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

Sarah Robinson Alisa Tazhitdinova

Abstract

We collect detailed data on U.S. state personal income, corporate, sales, cigarette, gasoline, and alcohol taxes over the past 70 years to shed light on the determinants of state tax policies. We provide a comprehensive summary of how tax rates have changed over time, within and across states. We then use permutation analysis, variance decomposition, and machine learning techniques to show that the timing and magnitude of tax rate changes are not driven by 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

*Sarah Robinson: Robert Day School of Economics and Finance, Claremont McKenna College (sarah.robinson@claremontmckenna.edu); Alisa Tazhitdinova: Department of Economics, UCSB and NBER (tazhitda@ucsb.edu). We thank Sutirtha Bagchi, Youssef Benzarti, Johannes Fleck, John Friedman, Daniel Garrett, Ricardo Perez-Truglia, Kim Rueben, Cailin Slattery, Gonzalo Vazquez-Bare, Matthew Weinzierl, Francis Wong and seminar participants at Stanford, UC Berkeley, UCSB, 2022 NBER Spring Public Economics meetings, 2021 NTA meetings, CESifo Public Economics Webinar, Mannheim Taxation Conference, RIDGE Public Economics Workshop, Texas A&M Public/Labor Economics Workshop, and UTAXI for insightful suggestions. We thank Peter Feng, Duc Khuong, Sarah Papich and Yaoqi Yang for excellent research assistance.

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 direction of tax rate trends over the past 70 years, including the degree of convergence or divergence across states, and compare these outcomes to the long-term predictions of fiscal federalism models. We further examine the frequency of tax rate changes, the degree to which changes in one tax overlap with changes in another, and the persistence of rates over time.

Next, we use permutation analysis, variance decomposition, and machine learning techniques to evaluate to what extent the *timing and magnitude* of tax rate changes are driven by incentives prominently featured in economic models. Broadly speaking, public economists highlight the importance of taxes for redistribution, revenue collection, and addressing externalities, while macroeconomists employ taxes as a policy stabilization tool. Political economists call attention to the importance of voter preferences, as well as political and institutional frameworks in tax setting processes. Finally, fiscal federalism models spanning all fields stress the importance of state competition on policy outcomes. These theoretical factors map well into policy motivations of the legislators: Romer and Romer (2010) show that at the federal level, most tax changes have a "clearly identifiable motivation that falls into one of four broad categories: offsetting a change in government spending; offsetting some factor

[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).

other than spending likely to affect output in the near future; dealing with an inherited budget deficit; and achieving some long-run goal, such as higher normal growth, increased fairness, or a smaller role for government." Motivated by this, we consider *economic influences*, such as competition and changing revenue requirements due to economic downturns or federal mandates; *political influences*, such as the election cycles, composition, and changes of political powers within the state; *institutional features*, such as the size of state legislatures, term limits, balanced budget requirements, and voter initiative rules; *demographic influences*, such as population measures, labor force participation rates, poverty measures, and demographic compositions; 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 the factors most frequently featured in economic models of tax policy, taken together, can explain the tax-setting processes. We formally show that in a broad set of policy-setting models and as long as policymakers are not evenly split, tax policy should be highly predictable even if policymakers' preferences are somewhat idiosyncratic. Empirically, this implies that a flexible machine learning algorithm incorporating the 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 a 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 – the top personal income tax rate, top corporate tax rate, standard sales tax rate, cigarette tax per pack, gasoline tax per gallon, and spirit tax per gallon. By focusing on (top) statutory rates, our analysis centers on tax features that are important for inequality considerations and that are likely to be most salient to voters. To ensure our results are as comprehensive as possible, we also collect information on other features of tax policy: the first-bracket personal income tax rate, married exemption, bottom and top income brackets, state EITC rates, deductibility of federal income taxes, sales tax inclusion rules, and various corporate tax features: e.g., number of years allowed for loss carry back and carry forward, apportionment weights (payroll, property and sales), and minimum corporate tax rate. We treat each state as an individual decision maker and for this reason do not weigh results by population.

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 have exhibited stable levels of 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 a similar level of policy heterogeneity during the last 30 years of the century. As shown by Rhode and Strumpf (2003), the observed trends thus do not lend support to Tiebout-sorting models (which predict divergence of tax rates in the presence of lower mobility costs) or of race-to-the-bottom competition models (which typically predict convergence). Overall, long-term trends suggest that competition forces – while important – are unlikely to be the primary drivers of tax policies.

Second, despite the relative stability of average rates, states implemented many tax rate changes during the studied period. In an average year, 20 states changed at least one tax rate. Furthermore, states frequently change

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

more than one tax rate at a time: 36% of state tax changes involve changes of two or more tax rates, and 13% of changes involve three or more rates. We show that states vary dramatically in how frequently they change tax rates, with more frequent changers favoring smaller tax changes. While sales and excise taxes followed a well-defined trend in nearly all states over time, income and corporate tax trends vary, with states frequently exhibiting fluctuating patterns. We see some persistence in tax rate levels, but overall conclude that the magnitude of tax rate changes appears to be rather unpredictable. With the exception of the personal income tax, the correlation between the rate in 1950 and the rate in 2020 is less than 20%. While Democratic-leaning states tend to have higher tax rates on average, the rates of Democratic- and Republican-leaning states largely overlap.

Third, we show that the timing and magnitude of tax rate changes are difficult to predict, suggesting that either taxes are not legislated "in response to" economic and political events as assumed in economic models, or that the response is often highly nuanced or untimely, perhaps due to legislative gridlock. We start by using permutation techniques to investigate what share of tax rate changes follow an event of interest highlighted in economic models: a recession or boom (as macroeconomic stabilization tool), the introduction of an unfunded federal mandate (externally driven increase in spending), a neighboring state's tax change (competition), or a change of majority party (a change in voter preferences or political environment). 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-occurrence are not dramatically different from the simulated benchmark, suggesting that these events have a limited influence on the timing of tax changes, despite being prominently featured in models, or that their influence is untimely.

We continue this analysis by turning to a variance decomposition approach and machine learning techniques. Overall, we find that our extensive set of explanatory variables that covers federal changes, economic needs, neighborly competition, institutional features, political factors, and demographics explains less than 20% of variation in the timing and magnitude of tax rate changes, even when employing machine learning techniques that allow for various interactions and flexible functional forms. Interestingly, variance decomposition suggests that tax rate increases and tax rate 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' tax rates levels, and own other tax rate levels are more important for tax increases, while balanced budget provisions are more important for decreases.

Our main analysis focuses on changes in a specific tax rate within a specific year, but aggregating changes across time or across tax types results in similar conclusions. We first explore changes in tax rates from one *decade* to the next, and show that explanatory power increases only modestly. Since decade analysis is less prone to measurement error, this further increases our confidence that the result is not driven by measurement error. We then show that explanatory power remains low when considering *any* change in tax rates, and actually decreases when considering changes in two or more tax rates.

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 later, that showed that tax policies respond to economic, political and institutional features. We build on this work to show that while these factors affect tax policy in an economically meaningful and statistically significant ways, they account for a small share of the overall tax variability.

Our interpretation of the results is that either economic, political, and institutional factors are not the primary determinants of tax policy, or that they operate in a highly nuanced rather than consistent and predictable way. Our analysis omitted many factors that could plausibly explain the remaining variation in tax policy. Some of these, such as lobbying and political contributions, have the potential to affect tax policy directly.[3] Other factors may influence

[3]Political literature so far has found little support for such *quid pro quo* links in general (Ansolabehere et al., 2003), and for tax policies specifically. For example, Slattery et al.

tax policy indirectly, for example by shaping how legislators respond to factors already studied. Alternatively, the legislative process may be so complex that idiosyncratic factors create substantial randomness in the timing and nature of policy responses.[4] This would imply that tax policy is unnecessarily volatile and uncertain, resulting in excess state tax revenue volatility, business cycle volatility, and policy uncertainty that can have detrimental effects on growth and the welfare of state residents (see e.g., Seegert, 2015).

Our findings are relevant for empirical researchers who rely on tax variation as a source of identification. While our results do not imply that tax changes are outright "exogenous," they do suggest that the bias from omitting institutional, political, and economic factors is likely to be small in studies that exploit sharp variation in tax changes and focus on short-run outcomes. Simply put, the tax setting process appears to be sufficiently complex so that the exact timing of tax changes is sufficiently random. However, longer-term estimates need to be interpreted with caution as some tax rates appear to follow a trend. Finally, researchers should be careful when attributing estimated effects to a specific tax change since many tax changes are implemented as part of a package i.e., at the same time as changes in other tax rates.

A caveat to our analysis is that, while we try to paint a comprehensive picture of state policies, these policies are very complex and hard to summarize. Because of this, we focus on explaining changes in specific features of tax policy instead of comparing effective tax burdens across states. We choose to focus on tax rates because these are most salient to voters, subject to extensive media coverage, and are changed frequently. In contrast, isolated tax base rules (that we study) are changed infrequently, even though altogether they are key to understanding the amount of tax revenue a given tax generates (Suarez Serrato and Zidar (2018)). Relatedly, we only explore changes to state tax rules but ignore changes at the local level. Our empirical analysis, however, includes

(2023) show that state tax policies did not change in response to independent corporate expenditure increases as a result of the *Citizens United* ruling.

[4] 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.

year or decade fixed effects, and allows for differential predictions over time through interactions with decade dummies. Thus while we are not able to measure the influence of local policies on state policies, we account for broad trends via fixed effects. Our analysis also does not account for differences in the cost of living across states. 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.[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 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.

[5]Moreover, property taxes vary across localities within states, to a much larger extent than other types of taxes. To mitigate the importance of this exclusion, we include in our predictive analysis shares of 1995 tax revenues attributed to each tax type, thus controlling for states' tax structures.

[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.

Consistent with previous work, we confirm that the competitive, political, and institutional forces highlighted in economic models matter, but show that they explain a relatively small share of fluctuations in tax policy.

Furthermore, 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 Suarez 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.

1 Should Tax Policy be Predictable?

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

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

The second set of models treats policy makers as potentially self-interested utility-maximizing agents who may or may not take voter preferences into account. The most well-known of these models, the median voter framework, is fully deterministic – thus as long as the median voter's preferences are observed to policymakers, they should be observable to researchers. This intuition, however, can be extended to settings with idiosyncratic shocks, where policymakers (or voters) "tremble" when making choices. In these frameworks, tax policy should still be highly predictable, as long as the appropriate measures of aggregate policymakers' preferences and relevant decision-making factors can be observed. To build intuition, consider the outcome of a 70-30 weighted coin flip. If we were to predict the outcome of an individual flip, we would fail approximately 30% of the time. However, if our goal is to predict whether 100 coin flips will result in a majority heads outcome, we are likely to succeed with nearly a 100% probability. Note, however, that the majority heads outcome becomes harder to predict as the coin gets closer to the 50-50 unweighted case.

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

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

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

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

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

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 thus making policy outcomes potentially as difficult to predict as individual votes.

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

2 Data

2.1 Tax Rate Data

We collect data on top and minimum personal income, top and minimum 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. 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.

In addition, we collect information on tax base features: income thresholds for minimum and top tax rates, personal income tax exemptions, whether federal tax liabilities are deductible, state EITC rates, and the inclusion of food and prescriptions in the sales tax base. We also utilize policy measures of the corporate tax base from Suarez Serrato and Zidar (2018). This data covers the following details: investment tax credit rate, number of years for loss carryback and carryforward, whether the federal income tax base is the state tax base, whether state has franchise tax, whether the state follows federal accelerated depreciation, whether the state follows accelerated cost recovery system depreciation, whether the state follows federal bonus depreciation, and state tax apportionment weights (payroll, sales, and property). The Suarez Serrato and Zidar (2018) data ends in 2010-2015, so we extend the series for apportionment weights and loss carrybacks/forwards to 2020.

