The University of Chicago

Evaluating Merits of State-Level Marginal Personal Income Tax Implementation

The Positive, Negative, and Inconclusive Empirical Impacts of State-Level Personal Income Tax Structure Changes on State-to-State Population Flows and Overall Personal Income Tax Revenue

By Juliet Goswami

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Paper presented to:

Public Policy Studies Preceptor, Daniel Sonnenstuhl

Faculty Advisor, Maria Bautista

Department of Public Policy Studies

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Abstract

Two recent, opposing trends in state-level tax policy changes have revitalized the debate on the utility of instituting or eliminating graduated personal income tax regimes. Proponents of implementing such a system from flat or no personal income taxes argue that the system redistributes wealth effectively; opponents argue that such a tax system will inspire high-earners to emigrate to lower-tax states, with the resulting system actually being more regressive than a flat tax regime. The extensive body of relevant literature lacks comprehensive scope, does not conduct a causal impact analysis of treatment, and/or fails to implement consistent evaluative methodology on a broad range of taxation change data. This paper utilizes a difference-in-differences regression analysis to establish statistical significance of treatment effect and qualitatively reviews key tax changes for further explanation of resident behavioral changes. The monolithic viewpoints of most of these papers are poorly suited for the subject of tax reform given that I found that the treatments' causal impacts on personal income tax revenue and population flows vary wildly between states and time periods. Therefore, I recommend that policymakers approach state-level tax reform holistically, considering the purpose of potential reforms as well as the current economic and social structures within the state, and only consider case studies of tax changes in very similar states. Otherwise, policymakers risk greatly misunderstanding the causality of studied tax changes.

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Introduction

"Read my lips: no new taxes!" The words spoken by then-Vice President and 1988 presidential candidate George H.W. Bush – and his reversal's impact on his political fate in the 1992 presidential election – capture the tempestuous relationship between citizens and taxation in the United States. From the first acts of rebellion against the British Crown to Bush's political demise in 1992, to the regular threats of government shutdowns of the 2010s and 2020s due to controversial tax policy adjustments, the American people have always had a contentious relationship with taxation. With wealth and income inequality reaching new heights in the United States (Horowitz et al 2020), increasing numbers of Americans believe that wealth should be redistributed and do not believe that the wealthy are paying their fair share of taxes (Gallup). Progressive income taxes are seen as a means to redistribute wealth, and have existed in its modern federal form since 1913 (Congress 1913). However, the theoretical and political discourse significantly diverges regarding the purpose and feasibility of state-level progressive personal income taxes. This paper explores the salient issue of state-level progressive personal income taxation (PIT) system implementation, and its relationship to overall state-to-state migration flows and state personal income tax revenue. These relationships are the focus of the main arguments for and against implementing a graduated personal income taxation system; will the highest income earners in a state move when these more targeted taxation systems are implemented? Is overall PIT revenue actually affected negatively by these systemic taxation changes? This paper seeks to answer these questions through a two-part research framework.

The topic of personal income taxation, under a graduated structure or otherwise, has received plenty of attention from pundits, activists, and academics alike; however, the patchwork of state policies makes effective and meaningful scrutiny of this topic difficult, and all three groups tend to approach the subject of progressive taxation on the federal rather than state level. When not ignoring state-level taxation systems, analyses often verge on hyper-theoretical or fail to consider the multiple relevant variables of interest potentially impacted by a structural tax change. I recognize the lack of practical academic articles with appropriate state-level and empirical nuance on the subject, and recognize the importance of such research given the opposing state taxation change trends in the United States in the recent few years. Therefore, with this paper, I aim to provide an empirical quantitative and qualitative study of how state-level personal income tax implementation from a flat-tax or no-tax environment may impact a state's population flows and PIT revenue with this paper.

I implemented a mixed-methods, two-step approach, as both the quantitative and the more intangible qualitative aspects of a state and its tax system are relevant to any systemic policy change's impact. I identified three key areas of change in state personal income tax structure (the number of brackets, the highest bracket tax rate, and the highest income bracket) since 2000. After eliminating states with tax environments too volatile to establish meaningful trendlines, I determined specific treatments of interest – treatments are defined as year of change(s) in one, two, or all of those three key areas in one state. I pair 'treated' states with another, qualitatively similar state without any changes in the same time period. I then utilize a simple two-way fixed effects difference-in-differences (DiD) regression analysis of the pairing while controlling for economic and social data that may otherwise violate the parallel trends assumption of the DiD research approach. Lastly, recognizing the limitations of this quantitative research approach, I provide a deeper qualitative analysis of a select few treatments in North Carolina, Pennsylvania, Utah, New York, California, Illinois, Minnesota, and District of

Columbia to provide greater empirical depth to my findings beyond the regression analysis findings in the second step of my research design.

Through this two-step, mixed-methods approach, I have found that instead of providing homogenous evidence supporting or rejecting implementation of graduated income tax systems, the results are largely inconclusive, and outcomes are appear to be hyper-specific to the treated state. As such, I recommend that state legislators and voters understand that the real impact of instituting a graduated income tax structure will have vastly differing impacts depending on the state and time period. As these stakeholders weigh the expected impact of a flat personal income taxation structure changing to a graduated structure, they should consider the following tripartite framework: (1) What is the purpose of the proposed law? Different purposes require different metrics of success and will result in some research papers being highly relevant and others as studying irrelevant variables; (2) What is the current economic health, social structure, and industries of the given state? Some states that have exceptional economic and social diversity appear to have statistically significant positive treatment effects from intensifications in graduated income tax structures, while other, less stable states appear to struggle under temporary flat-rate increases; and (3) Consider case studies from other states, but only weight states with extraordinarily close similarities heavily. Given the inconclusive evidence from this detailed causal impact analysis, and the additional caveats set forth in the qualitative analysis of hyper-specific state qualities, stakeholders considering a dramatic change to their tax systems (both instituting and eliminating a graduated tax stratification) should understand the limits of monolithic findings and be wary of broad case study pertinence to their own potential change in their tax code.

Background

Definitions of Terms

There are many different forms of personal income and methods to tax them. According to the Urban Institute, “individual income tax (or personal income tax) is a tax levied on the wages, salaries, dividends, interest, and other income a person earns throughout the year” (“State and Local” 2022). Different income types are occasionally taxed separately from each other under certain jurisdictions; however, for the purposes of this paper, I largely consider these types of taxation as the same and comparable except for New Hampshire’s and Tennessee’s taxation regimes, which only taxed dividends and capital gains respectively. This paper uses the terms personal income tax (PIT), individual income tax, and income tax interchangeably – when referencing other forms of income tax, such as corporate income tax, this paper will include the appropriate modifier.

There are two main forms of personal income tax structure observed in this study: graduated and flat. States without a personal income tax are not included in the quantitative analysis, since they have had static structures in the studied time period and provide imperfect comparisons to other states’ taxation systems.

A graduated income tax, also known as a progressive or marginal income tax, “is the additional tax paid for every additional dollar earned as income. Tax systems employing marginal tax rates apply different tax rates to different levels of income. As income rises, each additional bracket of income is taxed at a higher rate” (Langager 2023). Under a graduated income tax regime, there are at least two tax brackets – meaning that stratifications of income levels that have different tax rates – and corresponding tax rates to those brackets.

Under a flat (or fixed rate) tax regime, the tax rate "does not change with flat taxes, regardless of the individual's income. No matter how much a person makes, they would be taxed at the same percentage" (Langager 2023). Some articles refer to tax systems which contain no personal income taxes as a flat rate individual income tax (a flat rate of 0 percent). However, for this paper, I will distinguish between these two forms of taxation. Therefore, some sources may state that there are a greater number of flat rate personal income tax systems than this study states for a specific year (Henderson 2023). Additionally, some states have a graduated income tax with two tax brackets, and the rate for the lower income tax bracket is 0 percent, and a single rate is applied for income over the second bracket's threshold (Tax Foundation 2013). Some academic articles refer to these systems as flat rate, but this paper recognizes these regimes as graduated (Henderson 2023).

I also utilize the term 'states' throughout this paper. For the purposes of this study, this term refers to all fifty states within the United States in addition to the territory District of Columbia (also referred to as 'Washington D.C.' and 'D.C.').

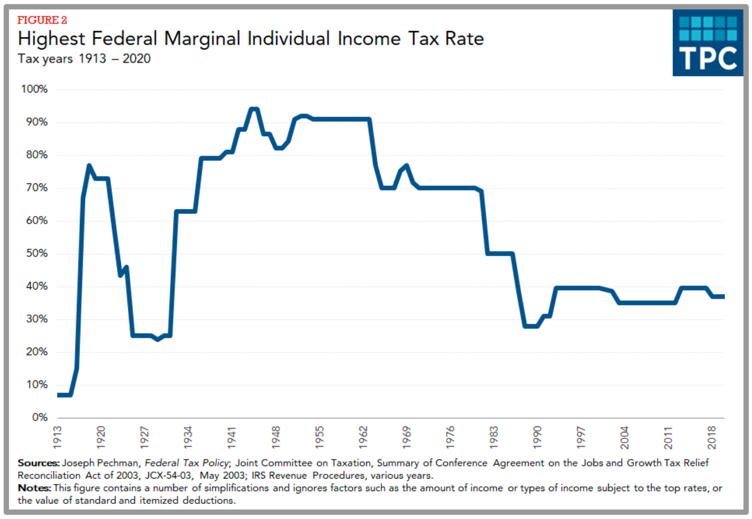
History of Personal Income Taxation in the United States (Federal, State, and Local)

Overview of Federal Personal Income Taxation in the United States

For the first ninety years of its national history, the United States had no form of personal income tax. Instead, "most of these [early taxes] were excise taxes—taxes imposed on specific goods or services, such as alcohol and tobacco. The government also tried direct taxation—taxing things an individual owned. That didn't last, and the feds went back to collecting excise taxes" (Fontinelle 2023). However, with the financial demands that the Civil War imposed onto the federal government, the government created an initial version of a flat rate tax on income above a certain level along with the creation of the Internal Revenue Service (Congress 1913); the government initially raised the income tax rate after the end of the war, but "the Grant administration sponsored the repeal of most of the 'emergency' taxes," including this income tax, in 1872 (Fox 1986). The constitutionality of an income tax was fiercely debated throughout the rest of the 19th century, but arguments subsided with an 1894 federal income tax rule unconstitutional the next year. Following a particularly disastrous boom-and-bust economic cycle in the first decade of the 20th century, debate reignited. The resulting failure of tariff reform in 1910 fueled "efforts toward ratification of the constitutional amendment for an income tax" ("Federal Income"). Supporters of federal tax reform managed to successfully push through the passage of the Sixteenth Amendment, which changed the Constitution to officially allow the federal government to levy direct income taxes. Soon after, Congress passed the modern graduated income tax in 1913 ("Federal Income").

However, the passage of this Amendment did not end debate about the income tax. The highest income tax bracket tax rates had been the subject of significant controversy and change through the different political and economic cycles in the past century. Rates increased steeply with the onset of World War II and decreased significantly after the Armistice of 1918. During the Great Depression, the highest bracket rate increased again to record highs, and remained above 70 percent until the Reagan administration passed significant tax rate cuts. Since the 1990s, the top tax rate has remained relatively stable, between 35 and 40 percent. Increases in federal personal income tax remains a particularly contentious political issue weighted against state taxation, with significant raises in rates having little chance of passage in Congress.

Figure 1. Line Graph of Highest Federal Marginal Individual Income Tax Rate



(Petchman 2022)

Overview of Local Personal Income Taxation in the United States

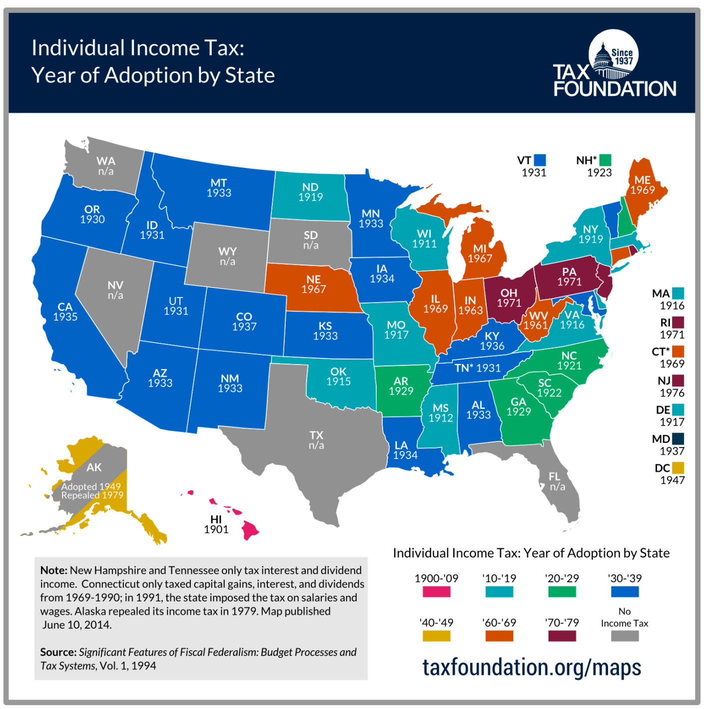
Some localities levy an additional tax on personal income on top of state and federal income taxes, called a local or municipal income tax. Philadelphia, Pennsylvania was the first city to implement a local tax in 1939, and the policy gained support and passed in other cities after the 1960s (Walczak et al 2023). The following states have at least one locality that imposes a local income tax: Alabama; Arkansas; California; Colorado; Delaware; Indiana; Iowa; Kentucky; Maryland; Michigan; Missouri; New Jersey; New York; Ohio; Oregon; Pennsylvania; West Virginia (Kappel 2022). Collection, form, rate assessments, computation, and spending of these taxes are determined by the relevant jurisdiction.

