer as to whether recessions necessitate tax changes, since the observed occurrences depend on the frequency of recessions. Figure 7 explores this question further by showing the share of recession episodes that lead to a tax change, separately for episodes of state-specific recessions and federal recessions. Personal income tax rates change in 10-29% of state recessions, corporate taxes are changed in 20-25% of cases, while sales taxes are changed in 12-27% of recessions. Once again, Republican states appear to be less active than Democratic states in response to recessions. Overall, Figures 6(c)-(d) and Figure 7 provide suggestive evidence that most tax changes are unlikely to be driven by ongoing recessions.

Finally, Figures 6(e) and (f) explore what share of tax changes occur in response to federal mandates. For both Democratic and Republican states we see no difference between the observed co-occurrence rates and the simulated, suggesting that the federal mandates are unlikely to result in timely tax changes. To the extent that federal mandates are frequent (a new mandate was introduced or became effective in 40% of years), they are likely to influence tax policy but not in an urgent way.

Figures 6-7 explore the frequency of tax changes but not their direction. Figure 8 explores whether the tax changes that coincide with neighbors' tax changes, recessions and federal mandates are tax increases or decreases. Once again, we show these responses separately for Democratic- and Republican-leaning states. As a point of comparison, Figures (a) and (b) show the composition of tax changes in all years.

Several key observations stand out: neighboring states' changes are generally followed with tax changes in the same direction, but not always. Importantly, many of the changes are increases, rather than decreases, and the relative share of decreases/increases approximately matches the averages in the top panel. During recessions, Democratic states appear to be more likely to raise personal taxes but lower corporate and gasoline taxes, while Republican states tend to increase income taxes and lower sales and gasoline taxes.

4.2 Party Control Changes and Election Cycles

Next we explore to what extent tax changes appear to be driven by political incentives. Previous research has documented that governments can be more or less successful at passing reforms when having full versus partial control of the legislative chambers and governorship (Roubini and Sachs (1989), McCubbins (1991), Alt and Lowry (1994), Castanheira et al. (2012), Bernecker (2016)). We start by exploring whether tax changes primarily occur after majority party switches, and whether tax changes are more likely to happen when one party holds majority in both chambers of legislatures and of the governorship. The top row of Figure 9(a) shows the breakdown of party affiliations of the House majority, Senate majority and Governor during the 70 year period we study. In 53% of observations, a given party holds majority in all three offices, and roughly one fifth of these (11%) represent first term years after one of the majorities was switched. In 28% of observations, the House and Senate majorities coincide but differ from governor's party affiliation. Finally, 18% of observations represent years with divided House and Senate majorities.

The overall shares of the top row can be compared to shares of political structures when tax changes occur. Since the shares in all rows of Figure 9(a) are quite similar, this suggests that tax changes are not disproportionately likely to occur when party controls change. A small exception to this rule are changes of sales tax rates: these are less likely to occur during periods of divided governments but the differences are relatively small. This finding is perhaps not surprising in light of the fact that Republicans or Democrats hold the majority of both legislative chambers in 82% of years, providing them with ample opportunities for changes. The results are similar, when looking separately at safe Democratic and Republican states (Figure 9(b) and (c)), or when focusing on the 50% largest tax changes (Appendix Figure B.10). Appendix Figure B.11 suggests, however, that there are some heterogeneities across Republican and Democratic states when considering tax increases and decreases separately.

Next, Figure 10 explores to what extent presidential elections affect states' tax policies. Specifically, we break states into four categories based on whether the state is "happy" or "upset" about the election outcome (i.e. whether the winning presidential candidate won in the state or lost), and whether the winning candidate matches the majority party of the state's legislatures (both lower and upper chambers). The top row summarizes the share of years a given outcome occurs, which then can be compared to shares when given tax changes occur.[14] Figure 10 shows two notable patterns: states that vote for a Republican candidate that loses are significantly less likely to pass a tax increase of any tax type. Interestingly, this happens irrespective of whether the Republicans hold a majority in the state's legislature or not. We see the opposite pattern for states that vote for Democratic candidates: they are more likely to pass tax increases when their preferred candidate loses. The observed pattern is thus consistent with polarization in tax policy and may represent a response to *anticipated* federal tax policies.

Previous work has also documented notable relationships between fiscal policies and election cycles, suggesting that political incentives often play a more important role than economic needs (Mikesell (1978), Rosenberg (1992), Nelson (2000), Ashworth et al. (2006), Rose (2006), Veiga and Veiga (2007), Katsimi and Sarantides (2012), Foremny and Riedel (2014), Chang et al.

[14] For example, for state-year observations that vote for a Democratic nominee, 56% result in that candidate winning and 44% losing. In 62% of states voting for a Democratic candidate, states' legislative majority was Democratic.

(2020)). Figure 11 explores whether election cycles drive observed tax changes. Each figure shows the share of tax changes that occur in each year of the election cycle, where year 1 represents the first year *after election*, while year 2 and year 4 represent election years in 2-year and 4-year election cycles respectively. We see a small increase in tax changes in the year before the presidential and gubernatorial elections and a slight increase in tax changes the first year after gubernatorial elections but the differences are small. Overall, Figure 11 suggests that election cycles – whether presidential, gubernatorial, or legislative – are unlikely to drive the timing of tax changes in the U.S., since tax changes are roughly equally spread out across years. Appendix Figure B.12 and B.13 provide similar evidence separately for tax increases and tax decreases.

4.3 Institutional Influences

Finally, institutional rules such as term limits, legislature size, voter initiative rules and balanced budget rules may impede or encourage tax changes. Figure 12 explores whether tax changes are more likely to occur in states with certain types of institutional rules. Overall, Figure 12 suggest that these rules are likely to have indirect effects on tax policy rather than driving it. We do not see any systematic or dramatic differences in the number of tax changes across different types of institutions. The only exception appears to be deficit rule: states that allow deficits are significantly more like to change their taxes. Appendix Figures B.14 and B.15 show that these changes include both tax increases and tax decreases. Rainy day funds are also correlated with more frequent tax changes, but the evidence is not as robust.

5 How Much of Tax Policy Can We Explain Overall? A Comprehensive Approach

In this section we take a comprehensive approach to try to explain the observed variation in the timing and magnitude of tax changes. In contrast to previous work that focused on seeking out individual causal relationships, we consider numerous influences together instead of emphasizing a specific channel. We start by creating a comprehensive summary of plausible tax determinants identified in the previous work and summarized in Appendix Table A.1. This allows us to identify an extensive list of explanatory variables that we use in our analysis, summarized in Appendix Table A.2. Altogether, these variables paint a detailed picture of the economic, political and institutional situation of the states.

We then explore to what extent our explanatory variables are able to explain the observed variation in tax policy. We start by using a simple linear regression model to investigate the explanatory power of identified variables. The advantage of this approach is that it allows us to explore the relative explanatory power of chosen variables. It is possible and likely, however, that the relationship between economic, institutional and political factors and state tax policies is more nuanced than the simple linear model would allow for. For this reason, we then turn to machine learning techniques to allow for more flexible modeling approaches, including both supervised algorithms and unsupervised clustering techniques.

5.1 Simple Linear Model and Variance Decomposition

We start by using a simple linear regression model. Because our explanatory variables are not orthogonal, most covariates contribute to the explanatory power in a non-unique way. For this reason, we use a Shapley decomposition method to assign each group of variable's contribution to the overall explanatory power, measured by the R^2. We consider 11 groups of explanatory variables. First, we account for a linear time trend, and second, for 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. Third, we account for economic influences: federal and state-level recessions and federal mandates. Next, we consider three sets of state institutional features which cover both time-invariant rules such as size of legislatures, balanced budget provisions, as well as time-variant rules such as existence of rainy day funds and term limits. Our seventh group accounts for political influences: party of legislatures' majorities and governorship and their strength, number of party switches, whether this is the first year of new party in charge, state and federal government shutdowns, outcomes of presidential elections. Eighth, we include variables that measure neighboring states' (top income, top corporate, sales, cigarette, gasoline and alcohol) tax policies – average tax rates of the neighbor and indicators of tax changes. Ninth, we control for other tax rates in the state, including lagged values. Tenth, we include state demographics: population measures (total, labor force, employment to population, density), unemployment rates, 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. Our last 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. Finally, for completeness we also measure how the R^2 increases when state and year fixed effects are included, to account for remaining time-invariant state characteristics and state-invariant time effects. The exact list of 129 included variables is available in Appendix Table A.2.

Variance decomposition results are summarized in Figures 13-14, which show the shares of total explained variation attributed to the above-mentioned groups of explanatory variables. Figure 13(a) summarizes decomposition of tax rate levels (in pp or in 2020 dollars), while 13(b) and (c) show tax changes in dollars or pp (all or largest 50% of tax changes). Figure 14 focuses on the timing of tax changes, and thus perform decomposition of indicators of tax rate increases and decreases respectively, looking at all tax changes (figures (a) and (b)) or the largest 50% of changes (figures (c) and (d)).

We find that nearly all of the *tax rate level* variation can be explained with our chosen variables. However, most of explanatory power comes from lagged own tax rate and past (1995) tax rates. Put simply, past tax rates do an excellent job of predicting future tax rate levels since taxes rarely change dramatically. Most importantly, this decomposition does not distinguish between within-state variation and across-state variation and therefore 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* and the *timing of tax changes* is significantly weaker. For example, the explanatory power decreases to under 20%, with a non-trivial share attributed to state and year fixed effects. Unsurprisingly, when focusing on the magnitude of tax changes, past tax rates play a less important roles. Instead, federal tax rates, political and demographic factors increase in relative importance. We see some variation in the relative importance of factors for different tax rates, the overall ranking is generally consistent across tax types.

Our ability to explain the timing of tax changes is equally weak – at most 30% or less. Interestingly, the tax increases and decreases appear to be influenced by different factors. For example, tax increases are substantially more influenced by federal tax policy than tax decreases. Similarly, economic factors (recessions and mandates), other tax rate levels are more important for tax increases. Political factors are important for both and account for less than one quarter of overall explanatory power.

5.2 Enriched Models Using LASSO and Random Forest

The results of Section 5.1 showed that a simple model does a poor job explaining the timing and magnitude of tax changes. While we have collected extensive information about the institutional, political and economic environment of the states, our model so far only allowed for simplest relationships between these variables and tax policy. In this section, we consider a richer set of models, by allowing for interactive terms in our models. We use two approaches: LASSO and Random Forest.

Since it is not possible nor desirable to include all of the possible variables in the analysis, we employ LASSO techniques to select the model with best predictive powers. The LASSO approach selects a model that minimizes the prediction error while keeping the model not too complex by including a penalty parameter that increases in model complexity. The practical implementations of the LASSO method varies in penalty functional forms approaches to determining the optimal model. 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 models yield similar qualitative results.

Random forest is another 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 3 summarizes our results. As our baseline comparison we take the models from Section 5.1 which included 129 "core" variables. Next, we use LASSO to select the best model using an extended set of variables: all interactions created using our 129 variables as well as 8 decade indicators – a total of 22,455 variables. Finally, the random forest algorithm uses all 129 core variables, the 8 decade indicators as well as 2nd and 3rd degree powers of all non-indicator, non-tax variables – a total of 196 variables (note that the random forest algorithm automatically explores variable interactions via its "tree" structure). The results summarized in Table 3 are based on 100 random splits of the data into a training sample (80%) and a test sample. We must note that both LASSO and random forest algorithms require a number of choices made by a researcher, Table 3 presents the results from the "most promising" specifications. While the quantitative results vary depending on specification, the qualitative results do not.

Table 3 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%.

Overall, we find that tax policy is not well explained by the economic, institutional and political factors that we accounted for in this study. It is unlikely that the low predictive power is due to misspecification, as we consider both interaction terms and nonlinear specifications. Instead, it suggests that other factors – not considered by us – may drive tax policy or that tax policy is truly idiosyncratic.

5.3 Using Machine Learning to Group States

In this section, instead of trying to predict state tax policies, we use machine-learning techniques to identify groups of states with similar tax structures. We will group states based on similarities in 6 key tax types: top personal income and corporate rates, sales tax rate, gasoline, cigarette and alcohol spirit excise rates. Since states change their policies over time, we will allow states to belong to different groups in different years, thus treating each state-year observation as a separate unit.

Since the grouping algorithms organize the data based on similarity of the grouping variables only, the algorithm is agnostic to what causes the formation of such groups. The nature of the groupings can then be explored by seeking relationship between identified groups and plausible causes. For this reason, this group of machine learning techniques is called "unsupervised," as their goal is to discover hidden patterns in the data without researcher's involvement. We use two techniques to identify state groups: a partitioning method and a hierarchical clustering method.

Partitioning method – k-means algorithm. The intuition behind k-means approach is very simple: the algorithm partitions the data into K clusters, such that the units within each cluster are similar, but they are dissimilar to units in other clusters. Units' similarity is measured by distance, which can be calculated in various ways – absolute value distance, Euclidian distance, etc. The algorithm starts by randomly choosing cluster centroids and then assigning each data point to the closest centroid. Cluster centroids are then re-calculated based on the mean value of points within each cluster, after which points are again re-assigned to closest clusters. The process iterates until no changes in cluster assignments are needed.

The k-means algorithm performs well when the underlying data features (multi-dimensional) spherical clusters of approximately even size that are well-spaced out, and does not perform well when the nature of clusters is more complex or when clusters are highly uneven in size. Furthermore, the clustering approach is not stable in the number of clusters K, in a sense that the resulting clusters may group different units for different choices of K. Finally, finding the globally optimal solution to a k-means problem is practically infeasible even for a small number of clusters or data points. The practical implementation, therefore, searches for local minima which often results in incorrect clustering.

Applying the k-means approach to state tax rule data does not yield satisfying results: the resulting clusters are not stable and vary wildly depending on the randomly chosen starting point. The results are not stable irrespective of the number of clusters chosen, the choice of distance measure, and irrespective of the years included (e.g. using all state-year observations or running k-means separately on each year or decade of years). The failure of the k-means approach is likely due to one of three reasons: (1) the true clusters are not spherical in nature, (2) the clusters are of uneven size, and/or (3) the data is not truly clustered.

Hierarchical clustering method – bottom-up Ward algorithm. In contrast to k-means approach that requires the researcher to specify the number of clusters in advance, the hierarchical approach groups observations in a sequential manner resulting in stable group assignments. The algorithm starts by assigning each observation to its own cluster, thus "partitioning" the N data points into N clusters. Then the algorithm merges two closest clusters, thus partitioning the data into $N-1$ clusters. The algorithms proceeds merging clusters sequentially until all clusters are merged into one cluster. Various measures can be used to measure distances between clusters: e.g. single linkage measures the shortest distance between any one point in one cluster and any point in another cluster, while the complete linkage measures the opposite

– the farthest distance between any two points. In our implementation, we use Ward method which measures the sum of square of the distances (i.e. the variance).

Hierarchical approach is simple, fairly consistent in its implementation and presents a hierarchy that can be used to select the number of clusters. The algorithm, however, suffers from several disadvantages. First, it provides very different results depending on the linkage method, with some linkage methods resulting in undesirable clustering. Second, the sequential nature of the algorithm does not allow for correction of mistakes made in the previous steps, which can again result in undesirable cluster selections.

Applying Ward hierarchical clustering method to our data results in groupings summarized in Table 4 for seven groups.[15] Since states can move between groups, Table 4 lists states that belong to a given group for at least 18 out of 20 year in 1950-1969 or in 2001-2020, or for at least 28 years out of 31 in 1970-2000, thus also describing the movement of states across groups. The first column of the table shows average tax rates in each group, irrespective of years. Several observations stand out. First, only 7 states remained in the same group over the 70 year period – these are WY (group 1); AL, MS, PA, UT, VA (group 2) and OR (group 3). Other states gradually move across groups, typically belonging to 2-3 groups over the years. Second, the algorithm's groupings also suggest that tax policy generally changed over time, since several groups are predominantly comprised of state-year observations in the first half (group 6 and 7) or the second half (group 3, 4 and especially 5) of the period. Third, we see that groups are not cleanly split by party dominance. While the first two groups include many safe Republican states, other groups are mixed, including in 2001-2020 years, the period we used to define safe Republican and Democratic states.

[15] These seven groups can be further split into subgroups, we focus on 7 groups for conciseness.

6 Conclusion

In this paper we explore determinants of state tax policy in the past 70 years. We document that while tax policy shows a fair amount of persistence over time, it also shows a tremendous amount of variation, both across states, and within states over time, including signs of increasing polarization between Democratic and Republican states. We consider numerous explanations for observed variation – economic, political and institutional influences – but conclude that most tax changes are difficult to predict. Overall, our best attempts explain less than 20% of observed tax variation, suggesting that more work needs to be done to understand the drivers behind state tax policy.

What are the possible explanations for the low predictive power? 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 the literature has largely focused on. Alternatively, policymakers may be evenly split in their preferences, making policy decisions highly unpredictable, as our conceptual framework demonstrated. Finally, it is also possible that the legislative process for tax policy may be so complex that 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. More work is needed to explore the nature of omitted explanatory factors and the source of idiosyncratic shocks. Since tax policy has direct consequences on state tax revenue and business cycle volatility, and can lead to policy uncertainty, excess tax volatility can have detrimental effects on growth and the welfare of state residents.

References

Aizenman, Joshua, Yothin Jinjarak, Hien Nguyen, and Ilan Noy, "The Political Economy of the COVID-19 Fiscal Stimulus Packages of 2020," NBER Working Paper 29360 October 2021.

Alesina, Alberto, Nouriel Roubini, and Gerald D. Cohen, *Political Cycles and the Macroeconomy*, MIT Press, 1997.

Alt, James E. and Robert C. Lowry, "Divided government, fiscal institutions, and budget deficits: Evidence from the states," *American Political Science Review*, 1994, pp. 811–828.

Asatryan, Zareh, Thushyanthan Baskaran, and Friedrich Heinemann, "The effect of direct democracy on the level and structure of local taxes," *Regional Science and Urban Economics*, July 2017, *65*, 38–55.

_ , _ , Theocharis Grigoriadis, and Friedrich Heinemann, "Direct Democracy and Local Public Finances under Cooperative Federalism," *The Scandinavian Journal of Economics*, 2017, *119* (3), 801–820. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/sjoe.12169.

Ashworth, John, Benny Geys, and Bruno Heyndels, "Determinants of tax innovation: The case of environmental taxes in Flemish municipalities," *European Journal of Political Economy*, March 2006, *22* (1), 223–247.

Baicker, Katherine, "The spillover effects of state spending," *Journal of Public Economics*, February 2005, *89* (2), 529–544.

_ , Jeffrey Clemens, and Monica Singhal, "The rise of the states: US fiscal decentralization in the postwar period," *Journal of Public Economics*, 2012, *96* (11-12), 1079–1091.

Baker, Scott R., Nicholas Bloom, Brandice Canes-Wrone, Steven J. Davis, and Jonathan Rodden, "Why Has US Policy Uncertainty Risen since 1960?," *American Economic Review*, May 2014, *104* (5), 56–60.

_ **, Pawel Janas, and Lorenz Kueng**, "Correlation in State and Local Tax Changes," *Available at SSRN 3648513*, 2020.

Bernecker, Andreas, "Divided we reform? Evidence from US welfare policies," *Journal of Public Economics*, October 2016, *142*, 24–38.

Besley, Timothy and Anne Case, "Does Electoral Accountability Affect Economic Policy Choices? Evidence from Gubernatorial Term Limits," *The Quarterly Journal of Economics*, August 1995, *110* (3), 769–798.

_ **and** _ , "Incumbent Behavior: Vote-Seeking, Tax-Setting, and Yardstick Competition," *The American Economic Review*, 1995, *85* (1), 25–45. Publisher: American Economic Association.

Besley, Timothy J. and Harvey S. Rosen, "Vertical externalities in tax setting: evidence from gasoline and cigarettes," *Journal of Public Economics*, 1998, *70* (3), 383–398.