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 studying tax changes, we disregard tax changes that are smaller than 0.1 percentage points for personal, corporate income tax and sales taxes. For excise taxes, we disregard tax changes that are smaller than $0.005. The latter restriction allows us to disregard the frequent but small changes of gasoline taxes that arise from automatic adjustment rules implemented in some states. We consider all tax changes as independent observations, even when these changes were legislated as a set of reforms. We do so because legislative decisions are frequently overturned: temporary tax changes often do not expire as scheduled and instead turn into permanent changes, while scheduled tax changes are often 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 important effects on tax policy. Our choice of factors has been motivated both by political economy and fiscal federalism studies that directly explore tax setting processes, as well as by economic models in general. While we are not able to include all plausibly relevant factors, we consider a wide range of explanatory variables. In this section we briefly summarize the nature of our data, details are available in Appendix Section A. The complete list is available in Table 1.

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

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

The fifth, sixth, and seventh groups consider state institutional features which cover both time-invariant rules such as size of legislatures, balanced budget provisions, as well as time-variant rules such as the existence of rainy day funds, term limits, whether states require supermajorities and type for tax increases, and whether the state is a right-to-work state. Our eighth group accounts for political influences: party of legislatures' majorities and governorship and the strength of majority, number of party switches, whether this is the first year of new party in charge, state and federal government shutdowns, outcomes of presidential elections, and DW-NOMINATE scores of state representatives/senators. Again, we account for contemporaneous, lagged, and lead values.[7]

Ninth, 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. Tenth, we control for other tax rates in the state, including lagged values. 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. Including these variables allows us to control for the structure of tax system in the state, e.g. the importance of each tax type or lack of such.[8]

Finally, for completeness we also measure how the adjusted R^2 increases when state and year fixed effects are included, to account for remaining time-invariant state characteristics and state-invariant time effects.

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

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

3 How Have Tax Rates Changed Over Time?

3.1 Long-Term Trends

Figures 1 (a) and (b) show the unweighted average tax rates across 50 states and, when applicable, corresponding federal rates. Averages weighted by population are available in Appendix B.1 and are very similar. 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 personal 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.[9] 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 the most homogeneous. The large decrease in heterogeneity of income and sales taxes could either be due to adoptions of

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

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 (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, as argued by Rhode and Strumpf (2003), 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.

Additional results are available in the appendix: Figure B.2 shows how the long-term trends vary by region. Overall, all regions follow a similar pattern but the changes are more pronounced among Northeast and Midwest states, and lowest among South states. Figure B.3 shows long-term trends for other tax rules, such as minimum tax rates, tax brackets, and corporate tax rules. Similarly to results in Figures 1, we do not see much of a convergence or divergence among most tax rules.

3.2 Timing of Tax Changes

Figure 2 shows the percent of states that increase (resp. decrease) a given tax rate in each year.[10] The grey vertical lines highlight changes in corresponding federal tax rates. Alcohol taxes are adjusted the least frequently, by 5% of states on average each year. Gasoline taxes are changed the most frequently, by 17% of states in an average year. Across all tax rates, each year saw an average of 20 states changing at least one tax rate, ranging from 4 states in 1952 to 35 states in 1983.

[10] The percent of states that change the tax rate is conditional on already having the tax.

With the exception of top personal and corporate tax rates, most tax rates have been increasing over time. Income taxes (both personal and corporate), on the other hand, saw a large number of tax increases prior to 1980, but since then have mostly decreased. Importantly, we see that while tax changes are numerous, they do not appear to follow a well-defined pattern. For example, we do not see a consistent clustering of tax increases or decreases around federal tax changes, nor do we see clustering of tax changes in general, as predicted in some models of state competition. Finally, tax increases and decreases often occur in the same year.

Next, we explore whether different tax types are changed in the same year, and if yes, whether states tend to increase or decrease all tax rates across the board, or instead, shift tax structures by increasing some rates while decreasing others. In Figure 3, among the increases (or decreases) in each tax on the x-axis, the vertical bars specify the share that coincides with an increase (or decrease) in another tax type in the same state and year. For example, Figure 3 (a) shows that among all of the times that states increased the personal income tax, 10% occurred alongside a decrease in the alcohol spirit tax in the same state and year. The results are striking: a large number of tax changes occur simultaneously! Overall, 36% of state tax changes involve changes of two or more tax rates, and 13% involve three or more rates.

This pattern is particularly true for tax increases, and for personal, corporate, and sales tax rates. We see that 46% of top income tax rate increases coincided with a corporate rate increase, and 23% coincided with a sales tax rate increase. Meanwhile, personal income tax decreases coincided with corporate tax decreases in 26% of cases. Corporate tax increases and decreases also show a high overlap with both personal and sales taxes. However, Figure 3(d) provides strong evidence against tax substitutions: when states increase their tax rates, they rarely cut other tax types to compensate. Instead, we find many instances of multi-tax increases or decreases. A possible explanation for the observed patterns is that certain combinations of tax changes are more politically feasible than others (Bierbrauer et al., 2021).

Figure 3 highlights the importance of paying attention to other tax changes when using cross-state tax variation in empirical studies. This is particularly important for researchers that employ variation in personal, corporate and sales taxes, as well as for studies of tax increases in general, as these are most likely to occur as a bundle. Empirical researchers must be mindful of such co-occurrences when attributing their estimated effects to a particular tax change.

Finally, Appendix Figure B.4 shows similar evidence but focusing on the minimum and top income tax rates among states with progressive tax schedules. Once again we see a a large degree of co-occurrences among increases and decreases, however, the rates differ: top income tax rates increase in 61% of the cases when the minimum rate increases, but the minimum rate is raised in 35% cases of top rate increases, with similar pattern for corporate rates. Put simply: top rates are changed more frequently than minimum rates.

3.3 Heterogeneity in the Frequency of Changes

Figure 4 explores the extent to which states differ in how often they change tax rates and how. Figure 4(a) orders states by the total number of personal, corporate, sales, cigarette, gasoline, and spirit tax changes. The number of changes varies dramatically across states: over the 70 year period studied, the four least active states – AK, AL, VA, and WY – changed the six tax rates fewer than 20 times. On the other hand, the most active states – CT, NE, and NY– changed their taxes more than 80 times, i.e., more than once per year on average. Overall, states that do not have certain taxes – in particular personal income taxes (AK, FL, NH, NV, SD, TN, TX, WA, WY), 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 six types of taxes.

Figure 4(b)-(g) explore 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. For all tax rates we see a weakly negative relationship between the size of tax changes and frequency of changes, with this relationship being most pronounced for sales, cigarette and gasoline taxes.

3.4 Tax Rate Level Persistence And Political Leanings

Figure 5 shows how tax rates have varied over time within each state. For each tax rate, we show the tax rate in 1950 (or the year that tax was adopted), the tax rate in 2020, as well as the average, minimum, and maximum over the time period. Furthermore, we color each state in blue, red, or grey depending on their political leanings in most recent years. Specifically, we break down states into three groups based on states' pledges in recent 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.2). All other states are considered swing states. Figure 5 thus shows how much tax rates deviated from the mean during the studied period, and whether state tax changes generally moved in the same direction or saw a large number of fluctuations around the mean.

We see that for personal and corporate income taxes, most states exhibit a fluctuating pattern: for many states, 1950 tax rates are at or near the minimum, yet, 2020 rates are often below the maximum, and in many cases below the mean. However, consistently with Figure 4, states vary dramatically in their tax ranges. For some states, e.g. PA, IN, AL, VA, KY, LA, we see minimal changes of the top income tax rate. For other states, we see significant swings: DE's top income tax rate ranged from 3pp to 19.8pp, despite the fact that the rates in 1950 and 2020 were very similar (6.25pp and 6.6pp respectively).

In contrast to income taxes, sales and excise taxes show a one-directional pattern. We see that almost all states increased their sales tax and cigarette tax over time and that in many states, the 2020 sales tax rate is at the highest level sales tax has ever been. Low cigarette taxes generally reflect lack of inflation adjustments rather than active tax changes. The opposite pattern is seen for gasoline and alcohol spirit taxes: current tax rates are at their lowest point in the past 70 year period for most states.

Figure 5 also shows that there is limited persistence in tax rates over time. Some states increased their rates dramatically, others less so, and the magnitude of change is not well correlated with the starting or ending rates. While the correlation between 1950 and 2020 rates for the personal income tax is 32%, it is substantially smaller for the other tax rates: -6% for corporate income, -4% for sales, 16% for cigarette, -11% for gasoline, and 15% for alcohol.[11]

Finally, we see that there are more Democratic-leaning states at the higher end of the tax rate distribution and more Republican-leaning states at the lower end. Yet, the differences are rather small, and there is substantial overlap. Therefore, political leanings affect tax policies but do not provide an exhaustive explanation of tax rate levels.

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 and the numerous tax changes over time 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, term limits, legislature size, session duration, and voter initiative rules.

We ask how much of the tax policy variation can be explained by these factors using three complementary approaches. First, we consider each potential cause individually and conduct a permutation analysis where we calculate

[11] Correlations between each state's *rank* in 1950 and 2020 are very similar. Correlations across tax rates types are available in Table A.3.

the share of tax changes that occur after an event, relative to the share that would occur if tax changes are randomly timed. Second, we combine all factors together in a simple linear model, and investigate how much of the variation in tax changes can be explained as well as the explanatory power of individual factors. Third, we consider a more flexible set of models that allow for interactive terms, using LASSO and random forest techniques.

4.1 Permutation Analysis

To understand whether taxes respond to economic needs, we explore the extent to which 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. In this section, we omit alcohol spirit taxes from our analysis because tax changes are very infrequent.

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. For excise taxes, we consider geographical neighbors, since competition is likely to be driven by cross-border shopping. For all other taxes, we define neighbors based on migration flows, following Baicker (2005). 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 the legislative process can be slow yet observable by other states, 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 (Eugster and Parchet, 2019).

Recessions. Economic downturns may force states to increase or decrease taxes in order to collect more revenue or to stimulate their economy (Campbell and Sances, 2013; Cashin et al., 2018). To the extent that states are generally required to balance their budgets on a 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 A.4. 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 a neighbor's 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. Appendix Figure B.6 shows that our results are robust to the choice of window, while Figure B.7 shows that results are similar when focusing on largest 50% of tax changes.

Figure 6(a) shows some support for 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 neighbor's tax change than a pure coincidence would predict. However, the changes in personal and corporate income taxes just barely exceed the placebo comparison, thus suggesting that they are largely 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.

Figure 6(b) explores what share of tax changes occur during recessions: between 10% and 22% of tax changes occur during the years of recessions. Nonetheless, most of these occurrences appear to be coincidental: the observed shares are very similar in magnitude to simulated shares. While Figure 6(b) tells us what share of tax changes could in principle be explained by recessions, it does not provide us a clear answer as to whether recessions necessitate tax changes, since the observed occurrences depend on the frequency of recessions. Figure B.5 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 22% of state recessions, corporate taxes are changed in 24% of cases, while sales taxes are changed in 22% of recessions. Taxes are changed significantly less frequently during federal recessions: only in 6-9% of cases. Overall, Figure 6(b) and Figure B.5 provide suggestive evidence that most tax changes are unlikely to be driven by ongoing recessions.

Finally, Figure 6(c) explores what share of tax changes occur in response to federal mandates. Again, 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 explores the frequency of tax changes but not their direction. Figure 7 explores whether the tax changes that coincide with neighbors' tax changes, recessions and federal mandates are tax increases or decreases. As a point of comparison, Figure (a) shows 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. During recessions, states are more likely to increase personal and corporate taxes than decrease them. But overall, the relative share of decreases/increases approximately matches the averages in the top panel.

Party Control Changes. 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 a majority in both chambers of the legislature and holds the governorship. The top row of Figure 8(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 8(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 8(c) and (d)) and even swing states (Figure (b)), or when focusing on the 50% largest tax changes (Appendix Figure B.8). Appendix Figure B.9 suggests, however, that there is some heterogeneity across Republican and Democratic states when considering tax increases and decreases separately.

Next, Figure 9 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.[12] Figure 9 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.

[12] 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.