Local income taxes do impact intrastate population flows ("Local Tax" 2021), but I do not include any data measuring its impact in my analysis. Relevant stakeholders may choose to move because of increased local taxes, but lower costs may motivate them to move within the state to suburbs or rural areas of the same state to maintain ties to their network. As such, given that it is impossible to accurately measure the split between local and interstate migration as a result of local tax system changes with extant data, it is ignored as a feature of parallel trends.

History of State Personal Income Taxation in the United States

Hawaii was the first state to implement a modern personal income tax, doing so in 1901, which was technically before the territory had become a state (Drenkard 2014). Hawaii, Wisconsin, and Mississippi all established personal income taxes before the creation of the modern federal income tax in 1913; however, the passage of the federal amendment triggered a widespread adoption of state-level personal income taxes around the country, with most states that implement such a tax adopting an initial form of individual income taxation before 1940.

Figure 2. Individual Income Tax: Year of Adoption by State



(Drenkard 2014)

The most recent state to adopt an individual income tax was New Jersey, which did so in 1976. Florida, Nevada, South Dakota, Texas, Washington, and Wyoming have never levied a personal income tax of any kind, and in 1979 Alaska became the first (and until 2022, when Tennessee officially repealed its last bracket and rate, the only) state to eliminate its personal income tax altogether. Connecticut is the most recent state to implement a graduated income tax from an existing flat tax regime, having done so in 1996 (Divonguoy and Hill 2020). Personal income taxes never applied to wage income in New Hampshire and Tennessee (states which respectively are currently and have recently completed phasing out income tax entirely respectively), instead applying only to capital gains and dividend income (Fritts 2023). Connecticut became the only state to have expanded its definition of income to include wage income in 1991, having previously only taxed dividends (Drenkard 2014).

In states with personal income tax regimes, the tax rates, the number of brackets, and the brackets themselves are subject to regular change. However, changing between forms of taxation (graduated, flat, and none) is still rare, and largely has occurred outside of a time period with reliable, accurate, and consistent panel data collection (2000 - 2020). Panel data is spotty, inconsistently collected, and/or inaccessible across all states in the U.S. before 2000, and the COVID-19 pandemic has made data collection efforts unreliable after 2020 ("Frequently Asked" 2021). This makes quantitatively evaluating causal impacts of changing a state personal income tax regime from a flat to graduated rate exceptionally complicated, given that relevant system changes have occurred outside of this time period.

Current State-Level Personal Income Tax Regimes

Personal income taxation, particularly on the state-level, is highly controversial, and rates – sometimes the whole practice of personal income taxation – are constantly in flux between states (Appendix B). As of February 2023, forty-three states and the District of Columbia levy a personal income tax of some kind while the remaining seven states do not have any form of individual income tax; however, for the states that do implement some form of personal income taxation, the rates, brackets, and even the definition of taxable personal income varies (Vermeer 2023). For example, Washington state only taxes capital gains – a recent change as of 2021 and held up in the state Supreme Court this year (Vermeer). Currently, thirty states and D.C. utilize a graduated tax structure. The remaining eleven states have a flat tax structure.

This variance of state taxation systems extends to a varied reliance on PIT revenue as well. Some states are heavily reliant on personal income tax revenue to support the state government: At the higher end of reliance, personal income tax revenue funds between 20 and 24 percent of the state budgets for Massachusetts, Maryland, and New York. On the other hand, only 4 percent of North Dakota's budget relies on PIT revenue ("State and Local" 2022). Given that states have wildly diverging taxation methods, and unique economies and populations, meaningful taxation policy comparisons and evaluations are exceptionally difficult.

Recent Discourse and Changes to State-Level Personal Income Taxation Systems

The volatile relationship with Americans and their taxation has been particularly pertinent since the turn of the millennium. The federal personal income tax rate for the highest income earners decreased in the early 2000s under the Bush tax cuts, returning to pre-Bush marginal tax rates under Obama before decreasing again (still above Bush-level marginal tax rates) under the Trump administration (McCarthy 2021). Meanwhile, with the exception of a handful of states, state-level personal income tax rates have been largely decreasing for the past two and a half decades (Appendix B). In the past five years, however, many states have begun to debate legislation that would increase the marginal tax rate on the highest income earners, or would transition a flat personal income tax to a graduated tax (Appendix B, “Massachusetts Question 1” 2022, “Illinois Allow” 2020). This coincides with the fact that since the Great Recession, a greater percentage of Americans support wealth redistribution via income taxation than those who do not (Newport 2022). While, like many policy issues, opinions typically fall along partisan lines (Horowitz et al 2020), viewpoints of changing a flat personal income tax rate system to a graduated tax structure take on shades of gray beyond many other hot-button issues in the United States.

For example, the historically blue states Illinois and Massachusetts have both levied a flat individual income tax rate since their inception of a personal income tax, and have both recently had statewide ballot questions regarding the implementation of a graduated taxation system. Illinois voters rejected the proposed tax system change by a six and a half point margin in 2020 (“Illinois Allow” 2020), while Massachusetts voters accepted the proposed change by an even slimmer four and a half point margin (“Massachusetts Question 1” 2022). These narrow differences highlight how voter opinions are not exclusively defined by party ideology, especially given that Massachusetts and Illinois voters had rejected similar ballot measures in prior decades (“Illinois Allow” 2020, “Massachusetts Question 1” 2022). There have also been simultaneous tax policy waves in other states changing the state-level income tax structure from graduated tax rates to a single flat rate, with five states debating or adopting legislation to this effect in 2022 alone (Walczak 2022).

There are generally two main blocs arguing either side of the case for the implementation of state-level individual income tax increases, particularly for policy changes that alter the tax structure from a flat to graduated form. Proponents argue that such a tax system decreases income inequality and successfully raises state income tax revenue, and has the highest earners paying similar percentages out of their total estate in comparison to lower-income residents (Byerly-Duke and Davis 2023). Opponents, apart from those who disagree with personal income taxation on principle (Rothbard 1982), argue that states having different income taxation systems incentivizes interstate migration of the highest income earners and/or those high earners to disguise their overall taxable income when filing (Horowitz 2022). The former is a particularly highlighted point by opponents because barriers to interstate labor mobility are low in comparison to the international mobility and legal barriers (migration costs are minimal and visas/work permits are unnecessary); the latter claimed effect, at best, operates in a gray legal sphere. Opponents' arguments against state-level marginal income taxes claim that implementation of such changes will result in the opposite effect than was intended; as high earners will move to states with low to no state-level income tax, the overall state income tax revenue will functionally decrease, and the tax burden will shift to lower-income residents (Holmes 2020). A secondary concern of shifting a flat rate system to a graduated rate system is that states with a graduated structure have more tax structure volatility, which are undesirable to top earners and will incentivize the highest earners to move to a state with a less complicated tax structure (Merriman 2020).

As previously mentioned, the heterogeneity of state-level taxation systems makes meaningful causal analyses of state tax policy changes' implications difficult. Existing literature partially addresses the issues surrounding state taxation policy changes but does not provide a holistic analysis with recent data, and sometimes ascribes negative economic changes in a state to tax increases without actually establishing a causal mechanism in graduated income tax increases. However, policy guidance is vital, as "2022 will see at least four states move from a progressive personal income tax system with multiple tax brackets to an income tax code with one flat rate" (Gleason 2022). Given the increased legislative interest in increasing the marginal tax rate on the highest income earners, and particularly the interest in changing state-level personal income tax structure from a flat rate to a graduated rate system, this paper aims to provide a fulsome empirical analysis of existing state-level systemic personal income tax changes, data to better equip stakeholders considering changes to their taxation systems.

Literature Review

There has been significant study in the field of progressive taxation, with economists analyzing the tradeoff of equity and efficiency in implementation of such a taxation policy. Diamond and Saez (2011) analyzes optimal tax theory by modeling a progressive taxation system and gives several recommendations on implementing the policy on a federal level. The authors define the intent of the policy as the achievement of optimal social welfare. Through their model, even adjusting for behavioral responses to taxation changes, Diamond and Saez find that the optimum marginal tax rate can be found when the average tax burden is weighted against marginal welfare benefits. However, this paper is highly theoretical and studies the policy as a federal phenomenon; high-income earners' behavioral responses are somewhat limited by mobility constraints (such as citizenship and residency), whereas state-to-state migration is a much easier feat. Additionally, while this study has generated several papers further supporting marginal tax rates on high income earners (Kindermann and Krueger 2014, Mattauch et al 2021, Keane 2021), it is in direct conflict with the findings of others (Agrawal et al 2022, Kindsgrab 2022, Uribé-Teran 2021). Dincecco and Troiano (2015) broadly studies the introduction of new income taxes on the state-level, though does not standardize by type of income taxed nor between flat, graduated, and no tax systems; the authors find that the introduction of new income taxes is associated with increases in overall state revenue, though the results are also associated with political ideology. This study does not isolate taxation systems, and does not address state-to-state migration; it also fails to address correlation, let alone causation. Young et al (2016) finds "that millionaire tax flight is occurring, but only at the margins of statistical and socioeconomic significance" – regardless, it does not address questions of change in overall state income tax revenue as well. Dai et al (2020) finds that, with decreasing international labor mobility, the total taxable income for a country falls – additionally, "the country with labor inflow (outflow) implements over 10% lower (higher) marginal tax rates than suggested by the autarky equilibrium of Kanbur and Tuomala (2013)." This paper only studies international labor flows, not state-to-state migrations within a single country. The theory behind Dai et al (2020) aligns with some older tax theory, such as that set forth in Wildasin (1993). Wildasin draws upon state income tax changes in the US between 1986 and 1988 and calculates how the tax burden shifts from mobile to immobile households, limited by the elasticity of state-to-state labor demand: the findings "provide at least some rough indication of the harm that lower-income residents and other owners of immobile factors in a given state might suffer as a result of the imposition of higher tax burdens on mobile high-income households" (Wildasin 1993). However, the data studied by this paper are old, and Wildasin utilizes minimal causal analysis. A 1996 Congressional Budget Office report examined the effects of changes in after-tax wage labor, but while the authors find "little compelling evidence that high-income taxpayers have substantially higher elasticities with respect to their labor input than other taxpayers," its relevance to this paper is limited due to its study of after-tax effects, not tax itself, as a function of movement (McClelland and Mok 1996). Finally, while this paper will touch upon tax avoidance, papers such as Horowitz (2020) have found data unable to support strong, substantial causal evidence. As such, only refer to tax avoidance's potential relevance in applicable analysis, but have not incorporated it specifically into my research question.

Some published case studies relate closely to my research question and provide a roadmap on how I conduct my qualitative review of certain treatments. Rauh and Shyu (2019) studies the impact of the state's 2012 measure to increase state-level marginal income taxes from 1 to 3 percent for the top tax brackets. This case study diverges distinctly from the previously mentioned studies by drawing a causal inference, finding that "outward migration and behavioral responses by stayers together eroded 45.2% of the windfall tax revenues from the reform in 2013, with the extensive margin accounting for 9.5% of this total response". I expand on this case study using similar methodologies to create a more fulsome mosaic of state-level taxation systems across the United States.

There are a few key weaknesses that extend across most of these papers, and to other academic and political analyses of personal income taxation system changes as well. One of these weaknesses is that the authors attempt to find a completely binary 'answer' to this research question; they expressly try to establish a finding that declares the implementation of graduated personal income tax systems as either entirely beneficial or entirely detrimental for every state's financial status and overall wellbeing. Some research papers studying state-level taxation changes' effects allow for greater variation between states, such as Gale and Samwick (2014). However, these reviews tend to focus on the overall outlook of the state's economy, rather than the key variables of interest of this paper – the migration flows and overall personal income tax revenue. Additionally, many of the research designs in the previously discussed papers only include subsets of data, or utilize data from before 2000. These data, while contemporarily applicable, were collected differently and held under differing data standards (Rudell 2018), and the economic structures of most states and of the United States as a whole have changed drastically since the 1990s. Having noticed these data issues, I sought to incorporate a more nuanced and time-relevant approach to state and systemic tax differences into my research design.

Reviewing this literature shows that there is strong dissent in this field, but little analysis of state-to-state migration flows *and* overall state income revenue; moreover, very few studies seek to estimate *causal* impact of changes in state-level marginal income tax rates. My paper addresses those two variables in tandem while evaluating causal impact of 'treatment,' or a tax change. I first conducted a causal analysis of these factors for over 23 states' treatments. In these approaches, I gave special attention to variance in state income tax code changes for states of similar socioeconomic and sociopolitical backgrounds. After conducting this larger-scale analysis, I selected a subset of these treatments for a further qualitative review to further evaluate treatment as a causal mechanism.