Binder, Sarah A., *Stalemate: Causes and Consequences of Legislative Gridlock*, Brookings Institution Press, May 2004.

Bjrnskov, Christian and Niklas Potrafke, "The size and scope of government in the US states: does party ideology matter?," *International Tax and Public Finance*, August 2013, *20* (4), 687–714.

Boadway, Robin and Jean-Franois Tremblay, "Reassessment of the Tiebout model," *Journal of Public Economics*, 2012, *96* (11-12), 1063–1078.

Bordignon, Massimo, Floriana Cerniglia, and Federico Revelli, "In search of yardstick competition: a spatial analysis of Italian municipality property tax setting," *Journal of Urban Economics*, September 2003, *54* (2), 199–217.

Bozzano, Monica, Paola Profeta, Riccardo Puglisi, and Simona Scabrosetti, "Women' Voice on Redistribution: From Gender Norms to Taxation," SSRN Scholarly Paper ID 3819099, Social Science Research Network, Rochester, NY 2021.

Buettner, Thiess, "Tax base effects and fiscal externalities of local capital taxation: evidence from a panel of German jurisdictions," *Journal of Urban Economics*, July 2003, *54* (1), 110–128.

Case, Anne C., Harvey S. Rosen, and James R. Hines, "Budget spillovers and fiscal policy interdependence: Evidence from the states," *Journal of Public Economics*, October 1993, *52* (3), 285–307.

Castanheira, Micael, Gatan Nicodme, and Paola Profeta, "On the political economics of tax reforms: survey and empirical assessment," *International Tax and Public Finance*, 2012, *19* (4), 598–624.

Chang, Andrew C., Linda Cohen, Amihai Glazer, and Urbashee Paul, "Politicians avoid tax increases around elections," *Available at SSRN*, 2020.

Chirinko, Robert S. and Daniel J. Wilson, "Tax competition among U.S. states: Racing to the bottom or riding on a seesaw?," *Journal of Public Economics*, November 2017, *155*, 147–163.

Congressional Research Service, "Unfunded Mandates Reform Act: History, Impact, and Issues," Technical Report CRS Report R40957 2020.

Deskins, John and Brian Hill, "Have State Tax Interdependencies Changed Over Time?," *Public Finance Review*, March 2010, *38* (2), 244–270. Publisher: SAGE Publications Inc.

Devereux, Michael P., Ben Lockwood, and Michela Redoano, "Horizontal and vertical indirect tax competition: Theory and some evidence from the USA," *Journal of Public Economics*, 2007, *91* (3-4), 451–479.

Egger, Peter and Marko Koethenbuerger, "Government Spending and Legislative Organization: Quasi-experimental Evidence from Germany," *American Economic Journal: Applied Economics*, October 2010, *2* (4), 200–212.

Erler, H. Abbie, "Legislative term limits and state spending," *Public Choice*, 2007, *133* (3-4), 479–494.

Ferede, Ergete, Bev Dahlby, and Ebenezer Adjei, "Determinants of statutory tax rate changes by the Canadian provinces," *Economics of Governance*, 2015, *16* (1), 27–51.

Foremny, Dirk and Nadine Riedel, "Business taxes and the electoral cycle," *Journal of Public Economics*, 2014, *115*, 48–61.

Geys, Benny, "Looking across borders: A test of spatial policy interdependence using local government efficiency ratings," *Journal of Urban Economics*, November 2006, *60* (3), 443–462.

Gilligan, Thomas W. and John G. Matsusaka, "Fiscal policy, legislature size, and political parties: Evidence from state and local governments in the first half of the 20th century," *National Tax Journal*, 2001, pp. 57–82.

Goodspeed, Timothy J., "Tax structure in a federation," *Journal of Public Economics*, March 2000, *75* (3), 493–506.

_ , "Tax competition and tax structure in open federal economies: Evidence from OECD countries with implications for the European Union," *European Economic Review*, February 2002, *46* (2), 357–374.

Grumbach, Jacob M., "From Backwaters to Major Policymakers: Policy Polarization in the States, 19702014," *Perspectives on Politics*, June 2018, *16* (2), 416–435.

Gupta, Sanjeev and Joo Tovar Jalles, "On the political economy determinants of tax reforms: evidence from developing countries," Mimeo 2020.

Inman, Robert P. and Michael A. Fitts, "Political Institutions and Fiscal Policy: Evidence from the U.S. Historical Record," *Journal of Law, Economics, and Organization*, 1990, *6* (Special Issue), 79–132.

Kakpo, Eliakim, "On the Political Economy of State Corporate Tax Reforms in the U.S.," *Research in Applied Economics*, August 2019, *11* (3), 25–48. Number: 3.

Katsimi, Margarita and Vassilis Sarantides, "Do elections affect the composition of fiscal policy indeveloped, established democracies?," *Public Choice*, April 2012, *151* (1), 325–362.

Matsusaka, John G., "Fiscal Effects of the Voter Initiative: Evidence from the Last 30 Years," *Journal of Political Economy*, June 1995, *103* (3), 587–623.

_ , "Fiscal effects of the voter initiative in the first half of the twentieth century," *The Journal of Law and Economics*, 2000, *43* (2), 619–650.

McCarty, Nolan, "The Policy Consequences of Political Polarization," in Paul Pierson and Theda Skocpol, eds., *The Transformation of the American Polity*, Princeton University Press, 2007.

_ , Keith T. Poole, and Howard Rosenthal, *Polarized America: The dance of ideology and unequal riches*, second edition ed., MIT Press, 2016.

McCubbins, Mathew D., "Party Governance and U. S. Budget Deficits: Divided Government and Fiscal Stalemate," in "Politics and Economics in the Eighties," University of Chicago Press, 1991, pp. 83–122.

Mian, Atif, Amir Sufi, and Francesco Trebbi, "Resolving Debt Overhang: Political Constraints in the Aftermath of Financial Crises," *American Economic Journal: Macroeconomics*, April 2014, *6* (2), 1–28.

Mikesell, John L., "Election periods and state tax policy cycles," *Public Choice*, 1978, *33* (3), 99–106. Publisher: Springer.

NASBO, "Capital Budgeting in the States," Technical Report, National Association of State Budget Officers 2014.

NCSL, "Fiscal Brief: State Balanced Budged Provisions," Technical Report, National Conference of State Legislatures 2010.

Nelson, Michael A., "Electoral Cycles and the Politics of State Tax Policy," *Public Finance Review*, November 2000, *28* (6), 540–560.

Poterba, James M., "State Responses to Fiscal Crises: The Effects of Budgetary Institutions and Politics," *Journal of Political Economy*, August 1994, *102* (4), 799–821.

Rhode, Paul W. and Koleman S. Strumpf, "Assessing the Importance of Tiebout Sorting: Local Heterogeneity from 1850 to 1990," *American Economic Review*, December 2003, *93* (5), 1648–1677.

Rigby, Elizabeth and Gerald C. Wright, "The Policy Consequences of Party Polarization Evidence from the American States," in James A Thurber and Antoine Yoshinaka, eds., *American Gridlock: The Sources, Character, and Impact of Political Polarization*, Cambridge University Press, 2015.

Rork, Jonathan C., "Coveting Thy Neighbors' Taxation," *National Tax Journal*, December 2003, *56* (4), 775–787.

Rose, Shanna, "Do fiscal rules dampen the political business cycle?," *Public choice*, 2006, *128* (3-4), 407–431. Publisher: Springer.

Rosenberg, Jacob, "Rationality and the political business cycle: The case of local government," *Public Choice*, January 1992, *73* (1), 71–81.

Roubini, Nouriel and Jeffrey D. Sachs, "Political and economic determinants of budget deficits in the industrial democracies," *European Economic Review*, May 1989, *33* (5), 903–933.

Seegert, Nathan, "Tax Revenue Volatility," *Available at SSRN 2789889*, 2016.

Serrato, Juan Carlos Surez and Owen Zidar, "The structure of state corporate taxation and its impact on state tax revenues and economic activity," *Journal of Public Economics*, November 2018, *167*, 158–176.

Slattery, Cailin and Owen Zidar, "Evaluating state and local business incentives," *Journal of Economic Perspectives*, 2020, *34* (2), 90–118.

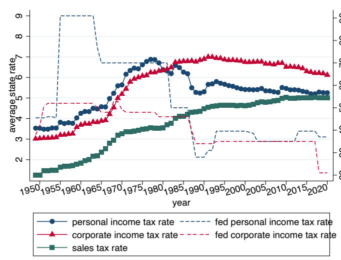
Tiebout, Charles M., "A pure theory of local expenditures," *Journal of Political Economy*, 1956, *64* (5), 416–424.

Veiga, Linda Gonalves and Francisco Jos Veiga, "Political business cycles at the municipal level," *Public Choice*, April 2007, *131* (1), 45–64.

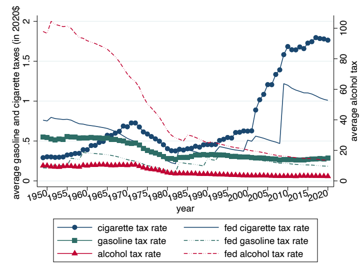
Figure 1: State Tax Rates Over Years

Panel A: All 50 States

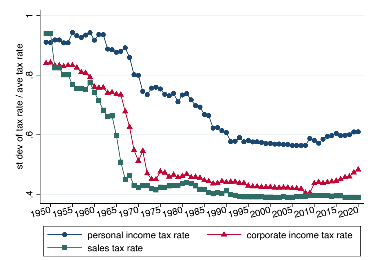
(a) Average Tax Rates



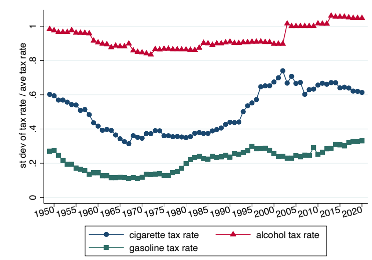
(b) Average Excise Taxes



(c) Heterogeneity

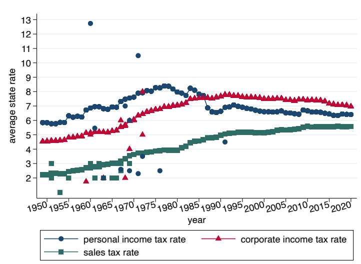


(d) Heterogeneity Excise

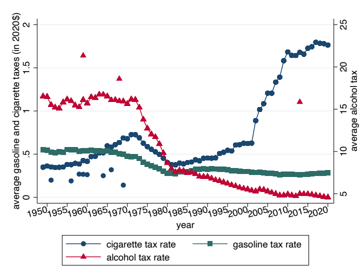


Panel B: States with Nonzero Rates

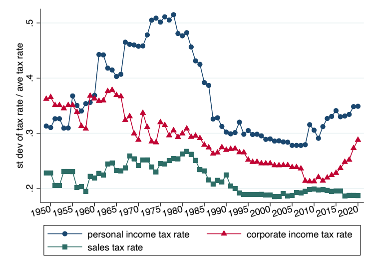
(e) Average Tax Rates



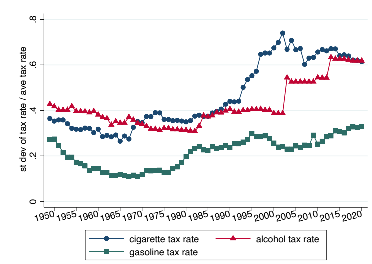
(f) Average Excise Tax Rates



(g) Heterogeneity



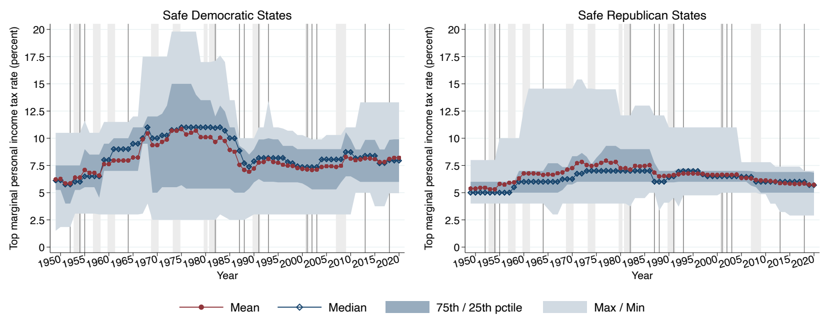
(h) Heterogeneity Excise



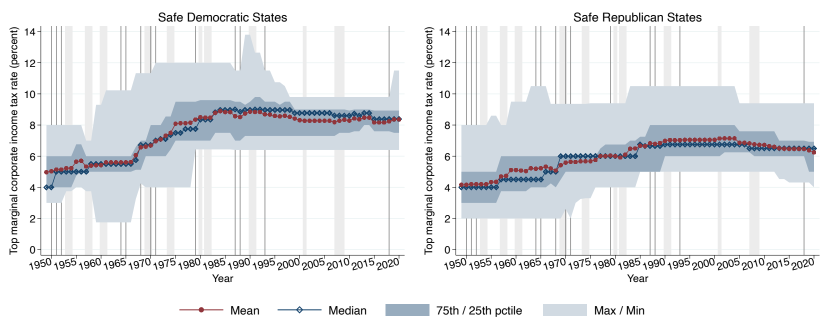
Notes: Figures (a) and (b) show average top personal income and corporate tax rates, sales tax rates, and average cigarette, alcohol (spirit) and gasoline tax rates, as well as corresponding federal tax rates. Figures (c) and (d) show the standard deviation of the state taxes divided by average tax rate (coefficient of variation). All states included, including those with zero rates. Figures (e)-(h) repeat the above but only for states with nonzero rates. Figures (e) and (f) in addition show new tax adoptions: tax rates levels and year of adoption.

Figure 2: State Tax Rates Over Years

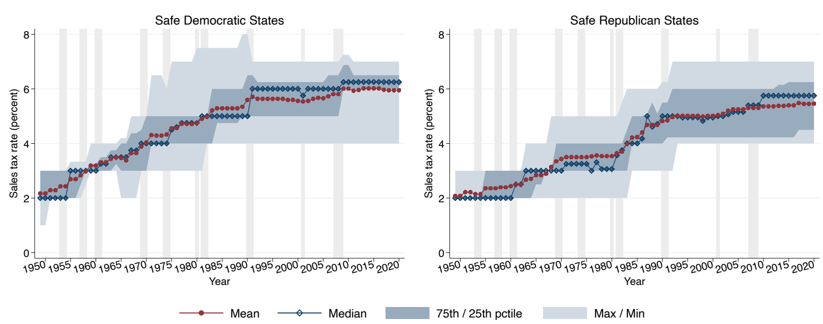
(a) Top Income Tax Rate



(b) Corporate Tax Rate



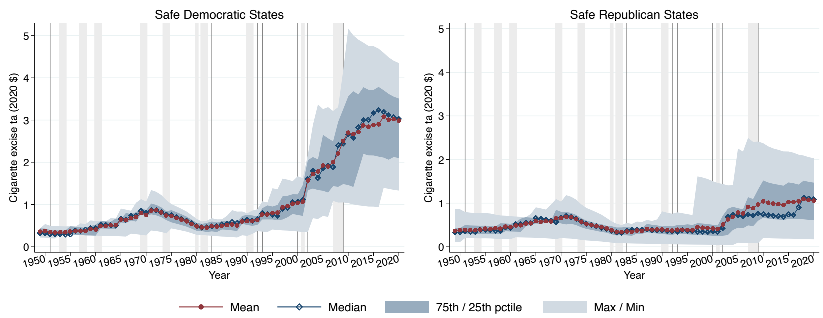
(c) Sales Tax Rate



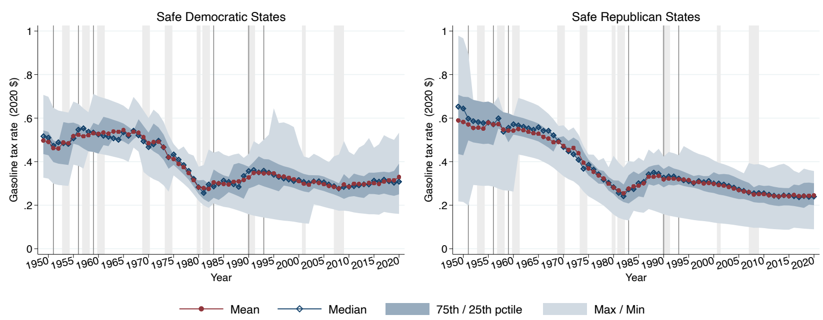
Notes: see next page.

Figure 2: State Tax Rates Over Years, Continued

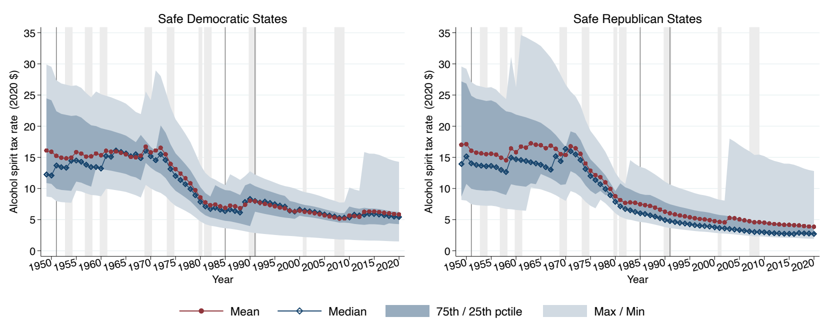
(d) Cigarette Tax



(e) Gasoline Tax



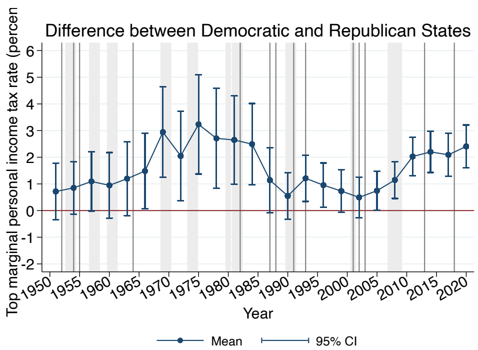
(f) Alcohol Spirit Tax



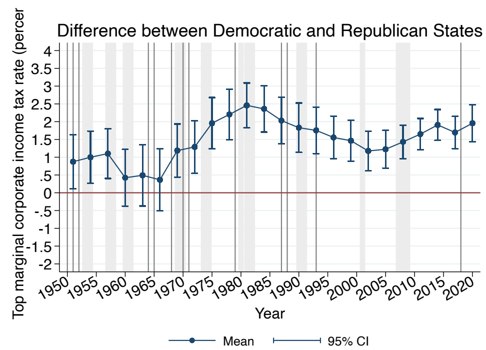
Notes: These figures show average, median, the 25th and 75th percentiles, as well as minimum and maximum of (a) state top income tax rates, (b) state top corporate tax rates, and (c) state standard sales tax rates, all in percent; (d) cigarette excise tax rates, (e) gasoline excise tax rates, (f) spirit excise tax rates, all in 2020 dollars. Only non-zero rates included. These statistics are shown separately for states that have only voted for a Democratic (Republican) presidential candidate since 2000 elections (see Table A.3). Gray bars identify national recessions; while gray lines identify changes in federal tax rates.

Figure 3: Is Tax Policy Becoming More Polarized?