4.2 Simple Linear Model and Variance Decomposition

Next, we combine all of the explanatory variables together in a simple linear regression model. This approach allows us to quantify the extent to which these factors can jointly explain the observed variation in tax policy, as well as the relative importance of each factor when controlling for the others. Because our explanatory variables are not orthogonal, most covariates contribute to the explanatory power in a non-unique way. For this reason, we use a Shapley decomposition method to assign each group of variable's contribution to the overall explanatory power, measured by the R^2.[13]

One may worry about endogeneity issues in our specifications since some explanatory variables are likely to be chosen simultaneously with our outcome variables. We allow for such endogeneity because we are interested in measuring the predictive power rather than causal estimates. Since the resulting predictive powers are low for all specifications we have considered, we err on the side of being too generous when choosing which variables to include. Nonetheless, we choose to exclude two potentially important but likely highly endogenous variables from the set of explanatory variables – expenditures and tax revenues. Changes in expenditures may either be driven by changing preferences or in response to economic needs. For example, state governments may choose to adjust expenditures instead of changing tax rates in order to balance budgets, or may need to increase tax rates due to increased demand for public goods. Alternatively, state governments may be pressured to increase tax rates in order to maintain steady levels of tax revenue despite changing demographics and spending patterns. Instead of including expenditures and tax revenues as explanatory variables, we attempt to control for the various underlying factors that may affect expenditures and/or revenues. For example,

[13]Another potential approach would be to use a Kitagawa-Oaxaca-Blinder decomposition method to understand the extent to which various factors can explain a gap in tax rates or changes between two groups. For example, Seegert (2016) documents a clear break in tax revenue volatility pre- and post-2000 and uses this approach to explain the gap between the two time periods. However, we do not observe a clear break in tax rates or changes across time or across states. As a result, we prefer a decomposition approach that seeks to explain the variation overall, without needing to separate similar states and years into two arbitrary groups.

we account for economic conditions (e.g., recessions or booms), demographics, and long-term trends. The latter, which we capture using linear trends in time as well as year or decade fixed effects, will account for broader secular trends such as increased spending on non-taxable services. Since expenditures and revenues are omitted from the set of explanatory variables, our preferred interpretation of the results is that taxes may not be very responsive to economic/demographic conditions *in part* because state governments adjust via other margins, e.g., by changing spending levels.

We include both level variables and change variables in our analysis – mainly those related to economic conditions (recessions, unemployment, inflation) or party control changes. We include these terms to account for possibly dynamic relationships. This also ensures that our specifications are econometrically consistent i.e., tax policy outcomes measured as changes are regressed on the changes in economic conditions (as well as the levels). At the same time, we choose to not include lags beyond 2 years because some events necessitate a speedy response – e.g., enacting tax reforms three years after a recession is unlikely to be useful.

Our analysis does not account for tax changes at the local level, including changes in property taxes. Our empirical analysis, however, includes year or decade fixed effects. The machine learning analysis discussed in the next section allows for differential predictions over time through interactions with decade dummies. Thus while we are not able to measure the influence of local policies (including property taxes) on state policies, we are able to account for broad trends via fixed effects and interaction terms. Decade interactions also allow our explanatory variables to influence state tax policies differently over time.

Variance decomposition results are summarized in Figures 10-11, which show the shares of total explained variation attributed to the above-mentioned groups of explanatory variables. Since the number of observations varies across tax rates, we show the adjusted R^2. Figure 10(a) summarizes decomposition of tax rate levels (in percentage points or in \$2020), while 10(b) and (c) show tax changes in p.p. or dollars (all changes or the largest 50% of tax changes respectively). Figure 11 focuses on the timing of tax changes, and thus performs 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 well at predicting future tax rates (especially combined with a linear trend and federal tax rates), because tax rates are somewhat persistent (see Section 3.4). Since this decomposition does not distinguish between within-state variation and across-state variation, it exaggerates our ability to predict taxes. For this reason, we next turn to explain the magnitude and timing of tax changes.

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

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

Figures 10-11 also show that focusing on the largest 50% of tax changes does not improve our predictive powers. A possible explanation is that the magnitude of tax changes is more idiosyncratic than whether the tax change is legislated in the first place. This explanation is consistent with the fact that explanatory powers are generally higher when focusing on the timing only, and when focusing on all changes rather than the largest ones.

One may worry that while predicting yearly changes may be difficult, predicting long-term changes may be easy. We test this possibility by conducting an equivalent analysis but using decade changes in Figure 12. One caveat to this comparison is that the adjusted R^2 does not perfectly account for changes in the relative number of observations and explanatory variables, making comparison of Figures 11 and 12 imperfect. With this caveat in mind, we see that the predictive power indeed increases. Importantly, the increase is not driven by one particular group of covariates – most groups explain a larger share of variation with the exception of own other tax rates. But the overall conclusion remains: tax changes are hard to predict, even in the long run.

There are two plausible explanations for why decade changes are more predictable. One, is that tax changes are costly to implement and therefore not every change in economic or political conditions results in action, e.g., similarly to investment decisions of firms. However, if this were the case, large tax changes should arguably be more predictable, since these are driven by stronger needs. This explanation is not consistent with evidence in Figures 10-11. Alternatively, our preferred explanation is that the increased explanatory power across all groups is consistent with the possibility of a long-term gridlock: economic, political, and demographic influences matter, but the timing of tax changes is volatile because of gridlock. Over time, however, changes in these factors do lead to changes in tax policy, making decade changes more predictable.

One may also be concerned that changes in any tax rate, or changes in more than one tax rate, are easier to predict than changes to a specific type of tax. Policymakers might desire to increase tax revenue overall, but view changes in the different tax rates as substitutes. And as discussed in Section 3.2, many tax changes occur simultaneously – it could be the case that these broader bundles of tax reform are more responsive to economic, political, and institutional factors than changes in only one tax rate. Thus in Figure 13, we consider a change in at least one tax rate, and a change in two or more tax rates. However, we do not find bundles of tax reform to be easier to predict. We are still only able to explain about 20% of the variation in whether any tax change occurs, and our ability to explain bundles of two or more tax changes is actually lower. The decision to change tax policy *in general* is difficult to predict, not just changes in a particular tax.

Results are similar when looking at other tax rules, though the predictive power is slightly higher (see Appendix Figure B.10). Most of this explanatory power, however, does not come from economic or political factors. Instead, federal tax rates and other tax rates matter. A likely explanation is the fact that tax base rules often change in conjunction with tax rates.

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

4.3 Enriched Models Using LASSO and Random Forest

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

Because it is neither possible nor desirable to include all possible nonlinear and interactive terms in a regression analysis, we employ LASSO techniques to select a subset of variables in a data-driven way. The LASSO 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 implementation of the LASSO method varies in penalty functional form 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 a machine learning technique that allows for more flexible modeling. To make predictions, the algorithm builds multiple decision trees using a different random subset of the variables provided and a different bootstrapped sample of the data. The final predictions are then obtained by averaging individual predictions from the randomly built trees. The randomness of the sample variables and the dataset used to build a given tree ensure that individual trees are not correlated. This gives random forest its high predictive power and partially shields it from overfitting.

Table 2 summarizes our results. As our baseline comparison we take the models from Section 4.2 which included 172 "core" variables as well as state and year fixed effects. Next, we use LASSO to select the best model using these variables plus decade fixed effects and the full set of interactions – a total of 27,794 variables. Finally, the random forest algorithm uses all 172 core variables plus decade fixed effects and quadratic and cubic terms – a total of 404 variables. (Note that the random forest algorithm implicitly allows for additional fixed effects and variable interactions via its "tree" structure). The results summarized in Table 2 are based on 100 random splits of the data into a training sample (80%) and a test sample. Both algorithms search for the best model using the training sample, and that model is then used to make predictions on the test sample. We must note that while both LASSO and random forest algorithms require a number of choices made by a researcher, Table 2 presents the results from the "most promising" specifications. While the quantitative results vary depending on specification, the qualitative results do not.

Table 2 shows that while machine learning algorithms improve the predictions, the improvement is modest. The random forest algorithm does an outstanding job making predictions in the training sample but out-of-sample predictions are still poor and typically fall well below 20%. Moreover, many predictions are negative, suggesting that the models selected by machine learning perform worse than a simple sample mean. Note that these models are not selected to maximize the predictive power in the 20% out-of-sample. Instead, model selection is performed using the K-fold approach, whereby the training data is divided into K folds and the model is trained/tested K times, each time using a different fold as a test sample and the rest as training data. Thus the final predictions shown in Table 2 present a true and independent test of the model's performance, by evaluating prediction on the 20% sample of data that has never been used to select a model.

5 Discussion and 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. We consider numerous explanations for this 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. It is unlikely that the low predictive power is due to misspecification, as we consider both interaction terms and nonlinear specifications.

What are the possible explanations for the low predictive power? One possibility is that our explanatory variables suffer from measurement error, biasing our results to zero. While we cannot address this issue directly, our decade analysis should be less prone to measurement error, yet it leads to similar results. Second, our analysis may have omitted potentially important drivers of tax policy, for example, lobbying and political contributions. Whatever these omitted factors are, they appear to play a more important role than the economic, political, and institutional influences we have considered. Third, policymakers may be evenly split in their preferences, making policy decisions highly unpredictable, as our conceptual framework demonstrated. Since most states have strong Democratic or Republican majorities in the state legislatures, this would imply that policymakers are not as split on taxes as their speeches would suggest (Gentzkow et al., 2019). Finally, 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. In this case, the economic, political and institutional factors indeed matter, but in a nuanced rather than systematic, stable and predictable way. 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.

Ansolabehere, Stephen, John M. De Figueiredo, and James M. Snyder Jr, "Why is there so little money in US politics?," *Journal of Economic Perspectives*, 2003, *17* (1), 105–130.

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*, December 1998, *70* (3), 383–398.

Bierbrauer, Felix, Pierre Boyer, Andrew Lonsdale, and Andreas Peichl, "Tax Reforms and Political Feasibility," 2021.

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

Boadway, Robin and Jean-François 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.

Campbell, Andrea Louise and Michael W Sances, "State fiscal policy during the Great Recession: Budgetary impacts and policy responses," *The ANNALS of the American Academy of Political and Social Science*, 2013, *650* (1), 252–273.

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.

Cashin, David, Jamie Lenney, Byron Lutz, and William Peterman, "Fiscal policy and aggregate demand in the USA before, during, and following the Great Recession," *International Tax and Public Finance*, 2018, *25*, 1519–1558.

Castanheira, Micael, Gaëtan Nicodème, 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.

Eugster, Beatrix and Raphaël Parchet, "Culture and taxes," *Journal of Political Economy*, 2019, *127* (1), 296–337.

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.

Gentzkow, Matthew, Jesse M. Shapiro, and Matt Taddy, "Measuring Group Differences in High-Dimensional Choices: Method and Application to Congressional Speech," *Econometrica*, 2019, *87* (4), 1307–1340. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA16566.

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.

Gupta, Sanjeev and João 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 in developed, 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, 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.

Romer, Christina D. and David H. Romer, "The Macroeconomic Effects of Tax Changes: Estimates Based on a New Measure of Fiscal Shocks," *American Economic Review*, June 2010, *100* (3), 763–801.

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, "The performance of state tax portfolios during and after the Great Recession," *National Tax Journal*, 2015, *68* (4), 901–918.

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

Serrato, Juan Carlos Suarez 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, Alisa Tazhitdinova, and Sarah Robinson, "Corporate political spending and state tax policy: Evidence from Citizens United," *Journal of Public Economics*, 2023, *221*, 104859.

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

Table 1: 172 Core Explanatory Variables

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

Notes: This table summarizes the 172 variables used in Sections 4.2 and 4.3. The simple linear analysis also includes state and year fixed effects (total of 291 variables). The LASSO analysis also includes decade fixed effects and the full set of interactions (total of 27,794 variables). The random forest algorithm also includes decade fixed effects and quadratic and cubic terms (total of 404 variables).

Table 1: 172 Core Explanatory Variables (continued)

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

Notes: See previous page.