Quantitative Data

This paper's quantitative research relies on pooled data from all states and Washington D.C. between 2000 and 2020 to ensure that the model results are reliable and salient to state-level taxation systems in the near future. To aggregate these data, I cleaned datasets from multiple sources to contain the same variables, units of measurements, time periods, and other relevant qualities to merge the cleaned sets. I then aggregated these data to create three files used as input for my built quantitative model: a dataset with an annual entry for each state and D.C. between the years of 2000 and 2020 containing information on that state's independent and controls; a dataset recording annual observations of personal income tax revenue by state; and a list of datasets which contain the yearly population flows between states. These pooled data offer a useful aggregation of the independent, dependent, and control variables relevant to my model. Hereafter, I refer to pooled cross-sectional data as panel data; these terms share similarities but technically the latter implies that all data in a given observation is collected at the same time and by the same source, which is not the case for this study (Mesquita and Fowler 2021).

I have broken down how data for each variable were collected and cleaned in Appendix A. All data observations are paired by state and year (pairing is also termed 'State-Year' throughout this paper).

Most existing datasets have only provided accounting and reports through 2020, or they heavily caveat their data after this time. The COVID-19 pandemic has affected data collection and cleaning, and detailed, accurate disaggregation of the 2020 Census's data had not been released as of February 2023 ("Next 2020" 2022). Therefore, to maintain data hygiene and the accuracy and reliability of model results, this study does not utilize data published for the years after 2020. This limits difference-in-difference exploration of taxation system changes occurring 2018 and later, as I cannot establish trendlines of adequate length.

My difference-in-differences model analyzes all of the following variables to establish presence of a causal mechanism between the independent variables (also referred to as IVs in this paper) and the dependent variables (also referred to as DVs in this paper). The means through which this is done and the purpose of each variable's inclusion in this study's model is discussed further in **Methods**.

IV = Independent Variable; DV = Dependent Variable; C = Control; QoL = Quality of Life measurement

(1) Personal Income Tax Rates (IV), (2) Number of Income Tax Brackets (IV), (3) High and Low Taxable Income Brackets (IV), (4) State-to-State Migration Flows (DV), (5) Personal Income Tax Revenue (DV), (6) State Population Data (C), (7) Unemployment Rates (C), (8)

Corporate Income Tax Revenue (C), (9) State GDP (C), (10) Per Capita Personal Income (C), (11) QoL – Per Capita Personal Consumption Expenditure (C), (12) QoL – Health Insurance Coverage (C), (13) QoL – Public High School Graduation Rates (C).

Pooling Datasets

This section describes the process through which I aggregated the cleaned datasets into the three input files.

<u>Folder of Population Flows</u>

For the population flows files, each CSV file is loaded into a dataframe and all inflow and outflow data are cast to numeric values for easy statistical analysis. Once I created the dataset, I entered it sequentially into a list of dataframes, and each year's dataframe can be accessed via index. For example, the dataset representing the population flows in the year 2000 is indexed in this list at 1. Each observation within a dataframe records the number of emigrants from an origin state to all other states, Washington D.C., and in total in a given year. Each annual dataframe includes 51 observations, which represent each state and Washington D.C. The 52nd observation in each dataset represents the total number of new residents from other states and Washington D.C. to a state in a given year.

<u>Independent and Control Variables Dataset</u>

For the independent and control variables dataframe, each observation records a state's values for each of those variables in a given year. To do this, I dropped the irrelevant columns from the independent variables dataset created in Appendix A, and filtered the results so that the dataset only contains observations from 2000 to 2020. After I replaced the NaN values with 0 for the tax rate and highest bracket columns (the observations represent flat rate tax regimes), the data are merged with each control variable dataset (each of these datasets are cleaned such that this merge can occur seamlessly by ‘Year’ and ‘State’ observations).

Personal Income Tax Revenue Dataset

The third file records personal income tax revenue by state for many years. In its cleaned form, each State-Year observation in the dataframe records the personal income tax revenue annually from 1942 through 2021 for each state. Other than pivoting this dataset longer, resulting in each observation recording a state-year-personal income tax revenue triad, no changes were needed to be made to the form or content of the file after its initial clean (detailed in Appendix A).

Summary Statistics

Folder of Population Flows

This folder contains 21 datasets and cannot be represented by a single summary. However, I have included the summary information of the dataset representing the year 2000 to provide a summary as a useful example of the form of and value distribution in this dataset. Each dataset contains 53 columns and 52 observations, though in reality appear more like a grid with identical column and row values. Each observation was a state’s given outflows in a year, while each column contains a state’s inflows.

Column 1: Origin

Contains 51 unique string values (state names and “Total”). The “Total” row represents the observation of each subsequent columns’ (which represents each states’) total population inflow from all other states (the sum of every column).

Columns 2-52: State names

Contains continuous integer values representing the number of migrants moving to the state specified by column name. When a destination column is the same as the origin row, that observation takes on a NaN value that registers as a 0 for summative functions.

Column 53: Total

Contains continuous integer values representing the number of emigrants leaving a given row's origin state.

Please refer to Figures 3 and 4 for further summative information and a visual representation of this example dataset respectively.

<u>Figure 3. Summary of 2000 Population Flows Dataset</u>

Origin	ALABAMA	ALASKA	ARIZONA	ARKANSAS	CALIFORNIA	COLORADO	CONNECTICUT	DELAWARE	DISTRICT OF COLUMBIA	FLORIDA	GEORGIA	HAWAII
Length:52	Min. : 32.0	Min. : 11	Min. : 99.0	Min. : 20.0	Min. : 369	Min. : 130.0	Min. : 0.0	Min. : 10.0	Min. : 11.0	Min. : 253	Min. : 102.0	Min. : 28.0
Class :character	1st Qu.: 133.5	1st Qu.: 99	1st Qu.: 506.5	1st Qu.: 84.5	1st Qu.: 1438	1st Qu.: 589.5	1st Qu.: 123.5	1st Qu.: 36.5	1st Qu.: 57.5	1st Qu.: 1120	1st Qu.: 389.5	1st Qu.: 92.0
Mode :character	Median : 349.0	Median : 161	Median : 1201.0	Median : 282.0	Median : 2776	Median : 1439.0	Median : 241.0	Median : 69.0	Median : 119.0	Median : 2662	Median : 1173.0	Median : 194.0
	Mean : 1585.0	Mean : 496	Mean : 3784.4	Mean : 1181.1	Mean : 8873	Mean : 3349.4	Mean : 1446.8	Mean : 543.1	Mean : 833.7	Mean : 9205	Mean : 4741.5	Mean : 722.1
	3rd Qu.: 937.0	3rd Qu.: 302	3rd Qu.: 2477.0	3rd Qu.: 540.0	3rd Qu.: 5862	3rd Qu.: 1971.0	3rd Qu.: 703.5	3rd Qu.: 169.0	3rd Qu.: 338.5	3rd Qu.: 7194	3rd Qu.: 3050.0	3rd Qu.: 401.5
	Max. :40418.0	Max. :12649	Max. :96503.0	Max. :30117.0	Max. :226256	Max. :85411.0	Max. :36892.0	Max. :13848.0	Max. :21259.0	Max. :234730	Max. :120908.0	Max. :18414.0
	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1

IDAHO	ILLINOIS	INDIANA	IOWA	KANSAS	KENTUCKY	LOUISIANA	MAINE	MARYLAND	MASSACHUSETTS	MICHIGAN	MINNESOTA	MISSOURI	MISSISSIPPI
Min. : 12.0	Min. : 69	Min. : 43	Min. : 23	Min. : 27	Min. : 39.0	Min. : 27.0	Min. : 14.0	Min. : 63	Min. : 43	Min. : 84	Min. : 53.0	Min. : 53	Min. : 14.0
1st Qu.: 75.5	1st Qu.: 378	1st Qu.: 187	1st Qu.: 131	1st Qu.: 167	1st Qu.: 139.5	1st Qu.: 122.0	1st Qu.: 62.5	1st Qu.: 255	1st Qu.: 229	1st Qu.: 278	1st Qu.: 213.5	1st Qu.: 222	1st Qu.: 86.0
Median : 151.0	Median : 974	Median : 524	Median : 224	Median : 340	Median : 369.0	Median : 306.0	Median : 113.0	Median : 493	Median : 483	Median : 651	Median : 485.0	Median : 727	Median : 243.0
Mean : 831.9	Mean : 3759	Mean : 2211	Mean : 1074	Mean : 1405	Mean : 1652.9	Mean : 1306.6	Mean : 622.5	Mean : 2842	Mean : 2575	Mean : 2457	Mean : 1838.7	Mean : 2375	Mean : 1145.5
3rd Qu.: 310.0	3rd Qu.: 2360	3rd Qu.: 1171	3rd Qu.: 627	3rd Qu.: 630	3rd Qu.: 876.0	3rd Qu.: 702.5	3rd Qu.: 336.0	3rd Qu.: 1493	3rd Qu.: 1595	3rd Qu.: 1666	3rd Qu.: 1113.5	3rd Qu.: 1222	3rd Qu.: 549.5
Max. :21214.0	Max. :95849	Max. :56373	Max. :27389	Max. :35834	Max. :42148.0	Max. :33319.0	Max. :15873.0	Max. :72469	Max. :65667	Max. :62643	Max. :46886.0	Max. :60562	Max. :29210.0
NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1

MONTANA	NORTH CAROLINA	NORTH DAKOTA	NEBRASKA	NEVADA	NEW HAMPSHIRE	NEW JERSEY	NEW MEXICO	NEW YORK	OHIO	OKLAHOMA	OREGON	PENNSYLVANIA	RHODE ISLAND
Min. : 13.0	Min. : 112.0	Min. : 5.0	Min. : 12.0	Min. : 57.0	Min. : 18.0	Min. : 36	Min. : 33.0	Min. : 93	Min. : 120.0	Min. : 15	Min. : 35.0	Min. : 67	Min. : 7.0
1st Qu.: 81.0	1st Qu.: 418.5	1st Qu.: 39.5	1st Qu.: 107.0	1st Qu.: 215.5	1st Qu.: 52.0	1st Qu.: 188	1st Qu.: 156.5	1st Qu.: 491	1st Qu.: 294.5	1st Qu.: 159	1st Qu.: 190.5	1st Qu.: 313	1st Qu.: 38.0
Median : 154.0	Median : 1132.0	Median : 80.0	Median : 207.0	Median : 425.0	Median : 120.0	Median : 343	Median : 247.0	Median : 1008	Median : 692.0	Median : 365	Median : 441.0	Median : 563	Median : 72.0
Mean : 585.4	Mean : 4473.2	Mean : 310.4	Mean : 750.2	Mean : 2234.3	Mean : 938.8	Mean : 3095	Mean : 1113.4	Mean : 4861	Mean : 3091.2	Mean : 1456	Mean : 1885.0	Mean : 3436	Mean : 550.9
3rd Qu.: 384.5	3rd Qu.: 3048.5	3rd Qu.: 127.0	3rd Qu.: 404.5	3rd Qu.: 1023.0	3rd Qu.: 389.5	3rd Qu.: 1340	3rd Qu.: 441.0	3rd Qu.: 3270	3rd Qu.: 2545.5	3rd Qu.: 714	3rd Qu.: 816.5	3rd Qu.: 1923	3rd Qu.: 259.0
Max. :14927.0	Max. :114067.0	Max. :7914.0	Max. :19130.0	Max. :56975.0	Max. :23940.0	Max. :78923	Max. :28391.0	Max. :123959	Max. :78827.0	Max. :37140	Max. :48067.0	Max. :87613	Max. :13497.0
NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :3

SOUTH CAROLINA	SOUTH DAKOTA	TENNESSEE	TEXAS	UTAH	VERMONT	VIRGINIA	WASHINGTON	WEST VIRGINIA	WISCONSIN	WYOMING	Total
Min. : 57.0	Min. : 9.0	Min. : 76	Min. : 192.0	Min. : 30.0	Min. : 4.0	Min. : 129.0	Min. : 86.0	Min. : 11.0	Min. : 51.0	Min. : 7	Min. : 8923
1st Qu.: 177.5	1st Qu.: 47.0	1st Qu.: 228	1st Qu.: 986.5	1st Qu.: 127.5	1st Qu.: 28.5	1st Qu.: 531.5	1st Qu.: 436.5	1st Qu.: 38.5	1st Qu.: 245.5	1st Qu.: 64	1st Qu.: 21398
Median : 465.0	Median : 103.0	Median : 669	Median : 2553.0	Median : 226.0	Median : 65.0	Median : 1184.0	Median : 790.0	Median : 90.0	Median : 343.0	Median : 117	Median : 42212
Mean : 2164.0	Mean : 406.5	Mean : 2814	Mean : 7048.6	Mean : 1022.4	Mean : 389.5	Mean : 4516.9	Mean : 3089.1	Mean : 673.8	Mean : 1727.7	Mean : 411	Mean : 108948
3rd Qu.: 1304.0	3rd Qu.: 210.5	3rd Qu.: 2330	3rd Qu.: 5085.5	3rd Qu.: 465.5	3rd Qu.: 196.0	3rd Qu.: 2875.0	3rd Qu.: 1692.0	3rd Qu.: 360.5	3rd Qu.: 802.5	3rd Qu.: 219	3rd Qu.: 70667
Max. :55182.0	Max. :10365.0	Max. :71768	Max. :179740.0	Max. :26072.0	Max. :9931.0	Max. :115182.0	Max. :78771.0	Max. :17182.0	Max. :44056.0	Max. :10481	Max. :2832638
NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	NA's :1	

<u>Independent and Control Variables Dataset</u>

A thirteen-column dataset with 1.071 observations. Each observation records a state name, year, and their corresponding observations of the remaining eleven columns of data.