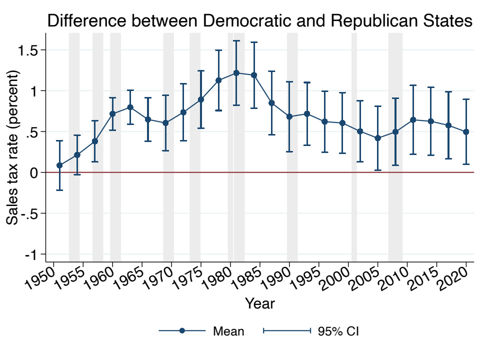
(a) Personal Tax



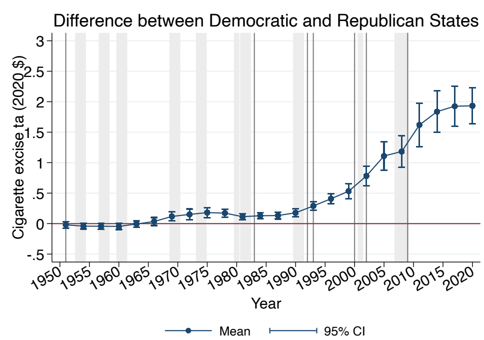
(b) Corporate Tax



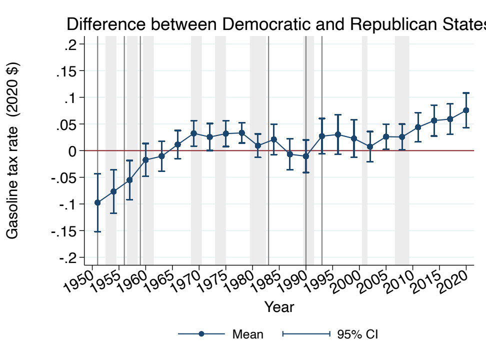
(c) Sales Tax



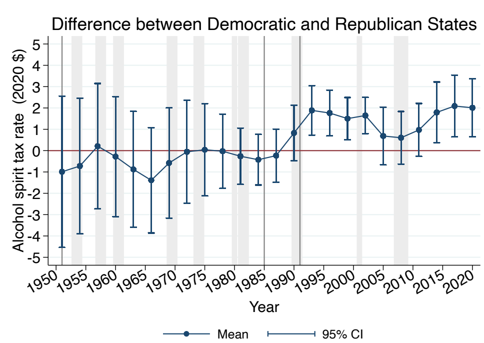
(d) Cigarette Tax



(e) GasolineTax



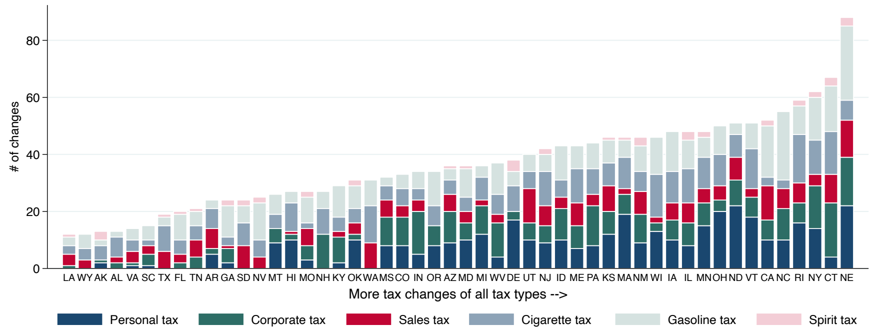
(f) Alcohol Spirit Tax



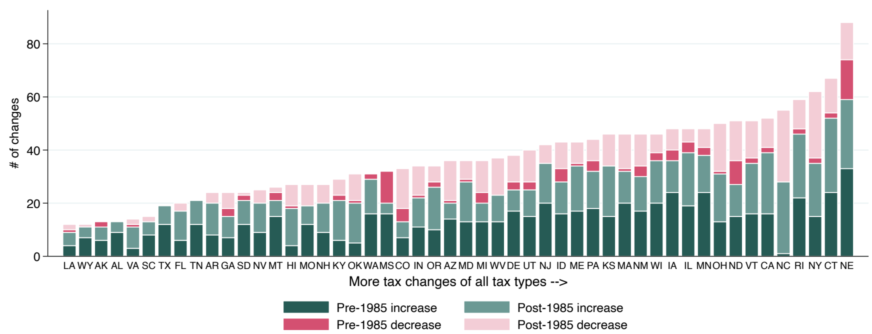
Notes: This figure shows the difference in means and corresponding 95% confidence intervals of tax rates in states that have only voted for a Democratic versus Republican presidential candidate since 2000 elections (see Table A.3). The differences are calculated for non-overlapping 3-year periods (e.g. 2020 value is the average of 2018-2020 values), only nonzero observations are included.

Figure 4: Tax Changes By State

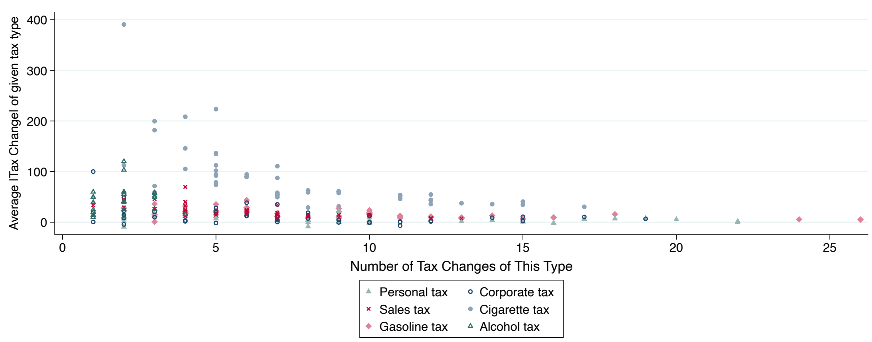
(a) Number of Tax Changes by State and Tax Type



(b) Number of Tax Increases/Decreases by State and Time Period



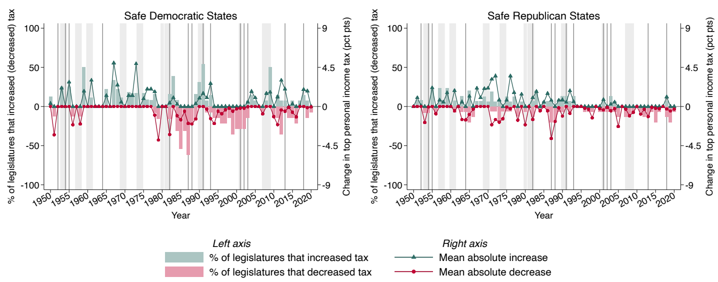
(c) Ave Tax Change vs Number of Tax Changes by Tax Type



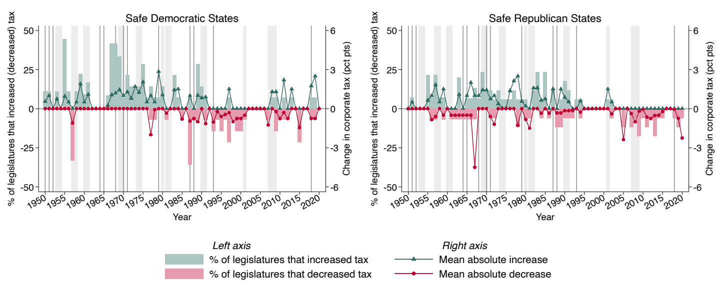
Notes: Figure (a) shows the number of tax changes in each state for six tax rates (top income tax rates, top corporate tax rates, standard sales tax rates, cigarette excise tax rates, gasoline excise tax, and spirit excise tax rates). Figure (b) shows the number tax decreases and increases that occurred for the above six tax rates before and after 1985. Figure (c) shows the relationship between average tax rate change in percent (y-axis) and the number of tax changes, separately for the above six tax rate types.

Figure 5: State Tax Rate Changes Over Years

(a) Top Income Tax Rate



(b) Corporate Tax Rate



(c) Sales Tax Rate

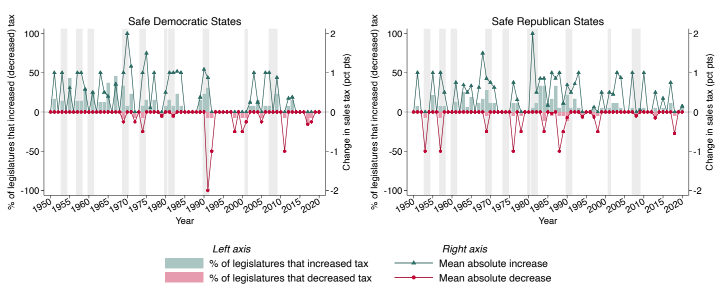
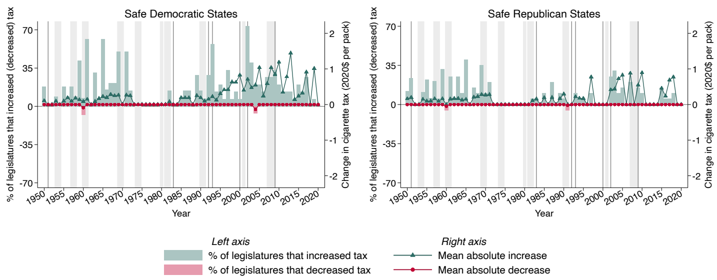
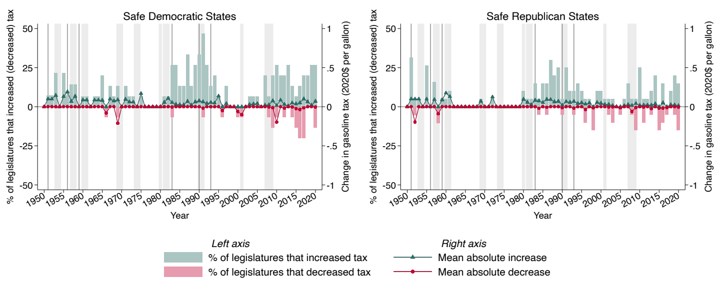


Figure 5: State Tax Rate Changes Over Years, Continued

(d) Cigarette Tax



(e) Gasoline Tax



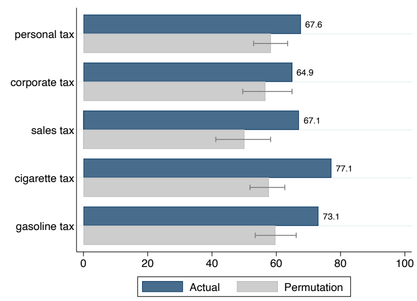
(f) Alcohol Spirit Tax

Notes: Left axis: the upper green bars (lower pink bars) show the percent of states that increase (decrease) their taxes in a given year. Right axis: the triangle series (dot series) show average size of tax increases (decrease) in pp or in 2020 dollars. These statistics are shown for (a) state top income tax rates, (b) state top corporate tax rates, and (c) state standard sales tax rates, (d) cigarette excise tax rates, (e) gasoline excise and (f) spirit excise tax rates. These statistics are shown separately for states that have only voted for a Democratic (Republican) presidential candidate since 2000 elections (see Table A.3). Gray bars identify national recessions; while gray lines identify changes in federal tax rates.

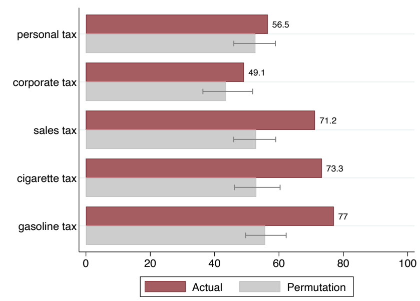
Figure 6: Percent of Tax Changes that Occur in Response to Economic Causes

Left: Safe Democratic States **Right: Safe Republican States**

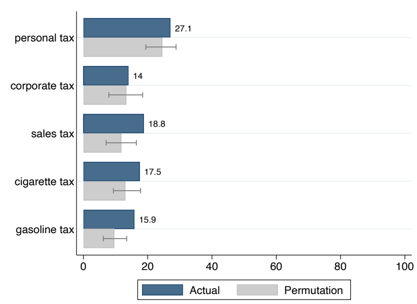
(a) following neighbor's change



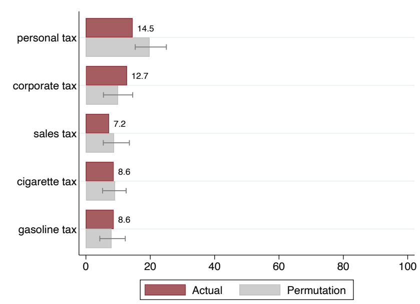
(b) following neighbor's change



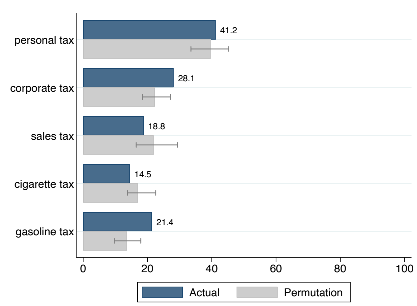
(c) during state recession



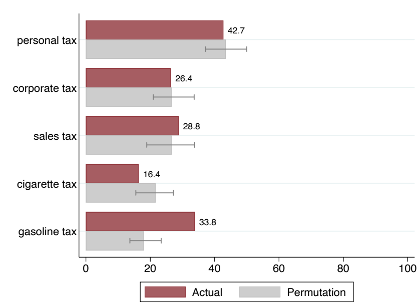
(d) during state recession



(e) following federal mandate



(f) following federal mandate

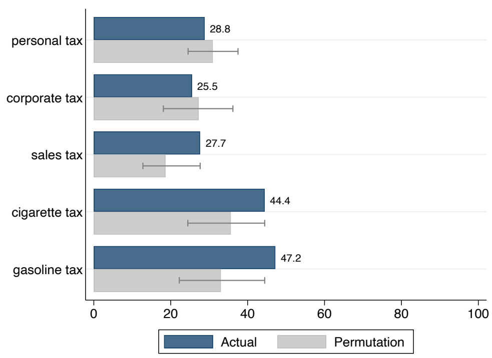


Notes: This figure shows the percent of tax changes that occur (a) in the same year or 1 year after neighboring state changes its tax rate; (b) during a state recession, or (c) in the years the federal mandate becomes enacted and/or effective. In all figures, the top blue/red bars show actual observed percentages, while the bottom grey bars show the simulated average, calculated by randomizing the timing of tax changes 100 times. The thin interval bars show the 5th and 95th percentiles of the simulated percentages. These statistics are shown separately for states that have only voted for a Democratic (Republican) presidential candidate since 2000 elections (see Table A.3).

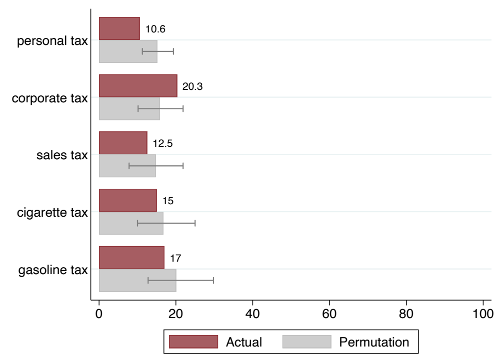
Figure 7: Percent of Recession Episodes that Result in Tax Changes

Left: Safe Democratic States **Right: Safe Republican States**

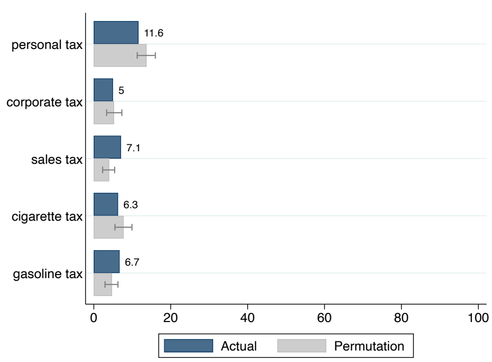
(a) state recession



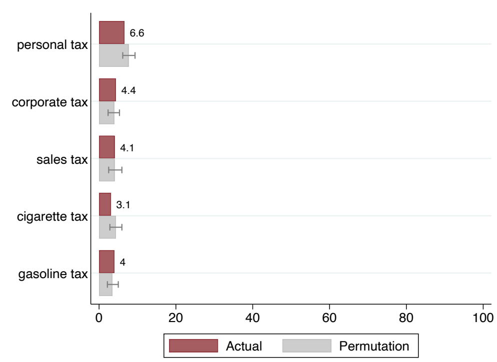
(b) state recession



(c) federal recession



(d) federal recession

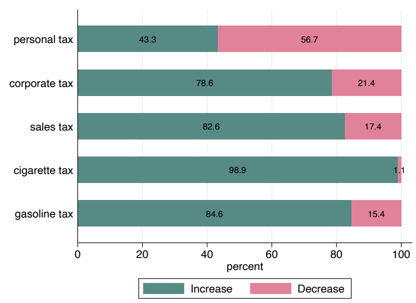


Notes: This figure shows the percent of (a) state recessions or (b) federal recessions that lead to a tax change. Each recession episode is counted as one recession and only one tax change (per tax rate type) is allowed per recession. In all figures, the top blue/red bars show actual observed percentages, while the bottom grey bars show the simulated average, calculated by randomizing the timing of tax changes 100 times. The thin interval bars show the 5th and 95th percentiles of the simulated percentages. These statistics are shown separately for states that have only voted for a Democratic (Republican) presidential candidate since 2000 elections (see Table A.3).

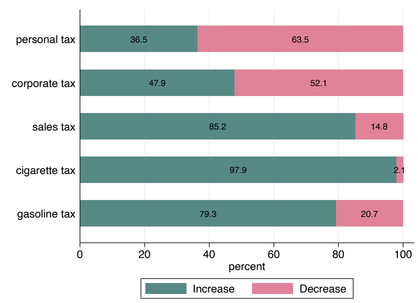
Figure 8: How Do Taxes Change?

Left: Safe Democratic States **Right: Safe Republican States**

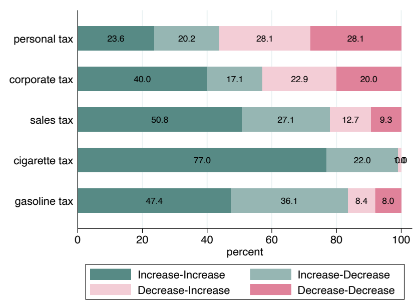
(a) all years



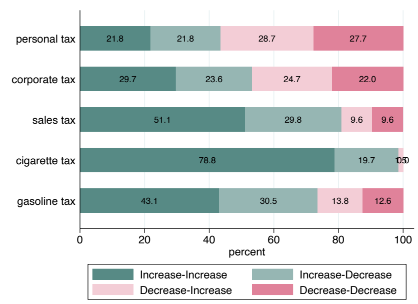
(b) all years



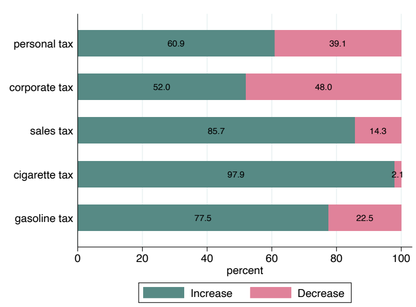
(c) neighbors' change



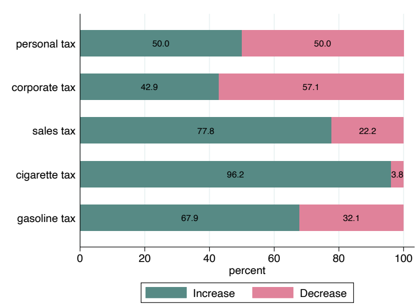
(d) neighbors' change



(e) state recession



(f) state recession

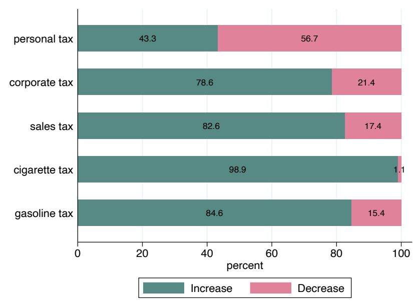


Notes: see next page .