Table 2: Machine Learning Results

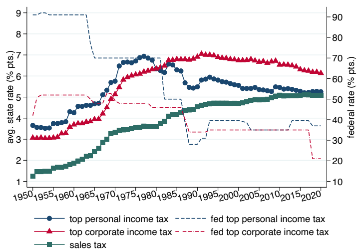
Outcome	Basic Regressions Training R^2	Basic Regressions Out-of-Sample R^2	Lasso Training R^2	Lasso Out-of-Sample R^2	Forest Tree Training R^2	Forest Tree Out-of-Sample R^2
Income tax change (pp)	0.2	0.00	0.27	-0.1	0.65	0.03
Corporate tax change (pp)	0.22	-0.49	0.09	-0.05	0.63	0
Sales tax change (pp)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

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

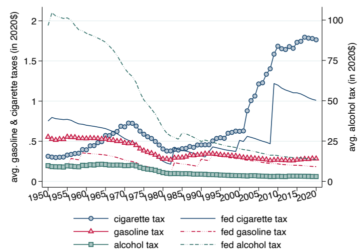
Figure 1: State Tax Rates Over Years

Panel A: All 50 States

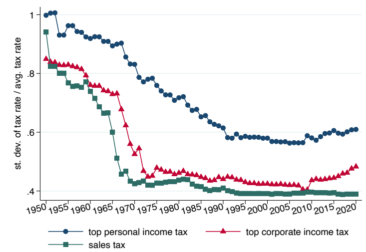
(a) Average Tax Rates



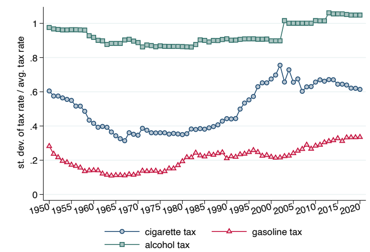
(b) Average Excise Taxes



(c) Heterogeneity

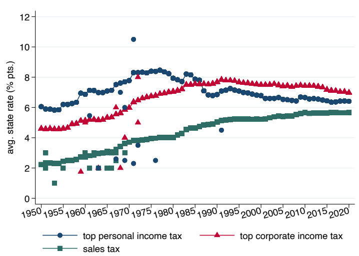


(d) Heterogeneity Excise

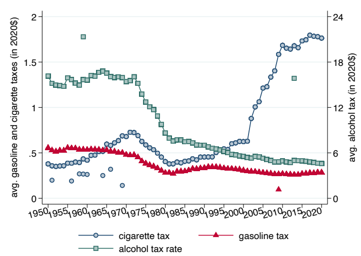


Panel B: States with Nonzero Rates

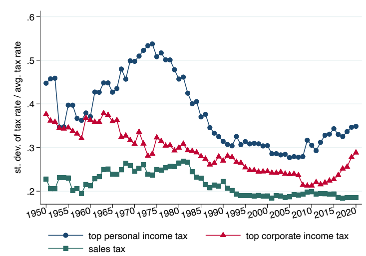
(e) Average Tax Rates



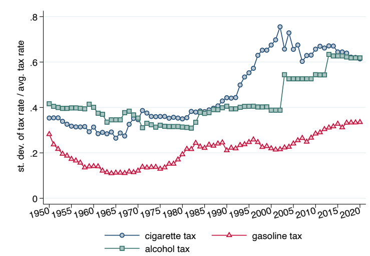
(f) Average Excise Taxes



(g) Heterogeneity



(h) Heterogeneity Excise



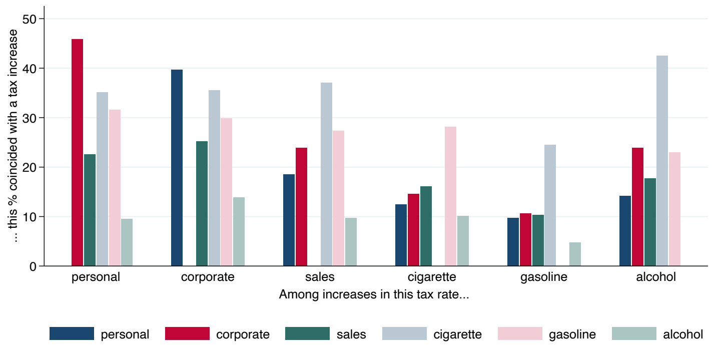
Notes: Figures (a) and (b) show average top personal income and corporate tax rates, sales tax rates, and average cigarette, alcohol (spirit) and gasoline tax rates, as well as corresponding federal tax rates. Figures (c) and (d) show the standard deviation of the state taxes divided by average tax rate (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. Population-weighted averages available in Appendix B.1.

Figure 2: Timing of Tax Changes

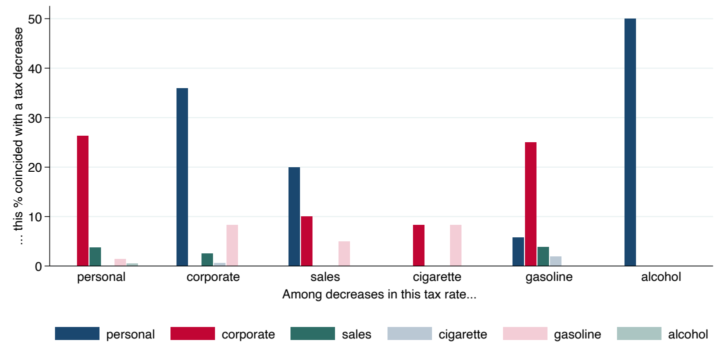
Notes: These figures show the percent of states that change a given tax rate in a given year (scatter points), increase it (green bars) or decrease it (pink bars). These statistics are shown for (a) top income tax rates, (b) top corporate tax rates, and (c) standard sales tax rates, (d) cigarette excise tax rates, (e) gasoline excise and (f) spirit excise tax rates. Gray lines identify changes in corresponding federal tax rates.

Figure 3: Simultaneity of Tax Changes in the Same State and Year

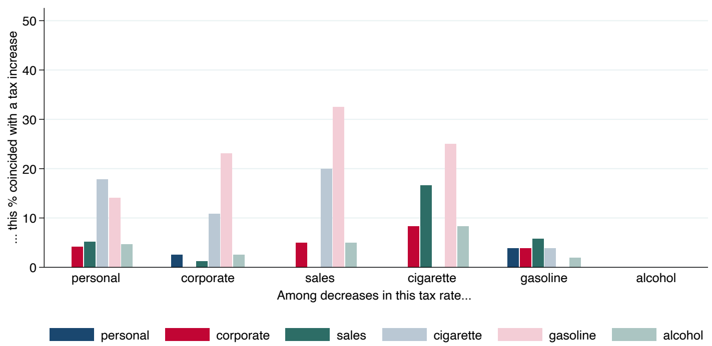
(a) % of Increases that Coincide with Increases



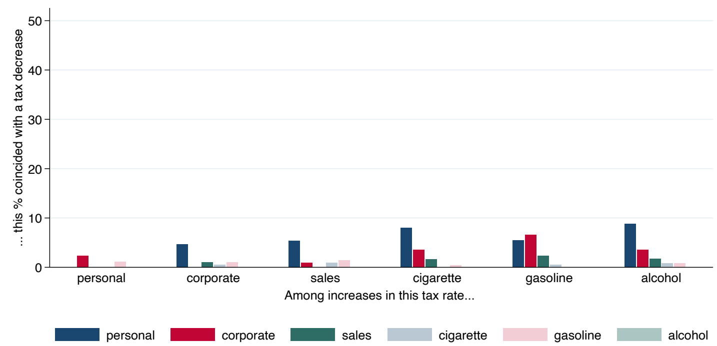
(b) % of Decreases that Coincide with Decreases



(c) % of Decreases that Coincide with Increases



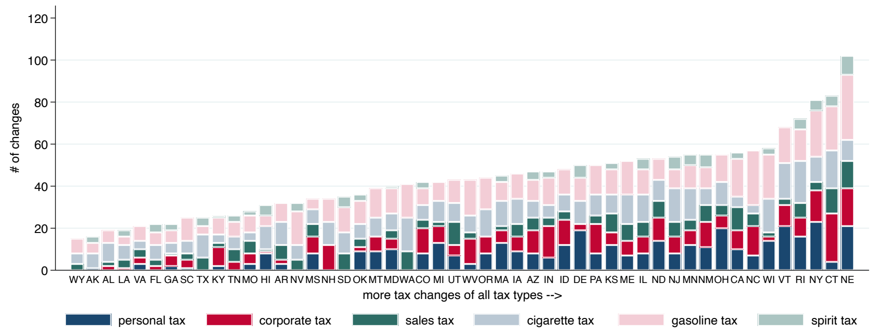
(d) % of Increases that Coincide with Decreases



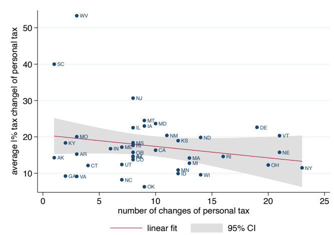
Notes: These figures explore the extent to which states change one tax rate while simultaneously changing another tax type (i.e., in the same year). Among the increases (or decreases) in each tax on the x-axis, the vertical bars specify the share that coincides with an increase (or decrease) in another tax type in the same state and year. These other tax types are identified by the color of the bar (top income tax rates, top corporate tax rates, standard sales tax rates, cigarette excise tax rates, gasoline excise, or spirit excise tax). For example, Figure (c) shows that among all of the *decreases* in top corporate income tax rates, 11% occured in the same year as an *increase* in the the cigarette tax rate in the same state.

Figure 4: Tax Changes By State

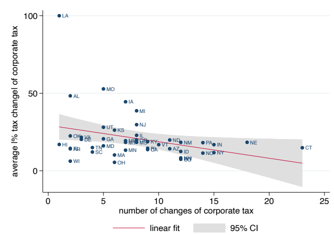
(a) Number of Tax Changes by State and Tax Type



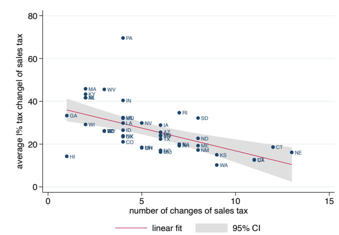
(b) Top Income Tax



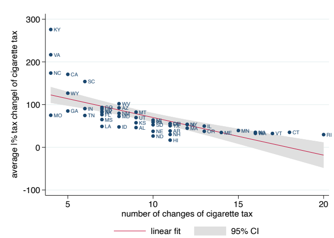
(c) Top Corporate Tax



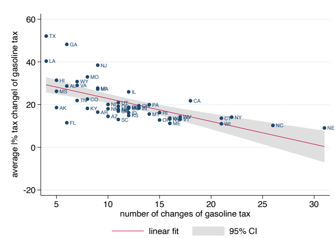
(d) Sales Tax



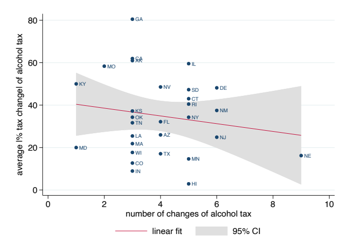
(e) Cigarette Tax



(f) Gasoline Tax



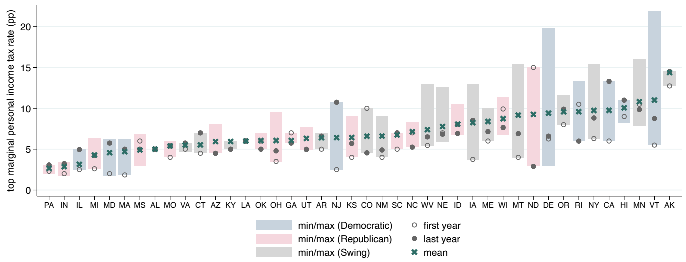
(g) Alcohol Spirit Tax



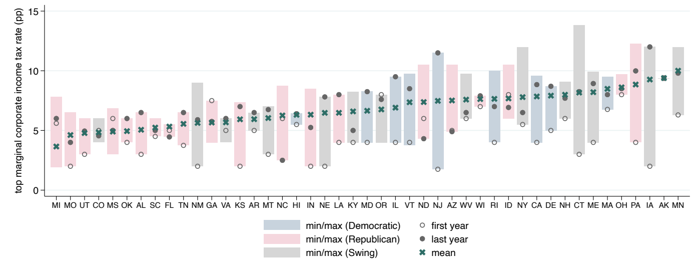
Notes: Figure (a) shows the number of tax changes in each state for six tax rates (top income tax rates, top corporate tax rates, standard sales tax rates, cigarette excise tax rates, gasoline excise tax, and spirit excise tax). Figures (b)-(g) show, for a given tax rate, the relationship between the number of tax changes and their magnitude (the average percent change in absolute value). Additionally displayed is the linear fit for this relationship, as well as the 95% confidence interval reflecting the uncertainty in both the slope and the intercept.