Column 1: State

Contains 51 unique string values (state names).

Column 2: Year

Contains 21 unique integer values (years 2000 through 2021). There is a uniform distribution of observations across each year.

Column 3: Tax Rate High

Contains continuous numeric values representing the tax rate on the highest bracket of the tax regime of the represented State-Year pair. Takes on value of 0 in a tax regime that does not have a personal income tax. Flat and graduated tax rates are represented in the same format for this column.

Column 4: Number of Brackets

Contains continuous integer values representing the number of income tax brackets under the tax regime of the represented State-Year pair. Takes on value of 0 in a tax regime that does not have a personal income tax and a value of 1 in a tax regime that utilizes a flat rate.

Column 5: Highest Income Brackets

Contains continuous integer values representing the lowest salary included in the highest tax bracket under the tax regime of the represented State-Year pair. Takes on value of 0 in a tax regime that does not have a personal income tax or utilizes a flat rate.

Column 6: Population

Contains continuous integer values representing the population of the represented State-Year pair.

Column 7: GDP

Contains continuous integer values representing the adjusted GDP of the represented State-Year pair.

Column 8: CIT

Contains continuous integer values representing the total corporate income tax revenue under the tax regime of the represented State-Year pair.

Column 9: Health Coverage

Contains continuous numeric values representing the percentage of the population represented by the State-Year pair with some form of health coverage.

Column 10: pcPersonalExpenditure

Contains continuous integer values representing the per capita personal expenditure of the population represented by the observed State-Year pair.

Column 11: pcInc

Contains continuous integer values representing the per capita personal income (wages) of the population represented by the observed State-Year pair.

Column 12: unemp

Contains continuous numeric values representing the unemployment rate of the population represented by the State-Year pair.

Column 13: gradrate

Contains continuous numeric values representing the complete public high school graduation rate of the observed State-Year pair (ex. the percentage of high school seniors who graduated from a public school in RandomState in Year was 78 percent).

Please refer to Figures 5 and 6 for further summative information and a visual representation of this dataset respectively.

Figure 4. Summary of Dataset Containing State-Year Observations of Independent Variables and Covariates, 2000-2020

```
> summary(dfIVC)
   State                Year       Tax Rate High    Number of Brackets Highest Income Brackets   Population             GDP               CIT              HealthCoverage  pcPersonalExpenditure      pcInc           unemp            gradrate
 Length:1071        Min.   :2000   Min.   : 0.000   Min.   : 0.000     Min.   :      0         Min.   :     610   Min.   :  23017   Min.   :     -118   Min.   :74.60   Min.   :17703          Min.   :21681   Min.   : 2.100   Min.   :51.30
 Class :character   1st Qu.:2005   1st Qu.: 4.630   1st Qu.: 1.000     1st Qu.:      0         1st Qu.: 1814560   1st Qu.:  75289   1st Qu.:   182097   1st Qu.:85.10   1st Qu.:28020          1st Qu.:33978   1st Qu.: 4.100   1st Qu.:74.62
 Mode  :character   Median :2010   Median : 6.000   Median : 4.000     Median :  16001         Median : 4406906   Median : 187927   Median :   389406   Median :88.50   Median :33110          Median :40411   Median : 5.200   Median :80.00
                    Mean   :2010   Mean   : 5.614   Mean   : 3.955     Mean   :  95673         Mean   : 6089871   Mean   : 312302   Mean   :   841378   Mean   :88.08   Mean   :33696          Mean   :41812   Mean   : 5.607   Mean   :78.96
                    3rd Qu.:2015   3rd Qu.: 7.150   3rd Qu.: 6.000     3rd Qu.:  69960         3rd Qu.: 6896741   3rd Qu.: 387274   3rd Qu.:   837938   3rd Qu.:91.20   3rd Qu.:38431          3rd Qu.:48122   3rd Qu.: 6.700   3rd Qu.:85.60
                    Max.   :2020   Max.   :12.300   Max.   :12.000     Max.   :5000000         Max.   :39501653   Max.   :2729226   Max.   :13792519   Max.   :97.50   Max.   :71454          Max.   :89735   Max.   :13.700   Max.   :94.00
                                                    NA's   :1                                                                                                                                                                    NA's   :13
```

Personal Income Tax Revenue Dataset

A 3-column dataset with 4,080 observations. Each observation records a state name, a year, and the personal income tax revenue corresponding to those two variables.

Column 1: State Name

Contains 51 unique string values (state names).

Column 2: Year

Contains 80 unique integer values (years 1942 through 2021). There is a uniform distribution of observations across each year.

Column 3: PIT

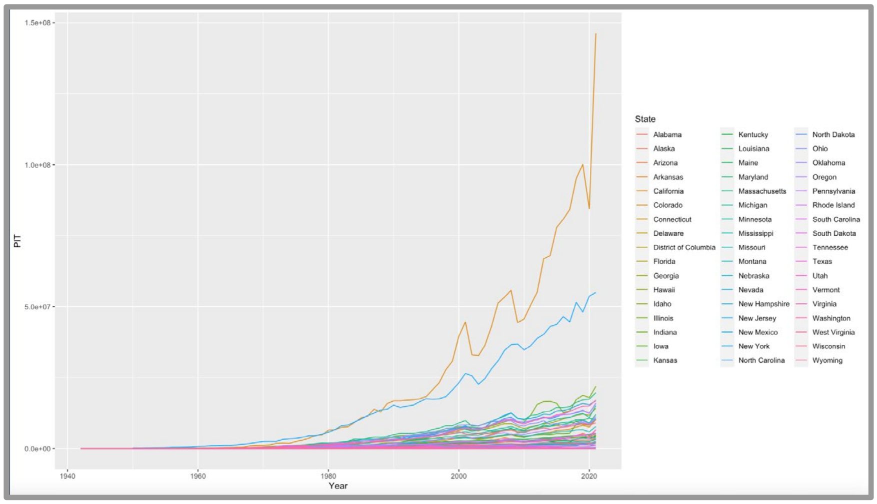
Contains continuous integer values representing personal income tax revenue. Any State-Year combination that does not have an observable PIT takes on a NaN value for this column.

Please refer to Figures 7 and 8 for further summative information and a visual representation of this dataset respectively.

Figure 5. Summary of Personal Income Tax Revenue Dataset observing State-Year Pair's Corresponding PIT Revenue, 2000-2020

```
    State                Year            PIT
 Length:4080        Min.   :1942   Min.   :        0
 Class :character   1st Qu.:1962   1st Qu.:     5483
 Mode  :character   Median :1982   Median :   219751
                    Mean   :1982   Mean   :  2254937
                    3rd Qu.:2001   3rd Qu.:  1945044
                    Max.   :2021   Max.   :146324579
                                   NA's   :185
```

Figure 6. State Personal Income Tax Revenue since 1942 (by State)



Aggregation Process for Difference-in-Differences Modelling

For each observed pairing with a treated unit and a control unit (a state with a tax change and a state without a tax change across a single time period), I created a comparison dataframe that is input into three regression models, a process described further in **Methods**.

To create this aggregate dataframe with only the necessary information include for a comparison of State Treated and State Control in a given time range, in which Treated has a tax change at time ChangeYear, I conducted the following steps:

1. Filtered the Personal Income Tax (PIT) Revenue dataset and the Independent and Control Variables (IVC) dataset, the result being that the only observations included are those taking place in the appropriate time range in States Treated and Control.
2. Created three columns in the IVC dataset titled "Treatment," "Time," and "DiD": the "Treatment" column takes on the value of 1 if observation's State = Treated and 0 otherwise (i.e., if observation's State = Control); the "Time" column takes on the values 0 if observation's Year < ChangeYear and 1 otherwise (i.e., if observation's Year =

ChangeYear); the “DiD” column represents if an observation is in the treated group after treatment year, and takes on the values of Treatment*Time (0 or 1)

3. Merged the PIT and IVC datasets on Year and State such that each State-Year observation contains the following columns in addition to “Year” and “State”: “Tax Rate High,” “Number of Brackets,” “Highest Income Brackets,” “Population,” “GDP,” “CIT,” “HealthCoverage,” “pcPersonalExpenditurs,” “pcInc,” “unemp,” “gradrate,” “Treatment,” “Time,” “DiD,” “PIT.”
4. Created empty columns titled “Inflow” and “Outflow” that have placeholder values of 0 in the merged dataset.
5. Only selected datasets representing years within the given time range from the folder of population flows’ datasets.
6. Iterate by index through each dataset left in the Folder of Population Flows and through the merged dataset at the same time (each iteration represents a year).
    a. Iterate through each row and save the values that represent the total inflows and outflows for Treated and Control’s Inflow and Outflow columns.

Result: After completing these two iterations, the merged dataset then had 19 columns. Each State-Year pair observes non-zero, non-NaN values for the following variables: “Tax Rate High,” “Number of Brackets,” “Highest Income Brackets,” “Population,” “GDP,” “CIT,” “HealthCoverage,” “pcPersonalExpenditure,” “pcInc,” “unemp,” “gradrate,” “Treatment,” “Time,” “DiD,” “PIT,” “Outflow,” and “Inflow”. Columns from this dataset can be subsetted to appropriately run a regression analysis on a tax change for one state in an observed pair of states in a given time period.

Figure 7. Example Dataset Summary (Arizona/Georgia pairing)

```
> summary(df_ArizonaComp)
    State                Year       Tax Rate High   Number of Brackets Highest Income Brackets    Population
 Length:38          Min.   :2000   Min.   :4.540   Min.   :5.0        Min.   :  7000          Min.   : 5160586
 Class :character   1st Qu.:2004   1st Qu.:4.540   1st Qu.:5.0        1st Qu.:  7001          1st Qu.: 6359201
 Mode  :character   Median :2009   Median :5.520   Median :5.5        Median : 78500          Median : 7695766
                    Mean   :2009   Mean   :5.362   Mean   :5.5        Mean   : 78705          Mean   : 7852725
                    3rd Qu.:2014   3rd Qu.:6.000   3rd Qu.:6.0        3rd Qu.:150000          3rd Qu.: 9591845
                    Max.   :2018   Max.   :6.000   Max.   :6.0        Max.   :152668          Max.   :10519389
      GDP              CIT            HealthCoverage  pcPersonalExpenditure      pcInc           unemp
 Min.   :208440   Min.   : 176874   Min.   :79.10   Min.   :22935         Min.   :26388   Min.   : 3.600
 1st Qu.:271950   1st Qu.: 370611   1st Qu.:81.83   1st Qu.:27518         1st Qu.:32107   1st Qu.: 4.725
 Median :352277   Median : 480346   Median :83.10   Median :30387         Median :35380   Median : 5.400
 Mean   :357370   Mean   : 558105   Mean   :83.74   Mean   :30323         Mean   :35605   Mean   : 6.221
 3rd Qu.:446806   3rd Qu.: 712393   3rd Qu.:85.50   3rd Qu.:33044         3rd Qu.:38516   3rd Qu.: 7.550
 Max.   :538605   Max.   :1017187   Max.   :90.00   Max.   :39220         Max.   :46855   Max.   :10.500
    gradrate       Treatment         Time              DID               PIT                Outflow            Inflow
 Min.   :58.70   Min.   :0.0   Min.   :0.0000   Min.   :0.0000   Min.   : 2090645   Min.   : 61486   Min.   : 71861
 1st Qu.:65.75   1st Qu.:0.0   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.: 3133748   1st Qu.: 77416   1st Qu.: 98735
 Median :72.25   Median :0.5   Median :1.0000   Median :0.0000   Median : 5408308   Median : 91486   Median :110834
 Mean   :71.34   Mean   :0.5   Mean   :0.6316   Mean   :0.3158   Mean   : 5672800   Mean   : 92702   Mean   :112499
 3rd Qu.:77.05   3rd Qu.:1.0   3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.: 7980571   3rd Qu.:105851   3rd Qu.:125012
 Max.   :84.67   Max.   :1.0   Max.   :1.0000   Max.   :1.0000   Max.   :11643781   Max.   :146048   Max.   :169517
```

Methods

To address my research question, I conduct two main avenues of analysis: a large scale difference-in-differences analysis of state pairings and qualitative review of a selected treatments, the latter reviewing the DiD results in the greater context of local contemporary political issues, legislation, cultural topics, and other elements divorced from state-level income taxation that may influence interstate migration. The larger-scale DiD analysis provides a consistent quantitative framework in which state-level changes in population inflows, population outflows and personal income tax revenue (the three DVs) can be evaluated against changes in a taxation system (the independent variables) while controlling for other data regarding state-specific quality of life and economic health (control variables, or covariates); it also allows for the causal mechanism of each analysis to be evaluated under consistent terms. The follow-up qualitative review of several of the treatments of interest allows for even greater understanding of the taxations system changes, and how alternative factors may impact the dependent variables studied.