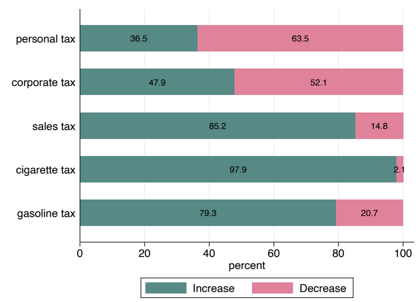
Figure 8: How Do Taxes Change? Continued

Left: Safe Democratic States **Right: Safe Republican States**

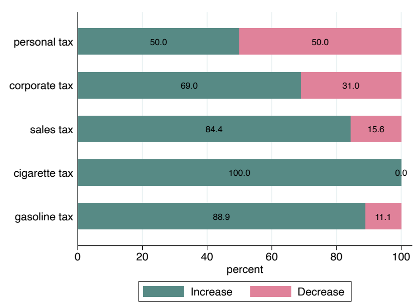
(a) all years



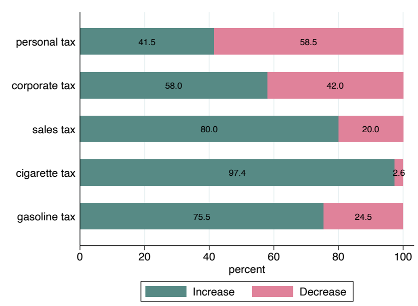
(b) all years



(g) federal mandates



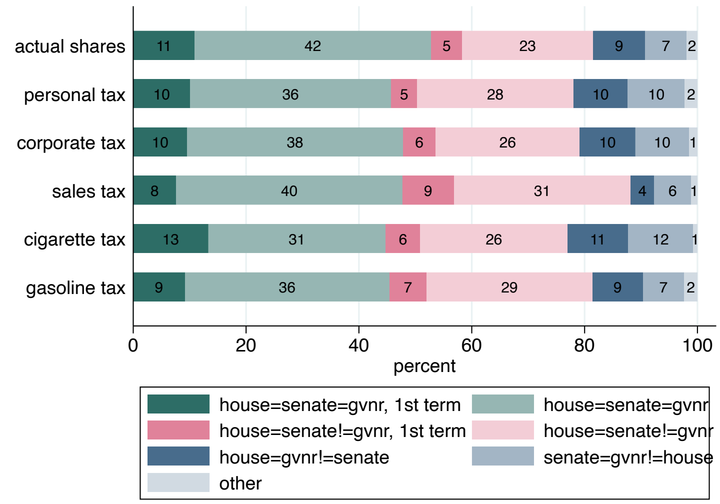
(h) federal mandates



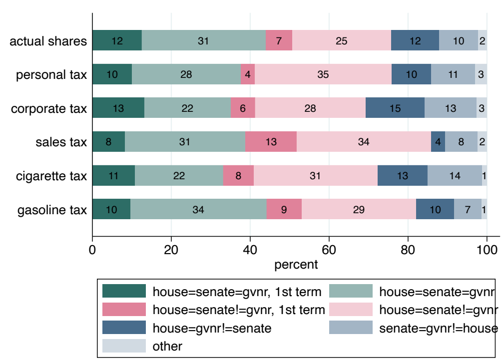
Notes: This figure shows the percent of tax changes that are increases or decreases and that occur (a)-(b) in all years, (c)-(d) in the same year or 1 year after neighboring state changes its tax rate; (e)-(f) during a state recession, or (g)-(h) in the years the federal mandate becomes enacted and/or effective. These statistics are shown separately for states that have only voted for a Democratic (Republican) presidential candidate since 2000 elections (see Table A.3).

Figure 9: Party Affiliation of Political Offices and Tax Changes

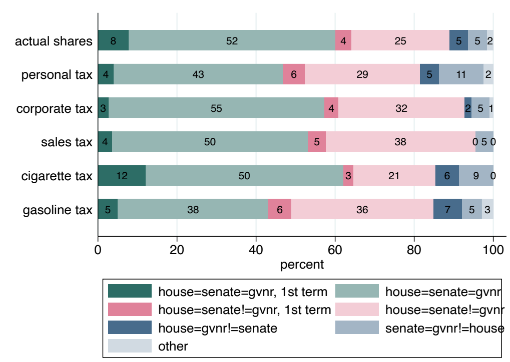
(a) all states



(b) Safe Democratic States



(c) Safe Republican States

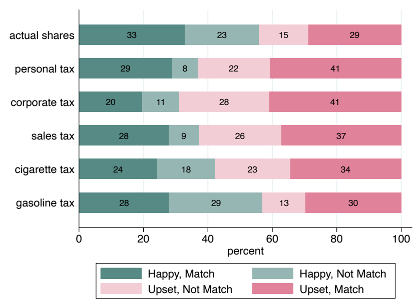


Notes: The top row of each figure shows the percent of yearly observations in which (i) the majority party of the House is the same as that of the Senate and of the Governor, and one of these three bodies switched party control; (ii) same as (i) but no party control change; (iii) House and Senate majorities are the same party, but Governor of a different party, and the joint majorities in House and Senate were obtained this term; (iv) same as (iii) but no party control change; (v) House majority matches Governor's affiliation but not Senate majority's; (vi) Senate majority matches Governor's affiliation but not House majority's; (vii) all other options (i.e. non-Democratic/Republican affiliations or lack of majorities). The next five rows show party affiliations in years when respective tax changes occur. Figures (b) and (c) provide these statistics separately for states that have only voted for a Democratic (Republican) presidential candidate since 2000 elections (see Table A.3).

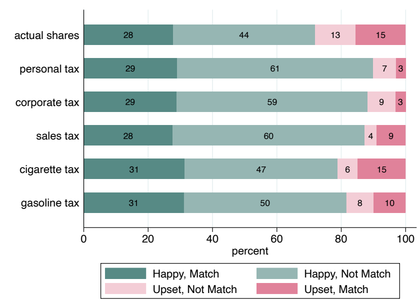
Figure 10: Presidential Election Outcomes and Tax Changes

Left: Vote Democratic **Right: Vote Republican**

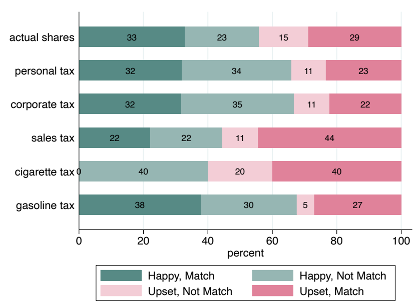
(a) Tax Increases



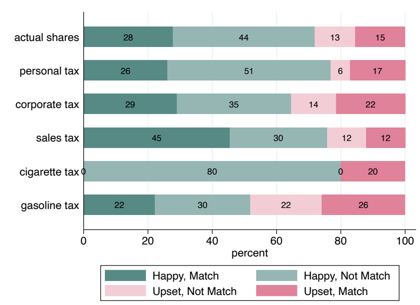
(b) Tax Increases



(c) Tax Decreases



(d) Tax Decreases

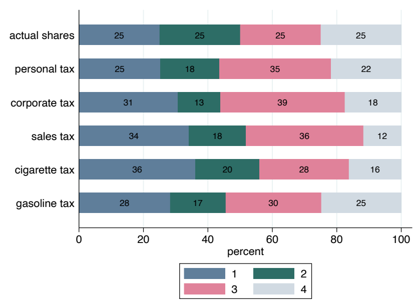


Notes: The top row of each figure shows the percent of yearly observations in which the state votes for a Democratic (left panel) or for a Republican (right panel) presidential candidate and that candidate wins ("Happy") or loses ("Upset"), while the state's House and Senate majorities match the preferred presidential candidate ("Match") or do not ("Not Match"). The other rows show similar break downs when tax increases or tax decreases of a given tax type occur.

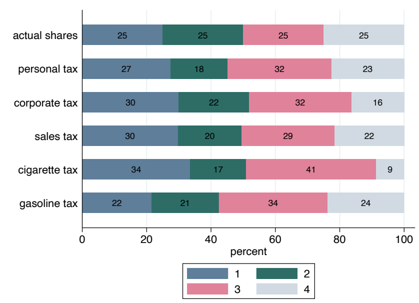
Figure 11: Election Cycles

Left: Safe Democratic States **Right: Safe Republican States**

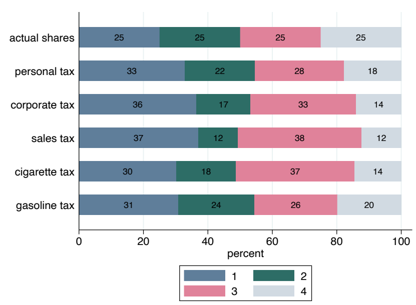
(a) Presidential Elections



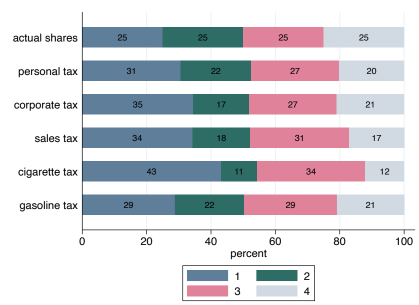
(b) Presidential Elections



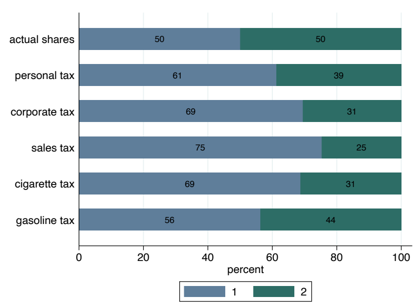
(c) Governor Elections



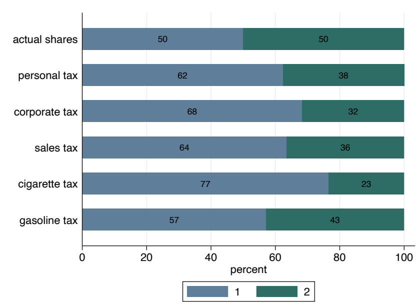
(d) Governor Elections



(e) House Elections



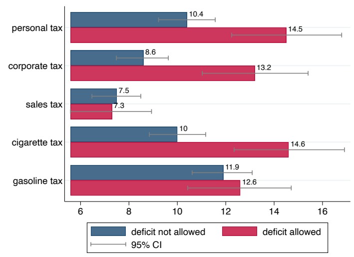
(f) House Elections



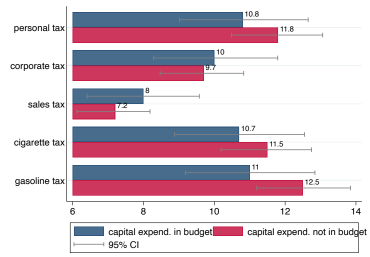
Notes: The top row of each figure shows the percent of yearly observations occurring during the studied time period. Years 1 through 4 identify first, second, third and fourth years post-election. The other rows show similar break downs but in years when tax changes of a given tax type occur. For gubernatorial and house elections, only states with 4-year and 2-year cycles are included respectively. Similar breakdowns, but separately for increases and decreases are available in Figures B.12-B.13.

Figure 12: Institutional Rules: Frequency of Tax Changes

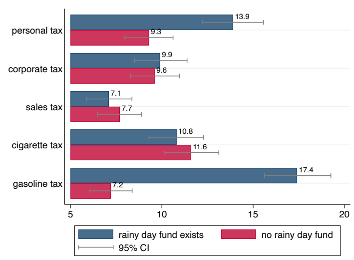
(a) Deficits



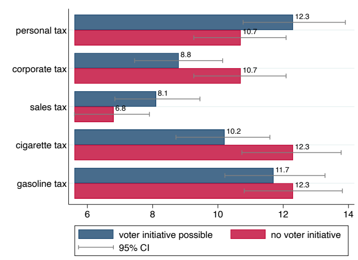
(b) Capital Expenditures



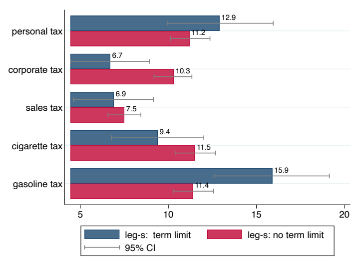
(c) Rainy Day Fund



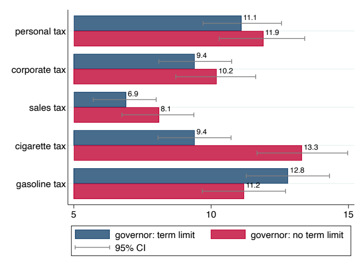
(d) Voter Initiative Rules



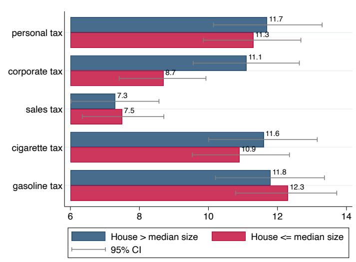
(e) Legislature Term Limits



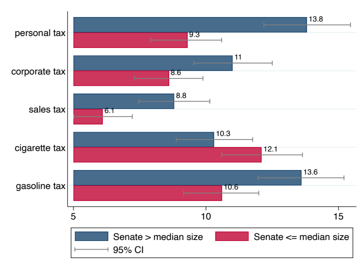
(f) Governor Term Limits



(g) House Size



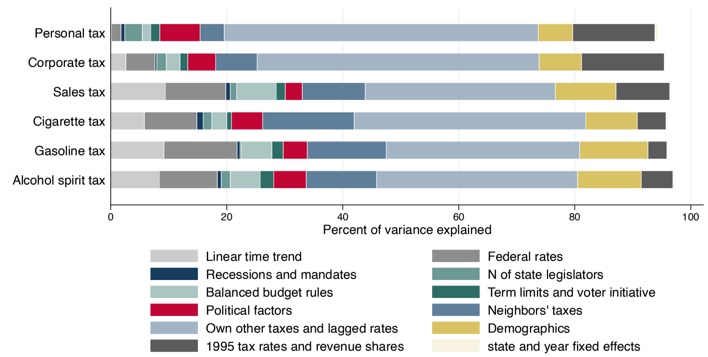
(h) Senate Size



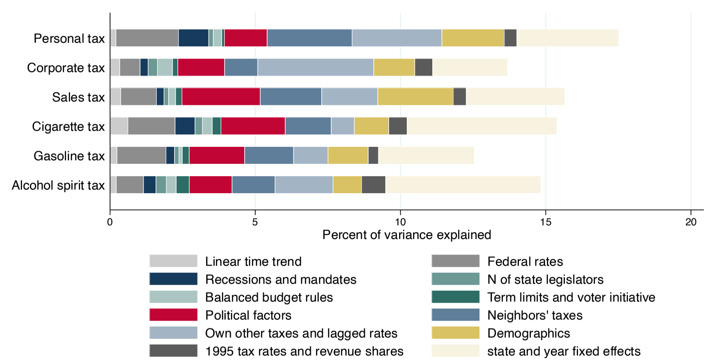
Notes: This table shows the frequency of tax changes in states with various institutional settings. Similar results but separately for decreases and increases are shown in Figures B.14-B.15.

Figure 13: Variance Decomposition

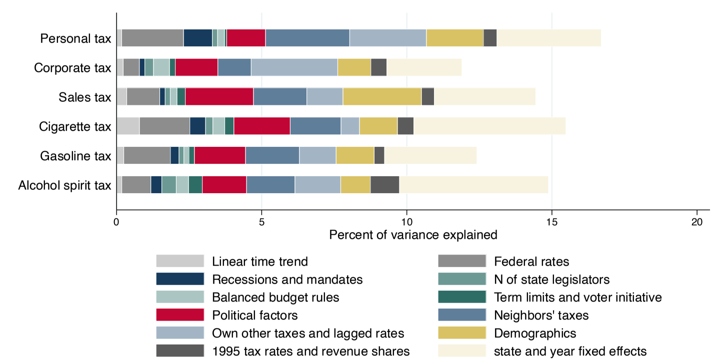
(a) Tax Rate Levels – All



(b) Tax Changes in \$ or % – All



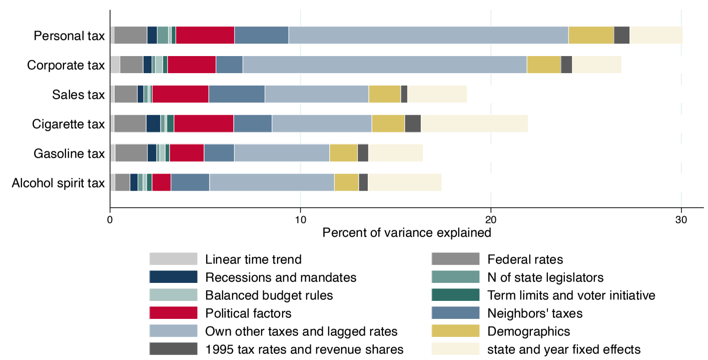
(c) Tax Changes in \$ or % – Largest 50%



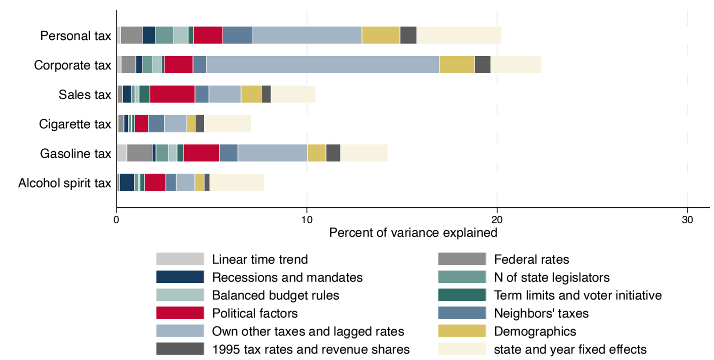
Notes: This figure shows Shapley variance decomposition of (a) all tax rates in pp or in 2020 dollars; (b) all tax changes (i.e. differences between given year's tax rate and the previous year's tax rate) in pp or in 2020 dollars; (c) same as (b) but only including 50% largest tax changes. All decompositions use 129 variables summarized in Table A.2.

Figure 14: Variance Decomposition

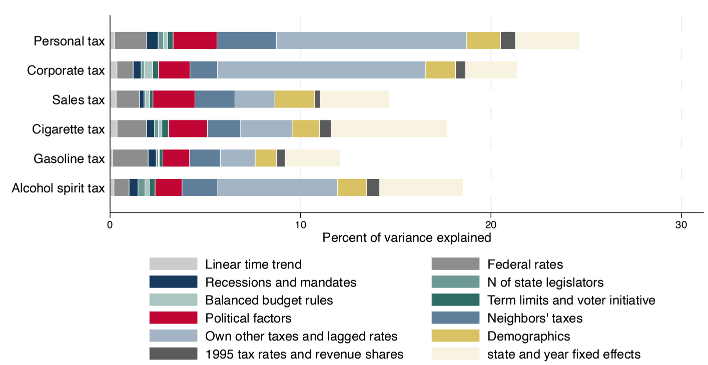
(a) Tax Rate Increase – All



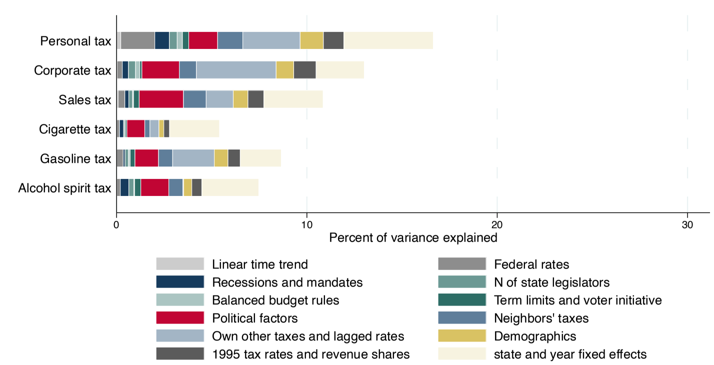
(b) Tax Rate Decrease – All



(c) Tax Rate Increase – Largest 50%



(d) Tax Rate Decrease – Largest 50%



Notes: This figure shows the Shapley variance decomposition of: (a) all tax rate increases (indicators for years when a tax increase occurs) and (b) all tax decreases (indicators for years when a tax decrease occurs); (c) and (d) – 50% largest tax increases and decreases, respectively; all using 129 variables summarized in Table A.2.