Figure 5: Persistence of Tax Rate Levels

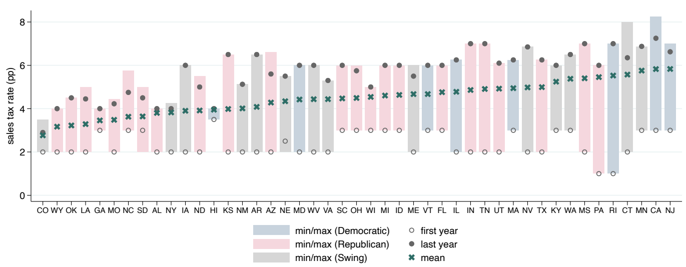
(a) Top Income Tax Rate



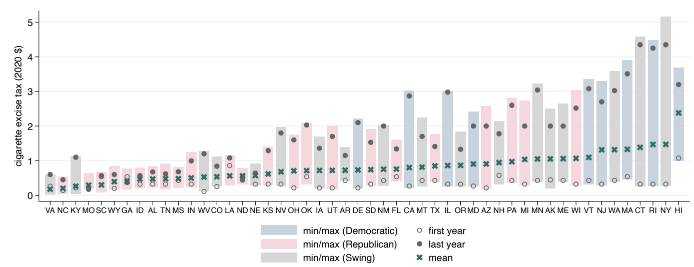
(b) Top Corporate Tax Rate



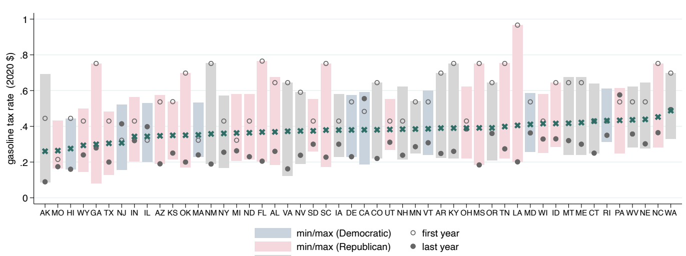
(c) Sales Tax Rate



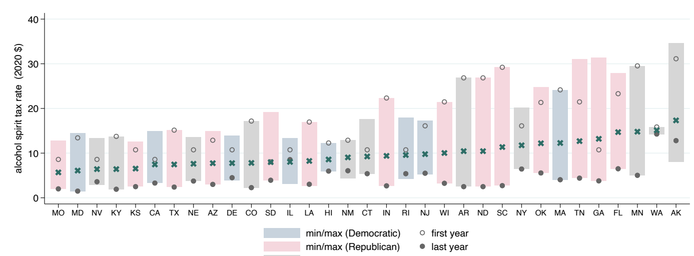
(d) Cigarette Tax



(e) Gasoline Tax



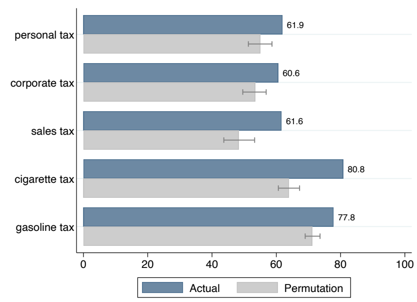
(f) Alcohol Spirit Tax



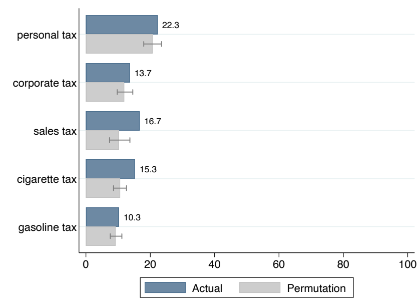
Notes: This figure shows the average tax rate, tax rate in 1950 or in the year of tax adoption, tax rate in 2020, as well as the min and max rates in 1950-2020. States are ordered by average tax rate, and only non-zero values are included. These statistics are shown for (a) top income tax rates, (b) top corporate tax rates, and (c) standard sales tax rates, (d) cigarette excise tax rates, (e) gasoline excise and (f) spirit excise tax rates.

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

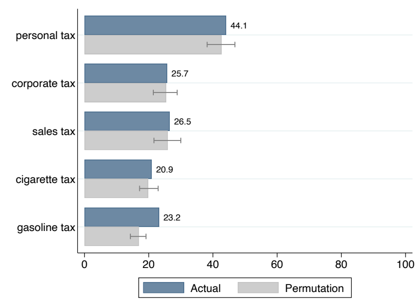
(a) Following Neighbor's Change



(b) During State Recession



(c) Following Federal Mandate

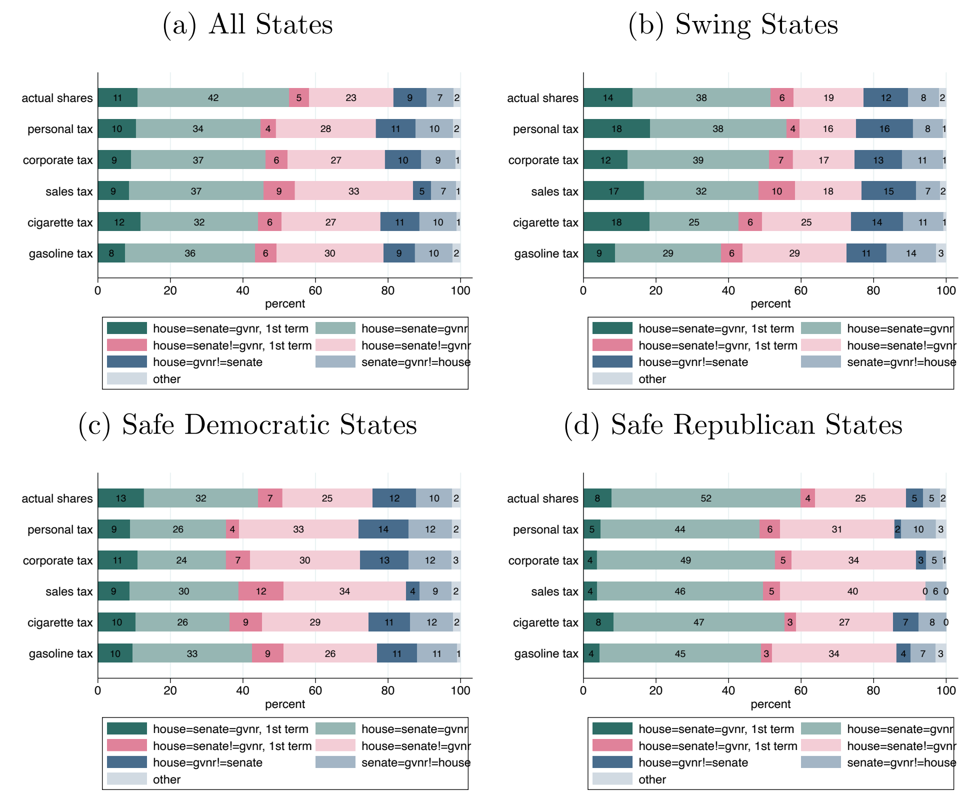


Notes: This figure shows the percent of tax changes that occur (a) in the same year or 1 year after neighboring state changes its tax rate; (b) during a state recession, or (c) in the years the federal mandate becomes enacted and/or effective. In all figures, the top blue bars show actual observed percentages, 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.

Figure 7: How Do Taxes Change?

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.

Figure 8: Party Affiliation of Political Offices and Tax Changes

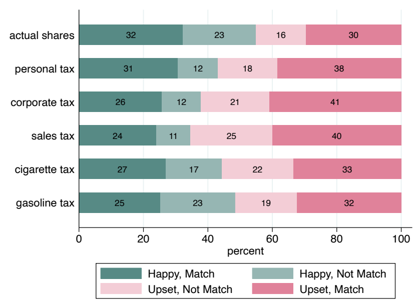


Notes: The top row of each figure shows the percent of yearly observations in which (i) the majority party of the House is the same as that of the Senate and of the Governor, and one of these three bodies switched party control; (ii) same as (i) but no party control change; (iii) House and Senate majorities 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), (c) and provide these statistics separately for states that have only voted for a Democratic (Republican) presidential candidate since 2000 elections (see Table A.2), and swing states.

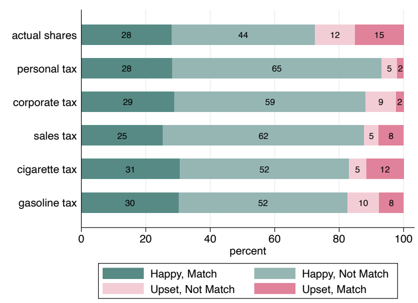
Figure 9: Presidential Election Outcomes and Tax Changes

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

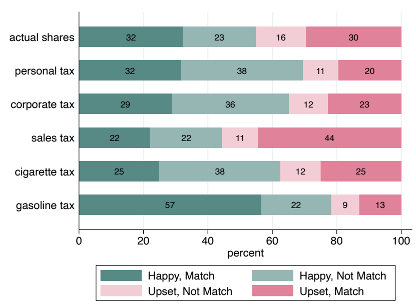
(a) Tax Increases



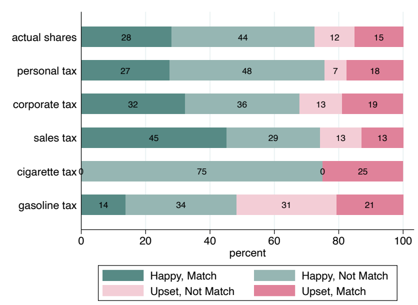
(b) Tax Increases



(c) Tax Decreases



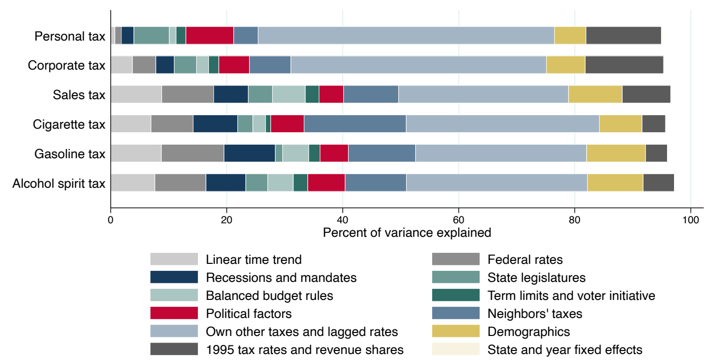
(d) Tax Decreases



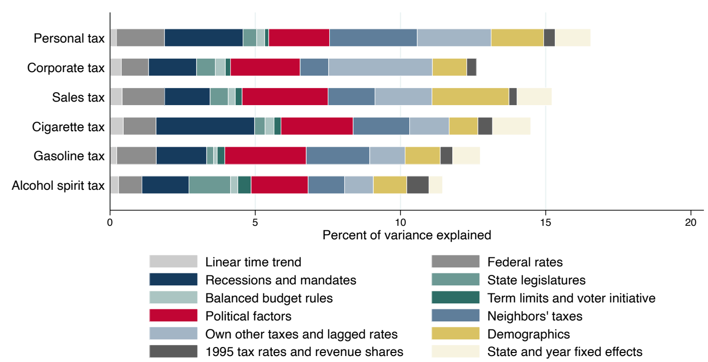
Notes: The top row of each figure shows the percent of yearly observations in which the state votes for a Democratic (left panel) or for a Republican (right panel) presidential candidate and that candidate wins ("Happy") or loses ("Upset"), while the state's House and Senate majorities match the preferred 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 10: Variance Decomposition

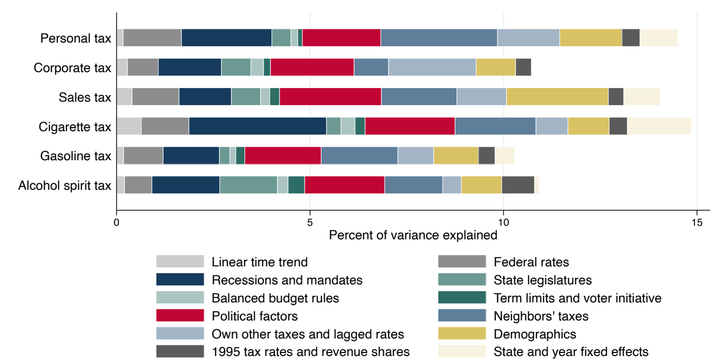
(a) Tax Rate Levels – All



(b) Tax Changes in \$ or % – All



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



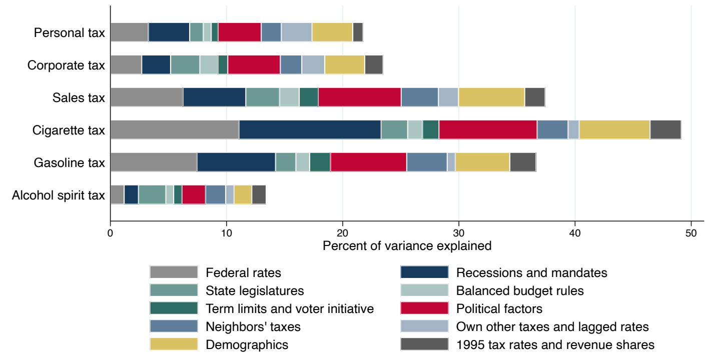
Notes: This figure shows the Shapley variance decomposition of adjusted R^2 for (a) all tax rates in percentage points or in 2020 dollars; (b) all tax changes (i.e., differences between a given year's tax rate and the previous year's tax rate) in p.p. or in \$2020; (c) same as (b) but only including 50% largest tax changes. All decompositions use the variables summarized in Table 1 plus state and year fixed effects.