Importantly, as established in *Recent Discourse*, no state has implemented a graduated income tax from no personal income tax **nor** has any state implemented a graduated income tax from a flat rate regime between 2000 and 2020. As such, this study requires extrapolation from recent tax changes that mimic such a process. For example, this includes assuming that increases in graduated income tax rates, the number of brackets, and/or the top income tax bracket would inspire similar behavior responses in high-earning taxpayers in a treated state as would be inspired in their equivalent populations in a theoretical state implementing a graduated income tax from a flat rate or from no personal income tax. I also assume that reverse changes would have reverse impacts; for instance, some states have changed their personal income tax structure to a flat rate, replacing their graduated regimes. In these states, I would expect for an increase in inflows, a reduction in outflows, and/or an increase in personal income tax revenue to support opponents of the implementation of a graduated PIT regime, and vice versa for that policy change's supporters. I make similar reversed assumptions to evaluate the claims made by proponents of implementing graduated income tax systems; if lowered rates, a decrease in the top bracket, or a decrease in the number of brackets had a positive causal impact on PIT revenue, a positive causal impact population inflows, and/or negative causal impact on population outflows, this supports graduated income tax proponents' arguments. This means that the resulting analysis, while not conducted on explicit examples of unidirectional graduated personal income taxation system shifts, still allows for reasonable evaluation of the arguments set forth in both sides of the policy debate.

Large-Scale Two-Way Fixed Effects Difference-in-Differences Analysis (Incorporating Qualitative Reasoning)

For both steps of the analysis, I considered how the results supported, rejected, or provided inconclusive results for the proponent and/or opponent claims about implementation of marginal individual income taxation systems set forth in *Introduction.* This research design utilizes the classic two-way fixed effects (TWFE) model, which is "a very common approach to estimating a linear model is to include both unit fixed effects and time fixed effects in ordinary least squares estimation" (Wooldridge 2021) to estimate effects of taxation changes, and evaluate them as causal mechanisms for changes in the state-level personal income taxation.

Choice of Dependent Variables, Isolation of Highest-Income Earners

There are relatively low costs to moving between states in comparison to moving between countries; for the latter, the financial and social barriers include changing citizen citizenship, international shipping of personal items, and isolation from family and friends in comparison to the former. However, there are still meaningful costs to changing residence between states that may inform behavioral responses of different taxpayers. People are typically restricted by the costs of finding a new job, housing, and transportation costs, among others (Tankersley and Guo 2014). As such, as previously mentioned in the *Literature Review*, labor responsiveness to changes in income taxation will vary by income. Not only are high-earners theoretically more able to move between states than low-earners, and could be motivated to move should it be in their financial interest, but they are also able to travel more easily to maintain personal networks in their origin state. Rauh and Shyu (2019) finds that changes in taxation systems can marginally affect labor supply in a given state, but the paper does not adequately study overall population flows, which is this study's variable of interest. Therefore, I expected migration flows and overall state personal income tax revenue to be affected by, and to be implicitly indicative of a high-income earner response to, changes in state tax code; given that those who are relatively unharnessed by barriers of interstate movement and most affected by increases in a tax rate and/or an implementation of a graduated income tax are the highest-earners, I expected this group's response, if there is any statistically significant reaction to treatment (a taxation change), could manifest in changes in population flows and personal income tax revenue after such systemic changes. Therefore, for each treatment (control unit and treated unit pairing) in this study, I run a difference-in-differences regression analysis for each of the following: population inflow, population outflow, and total personal income tax revenue.

Independent Variable(s)

As previously established in the *Literature Review* section, few research papers and think pieces provide analysis on time-specific pooled panel data, and even fewer employ research methods that establish a causal mechanism. Often, the authors of these articles only analyze a change in one variable relevant to a tax system change. For this analysis, I studied the impact of three independent variables that are explicitly relevant to the individual income tax system and their changes – (1) changes in the number of tax brackets; (2) change of the income in the highest bracket; and (3) change in the tax rate on the highest bracket. I focused my analysis on the brackets affecting the highest income earners, since they are the population of interest. I reviewed trends in each state and assigned a specific time period of examination so that there were enough data before and after treatment to establish trendlines for the DiD analysis. I then coded a single, binarized treatment variable based on the data's status as before or after 'treatment' (a tax change) – in the model I created, this is how the independent variable is represented. See **Quantitative Data** for further information about how I pooled these data, and Appendix B for all information regarding identified tax changes from pooled dataset with information during the years 2000-2022 in categories (1), (2), and (3).

Control Variables (Covariates)

While the difference-in-differences model is meant to allow comparison and evaluation of a causal mechanism in natural experiments – perfectly suited for policy implementation – it makes several distinct assumptions about the data that, naturally, this study's pooled dataset does not satisfy (see *Assumptions*). The strategic control/treated unit matching outlined in Control/Comparison Unit Matching partly satisfies the assumption regarding parallel trends by ensuring similar structural baselines, but to fully satisfy this assumption in addition to the assumption about a lack of treatment spillover effects, and to nullify other elements that may have affected the dependent variable outcomes, I have included specific covariates in this model. These control variables, definitionally continuous, also aid in establishing a similar baseline between the treated and controlled unit.

I considered these covariates in two nebulous groups based on their likely contributions to minimizing the influence of confounding effects, though many of these variables could fall into both or separate categories. An exception to this categorization is the covariate *Total State Population*, which I included in my model but does not fall neatly into either category. The first category controls for confounding variables indicative unit-specific economic health and structure:

- *State GDP.* Differences in state GDP leads to baseline economic differences, including differing predisposition to economic health, growth, and/or failure (Callen 2019).
- *Unemployment Rates.* A high unemployment rate "adversely affects the disposable income of families, erodes purchasing power, diminishes employee morale, and reduces economic output" in a given state (Picardo 2023). Different unit unemployment rates may lead to the treated unit having an artificially high or low relative personal income tax revenue because more or fewer residents are receiving taxable income in comparison to a control unit.
- *Corporate Income Tax Revenue*. State tax regimes include more than personal income taxes; another form of income taxes are those levied on corporate income. Several states with low personal income taxes will compensate with higher corporate income taxes. This could affect population flows, for example, because companies may choose to move states (and therefore its workers) to another state (Kiel 2022).
- *Per Capita Personal Income.* Significant changes in per capita personal income could artificially inflate or deflate PIT revenue.

The second covariate category controls for broad quality of life dissimilarities between states. These variables are as follows:

- *Per Capita Personal Consumption Expenditure.* Personal consumption expenditure is a "measure of the prices that people living in the United States, or those buying on their behalf, pay for goods and services" ("Personal Consumption" 2022). It has twofold indicators: on one hand, a resident would prefer to not have to pay higher prices for the same good, and could be priced out of their origin state in favor of a destination state; on the other hand, high expenditures on personal goods implies a certain level of consumer leisure available in an origin state in comparison to a potential destination state (Liberto 2023). This can be a feature of, or entirely separate from, reactions to personal income tax structure changes.

- *Health Insurance Coverage.* This provides an indication of state investment in public and private health. For example, a reason a taxpayer may emigrate is for better state-provided health insurance or stronger state requirements of health coverage in the destination state when compared to the origin state (like an elderly person looking to enroll in state health care who could have some pre-existing conditions). This reasoning could be entirely separate from any consideration of changes in income tax structure (particularly for retirees, who are likely earning far less taxable income upon retirement).
- *Public High School Graduation Rates.* This provides an indication of the quality of a state's education system. For example, a reason for a parent to leave their origin state may be because of the destination state's greater investment in public education in comparison to their home state, again completely divorced from any changes in personal income tax structure in either.

I chose these variables for their potential direct and indirect impacts on the studied dependent variables in a way that is not controlled through a DiD design. I did not include more covariates in this design, however, since this could lead to the issue of overfitting and ultimately nonsensical regression results regarding causal impact of tax changes on the dependent variables (Zhang 2014).

Control/Comparison Unit Matching Methodology (Qualitative and Quantitative)

This paper's two unit, two periods difference-in-differences research design requires pairing a state that has experienced a treatment (a tax system change) with a state that has not experienced any treatment in the same time period (has not had any changes to its tax regime). To ensure the validity of the comparison between the treated and untreated units, the baseline conditions should be the same (which can be considered a corollary of Parallel Trends assumption). In other words, the behavior of the units would mimic similar, parallel patterns should treatment not have occurred. As such, the comparison state must have the same type of tax regime. For example, I assume that change in a graduated tax regime will likely appear to have a much greater causal impact on any resulting changes in the dependent variables when compared against a control unit that does not levy a personal income tax versus a control state that has an unchanged graduated income tax regime. Maintaining unit pairings with strong similarities ensured that any statistically significant results are meaningful, and more indicative of unit response to treatment rather than other unit-specific, time varying discrepancies between the two units.

Considering this and understanding the need to minimize any time-varying differences between the two units, I sought to match the treated state with a control state most similar from the listed options. I weigh the following information when making a qualitative judgment to pair a treated state with its comparison state. The cited source for each variable acted as the data of comparison evaluation.

- *Political Leanings*. While behavioral responses to tax changes are not tied directly to political ideology ("Illinois Allow" 2020), political opinions do influence attitudes towards taxation. I looked for political party strength between the two states by their federal and state election results and voter roll party affiliation percentages ("States by Political" 2023).

- *Geographic Proximity.* The physical distance between units and the regions to which units belong establish cultural and industrial similarities (for example, both units being on the East Coast in comparison to one of them being in the Rockies?).
- *Demographic Breakdowns.* Unit populations sharing similarities in gender, racial, and education makeup establish similar unit population baselines ("State Comparisons").
- *Main Industries.* Comparable share of the same industries in two units implies similarities not only between economic outlook, but in worker activity and labor union power (Jones 2022). I evaluated both the significance of the top industries in each state, and also the contribution of the state's output to the national industry (Lang 2019).
- *Urban/Rural Divide, Important Cities.* The urban/rural split of a unit's population may have indicators of economic structure, response to structural tax changes, and civic engagement (Rakich 2020); additionally, units sharing an urban center (for example, New Jersey and Connecticut share New York City as a regionally important city, and neither benefit from New York state taxation) may indicate similar socioeconomic structure and economic dependencies.

Depending on the state, I qualitatively weigh similarities and differences in certain variables greater than other comparisons based on their strength and vitality to the units' societies and draw comparisons where possible in these areas. Ultimately, the control unit options are limited, and I had to make this judgment somewhat arbitrarily; however, this process allows for more weight to be leant to difference-in-differences results.

Assumptions of Difference-in-Differences Regression Model

The following are key assumptions of the DiD regression model and how I adjusted my initial model to satisfy them as applicable.

- *Parallel Trends.* An assumption inherent to the difference-in-differences model, the parallel trends assumption "requires that in the absence of treatment, the difference between the 'treatment' and 'control' group is constant over time" ("Difference-in-Difference"). That is, by using the units in this difference-in-differences regression model, conditions between the states must have remained parallel had it not been for the changes in the taxation system (the 'treatment'). These conditions include general health conditions, political trends, economic trends, inflation conditions, and national policy changes affect each state about the same. To better control conditions that might otherwise change the trends between the states, my regression model also includes several control variables for areas that may reflect trends that are not parallel between two states; these include isolated changes in corporate income tax structure and revenue.
    - This assumption extends to one of the measured dependent variables: migration flows. The migration flow data that I used is actually the number of returns filed with differing state residencies from the previous year's filing and the current year's filing, not exact population changes. The IRS recommends that everyone file a tax return just in case, but there may be some discrepancies. As such, I assumed that the general relationship between total state population flow and migration flows measured by filed personal returns maintains a stable relationship. To better control between regional population differences, I used a

control variable recording the real population counts for each state in the years covered in this analysis.

- *No Confounding Baseline Variables.* Another assumption inherent to the difference-in-differences model, the "intervention [variable is] unrelated to outcome at baseline" ("Difference-in-Difference"). This means the change in the outcome did not determine the implementation of the variable. I ensured that this is true by controlling for confounding variables in my models.
- *No Spillover Effects.* Another assumption inherent to the difference-in-differences model, no spillover effects can exist; no variables "can either increase or decrease the overall effectiveness of interventions" (Francetic et al 2022). Again, this assumption is ensured through the use of control variables.
    - There is no expectation of treatment (a tax change). This is a strong assumption to make in this case, given that there may be ongoing political discourse for many years before actual implementation. However, real taxation system changes are typically unable to be fully anticipated due to the nature of their passage (usually by ballot measure) ("Massachusetts Question 1"). For tax changes that are implemented over time, I set the binarized treatment to the first shift in the tax system.
- *Homogeneity of Variance, Stable Composition of Treated and Control Units.* Any errors in my regression analysis are the same across the independent variable and do not vary significantly over the IV values. Composition of the two groups remains relatively stable across groups – to ensure this, I implement the aforementioned covariates in my models.