Table 1: 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 Section 2.3 for details.

Table 2: Tax Change Trends

	Decreased 2pp+	Increased 2pp+	Fluctuated 2pp+
Personal Income Tax	CO, ND, RI, WI	AK, CA	AZ, CT, DE, IA, KS, MA, ME, MN, MT, NJ, NM, NY, OH, PA, VT, WV
Corporate Income Tax	OH	AL, DE, IA, IL, IN, KS, LA, MD, ME, MO, NE, NH, NJ, NM, RI, TN, VT	AZ, CA, CT, MA, MI, MN, ND, NY, PA
Sales Tax Rate		AR, AZ, CA, FL, IA, ID, IL, IN, KS, KY, LA, MA, MD, MI, MN, MS, ND, NE, NJ, NM, NV, OH, OK, RI, SC, TN, TX, UT, VT, WA, WV	CT, ME

Notes: This table groups states into three categories: (1) those whose tax rates decreased from 1950-1970 to 1971-1999 to 2000-2020 by more than 2 percentage points total, (2) those whose tax rates increased by more than 2 pp total, (3) those whose tax rates fluctuated, meaning the 1971-1999 average rate was either above or below both 1950-1970 and 2000-2020 averages. Safe Republican states are colored in red, while safe Democrat states are colored in blue (see Table A.3).

Table 3: Machine Learning Results

Outcome	Linear Regression Training R^2	Linear Regression Out-of-Sample R^2	Lasso Training R^2	Lasso Out-of-Sample R^2	Forest Tree Training R^2	Forest Tree Out-of-Sample R^2
Income tax change (pp)	0.26	0.04	0.11	0.03	0.65	0.00
Corporate tax change (pp)	0.17	-0.34	0.07	0.06	0.64	0.01
Sales tax change (pp)	0.14	-1.12	0.06	-0.35	0.64	-0.02
Cigarette change ($)	0.13	-0.44	0.10	0.06	0.66	0.00
Gasoline change ($)	0.15	0.06	0.08	0.01	0.66	-0.01
Alcohol spirit change ($)	0.12	-0.05	0.03	0.00	0.56	-0.10
Income tax decrease	0.18	0.07	0.24	0.01	0.69	0.09
Corporate tax decrease	0.21	-0.64	0.24	0.11	0.71	0.17
Sales tax decrease	0.10	-0.47	0.00	0.00	0.60	-0.04
Gasoline decrease	0.14	-0.03	0.16	0.02	0.66	0.06
Income tax increase	0.30	0.19	0.38	0.15	0.69	0.11
Corporate tax increase	0.28	0.07	0.35	0.08	0.68	0.08
Sales tax increase	0.18	-1.63	0.24	-0.01	0.66	0.01
Cigarette increase	0.20	-2.79	0.30	0.05	0.68	0.05
Gasoline increase	0.16	-1.41	0.24	-0.02	0.70	0.10
Alcohol spirit increase	0.22	0.01	0.17	-0.03	0.62	-0.03

Notes: This table compares the results of linear regression model 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 129 explanatory variables summarized in Table A.2. The LASSO model is estimated on the full set of interactions of above variables as well as decade dummies, resulting in 22,455 variables. Random forest is estimated over the 129 explanatory variables, decade dummies and 2nd and 3rd powers of non-indicator variables – 196 variables. Cigarette and alcohol tax decreases are omitted due to lack of events.

Table 4: Machine Learning Clusters Over Time

	Ave tax rates in group	1950-1969	1970-2000	2001-2020
1	$\tau_{inc} = 0$, $\tau_{corp} = 0$, $\tau_{sales} = 4.2$, $\tau_{gas} = 0.4$, $\tau_{cig} = 0.7$, $\tau_{spirit} = 1.4$	ME, MI, OH, WA, WY	WA, WY	NV, SD, TX, WY
2	$\tau_{inc} = 4.7$, $\tau_{corp} = 5.6$, $\tau_{sales} = 3.7$, $\tau_{gas} = 0.4$, $\tau_{cig} = 0.6$, $\tau_{spirit} = 0$	AL, IA, MS, NC, PA, UT, VA	AL, MI, MS, PA, UT, VA	AL, MI, MS, NH, PA, UT, VA
3	$\tau_{inc} = 9.2$, $\tau_{corp} = 8.1$, $\tau_{sales} = 3.1$, $\tau_{gas} = 0.4$, $\tau_{cig} = 0.8$, $\tau_{spirit} = 0$	OR	IA, MT, OR, VT	IA, ID, ME, MT, OR, VT, WV
4	$\tau_{inc} = 8.1$, $\tau_{corp} = 7.5$, $\tau_{sales} = 4.2$, $\tau_{gas} = 0.3$, $\tau_{cig} = 1$, $\tau_{spirit} = 7.4$		CA, NM	CA, DE, HI, NM, NY, OK
5	$\tau_{inc} = 5$, $\tau_{corp} = 7.5$, $\tau_{sales} = 5.4$, $\tau_{gas} = 0.3$, $\tau_{cig} = 1$, $\tau_{spirit} = 4.6$			AR, AZ, CO, IL, IN, KS, KY, LA, MA, MD, MO, ND, NE, SC, TN, WI
6	$\tau_{inc} = 8.3$, $\tau_{corp} = 6.4$, $\tau_{sales} = 2.1$, $\tau_{gas} = 0.5$, $\tau_{cig} = 0.6$, $\tau_{spirit} = 20$	AR, MA, MN, ND, NY, SC, WI		
7	$\tau_{inc} = 1.8$, $\tau_{corp} = 3.2$, $\tau_{sales} = 2.6$, $\tau_{gas} = 0.4$, $\tau_{cig} = 0.6$, $\tau_{spirit} = 13$	CT, FL, IL, IN, KS, MO, NE, NJ, NM, NV, RI, SD, TX	FL	AK

Notes: This table shows the seven clusters generated by the Ward hierarchical clustering procedure. Each state-year is treated as its own observation, therefore states can be assigned to different clusters in different years. This table only lists states that belong to each respective groups in 18 out of 20 years in 1950-1969 or in 2001-2020, or in 28 years out of 31 in 1970-2000. States that are not listed did not satisfy this requirement, i.e. they moved across clusters. Average tax rates in each group (in whichever years) are shown in the first column. Safe Republican states are colored in red, while safe Democrat states are colored in blue (see Table A.3).

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 A.2. In this section, we describe how we construct these explanatory variables.

Neighboring states. Our preferred method of identifying neighbors follows Baicker (2005). Using 2010 IRS population migration data, for each state, we identify five states that receive the largest number of out-migrants from that state. We focus on outflows because these are likely to be most important for tax competition. 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.

Recessions. We identify state recessions by applying the Bry-Boschan Method to Federal Reserve Bank of Philadelphia State Coincident Index (1979-2020) and yearly GDP values (1963-1978). The Bry-Boschan 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.

Demographics. 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. 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, 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 the number of prime age-adults (i.e. age 19-65). Labor force participation rate is estimated as the number unemployment 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.

Safe Republican and Democratic states. In some of our analysis we break down states into three categories: "safe" Republican, "safe" Democratic, or Swing state. Safe Republican (resp. Democrat) states are defined as those who had only voted for a Republican (resp. Democratic) presidential candidate in the past six elections, i.e. starting with 2000 presidential elections. The remaining states are considered to be swing states. Table A.3 summarizes these groups.

Southern Democratic states. In our analysis we distinguish Southern and Northern 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.

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.

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

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

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

Table A.2: 129 Core Explanatory Variables

Group	Type (N of var)	Variables included
1	Linear trend (1)	year
2	Federal rates (10)	rates and changes from previous year of top federal income tax rate, top federal corporate rate, and federal cigarette, gasoline, and spirit taxes
3	Recessions and mandates (7)	indicators: federal recession and one year lag, state recession and one year lag, 3 indicators for federal mandates: welfare-program-related, minimum wage change, and other
4	State legislatures (5)	number of seats in the lower chamber, number of seats in the upper chamber, average legislative session duration in calendar days, average salary (in 2019/20), average per diem expenses (in 2019/20)
5	Balanced budget rules (3)	indicators: whether budget deficits are allowed, whether capital expenditures are part of the budget, whether rainy day fund exists
6	Term limit and voter initiative (6)	indicators: whether there is governorship term limit, whether there is legislature term limit, whether this is a year in governor's last term, whether such a governor is Republican or a Democrat, whether voter initiatives are allowed
7	Political factors (30)	number of times governor party switched, number of times majority in house, in senate or both switched, share of Republicans/Democrats in the senate/house; indicators: majority-Republican legislature, majority-Democratic legislature, governor Republican, governor Democratic, Southern Democratic governor, Southern Democratic legislature majority, divided government (party of house, senate and governor is not the same), first term after governor party change, first term after senate party change, first term after house party change, federal government shutdown that year, state government shutdown that year, Democratic president, state's preferred presidential candidate lost, legislature majority matches the party of the winning presidential candidate in the state, indicators for each year in the presidential election cycle, indicators for each year in the gubernatorial election cycle, interaction term of divided government and deficit not allowed
8	Neighbors' taxes (22)	average tax rates in neighboring states this year and previous year; indicators of tax rate increases and tax rate decreases in neighboring states this or previous year; all separately for top income, top corporate, sales, cigarette, spirit and gasoline tax rates (decrease indicators omitted for cigarette and spirit taxes)
9	Own other taxes (11-18)	level and tax change regressions: level/change of other tax rates in the state top income, top corporate, sales, cigarette, spirit and gasoline tax rates; similarly in indicator regressions: indicators of tax rate increases and tax rate decreases in other rates; as well as lags of all 6 tax rates (decrease indicators omitted for cigarette and spirit taxes; own tax variables always omitted)
10	Demographics (22)	population, population density, labor force participation rate, employment to population ratio, unemployment rate, poverty rate, percent of black residents, percent of non-white and non-black residents, percent of children (0-17 years old), percent senior residents (65+ years old), median household income; as well as changes in these variables
11	1995 tax rates and revenue shares (12)	tax rate (top income, top corporate, sales, cigarette, spirit and gasoline) levels in 1995; 1995 tax revenue shares of income, corporate, sales, cigarette, spirit and gasoline taxes

Notes: This table summarizes variables used in simple linear analysis in Section 5.1 and Random Forest algorithm in Section 5.2, as well as the baseline set of variables used to construct interaction terms for LASSO analysis in Section 5.2.

Table A.3: "Safe" Republican and Democratic States

Safe Republican States	AL, AK, AR, ID, KS, KY, LA, MO, MS, MT, NE, ND, OK, SC, SD, TN, TX, UT, WV, WY
Swing States	AZ, CO, FL, GA, IA, IN, MI, NC, NH, NM, NV, OH, PA, VA, WI
Safe Democratic States	CA, CT, DE, HI, IL, ME, MD, MA, MN, NJ, NY, OR, RI, VT, WA

Notes: Safe Republican (resp. Democrat) states are defined as those who had only voted for a Republican (resp. Democratic) presidential candidate in the past six elections, i.e. starting with 2000 presidential elections. The remaining states are considered to be swing states.

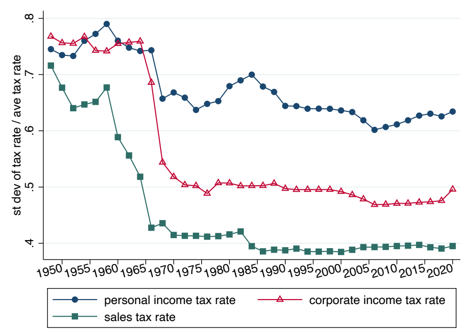
B Additional Graphs

Figure B.1: Lack of Convergence among Democratic/Republican States

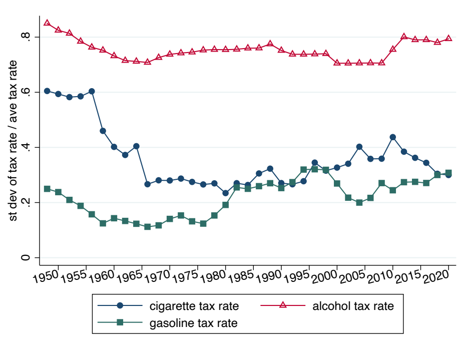
Left: Safe Democratic States **Right: Safe Republican States**

(a) Heterogeneity Over Time
Sales and Income Taxes

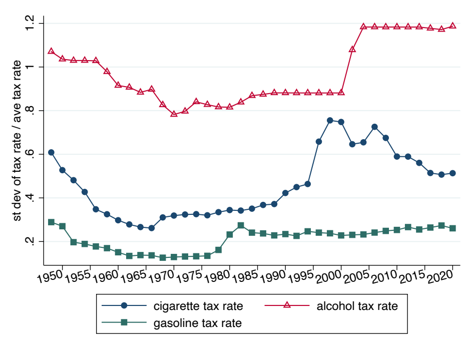
(b) Heterogeneity Over Time
Sales and Income Taxes



(c) Heterogeneity Over Time
Excise Taxes



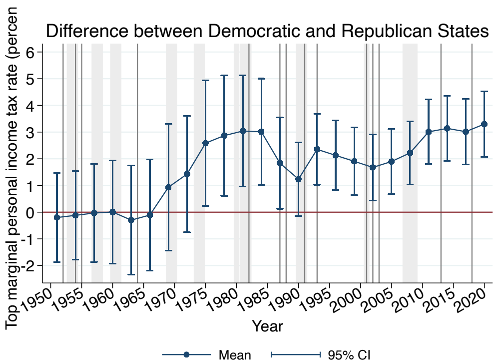
(d) Heterogeneity Over Time
Excise Taxes



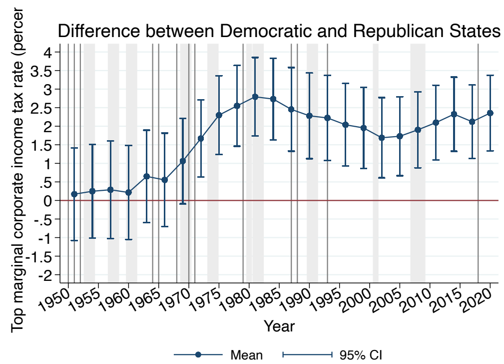
Notes: These figures show the standard deviation of the state taxes divided by average tax rate (coefficient of variation) separately for safe Republican and safe Democrat states (see Table A.3). All states included, including those with zero rates.

Figure B.2: Is Tax Policy Becoming More Polarized? Including Zero Tax Rates

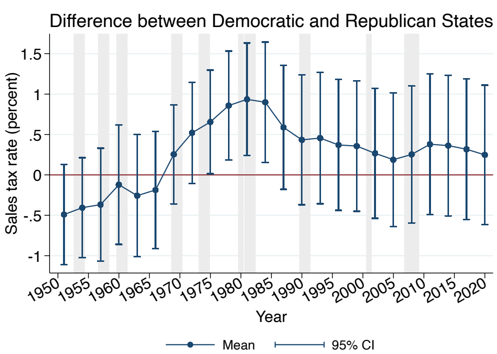
(a) Personal Tax



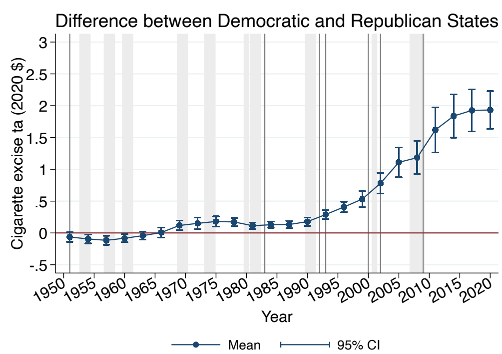
(b) Corporate Tax



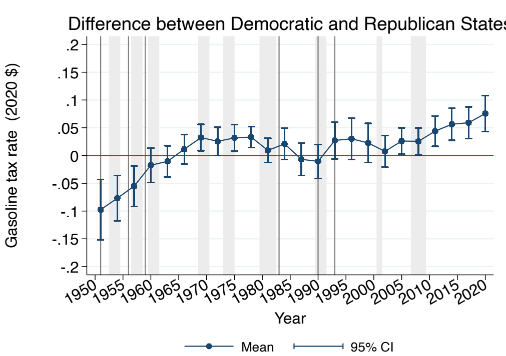
(c) Sales Tax



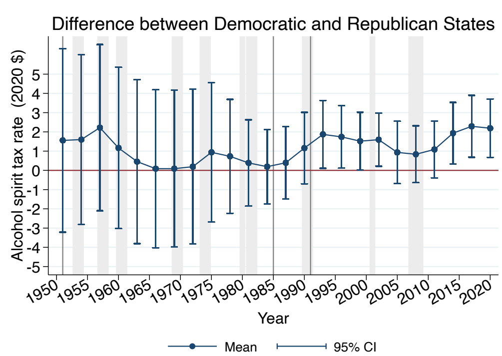
(d) Cigarette Tax



(e) GasolineTax



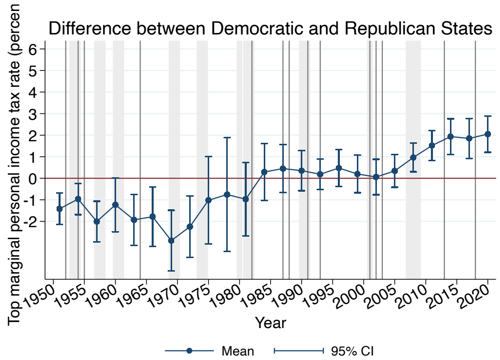
(f) Spirit Tax



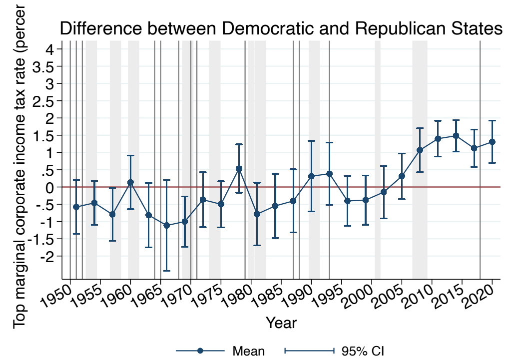
Notes: This figure shows the difference in means and corresponding 95% confidence intervals of tax rates in “safe Republican” and “safe Democratic” states, i.e. states that have only voted for a Democratic (Republican) presidential candidate since 2000 elections (see Table A.3).The differences are calculated for non-overlapping 3-year periods. All states are included, including those with zero tax rates.