Figure 11: Variance Decomposition

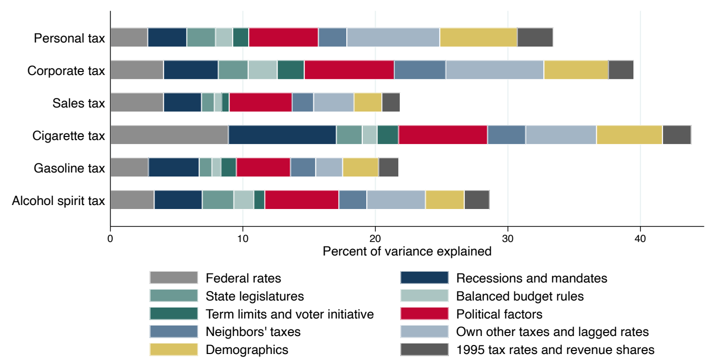
Notes: This figure shows the Shapley variance decomposition of adjusted R^2 for (a) all tax rate increases (indicators for years when a tax increase occurs) and (b) all tax decreases (indicators for years when a tax decrease occurs); (c) and (d) – 50% largest tax increases and decreases, respectively. All decompositions use the variables summarized in Table 1 plus state and year fixed effects.

Figure 12: Variance Decomposition - Decade Changes

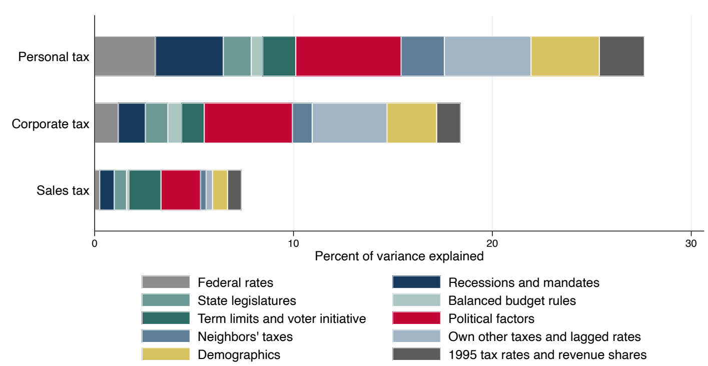
(a) Tax Rate Changes – All



(b) Tax Rate Increase – All



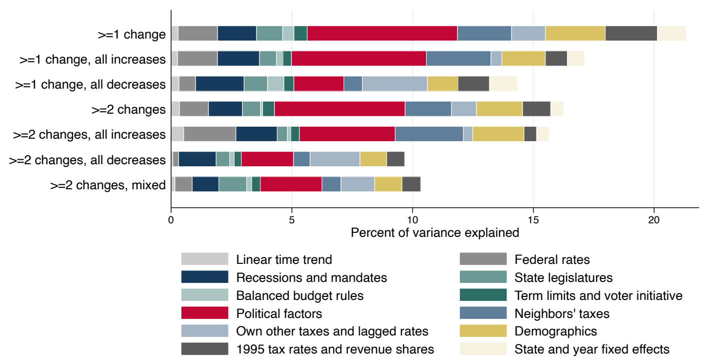
(c) Tax Rate Decrease – All



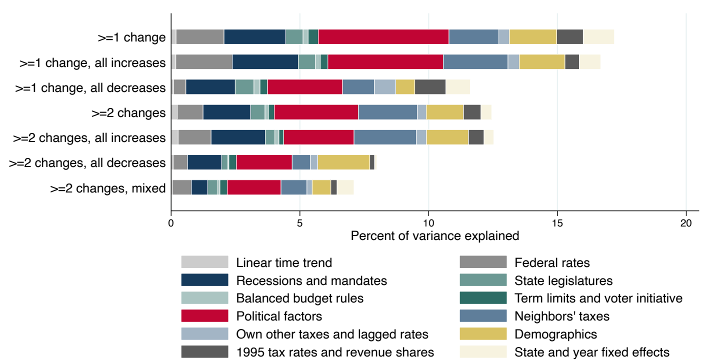
Notes: This figure shows the Shapley variance decomposition of adjusted R^2 for (a) all tax rate changes from one decade to the next in percentage points or \$2020, (b) all tax rate increases (indicators that tax rate increased over the decade), (c) all tax rate decreases (indicators tax rate decreased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

Figure 13: Variance Decomposition - Bundle Changes

(a) Tax Rate Changes – All



(b) Tax Rate Changes – Largest 50%



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

APPENDIX FOR ONLINE PUBLICATION

A Data Notes

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

Political Affiliations. We collect detailed information on the political affiliation of state legislators, both in the upper and lower chambers of legislatures, and that of the governor. Our data also allows us to identify years in which 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, and DW Nominate scores for state representatives and senators.

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.

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.2 summarizes these groups.

Institutional Rules. Previous work has also shown that state policy is influenced by institutional features, such as the number of legislators in the legislatures (Gilligan and Matsusaka (2001), Egger and Koethenbuerger (2010)), term limits (Erler (2007); Besley and Case (1995a)), balanced budget provisions (e.g. Poterba (1994)), and legislative initiative rules (Matsusaka (1995), Matsusaka (2000), Asatryan et al. (2017a), Asatryan et al. (2017b)). Therefore, in addition to the political affiliation of the state legislators and governors in each year, we collect information on institutional features of the state. The size of the legislatures – number of seats in each legislative chamber – has been obtained from Ballotpedia.[14] Information on the applicable term limits in state legislatures and when they were introduced has been obtained from the National Conference on State Legislatures (NCSL), while information on governor term limits was obtained from the Council of State Governments. We have identified all state-year observations during which an incumbent governor could no longer seek re-election because of the binding term limit. We also collect information on average durations of legislative sessions, as well as salaries and per-diem rates in 2019/2020 from NCSL. In contrast to the federal government, states are not allowed to carry budgetary deficits for prolonged periods of time. We collect information on the stringency of balanced budget rules as of 2010: whether the governor must submit a balanced budget, whether legislatures must enact a balanced budget, and whether deficit carry-forwards are allowed, all from NCSL (2010). We also identify states with separate capital budgets in addition to operating budgets using 2014 data from NASBO (2014). We also collect information as to whether states have a rainy day fund and the year it was adopted.

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

Neighbors. To investigate whether states change their tax rates in re-

[14]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.

sponse to competition, we identify tax rates in the neighboring states. We use two approaches to defining neighbors. First, we consider states as neighbors if they share a geographical border. We believe this is the best approach for excise taxes since individuals can purchase goods by driving to a neighboring state. Second, we use migration flows as measure of neighborliness, following Baicker (2005). Since tax competition is primarily concerned with out-migration, for each state, we identify five "neighbor" states that accept the largest number of migrants from that state, using 2010 state-to-state migration data from the IRS. While migration flows vary from year to year, the ranking of states, especially at the very top, appears to be fairly stable. For this reason – and due to the lack of consistent yearly data throughout the 70-year period – we use 2010 neighbors for all years. We calculate average tax rates in these five neighboring states, and we consider neighbors to change taxes if at least one of five states changed their tax rate. We use this approach to identify neighbors for all other tax types.

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

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

We use three sources to identify the federal mandate changes that are likely to have important economic consequences for state budgets. First, we use Congressional Budget Office (CBO) reports to identify mandates that exceed the "UMRA" threshold. A rapid increase in federal unfunded mandates led to the introduction of the Unfunded Mandates Reform Act of 1995 (UMRA), which required the CBO to estimate the costs of mandates to state and local governments, as well as the private sector, for new legislative proposals. While UMRA applies to most legislation that can impose enforceable duties, it typically does not apply to existing programs, Social Security, and legislation that cover national security and constitutional rights. Since UMRA's introduction in 1996, 15 laws have been enacted that have costs estimated exceed the 50 million 1996$ threshold (Congressional Research Service (2020)). Second, because UMRA did not apply before 1996, we look for costly mandates in the U.S. Advisory Commission on Intergovernmental Relations (ACIR) reports and National Conference of State Legislatures Mandate Monitor. Finally, we supplement these sources by hand-collecting information on historical changes to existing social welfare programs that are jointly funded by federal and state governments: AFDC/TANF, Food Stamp Program /SNAP, and Medicaid.[15]

Since our goal is to identify federal changes that may influence state tax policy, we focus on mandates that are large (i.e. likely to exceed the UMRA threshold) and are persistent in nature (i.e. affect state expenditures in all future years rather than impose a one-time burden). With these requirements in mind, we have identified 27 mandates summarized in Table A.4 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.[16]

[15] 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.

[16] For example, according to CBO calculations, federal minimum wage increases impose a

Demographics. We augment the political and institutional data with information on the demographics of each state. We obtain the poverty rate for 1980-2019 and population measures along with race and ethnicity breakdowns for 1969-2019 from the Census Bureau. We collect the unemployment rate, employment to population ratio, and labor force participation rate for 1976-2020 from the Bureau of Labor Statistics. Earlier year observations are collected from the Statistical Abstracts of the United States. Finally, we obtain information on state tax revenues, expenditures and total outstanding debt from Census Annual Survey of State Governments.

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

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

We collect the unemployment rate, employment to population ratio, and labor force participation rate for 1976-2020 from the Bureau of Labor Statistics. Unemployment rate and total unemployment for 1957-1975 were obtained

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.

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.

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

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

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

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: "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.

Table A.3: Correlation Matrix

	Top Personal	Min Personal	Top Corporate	Min Corporate	Sales	Cigarette	Gasoline	Alcohol Spirit
Top Personal	1	0.49	0.58	0.46	-0.04	0.06	-0.02	0.01
Min Personal	0.49	1	0.46	0.51	0.17	0.2	-0.12	-0.18
Top Corporate	0.58	0.46	1	0.8	0.18	0.19	-0.26	-0.03
Min Corporate	0.46	0.51	0.8	1	0.2	0.19	-0.17	-0.06
Sales	-0.04	0.17	0.18	0.2	1	0.29	-0.36	-0.26
Cigarette	0.06	0.2	0.19	0.19	0.29	1	-0.25	-0.06
Gasoline	-0.02	-0.12	-0.26	-0.17	-0.36	-0.25	1	0.27
Alcohol Spirit	0.01	-0.18	-0.03	-0.06	-0.26	-0.06	0.27	1

Notes: This table shows the correlation matrix of 6 tax rates. Personal and corporate income taxes are represented by top rates, all 50 states included.

Table A.4: 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

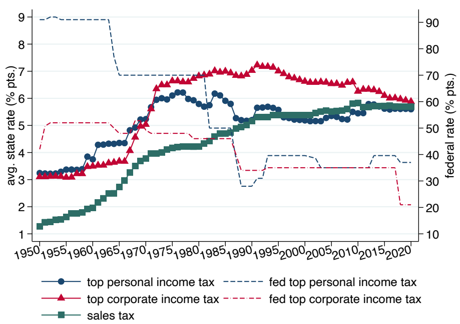
Notes: This table summarizes federal mandates enacted in 1950 or later that are likely to impose a substantial burden on state budgets, i.e. have projected costs that exceed the UMRA threshold ($50 million 1996 dollars). See Section A for details.