- *General Controls Assumptions.* I am assuming that the control variables I implemented feasibly cover the reasons for which people move that cannot be covered under parallel trends (the latter of which may include family proximity and other social concerns that are not state specific). Additionally, I assume that the data regarding personal income, GDP, and other economic indicators provide reasonable indications of economic health of a state, and that data such as health insurance access, per capita personal consumption expenditure, and public high school graduation rates provide reasonable indications of the quality of life of a state.
- *Behavioral Assumptions for High-Income Earners.* In this paper, I assumed that all high-income earners display similar behaviors, which would be that they leave a state if their state tax burden becomes intolerable; however, this behavior is likely highly varied in reality, and behavior of this group likely varies by state, personal background, etc.

While state-to-state migration may be a useful indicator of income tax change's effect on labor mobility, a more important measure is, in my opinion, the actual change in state income tax revenue. If a change in the state tax code causes high-income earner potential outflow, but overall, the state income tax revenue for the tax bracket stays stable or increases, and the tax burden does not shift on to lower-income residents, then the policy is still effective.

Limitations of This Methodology

There are a few limitations these models set on its findings based on the restrictions of the model and the data.

This panel data is somewhat complicated; not only are the 'treatments' (state personal income tax policy changes) staggered in implementation across multiple periods and multiple units, those treatments are 'dosages' – that is, quantitatively and concretely different, not binary – and units can have multiple treatments of different dosage, but not are all such. For a fulsome analysis of this panel data, this model would need a more experimental difference-in-differences design. An adjusted model similar to that set out in Callaway et al (2021) would have allowed me to use treatment variables that have heterogeneous dosages at different times (in this case, different changes in the highest bracket tax rates, number of brackets, *and* highest income bracket), while maintaining multiple dependent variables and including control variables. However, Callaway et al assumes only one dosage treatment across all units and time periods, and the panel data that I have collected show some units as receiving multiple dosage treatments over multiple periods. As such, I cannot properly analyze these data against itself as fulsome panel data; instead, I utilize a simple two period, two-unit difference-in-differences analysis.

There are obvious disadvantages to using this simplified model; the impact is measured only between the 'baseline' and the state with the taxation system change, not between several units (states) themselves. Additionally, this paper cannot study the dosage treatment effect and individualized independent variables' (disaggregated from the binarized variables) given that multiple units cannot be studied over time. However, given the limitations and structure of the data, and given the strong exceptionally, linearity claims, particularly strong parallel trends assumptions, and complication of treatment effect heterogeneity that would have had to have been addressed with such an adjusted difference-in-differences model (Callaway et al 2021), there would have been drawbacks to such an experimental design anyways. Additionally, this design allows for a finer comparison between types of taxation systems, such as allowing explicit qualitative comparison between the same type of system (for example, between graduated income taxation systems with a control and treated unit). This binarization also allows me greater flexibility to assign different treatment types (the model is equipped to handle, for example, both the establishment of a gradual elimination of a graduated tax system in favor of a flat tax system and a simple, one-time rate increase). Lastly, I do conduct a follow up qualitative review of treatments of particular interest, using the DiD results as a launch point but not as the only evaluative measure.

Another limitation of this structure is that it assumes generally linear trendlines when the relationship between the IVs and the DVs is not. There is distinct yearly variance over time that does not follow a specific linear pattern; however, over time, the trendlines in personal income tax revenue tends to be roughly linear because of its peg to inflation rate when considered in shorter time periods (roughly five years) (“IRS Provides” 2022). The nonlinear trend lines in personal income tax revenue tend to occur as taxation regimes have significant changes.

By the nature of the complex assortment of DiD design assumptions, while I addressed the assumptions through controls and unit matching, underlying trend differences may be points of weakness in which parallel trends did not hold tightly in the studied treatments. I may not have been able to measure all specific time-varying unit covariates, especially given the distinct lack of appropriate, available, and quantifiable data anyways.

Lastly, sparse data created an unavoidable limitation of this research design; ideally, to establish clear and consistent trendlines, in each regression, I would have preferred to include at least 12 observations with a roughly even split between pre- and post-treatment periods such that there are more observations than independent variables and covariates. However, given limited data availability and consistency, and to maintain finding salience to today (restricting my studied treatments to recent decades), the purpose of the model inevitably hampers this. I did eliminate treatments for which the data are not sufficiently complete to establish trendlines, or would lead to an entirely overfit model. Utilizing these selection criteria, this research paper studies a total of 23 treatments in its difference-in-differences model. Appendices C and D also include an illustrative treatment (Louisiana 2004 – 'Treatment 1') that does not fulfill these criteria.

Difference-in-Differences Model

Given the previously established independent, dependent and covariate variables, I have built three formulas describing their relationship, one for each outcome variable of interest (total personal income tax revenue, population inflow, population outflow) for a given state (Dobson 2014). I use the same baseline DiD equation (Equation 1) to create my models.

Equation 1. Baseline DiD Equation

$$Y_{ist} = \alpha + \gamma * treatment_s + \lambda * time_t + \beta(treatment_s * time_t) + (\sum_{i=1}^{n} control_i * \delta_i) + \epsilon_{ist}$$

In this case, Y_{ist} represents the outcome variable of a unit at a specific time; α represents the time-invariant variables (the regression intercept); binary variable $treatment_s$ and γ represent the sole contribution of treatment to the outcome; binary variable $time_t$ and λ represent the sole contribution of time to the outcome; binary variable $time_t$*$treatment_s$ represents the DiD estimator and β represents the causal effect of treatment; the sum term is an expression of the summation of continuous covariates and their coefficients; and lastly, an invariant term representing regression error.

The extended form of the equation ultimately takes on the following structure (Equation 2).

Equation 2. Expanded DiD Equation

$$Y_{ist} = \alpha + \gamma * taxChange_s + \lambda * treated_t + \beta(taxChange_s * treated_t) + \delta_{pop} * statePopulation + \delta_{GDP} * GDP + \delta_{unemp} * unemploymentRate + \delta_{CIT} * totalCorporateIncomeTaxRevenue + \delta_{pcInc} * percapitaPersonalIncome + \delta_{pcPCE} * percapitaPersonalConsumptionExpenditure + \delta_{coverageRate} * healthCoverageRate + \delta_{gradrate} * highSchoolGradRate + \epsilon_{ist}$$

I estimated each dependent variable's relationships with the binarized independent variable and covariates in the following three equations.

Equation 3. Population Inflow Equation

$$Y_{PopulationInflow} = \alpha + \gamma * taxChange_s + \lambda * treated_t + \beta(taxChange_s * treated_t) + \delta_{pop} * statePopulation + \delta_{GDP} * GDP + \delta_{unemp} * unemploymentRate + \delta_{CIT} * totalCorporateIncomeTaxRevenue + \delta_{pcInc} * percapitaPersonalIncome + \delta_{pcPCE} * percapitaPersonalConsumptionExpenditure + \delta_{coverageRate} * healthCoverageRate + \delta_{gradrate} * highSchoolGradRate + \epsilon_{inflows}$$

Equation 4. Population Outflow Equation

$$Y_{PopulationOutflow} = \alpha + \gamma * taxChange_s + \lambda * treated_t + \beta(taxChange_s * treated_t) + \delta_{pop} * statePopulation + \delta_{GDP} * GDP + \delta_{unemp} * unemploymentRate + \delta_{CIT} * totalCorporateIncomeTaxRevenue + \delta_{pcInc} * percapitaPersonalIncome + \delta_{pcPCE} * percapitaPersonalConsumptionExpenditure + \delta_{coverageRate} * healthCoverageRate + \delta_{gradrate} * highSchoolGradRate + \epsilon_{outflows}$$

Equation 5. PIT Equation

$$Y_{PersonalIncomeTaxRevenue} = \alpha + \gamma * taxChange_s + \lambda * treated_t + \beta(taxChange_s * treated_t) + \delta_{pop} * statePopulation + \delta_{GDP} * GDP + \delta_{unemp} * unemploymentRate + \delta_{CIT} * totalCorporateIncomeTaxRevenue + \delta_{pcInc} * percapitaPersonalIncome + \delta_{pcPCE} * percapitaPersonalConsumptionExpenditure + \delta_{coverageRate} * healthCoverageRate + \delta_{gradrate} * highSchoolGradRate + \epsilon_{PITrev}$$

R Implementation of Model

I used a multivariate multiple linear regression in R to construct a two-way fixed effects difference-in-differences model that studies individual treatment effects of the coordinated unit pairs (the "treated" state and a baseline state).

I created three models for each pairing, measuring effects of time, treatment, and controls on personal income tax revenue, population outflows, and population inflows. Following the formulas set forth in Equations 3-5, the regression code to compare each pair in R is as follows:

Figure 8. Three Example Regression Models

```
StatePITModel <- plm(PIT ~ Time + Treatment + DID +
                          GDP + Population + HealthCoverage + CIT +
                          pcPersonalExpenditure + pcInc + unemp + gradrate, data = stateData)
StateOutflowModel <- plm(Outflow ~ Time + Treatment + DID +
                       GDP + Population + HealthCoverage + CIT +
                       pcPersonalExpenditure + pcInc + unemp + gradrate, data = stateData)
StateInflowModel <- plm(Inflow ~ Time + Treatment + DID +
                          GDP + Population + HealthCoverage + CIT +
                          pcPersonalExpenditure + pcInc + unemp + gradrate, data = stateData)
```

Supplementary Qualitative Review of Select Treatments

Purpose

I supplemented my difference-in-differences analysis from the previous section for selected treatments with additional qualitative analysis to cultivate a stronger, more holistic understanding of trends over time for similar states upon the implementation of tax system changes; I studied treatments from a selection of states that I have found to be broadly representative of the current trends in state-level personal income tax regimes, and to also compare between treatments. A more qualitative review in which the DiD results are measured and weighed in conjunction with deeper knowledge of cultural, socioeconomic unit-specific shifts at given periods of time provides a means of comparison between treatments otherwise not available for the DiD results detailed in the previous section.

Selecting Treatments of Further Study

I selected treatments for further study using the following criteria:

- Changes between types of taxation systems (graduated to flat) (Appendix B)
- Statistically significant treatment effect on any or all of the dependent variables (Appendix B)
- Significant discourse (particularly within the state) surrounding the implementation of the treatment (searching results of online news articles on the proposed change in the tax code)
- In-state wealth/income distribution (Sommeiller et al 2016)
- Unexpected outcomes at a first glance – for example an increase in the top tax rate and no statistically significant impact on inflows or outflows, but a decrease in the personal income tax revenue (Appendix D)

Additionally, I sought to select treatments that occur in states with similar characteristics, structured so that the treatments affected similar baseline populations/economic structures and can be appropriately compared. To do this, I utilized a similar, though more rigorous and extensive, analytical framework as outlined in *Control/Comparison Unit Matching Methodology*. The qualitative review is done on treatments for which their treated units have a similar demographic background, similarly sized urban areas, similarly diversified economies, and, ideally, are compared against the same control units/states in the DiD analysis.

Analysis of Selected Treatments

For a more fulsome approach to the qualitative treatment reviews, I utilized a mixed methods approach. In each qualitative overview, I examined cultural, political, and other socioeconomic factors that may inspire an individual to move states of residence, and include information regarding public discourse and/or acceptance of tax changes from then-contemporary news articles.

With the qualitative approach, I made more meaningful comparisons between these state-level changes. Most treated states have similar population makeups and have multiple economic sectors; each has at least one large metropolitan area. Many of these states also have local income taxes, which inform the tax burden on residents as well. Political ideologies still vary by state, and the states belong to different geographic regions of the country. These are factors that are important to a person's decision making process for moving states, in addition to their tax bracket. In these deeper reviews, I was also able to isolate the destination state of those who leave their origin state after the origin state experiences a treatment (high tax treatment) as applicable. I weighted the intended uses or program cuts estimated to affect a state after treatment/a taxation system change, which may impact a resident's decision to remain in or leave the treated state – for example, earnings from an increased income tax rate may be earmarked for highway reconstruction, making the daily commute for a high-earner easier. That high earner may think that the intangible payoff of the tax increase will be worth the increased taxation burden in the long run. All of the selected treatments of further study have at least one other similar treatment in order for the results to have some meaningful juxtaposition.