Figure B.3: Is Tax Policy Becoming More Polarized? Including Zero Tax Rates

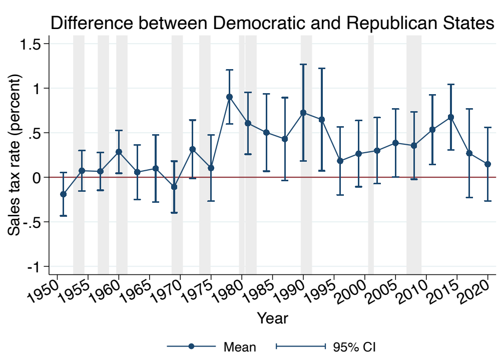
(a) Personal Tax



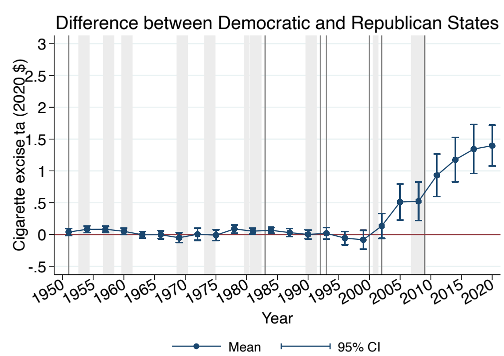
(b) Corporate Tax



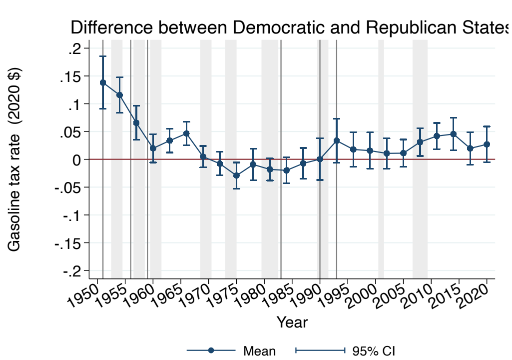
(c) Sales Tax



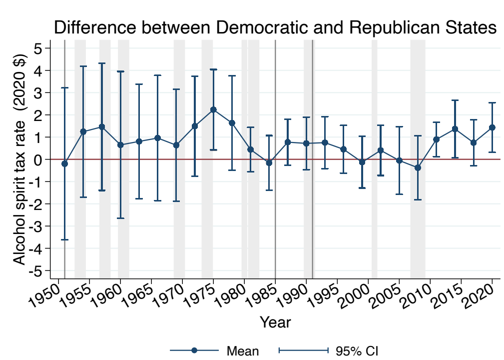
(d) Cigarette Tax



(e) GasolineTax



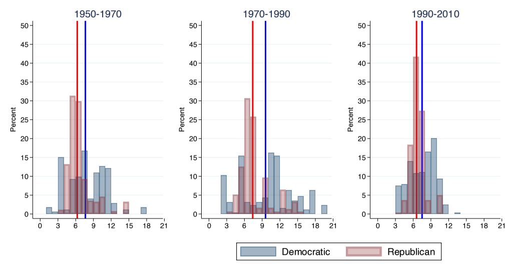
(f) Spirit Tax



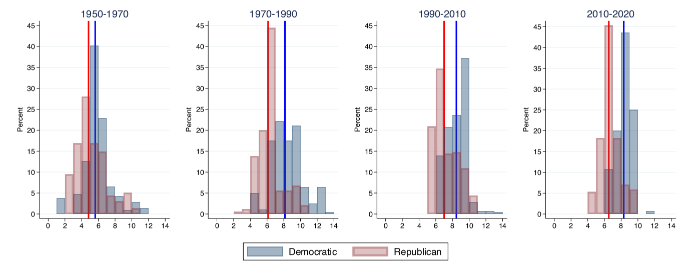
Notes: This figure shows the difference in means and corresponding 95% confidence intervals of tax rates in states with majority Democratic versus Republican legislatures, i.e. where both chambers have Democratic (Republican) majorities. The differences are calculated for non-overlapping 3-year periods, only nonzero observations are included.

Figure B.4: Distributions of Non-zero Tax Rates

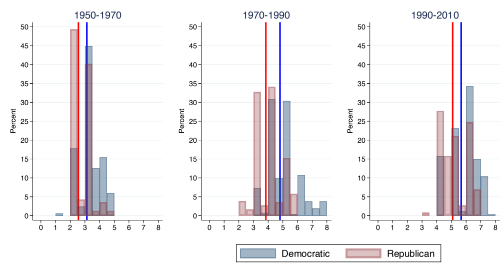
(a) Personal Tax



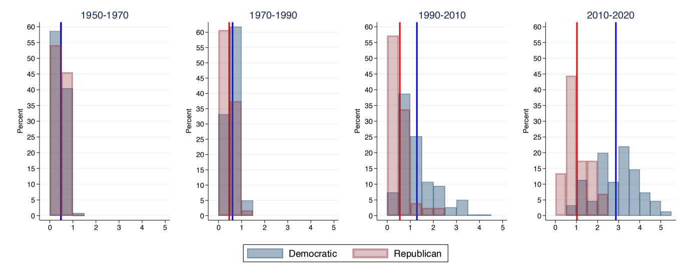
(b) Corporate Tax



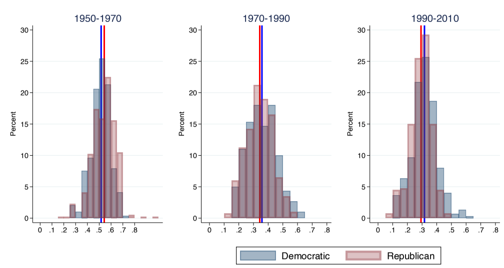
(c) Sales Tax



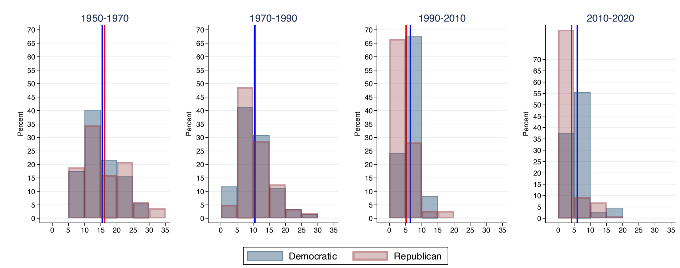
(d) Cigarette Tax



(e) Gasoline Tax



(f) Spirit Tax



Notes: These figures show distributions of tax rates in safe Democratic versus safe Republican states, i.e. states that have only voted for a Democratic (Republican) presidential candidate since 2000 elections (see Table A.3). The vertical red and blue lines identify average tax rates in Republican and Democratic states respectively. Only non-zero tax rates included.

Figure B.5: Personal, Corporate and Sales Tax Rates Time Series

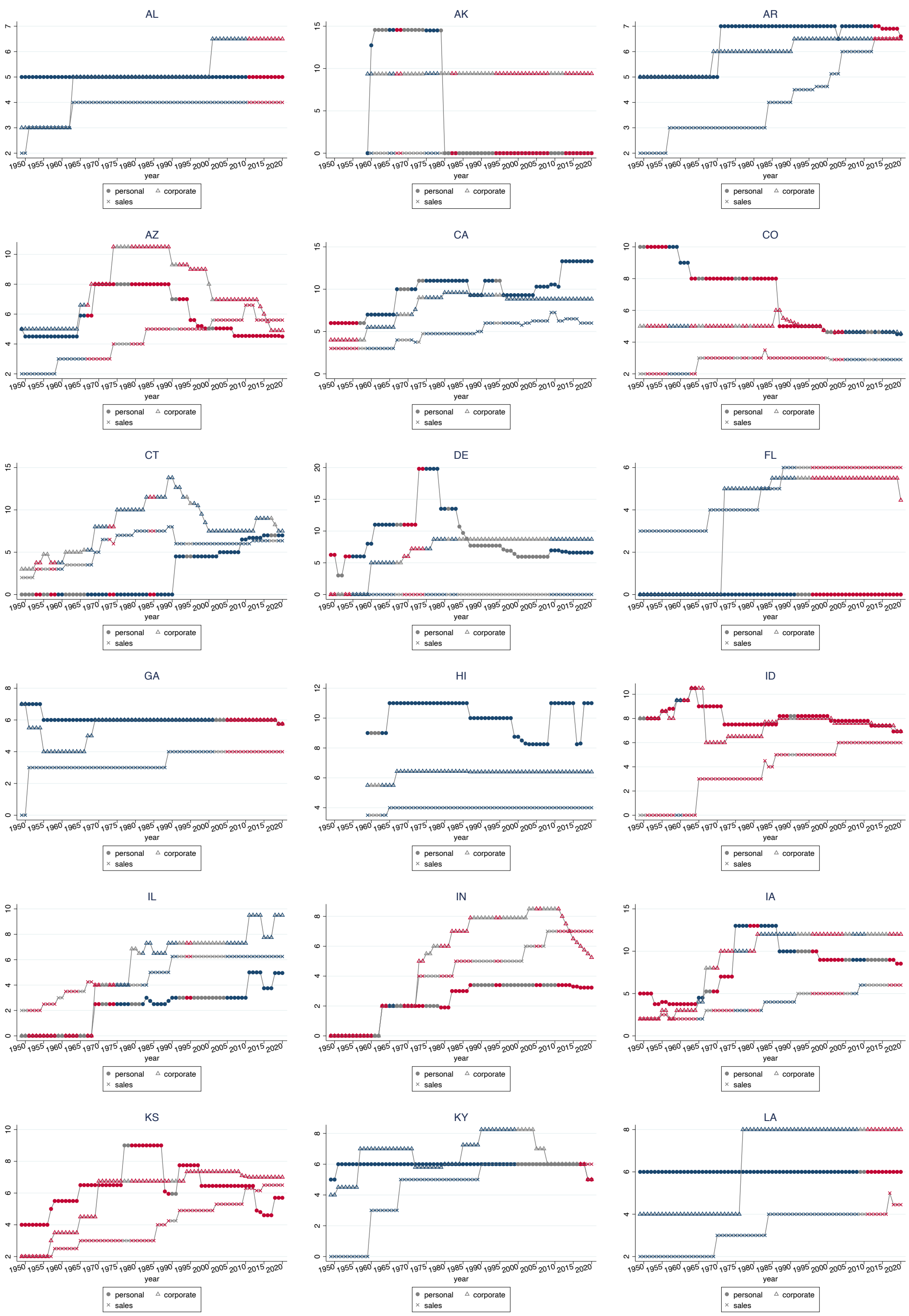


Figure B.5: Personal, Corporate and Sales Tax Rates Time Series

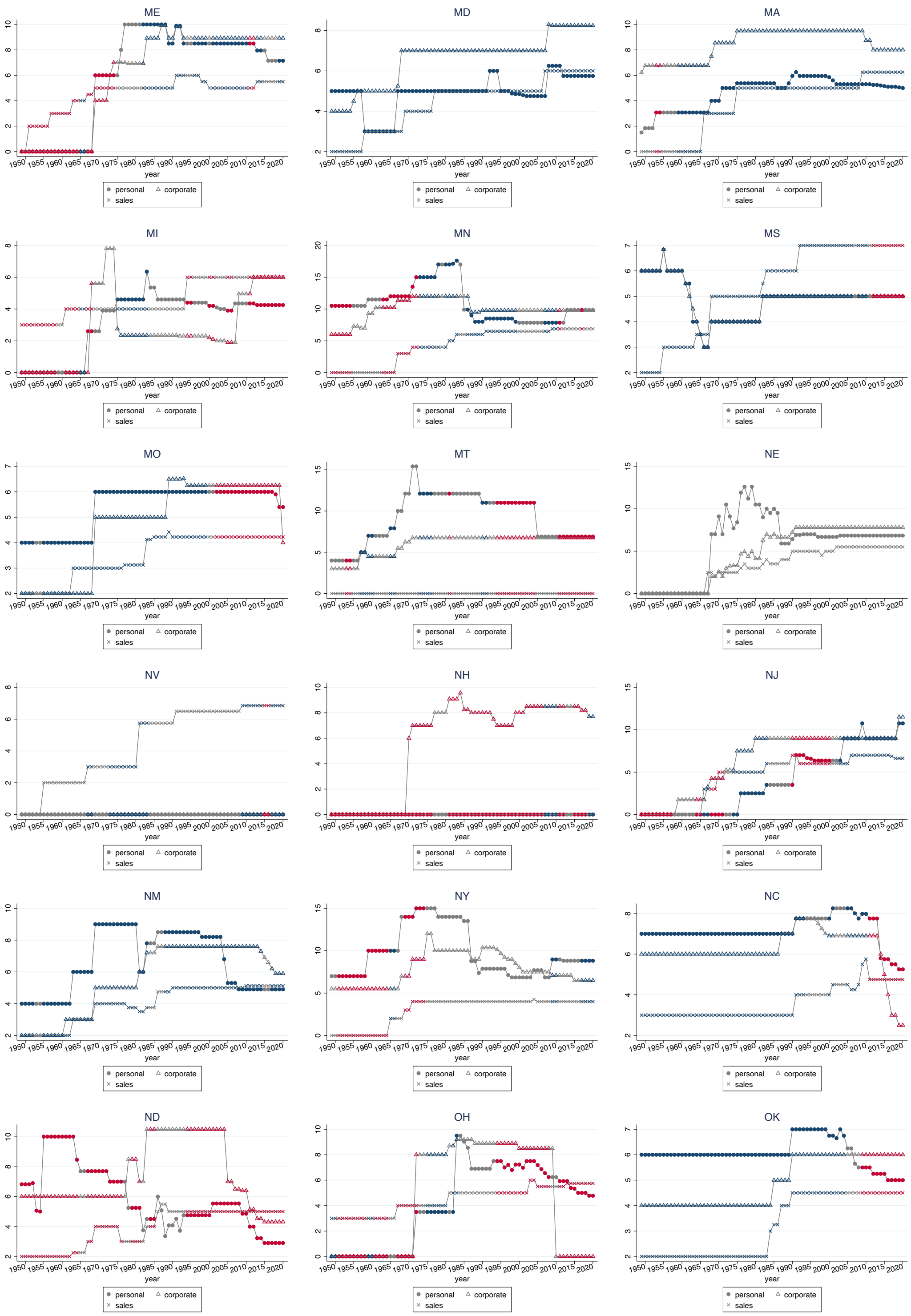
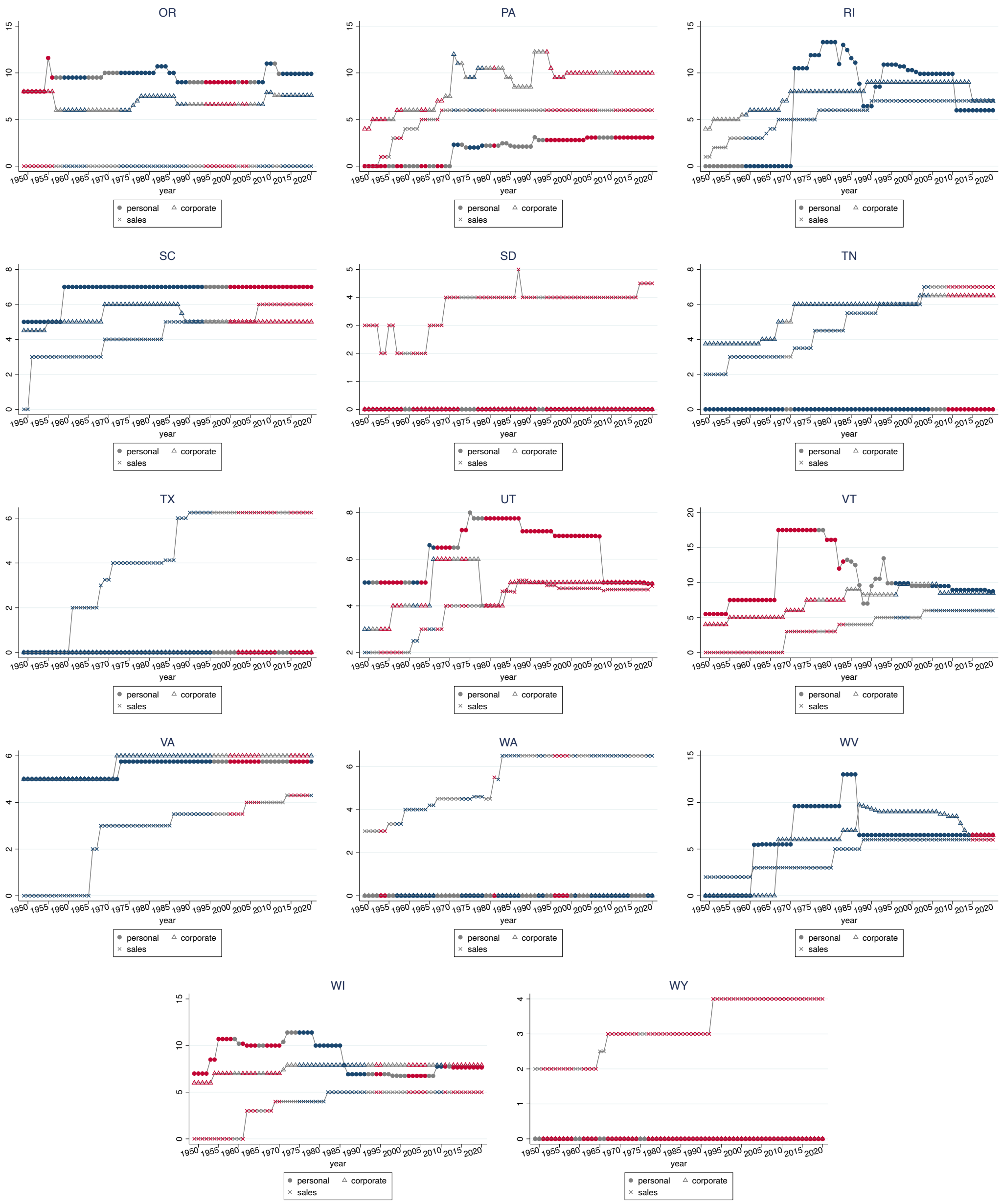


Figure B.5: Personal, Corporate and Sales Tax Rates Time Series



Notes: These figures show time series of top personal income tax, top corporate tax and general sales tax in each state. Red and blue colors identify years in which legislatures (both House and Senate) were majority Republican or Democratic respectively.