B Additional Graphs

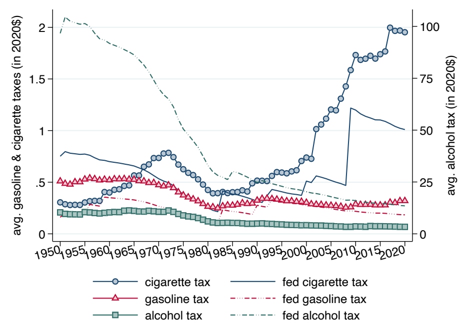
Figure B.1: State Tax Rates Over Years Weighted by Population

All 50 States

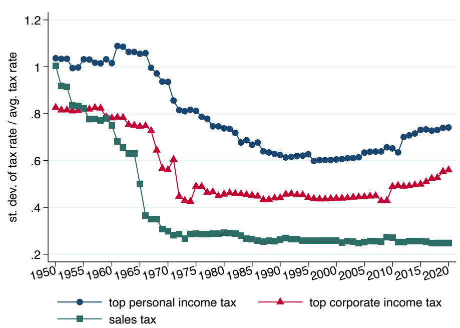
(a) Average Tax Rates



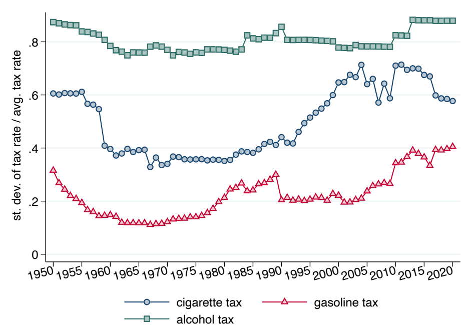
(b) Average Excise Taxes



(c) Heterogeneity



(d) Heterogeneity Excise

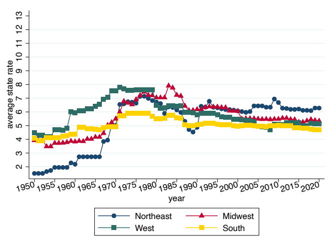


Notes: Figures (a) and (b) show average top personal income and corporate tax rates, sales tax rates, and average cigarette, alcohol (spirit) and gasoline tax rates, as well as corresponding federal tax rates. Figures (c) and (d) show the standard deviation of the state taxes divided by average tax rate (coefficient of variation). All states included, including those with zero rates. In all figures observations are weighted by population.

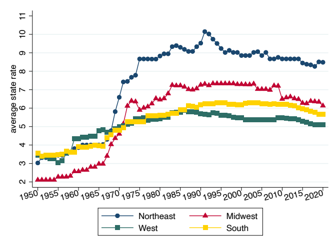
Figure B.2: Long Term Trends by Region

Panel A: Average Among All 50 States – By Region

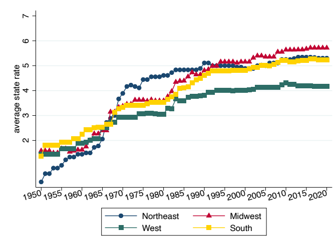
(a) Personal Income Tax



(b) Corporate Tax

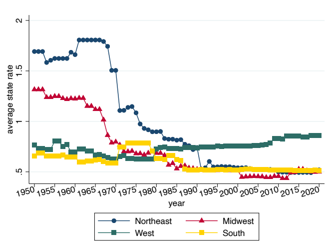


(c) Sales Tax

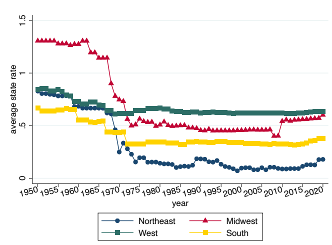


Panel B: Coefficient of Variation All 50 States – By Region

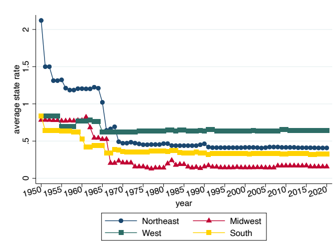
(d) Personal Income Tax



(e) Corporate Tax



(f) Sales Tax

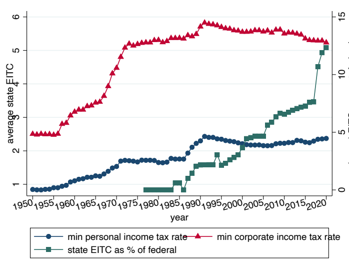


Notes: These figures show the average as well as the standard deviation of the state values divided by average value (coefficient of variation). All states included, including those with zero rates, but broken down by regions.

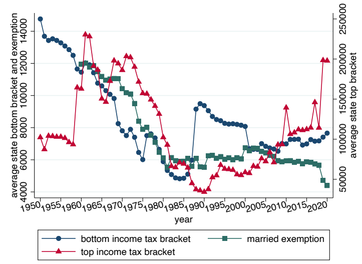
Figure B.3: Long Term Trends: Additional Tax Rules

Panel A: Average Among All 50 States

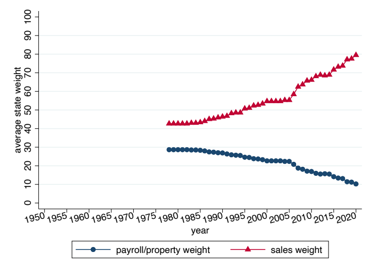
(a) Min Rates and EITC



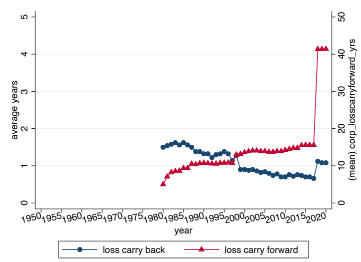
(b) Income Tax Brackets and Exemptions



(c) Corporate Apportionment Weights

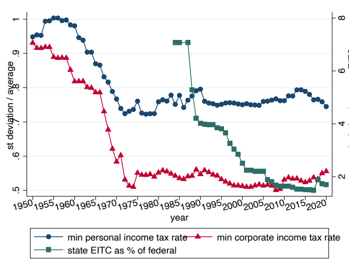


(d) Loss Rules

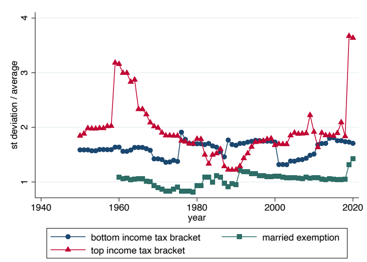


Panel B: Coefficient of Variation Among All 50 States

(e) Min Rates and EITC

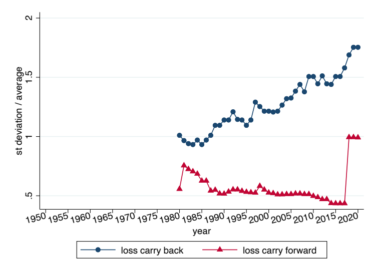


(f) Income Tax Brackets and Exemptions



(g) Corporate Apportionment Weights

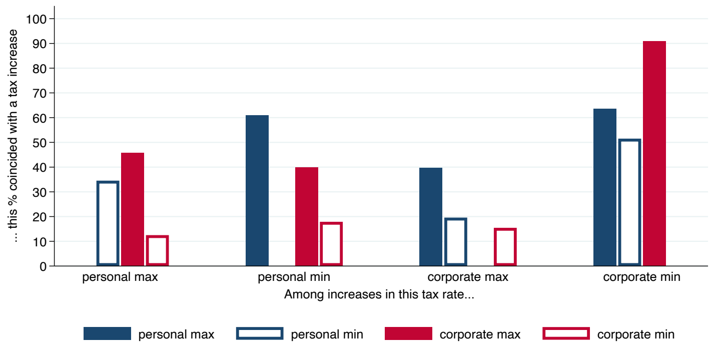
(h) Loss Rules



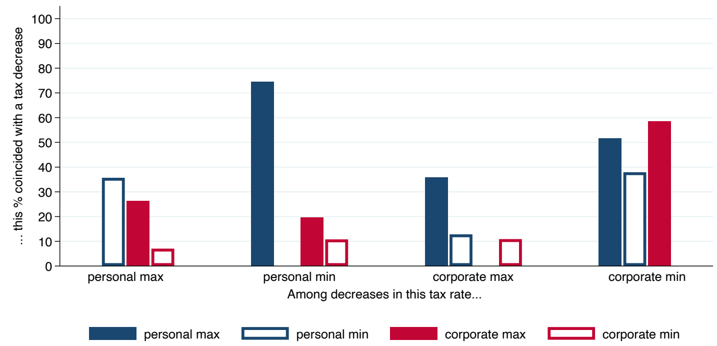
Notes: These figures show the average as well as the standard deviation of the state values divided by average value (coefficient of variation). All states included, including those with zero rates. Unlimited loss carryforwards are coded as 100 years.

Figure B.4: Simultaneity of Tax Changes: Min and Max Income Tax Rates

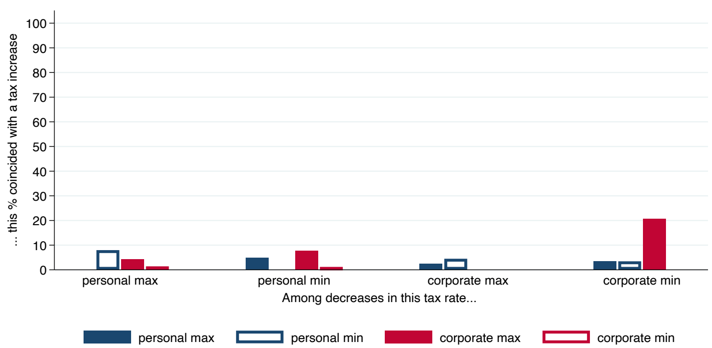
(a) % of Increases that Coincide with Increases



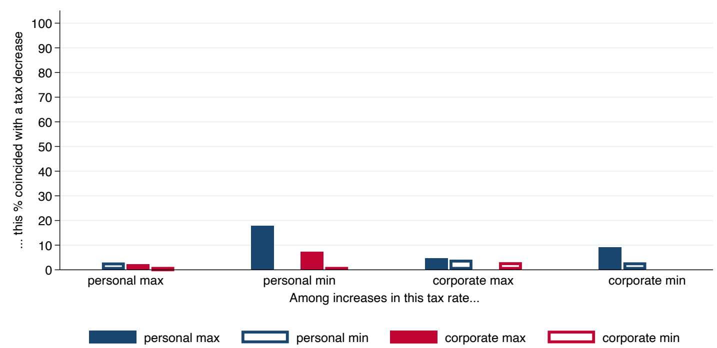
(b) % of Decreases that Coincide with Decreases



(c) % of Decreases that Coincide with Increases



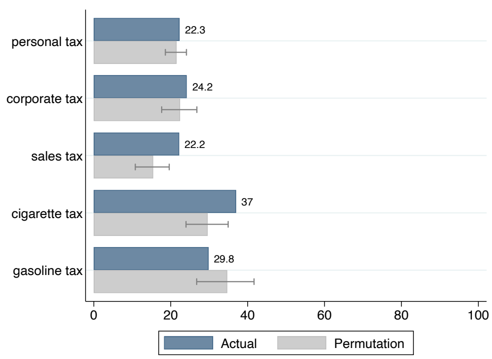
(d) % of Increases that Coincide with Decreases



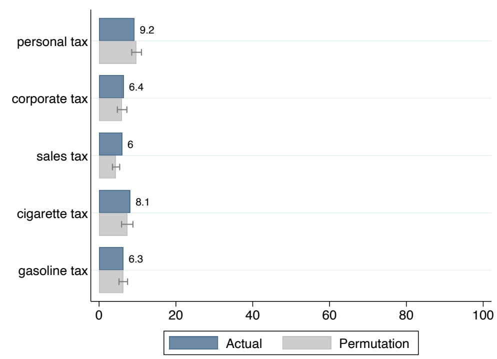
Notes: These figures explore the extent to which states change one tax rate while simultaneously changing another tax type (i.e., in the same year). Among the increases (or decreases) in each tax on the x-axis, the vertical bars specify the share that coincides with an increase (or decrease) in another tax type in the same state and year. These other tax types are identified by the color of the bar (top income tax rates, top corporate tax rates, minimum income tax, minimum corporate tax).