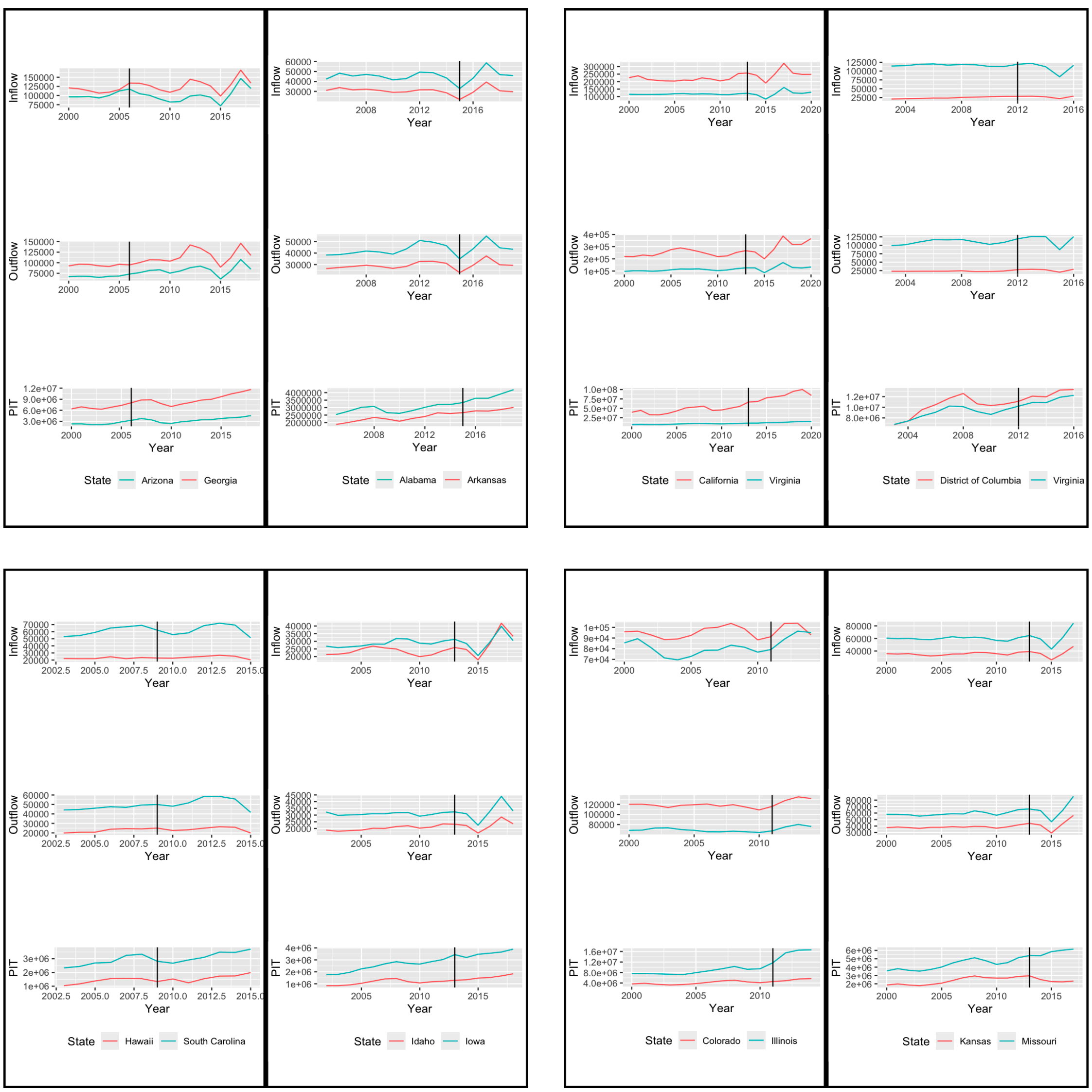
Results

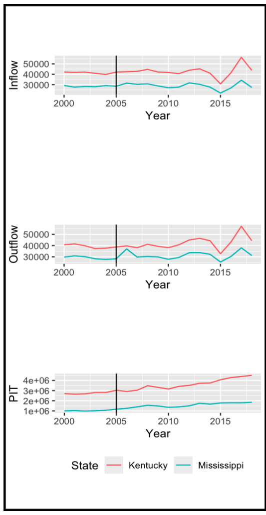
2000-2020 Difference-in-Differences Model

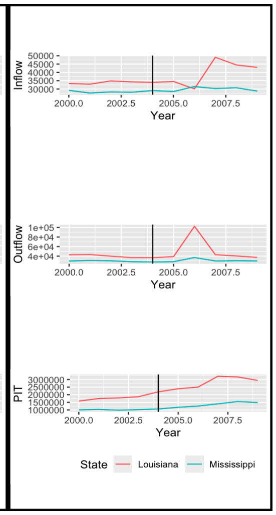
Visualizations of Initial Treatment Trends by Analyzed Pairing

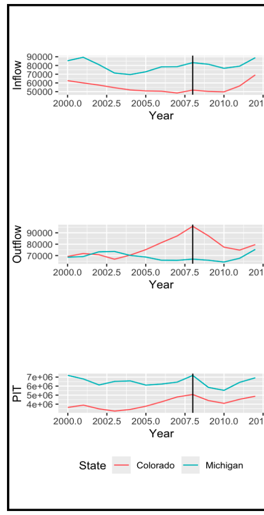
The following figure illustrates the raw dependent values plotted against the year for each control and unit in the pairing. The treatment year is demarcated by a black vertical line. These differences do not show the treatment effect, given that the control variables are not included, but the graphs do provide useful information about general trendlines, and also illustrate the overall fairly linear and matching relationship between the control and treated units in most pairings, indicating national trendlines that are not impacted by treatments.

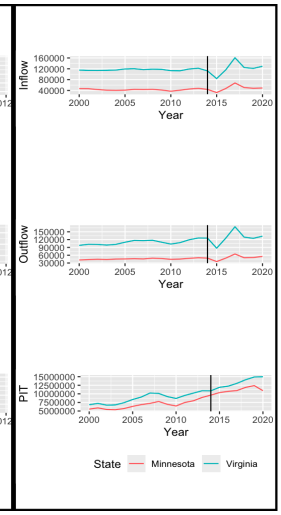
Figure 9. Visualizations of the Dependent Variables between Treated/Control Unit Pairings

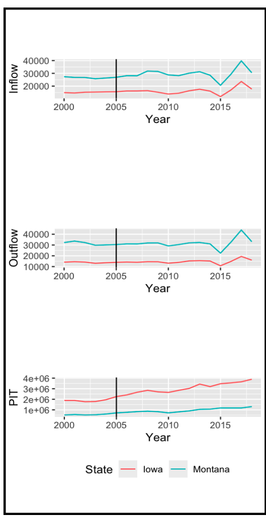


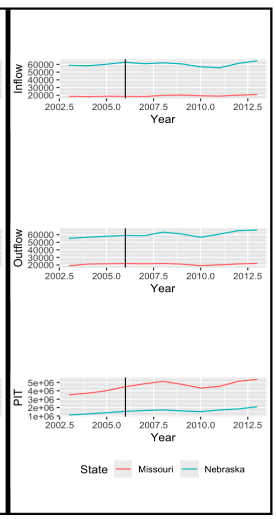

Inflow
Outflow
PIT
Year
State Kentucky Mississippi


Inflow
Outflow
PIT
Year
State Louisiana Mississippi


Inflow
Outflow
PIT
Year
State Colorado Michigan


Inflow
Outflow
PIT
Year
State Minnesota Virginia


Inflow
Outflow
PIT
Year
State Iowa Montana


Inflow
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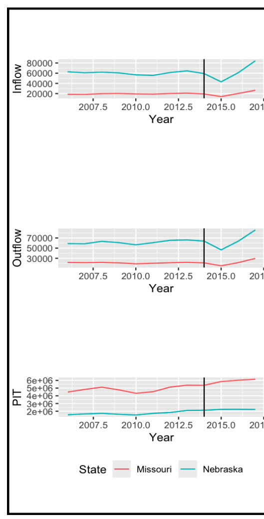
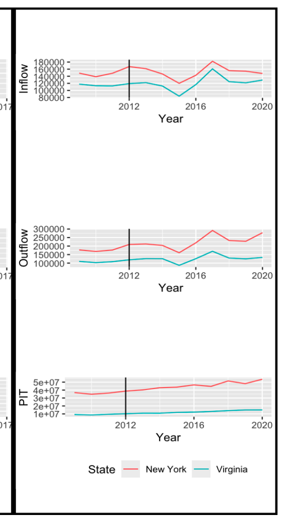
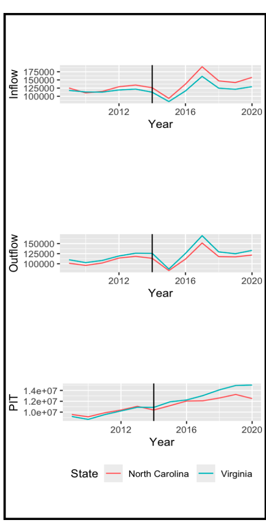
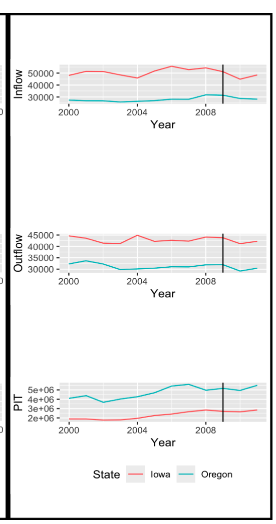
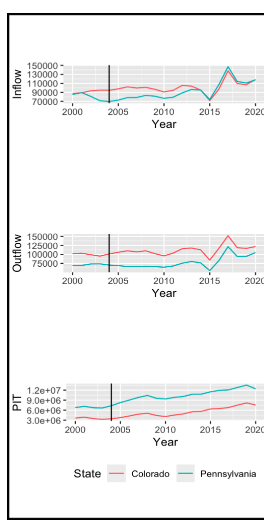
PIT
Year
State Missouri Nebraska

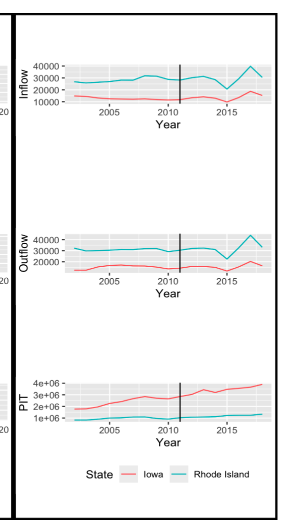

Inflow
Outflow
PIT
Year
State Missouri Nebraska

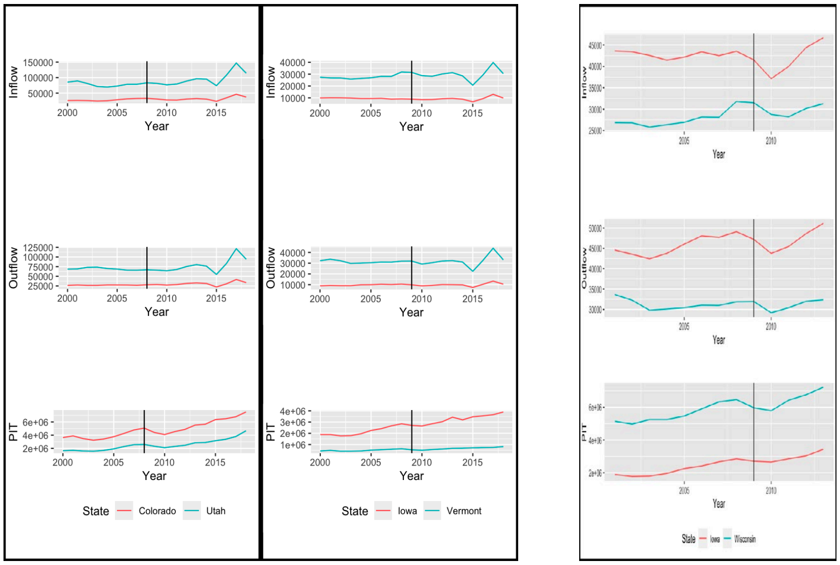

Inflow
Outflow
PIT
Year
State New York Virginia


Inflow
Outflow
PIT
Year
State North Carolina Virginia


Inflow
Outflow
PIT
Year
State Iowa Oregon


Inflow
Outflow
PIT
Year
State Colorado Pennsylvania


Inflow
Outflow
PIT
Year
State Iowa Rhode Island



This figure gives preliminary indications of each modeled treatments' impact, which will be explored in the next section.

Analysis Difference-in-Differences Model Findings

Ultimately, the results of the difference-in-differences regression models were inclusive and contradictory, particularly when considering evaluations of treatment as a causal mechanism (see Appendix D for greater detail and model summaries). Of the 23 treatments studied, eight treatments had DiD estimators of statistical significance, while the remaining fifteen did not. While I discuss the results together in this section, it is important to note that direct comparisons between states cannot be made; as such, the results are considered on an individual basis for their contribution to opponents of taxation increases/the implementation of graduated personal income taxes.

Some of these results strongly support the arguments of the proponents of the instantiation of a graduated personal income tax; the model representing California's significant increase in all studied IVs in 2013 provides the strongest case for the argument. It found that the DiD estimator was statistically significant ($p = 0.041$) for PIT revenue increasing, and that treatment did not have a statistically significant causal impact on population inflows ($p = 0.68$) *nor* outflows ($p = 0.10$).

Meanwhile, some of these results strongly support the arguments against the instantiation of a state-level graduated personal income tax system, and advocate for a flat rate or total elimination of personal income taxes. Two examples of this are Pennsylvania's increase in the tax rate for the highest income bracket in 2004 and Washington D.C.'s 2012 increase in all three IVs; both could support the opponents' claim that residents will not necessarily move, but underreport their income. By doing this, the state under-taxes their income and overall personal income tax revenue could decrease. In Pennsylvania, the models found that the treatment effect had a statistically significant negative impact on PIT revenue ($p = .062$), but no statistically significant impact on population flows. In D.C., the DiD estimator has a statistically significant negative impact on PIT revenue ($p = .020$) but no statistically significant impact on population flows.