Figure B.6: Excise Tax Rates Time Series

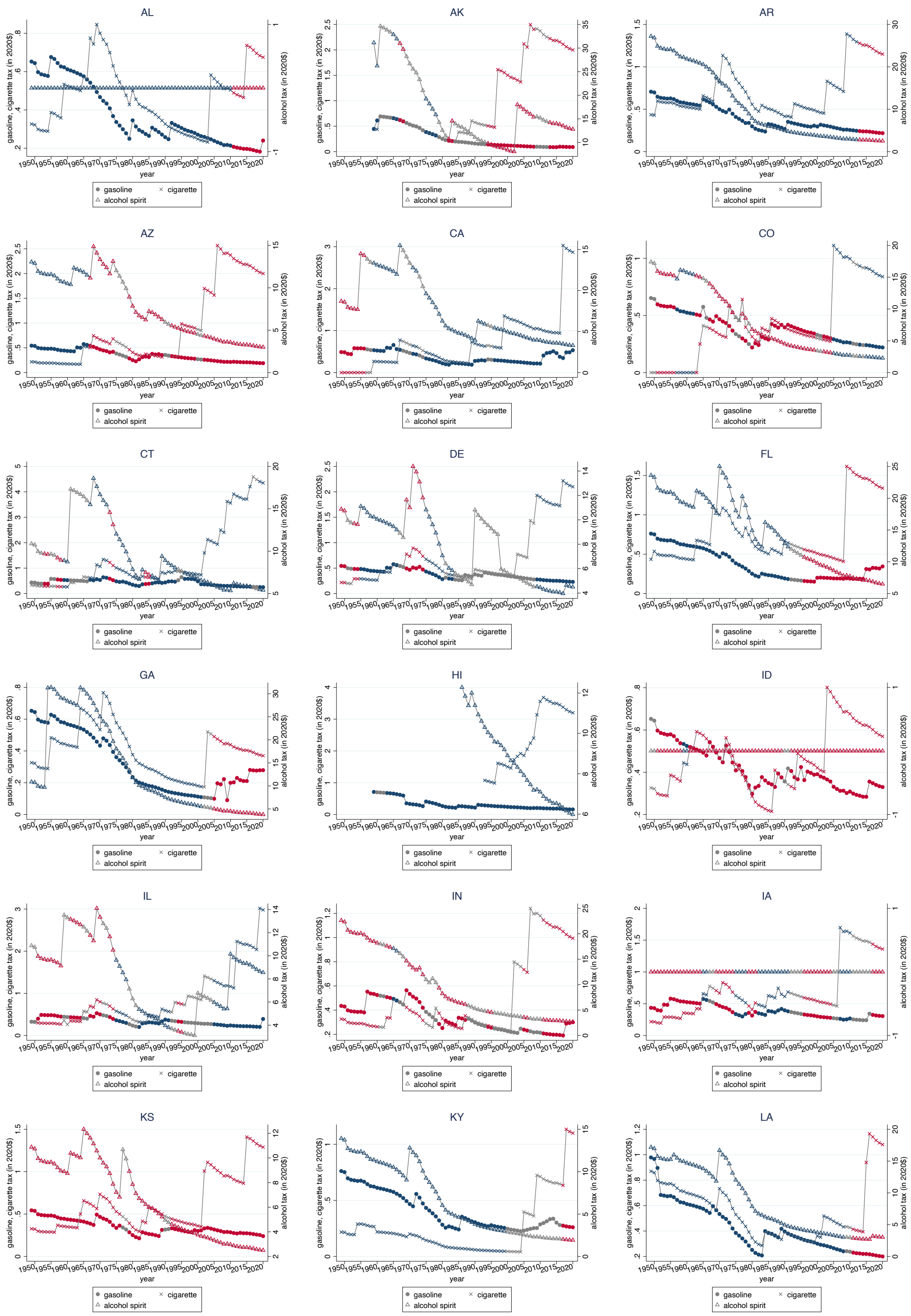


Figure B.6: Personal, Corporate and Sales Tax Rates Time Series

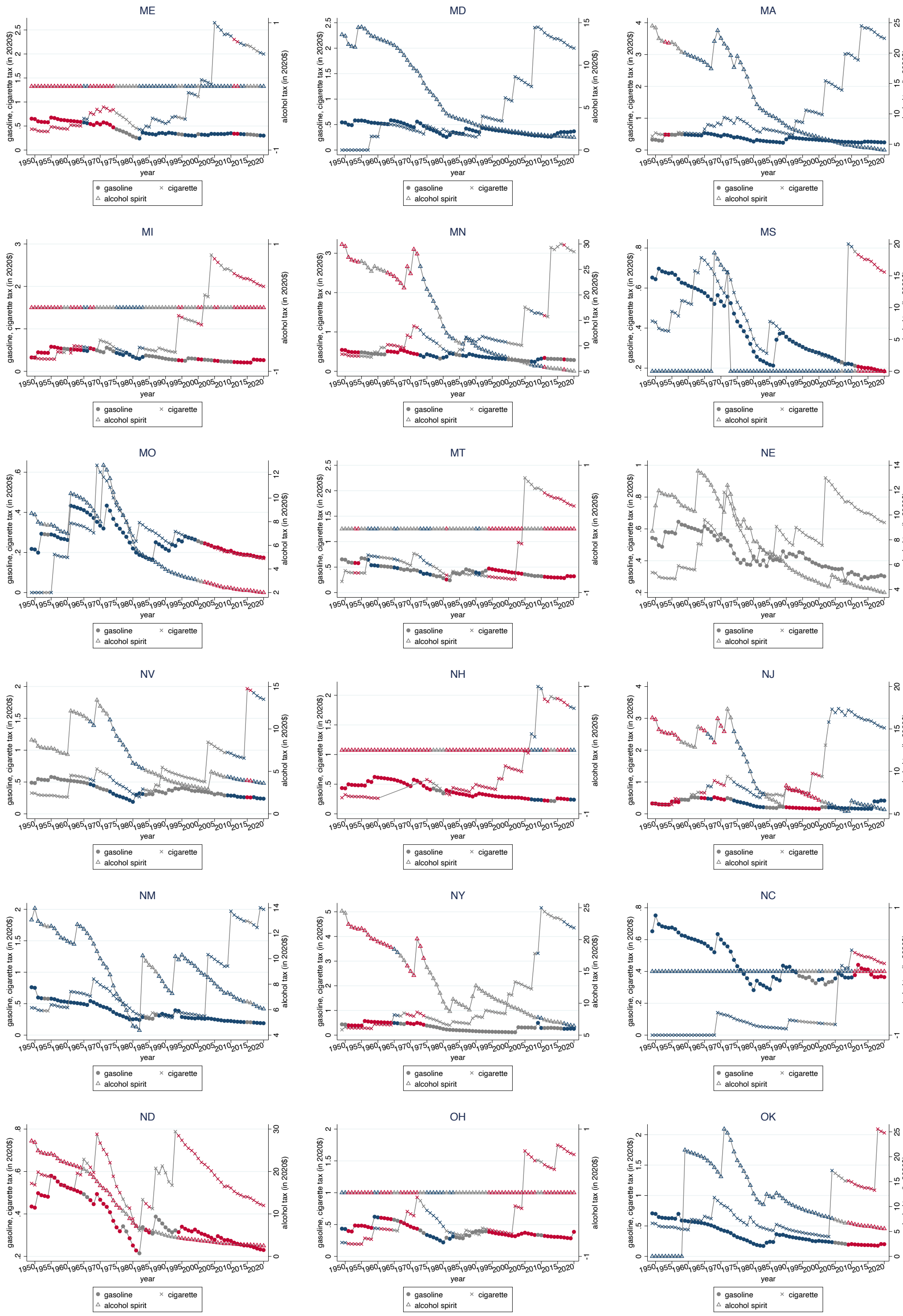
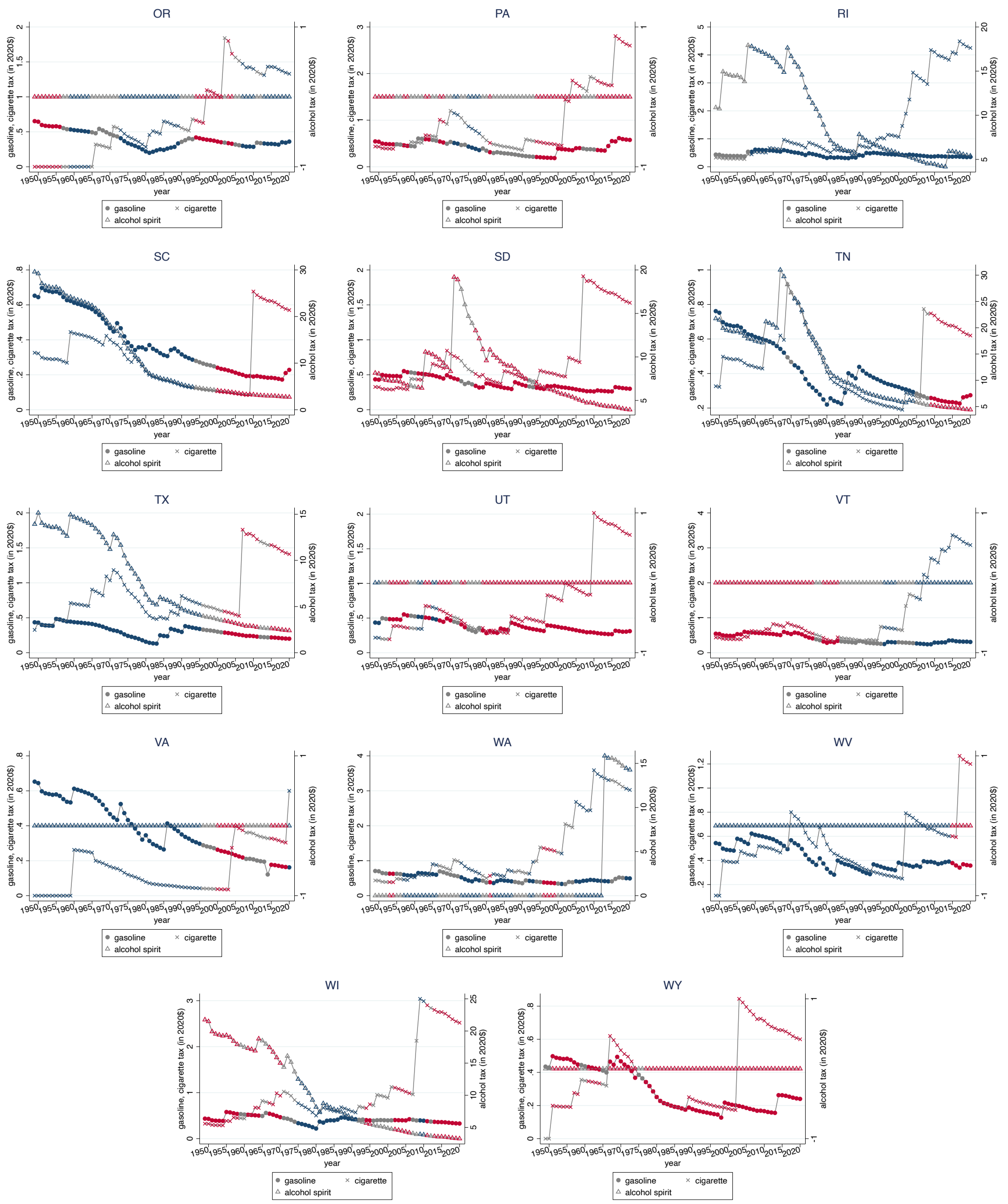


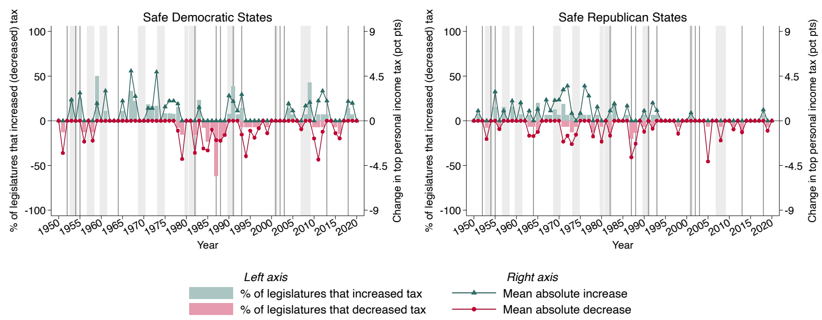
Figure B.6: Personal, Corporate and Sales Tax Rates Time Series



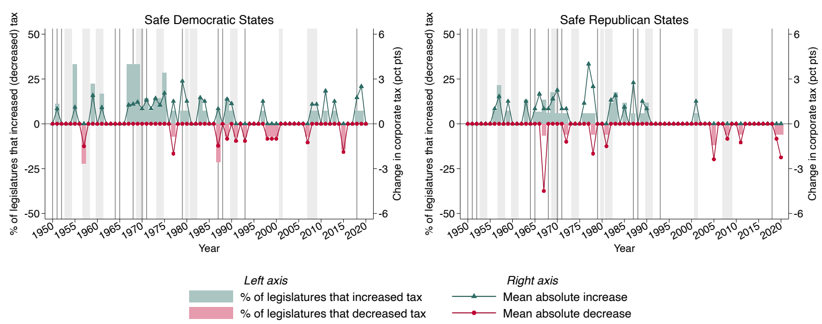
Notes: These figures show time series of cigarette, gasoline and spirit excise tax in each state. Red and blue colors identify years in which legislatures (both House and Senate) were majority Republican or Democratic respectively.

Figure B.7: 50% Largest Tax Rate Changes Over Years

(a) Top Income Tax Rate



(b) Corporate Tax Rate



(c) Sales Tax Rate

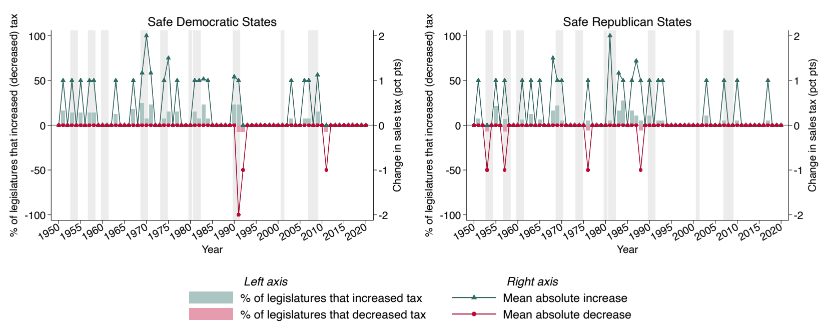
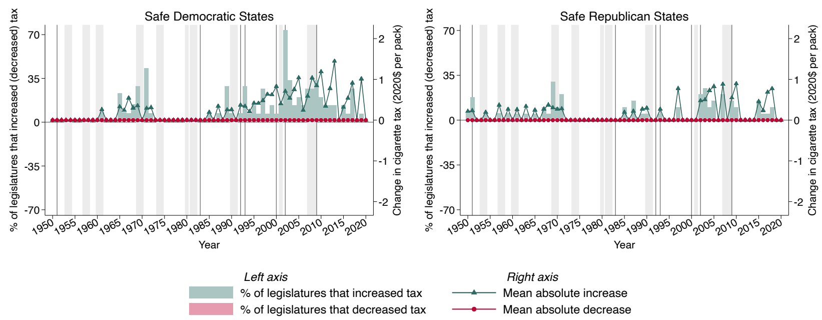
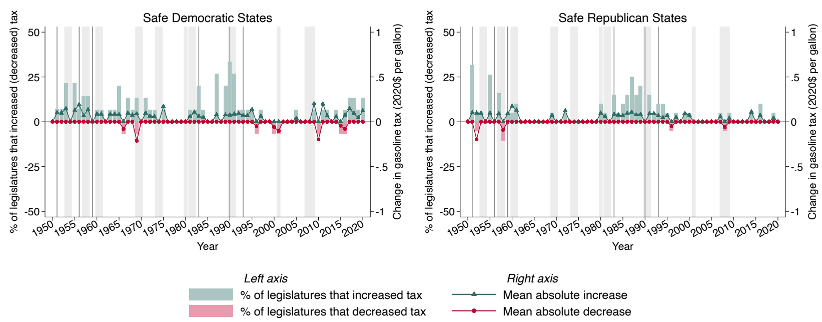


Figure B.7: 50% Largest Tax Rate Changes Over Years, Continued

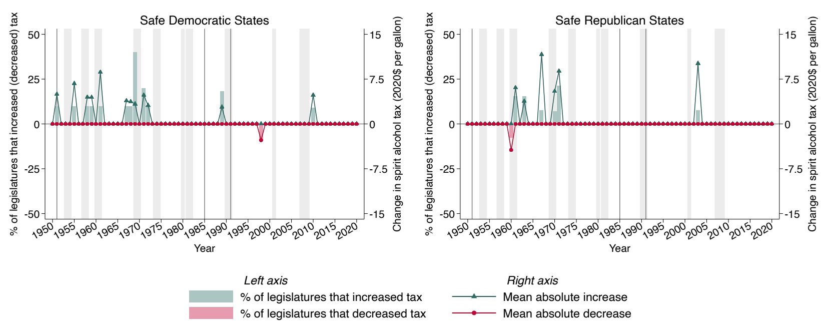
(d) Cigarette Tax



(e) Gasoline Tax



(f) Spirit Tax

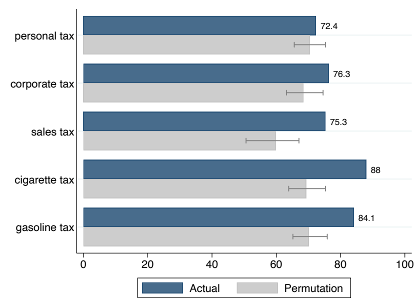


Notes: Left axis: the upper green bars (lower pink bars) show the percent of states that increase (decrease) their taxes in a given year. Right axis: the triangle series (dot series) show average size of tax increases (decrease) in pp or in 2020 dollars. These statistics are shown for (a) state top income tax rates, (b) state top corporate tax rates, and (c) state standard sales tax rates, (d) cigarette excise tax rates, (e) gasoline excise and (f) spirit excise tax rates. These statistics are shown separately for states that have only voted for a Democratic (Republican) presidential candidate since 2000 elections (see Table A.3). Only largest 50% of tax changes are included. Gray bars identify national recessions; while gray lines identify changes in federal tax rates.

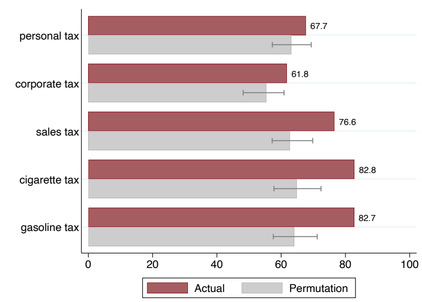
Figure B.8: Percent of Tax Changes that Occur in Response to Economic Causes

Left: Safe Democratic States **Right: Safe Republican States**

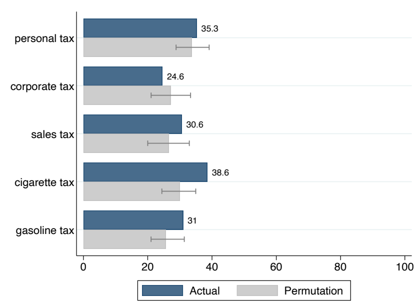
(a) within 3 years of neighbor's change



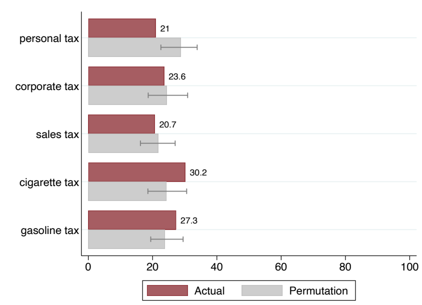
(b) within 3 years of neighbor's change



(c) 2 years after state recession



(d) 2 years after state recession



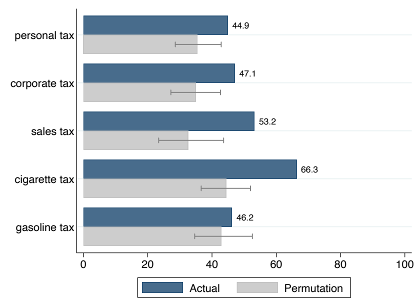
Notes: This figure shows the percent of tax changes that occur (a) within 3 years after neighboring state changes its tax rate; (b) during a state recession or a year after. In all figures, the top blue/red bars show actual observed percentages, while the grey bars show the simulated average, calculated by randomizing the timing of tax changes 100 times. The thin interval bars show the 5th and 95th percentiles of the simulated percentages. These statistics are shown separately for states that have only voted for a Democratic (Republican) presidential candidate since 2000 elections (see Table A.3).