Figure B.5: Percent of Recession Episodes that Result in Tax Changes

(a) State Recession



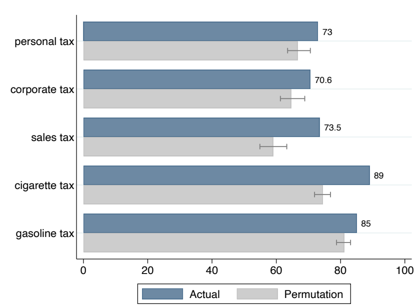
(b) Federal Recession



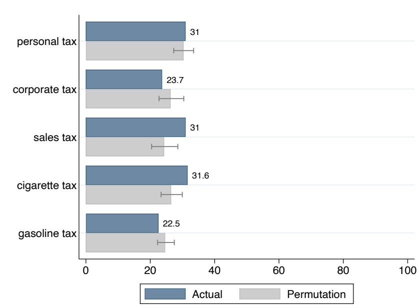
Notes: This figure shows the percent of (a) state recessions or (b) federal recessions that lead to a tax change. Each recession episode is counted as one recession and only one tax change (per tax rate type) is allowed per recession. In all figures, the top blue bars show actual observed percentages, 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.

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

(a) Within 3 Years of Neighbor's Change



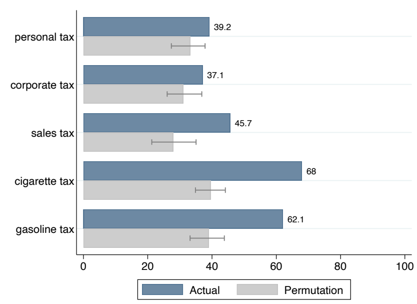
(b) 2 Years After State Recession



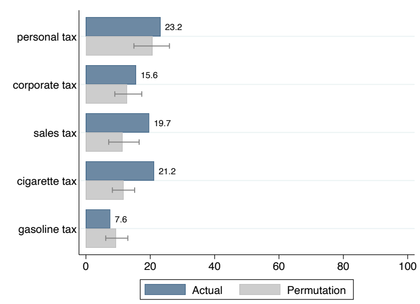
Notes: This figure shows the percent of tax changes that occur (a) within 3 years after neighboring state changes its tax rate; (b) during a state recession or a year after. In all figures, the top blue bars show actual observed percentages, while the grey bars show the simulated average, calculated by randomizing the timing of tax changes 100 times. The thin interval bars show the 5th and 95th percentiles of the simulated percentages.

Figure B.7: Percent of Large Tax Changes that Occur in Response to Economic Causes

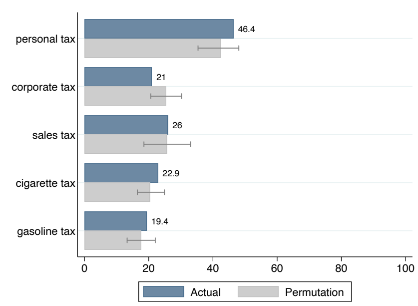
(a) Following Neighbor's Change



(b) During State Recession



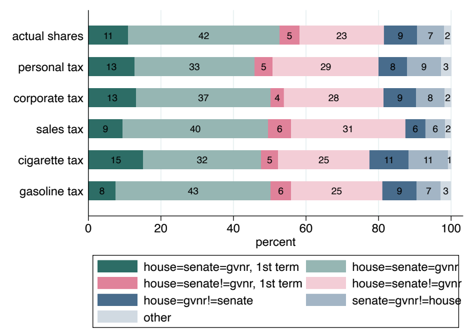
(c) Following Federal Mandate



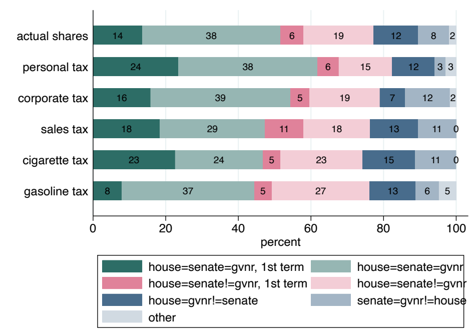
Notes: This figure shows the percent of large tax changes (top 50th percentile) that occur (a) in the same year or 1 year after neighboring state changes its tax rate; (b) during a state recession, or (c) in the year the federal mandate becomes enacted or effective. In all figures, the top blue bars 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.

Figure B.8: Party Affiliation of Political Offices and 50% Largest Tax Changes

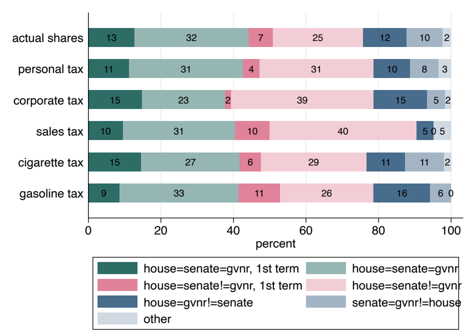
(a) All States



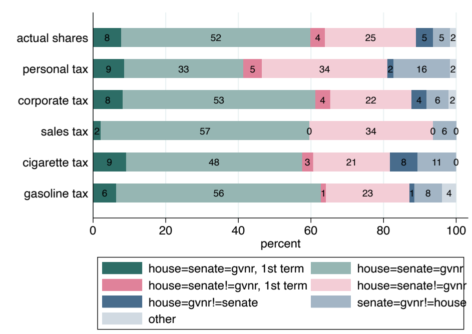
(b) Swing States



(c) Safe Democratic States



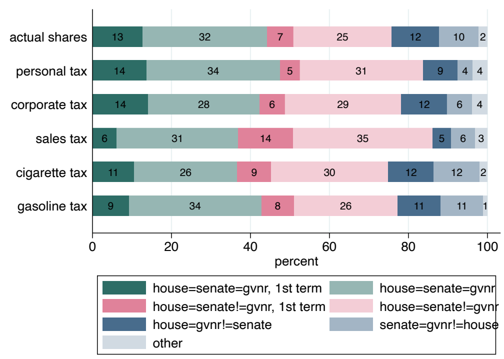
(d) Safe Republican States



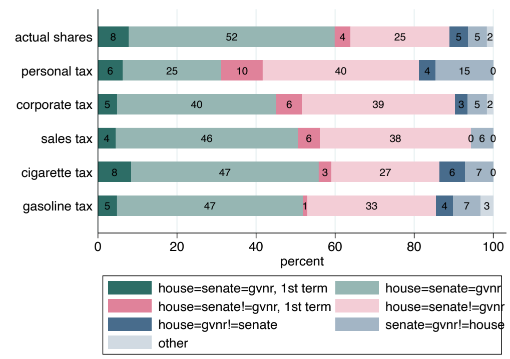
Notes: The top row of each figure shows the percent of yearly observations in which (i) the majority party of the House is the same as that of the Senate and of the Governor, and one of these three bodies switched party control; (ii) same as (i) but no party control change; (iii) House and Senate majorities 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 (c) and (d) provide these statistics separately for states that have only voted for a Democratic (Republican) presidential candidate since 2000 elections (see Table A.2), while Figure (b) for all other states.

Figure B.9: Party Affiliation of Political Offices and Tax Increases/Decreases

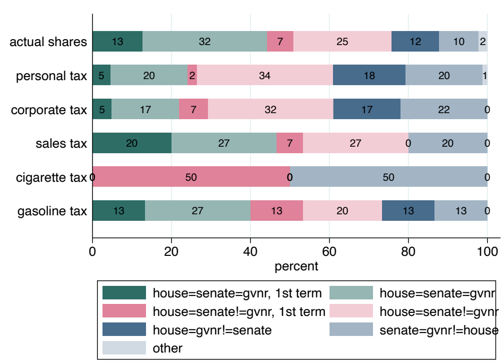
(a) Increases – Safe Democratic States



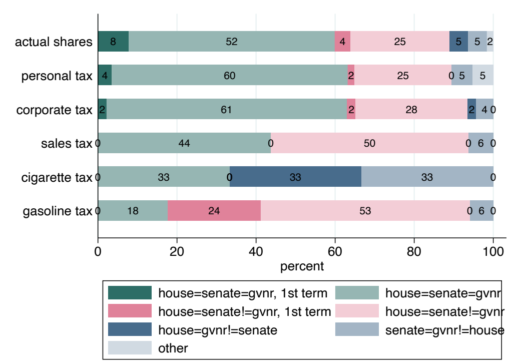
(b) Increases – Safe Republican States



(c) Decreases – Safe Democratic States



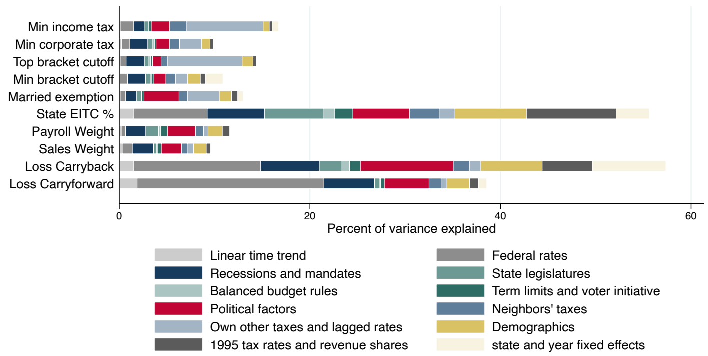
(d) Decreases – Safe Republican States



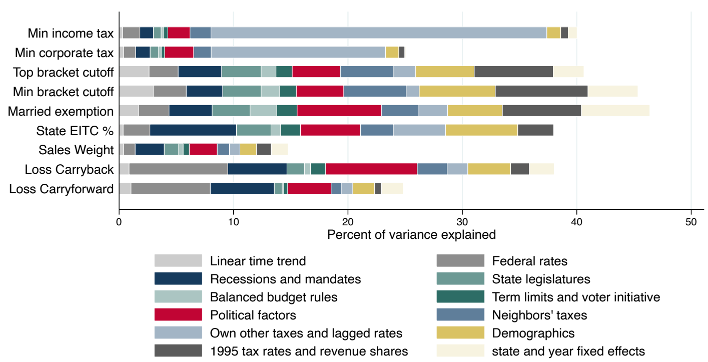
Notes: The top row of each figure shows the percent of yearly observations in which (i) the majority party of the House is the same as that of the Senate and of the Governor, and one of these three bodies switched party control; (ii) same as (i) but no party control change; (iii) House and Senate majorities 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.2) and for tax increases and decreases.

Figure B.10: Variance Decomposition – Other Tax Rules

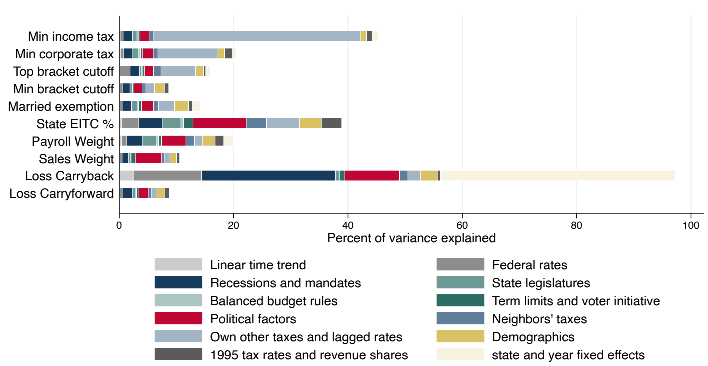
(a) Tax Rate Changes – All



(b) Tax Rate Increase – All



(c) Tax Rate Decrease – All



Notes: This figure shows the Shapley variance decomposition of adjusted R^2 for (a) tax rule changes (in \$, or pp, or otherwise), (b) all tax rule increases (indicators for years when a tax rule increase occurs), (c) all tax rule decreases (indicators for years when a tax rule decrease occurs). All decompositions use the variables summarized in Table 1 plus state and year fixed effects.