Figure B.9: Percent of Large Tax Changes that Occur in Response to Economic Causes

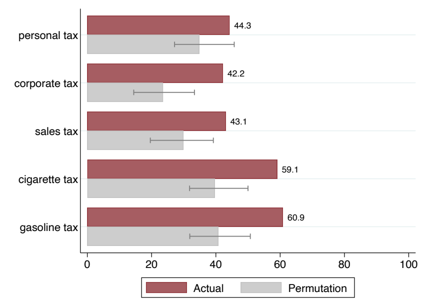
Left: Safe Democratic States

Right: Safe Republican States

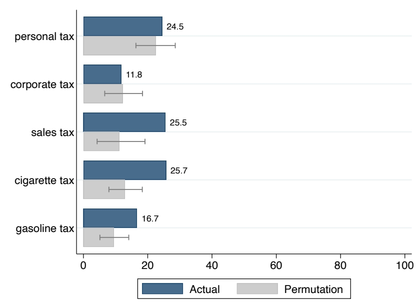
(a) following neighbor's change



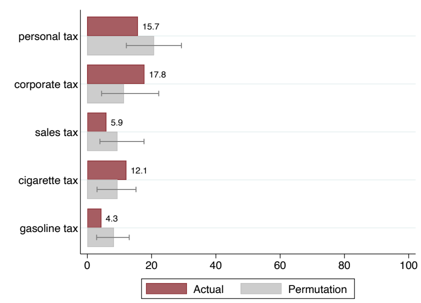
(b) following neighbor's change



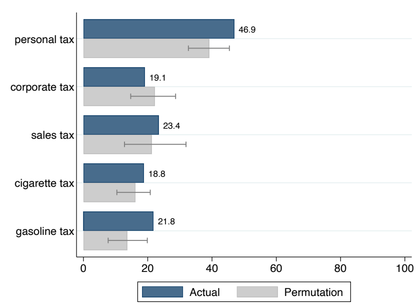
(c) during state recession



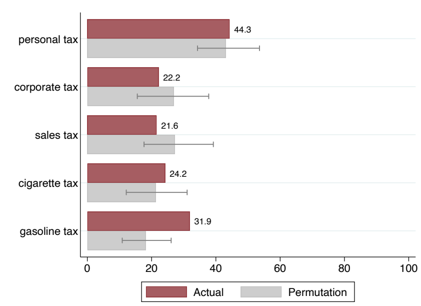
(d) during state recession



(e) following federal mandate



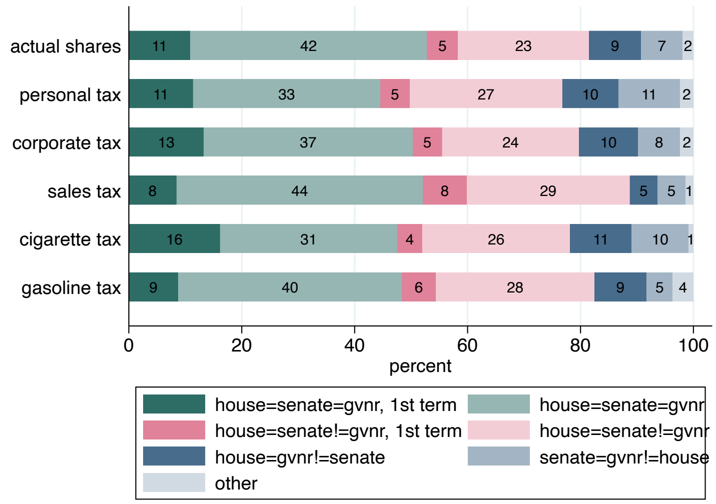
(f) following federal mandate



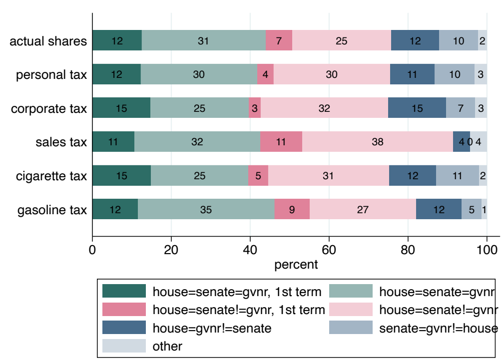
Notes: This figure shows the percent of large tax changes (top 50th percentile) that occur (a) in the same year or 1 year after neighboring state changes its tax rate; (b) during a state recession, or (c) in the year the federal mandate becomes enacted or effective. In all figures, the top blue/red bars show actual observed percentages, while the grey bars show the simulated average, calculated by randomizing the timing of tax changes 100 times. The thin interval bars show the 5th and 95th percentiles of the simulated percentages. These statistics are shown separately for states that have only voted for a Democratic (Republican) presidential candidate since 2000 elections (see Table A.3).

Figure B.10: Party Affiliation of Political Offices and 50% Largest Tax Changes

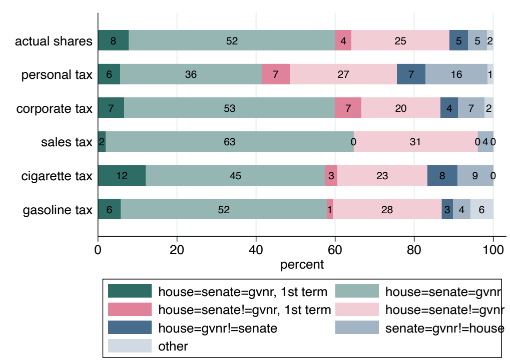
(a) all states



(b) Safe Democratic States



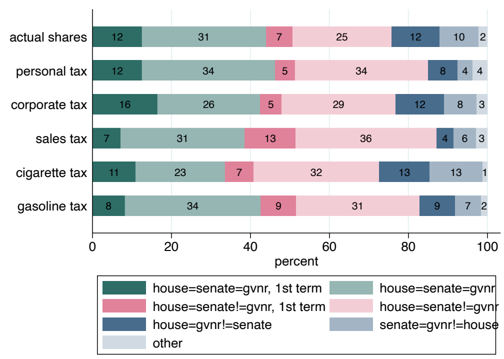
(c) Safe Republican States



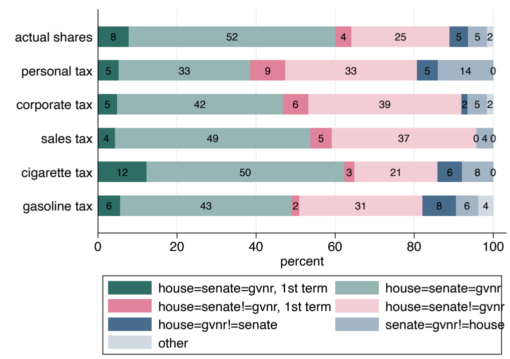
Notes: The top row of each figure shows the percent of yearly observations in which (i) the majority party of the House is the same as that of the Senate and of the Governor, and one of these three bodies switched party control; (ii) same as (i) but no party control change; (iii) House and Senate majorities are the same party, but Governor of a different party, and the joint majorities in House and Senate were obtained this term; (iv) same as (iii) but no party control change; (v) House majority matches Governor's affiliation but not Senate majority's; (vi) Senate majority matches Governor's affiliation but not House majority's; (vii) all other options (i.e. non-Democratic/Republican affiliations or lack of majorities). The next five rows show party affiliations in years when respective large (top 50% percentile) tax changes occur. Figures (b) and (c) provide these statistics separately for states that have only voted for a Democratic (Republican) presidential candidate since 2000 elections (see Table A.3).

Figure B.11: Party Affiliation of Political Offices and Tax Increases/Decreases

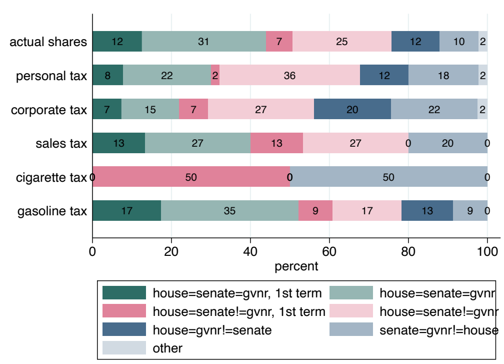
(a) Increases – Safe Democratic States



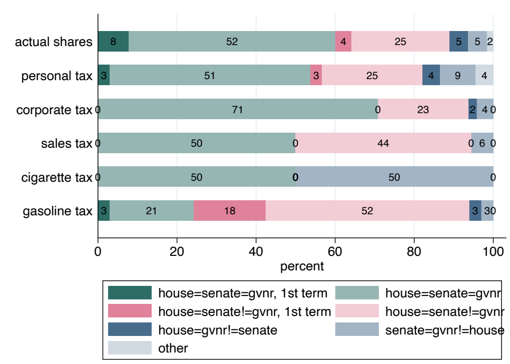
(b) Increases – Safe Republican States



(c) Decreases – Safe Democratic States



(d) Decreases – Safe Republican States

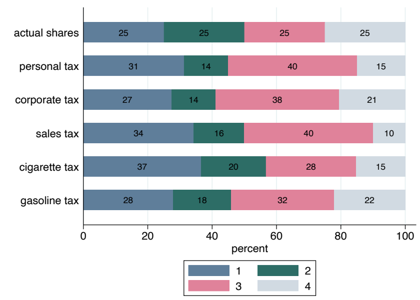


Notes: The top row of each figure shows the percent of yearly observations in which (i) the majority party of the House is the same as that of the Senate and of the Governor, and one of these three bodies switched party control; (ii) same as (i) but no party control change; (iii) House and Senate majorities are the same party, but Governor of a different party, and the joint majorities in House and Senate were obtained this term; (iv) same as (iii) but no party control change; (v) House majority matches Governor's affiliation but not Senate majority's; (vi) Senate majority matches Governor's affiliation but not House majority's; (vii) all other options (i.e. non-Democratic/Republican affiliations or lack of majorities). The next five rows show party affiliations in years when respective tax changes occur. These statistics are shown separately for states that have only voted for a Democratic (Republican) presidential candidate since 2000 elections (see Table A.3) and for tax increases and decreases.

Figure B.12: Election Cycles – Tax Increases

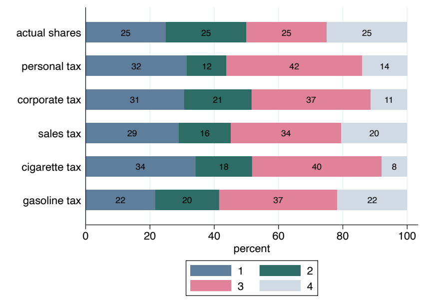
Left: Safe Democratic States

(a) Presidential Elections

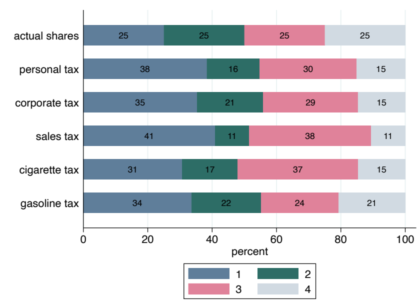


Right: Safe Republican States

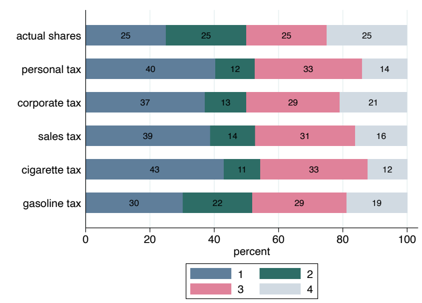
(b) Presidential Elections



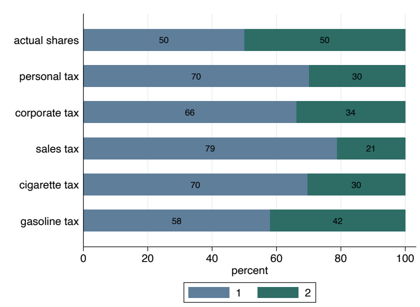
(c) Governor Elections



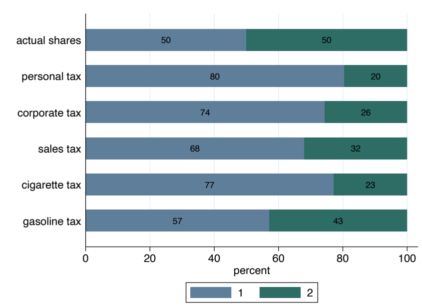
(d) Governor Elections



(e) House Elections



(f) House Elections

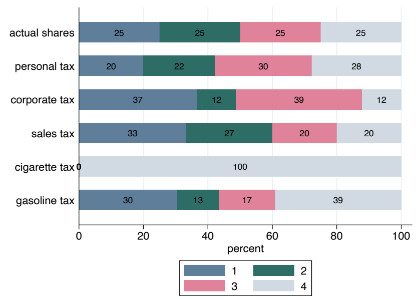


Notes: The top row of each figure shows the percent of yearly observations occurring during the studied time period. Years 1 through 4 identify first, second, third and fourth years post-election. The other rows show similar break downs but in years when tax changes of a given tax type occur. For gubernatorial and house elections, only states with 4-year and 2-year cycles are included respectively. These statistics are shown separately for states that have only voted for a Democratic (Republican) presidential candidate since 2000 elections (see Table A.3).

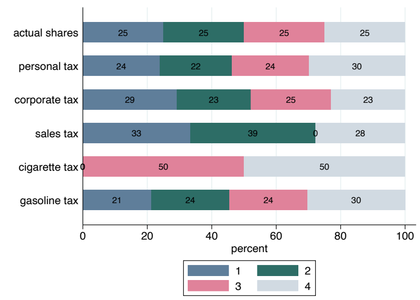
Figure B.13: Election Cycles – Tax Decreases

Left: Safe Democratic States **Right: Safe Republican States**

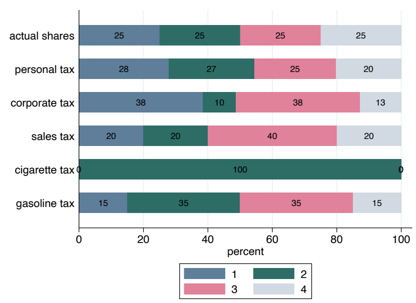
(a) Presidential Elections



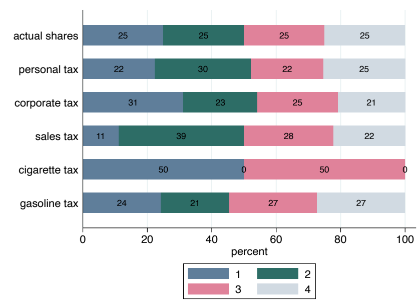
(b) Presidential Elections



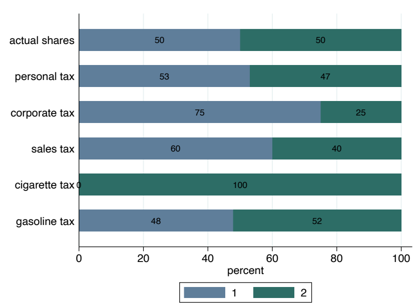
(c) Governor Elections



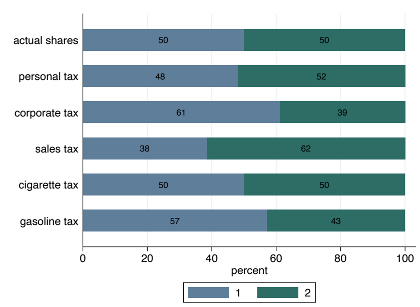
(d) Governor Elections



(e) House Elections



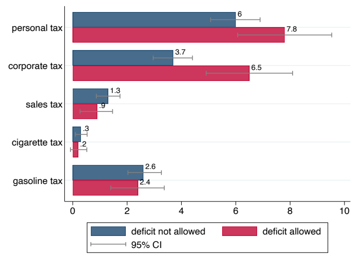
(f) House Elections



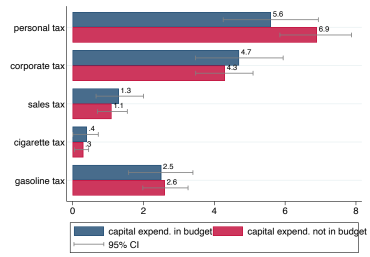
Notes: The top row of each figure shows the percent of yearly observations occurring during the studied time period. Years 1 through 4 identify first, second, third and fourth years post-election. The other rows show similar break downs but in years when tax changes of a given tax type occur. For gubernatorial and house elections, only states with 4-year and 2-year cycles are included respectively. These statistics are shown separately for states that have only voted for a Democratic (Republican) presidential candidate since 2000 elections (see Table A.3).

Figure B.14: Institutional Rules: Tax Decreases

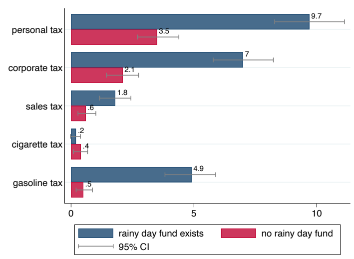
(a) Deficit Rules



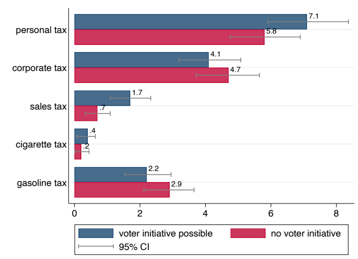
(b) Capital Expenditure Rules



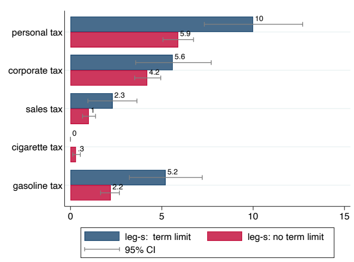
(c) Rainy Day Fund



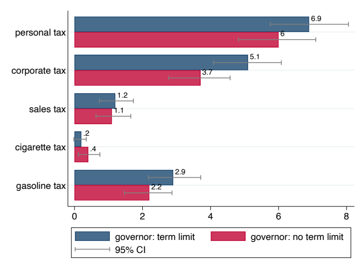
(d) Voter Initiative Rules



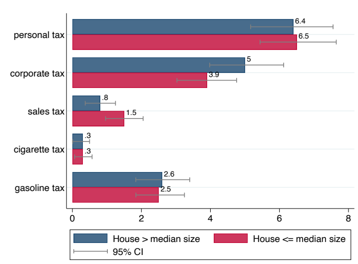
(e) Legislature Term Limits



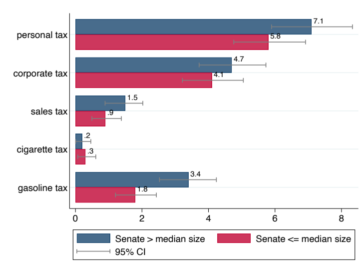
(f) Governor Term Limits



(g) House Size



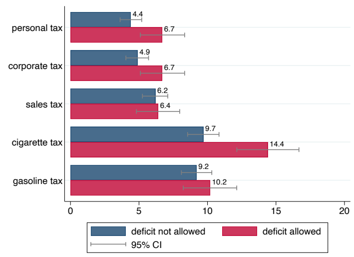
(h) Senate Size



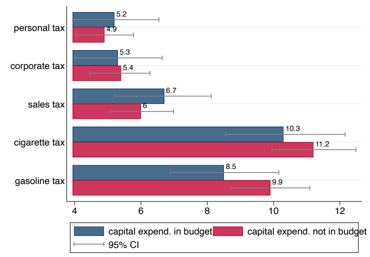
Notes: This table shows the frequency of tax decreases in states with various institutional settings.

Figure B.15: Institutional Rules: Tax Increases

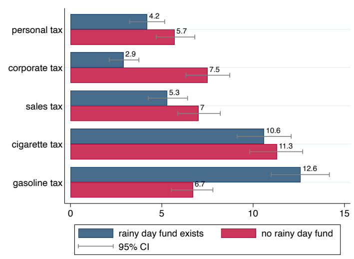
(a) Deficit Rules



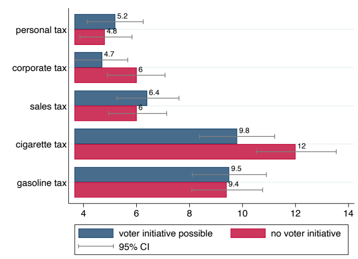
(b) Capital Expenditure Rules



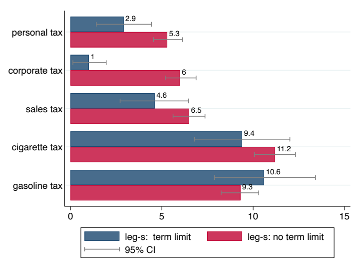
(c) Rainy Day Fund



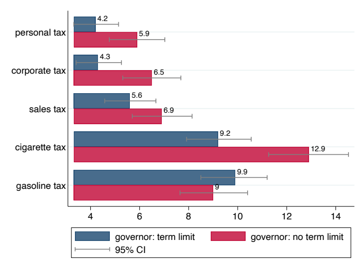
(d) Voter Initiative Rules



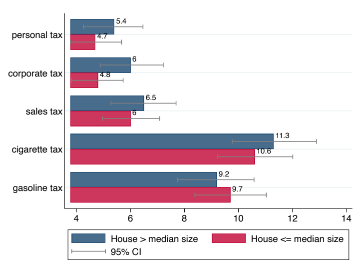
(e) Legislature Term Limits



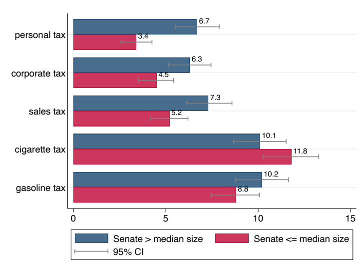
(f) Governor Term Limits



(g) House Size



(h) Senate Size



Notes: This table shows the frequency of tax increases in states with various institutional settings.