However, most treatment models provided mixed, sometimes conflicting, results. For example, in 2009, Hawaii[1] began to steadily increase all IVs, but this 'treatment' appeared to have no statistically significant impact on any of the dependent variables; in other words, despite significantly overhauling its tax system, Hawaii's changes in the trends of PIT revenue or population flows in either direction cannot be ascribed to the change. Other examples include the Minnesota 2014 increases in tax rate and number of brackets and the Wisconsin 2009 increases

[1] Hawaii's treatment was a bit different than most of the others explored. It explored a policy effect at passage, but not its implementation, as its implementation occurred in several doses over the years. Therefore, its results must be interpreted slightly differently.

in all IVs, which also showed that some changes implementing stronger graduated income taxation systems cannot be statistically linked to any changes in the three DVs. North Carolina's 2014 treatment was the elimination of the graduated income tax system in favor of a flat rate, and had a statistically significant ($p = 0.002$) negative causal impact on population inflows.

Table 1. Summary Table of Results (see Appendix D for expanded form)

Statistical Significance Found (*DiD estimator p-value < 0.05 for one, two, or three models*)	
Treatment	*Result*
Arizona 2006 slight rate decrease compared against Georgia 2000-2018	DiD estimator has a statistically significant negative impact on inflows
Arkansas 2015 slight rate decrease compared against Alabama 2005-2019	DiD estimator has a statistically significant negative impact on PIT revenue and outflows
California 2013 increased all IVs compared against Virginia 2000-2020	DiD estimator has a statistically significant positive impact on PIT revenue
District of Columbia 2012 increase in all IVs compared against Virginia 2003-2016	DiD estimator has a statistically significant negative impact on PIT revenue
Idaho 2013 decrease in rate and number of brackets compared against Iowa 2002-2018	DiD estimator has a statistically significant positive impact on PIT revenue and a statistically significant decrease in inflows
Illinois 2011 rate increase compared against Colorado 2001-2014	DiD estimator has a statistically significant positive impact on outflows
New York 2012 decrease in rate and increase in number of brackets and the highest bracket compared against Virginia 2009-2020	DiD estimator had a statistically significant positive impact on inflows
North Carolina 2014 start of eliminating graduated income tax in favor of flat compared against Virginia 2002-2020	DiD estimator had a statistically significant negative impact on population inflows.
Pennsylvania 2004 rate increase compared against Colorado 2001-2020	DiD estimator has a statistically significant negative impact on PIT revenue
No Statistical Significance Found (DiD estimator p-value > 0.05 for all three models)	
Hawaii 2009 with steadily increasing all IVs compared against South Carolina 2003-2015	
Kansas 2013 start of decreasing rate and a decrease in the number of brackets compared against Missouri 2000-2017	
Kentucky 2005 increase in the number of brackets compared against Mississippi 2000-2018	

Louisiana 2010 decrease in the highest bracket compared against Mississippi 2004-2020
Michigan 2008 slight increase in a tax rate compared against Colorado 2000-2012
Minnesota 2014 increase in rate and number of brackets compared against Virginia 2001-2020
Montana 2005 decrease in rate and number of brackets compared against Iowa 2000-2018
Nebraska 2006 increase in highest income bracket compared against Missouri 2003-2013
Nebraska 2014 change in highest income bracket structure compared against Missouri 2006-2017
Oregon 2009 increase in all IVs compared against Iowa 2000-2011
Rhode Island 2011 decrease in all IVs compared against Iowa 2002-2018
Utah 2008 moving graduated to flat system compared against Colorado 2000-2018
Vermont 2009 decrease in rates compared against Iowa 2000-2018
Wisconsin 2009 increase in all IVs compared against Iowa 2001-2013

Conclusions and Policy Implications

Ultimately, the DiD results are contradictory and inconclusive: some treatments provide statistically significant evidence that an increase in the IVs under a graduated income tax system will fulfill proponents' assurances (ex. California 2013); some treatment results indicate negative impacts on dependent variables (ex. D.C. 2012), supporting opponents' claims. More results, however, indicate that changes in IVs have no statistically significant impact, meaning that the hypothesis that the changes in DVs are not due to the treatment cannot be rejected when proponents and opponents of the policy would both expect treatment effects in at least one of the DVs.

These varied results imply that past changes in state-level taxation systems cannot be roundly used to explain changes in population flows or total personal income tax revenue; it is likely unproductive to aggregate or random case studies of statistically significant tax change impact, positively or negatively, on these variables in other states when investing little effort to analyze baseline differences. Looking purely at these figures cannot provide reliable evidence for high-income earner behavioral responses to graduated income tax implementation. Instead, when considering graduated income tax implementation or increasing any of the IVs, state legislators should most closely study states with similar socioeconomic structure and also qualitatively review other potential confounding variables unaddressed by the inclusion of covariates in the model.

Supplementary Qualitative Review of Select Treatments

Individual Treatment Analysis

With knowledge of general treatment trends from difference-in-differences models and the specific results of the DiD analyses, I then evaluated claims of treatment causality (or lack thereof) in individual state taxation changes identified from the previous section. To establish even stronger commitment to the parallel trends assumption necessary to establish causality, and to provide a more meaningful comparison, I isolated the following eight treatments that occurred in states with similar background qualities and fulfill elements of the criteria established in the **Methodology** section.

North Carolina 2014 gradual elimination of graduated personal income tax in favor of flat rate

DiD Result: A statistically significant negative treatment impact on population inflows.

North Carolina's passage of its graduated income tax repeal in 2013, becoming "only the third state at the time to ever do so, came on the heels of a population explosion in the previous 20 years and the election of the first Republican-held state legislature in a century (Gleason 2022). Its previous highest bracket rate was 7.75 percent, "which at the time was the highest personal income tax rate in the entire southeast" (Gleason 2022). Traditional North Carolinian industries included agriculture and textiles, but healthcare, aerospace and defense engineering, banking, financial services, and technology companies took their place with the rise of the IT revolution in the latter 20th century, fueling the state's population growth further (Medlin 2020).

However, this rise in population and new industries coincided with a rise in unemployment on the heels of the Great Recession (Balfour 2012). Before this tax change implementation, the state grappled with social issues, such as racist violence, sexual assault legal cases, high-profile death-sentence trials, and banning gay marriage in a statewide constitutional referendum in 2012 ("Racial Justice" 2021, Tucker 2014). Presidential vote margins narrowed, and flipped red in 2012 (ProCon 2021). Climate and public safety issues were also prevalent, with hurricanes and toxic waste spills prompting citizen concern about environmental and public health.

While economic tensions subsided with the Great Recession's effects receding, the time period after the passage of this tax system change continued the state's struggle with social and political issues. While legislation passed to codify the right to same-sex marriage in 2014, the state passed a law limiting the use of gender-affirming bathrooms for transgender people. Police violence targeting Black men also reached national news in the same year. Multiple hurricanes made landfall, forcing emergency evacuations of millions of residents.

Reviewing sociopolitical and economic trends that may have had an impact on the population flows and PIT revenue in North Carolina reveals that while social issues remained somewhat constant in frequency, severity, and topic, state political leanings and economic trends (such unemployment) did vary. As such, these elements could have impacted the PIT revenue and population flows as well, negatively affecting the former in particular, leading to inconclusive results regarding statistical relevance of treatment. Virginia (the control unit) and

North Carolina were both impacted by the Great Recession, but given the somewhat differing diversity of industry (with the secondary industries being manufacturing versus agriculture respectively), the parallel trends assumption likely did not entirely hold for the DiD model. PIT revenue was likely artificially depressed before the treatment, there could have been a statistically significant negative impact on PIT revenue as well in comparison to the PIT revenue received after treatment in North Carolina. This, in conjunction with the statistically significant decrease in population inflows to North Carolina, indicates that treatment could have had a negative impact on PIT revenue, supporting graduated individual income tax implementation proponents' arguments.

Utah 2008 elimination of graduated personal income tax in favor of flat rate

DiD Result: No statistically significant treatment effect on DVs.

Utah's 2008 tax system 'treatment' shows another elimination of a flat tax and was also not evaluated as having statistically significant impacts on any of the measured DVs.

There are many similarities between Colorado and Utah both before and after treatment, meaning that parallel trends likely hold enough to establish causality; their geographic proximity and similar responses to socioeconomic issues – such as the implementation of gay marriage and litigating the ACA – supports this argument ("States' Positions"). However, the states significantly politically diverged after 'treatment'; while Colorado took steps decriminalizing certain drugs and instituting firearm purchase background checks (Keyes 2015), Utah put restrictions on immigration, voted to decriminalize polygamy, and rejected environmental legislation (Pignanelli and Webb 2022). Additionally, Utah hosted the Winter Olympics in 2002, before treatment; this economic boon likely inflated PIT revenue and inflows observed trendlines before treatment ("Salt Lake's").

Given these differences, the elimination of a graduated personal income tax likely appealed to the same political trends signifying the increasing conservatism of Utah residents. As such, parallel trends do somewhat diverge, and so the lack of finding statistical significance does not necessarily imply a lack of treatment effect. Based on these findings, had Utah *not* implemented this taxation change, its PIT revenue could have decreased and/or outflows increased in relation to its inflows since residents preferred this kind of legislation emphasized by Republican lawmakers (Utah Department of State 2022). These findings, therefore, support opponent arguments. This supports opponent arguments.

Pennsylvania's 2004 flat rate increase

DiD Result: Treatment had a statistically significant negative impact on PIT revenue.

Pennsylvania's state constitution explicitly forbids the institution of a graduated income tax (Pennsylvania 1896), and its flat tax rate has largely been stable as one of the lowest rates among states that levy individual income taxes since 2000 (Hamill 2009). However, there was a slight increase (+0.27%) in the flat personal income tax rate in 2004 (Appendix B). Later efforts to increase the rate again, however, failed (Hamill 2009).

Unemployment was higher before the implementation of this taxation change, and aside from a brief dip in the first year of the Great Recession, job growth remained relatively stable and unemployment rates low in Pennsylvania after the 'treatment' ("Employment Change" 2021). Manufacturing still remained the central industry in the state over time ("Employment Change" 2021).

After, though likely unrelated to the implementation of this tax rate hike in Pennsylvania, social and public safety issues became increasingly centered in the public eye. Mass shootings, particularly those that were racially motivated, had a significant uptick in the 2010s ("Mass

Shootings”). Its ban on same-sex marriage was overturned as unconstitutional in 2014 (Bannister 2021). Three years earlier, the state limited citizenship access to immigrants who illegally entered the U.S. and attempted to block the implementation of the ACA (“States’ Positions”, Hartwell 2018).

Given these more controversial shifts taking place in Pennsylvania following treatment, it is possible that the PIT revenue was artificially depressed after treatment. However, given that employment rates and industry reinvestment rebounded quickly, these shifts are more likely due to actually measured impact. Notably, Colorado and Pennsylvania are hardly perfect matches to establish parallel trends; their lack of geographic proximity and common industries may provide distinct trend differences. As such, this statistically significant impact is likely less significant than implied by the *p-value*, and opponents of instituting a graduated income tax should not use it as evidence. Thus, these results provide meaningful evidence for neither the proponents nor opponents of implementing a marginal individual income tax regime.

New York 2012 decrease in rate and increases in number of brackets and the highest bracket

DiD Result: Treatment had a statistically significant positive impact on inflows.

New York’s 2012 tax system changes provide an interesting case study, as it decreased its top personal income tax rate, but also expanded its progressive individual income tax system. Typically, proponents of increasing/expanding the state-level graduated PIT system point to an increase in revenue but say little in regard to population *inflow*. This case study did not find a statistically significant negative relationship between treatment and outflows, supporting the proponent argument, but also did not find a statistically significant positive relationship between treatment and PIT revenue; instead, there was a statistically significant positive relationship between treatment and population *inflows*.

There are distinct underlying differences in trends between Virginia and New York – particularly politically and economically – but Virginia was the best comparison of the control unit options (Appendix C). Politically, Virginia is more politically and socially conservative across the state, and economically, Virginia's industry primacy lies far more in the agricultural and technology sectors than New York's industry primacy lies in financial services, healthcare, and professional/business services. Given these differences for which I did not control in the initial regression, I consider this positive relationship as more likely an indicator of uncontrolled time-varying, unit-specific trends rather than treatment.

The lack of statistical significance in the relationship between treatment and PIT revenue in New York may be a result of matching artificial depression from the financial crisis in 2008 and the COVID-19 pandemic, as the New York economy was particularly negatively impacted by these two events on either side of the treatment (McMahon 2012). Taking this into account, the PIT trendlines likely cannot be reliably measured as functions of treatment, but rather these events causing significant volatility. This result indicates the importance of economic diversity, adaptability, and preeminence in the 'success' in systemic graduated individual income tax increases.

California 2013 increase of all graduated IVs

DiD Result: Treatment had a statistically significant positive impact on PIT revenue.

California's DiD analysis poses similar issues to New York's DiD analysis; California and Virginia do not share particularly strong similarities that can support a robust parallel trends assumption. As such, treatment effects, including their statistical significance or lack thereof, are likely muted. Evaluating the economic trend differences of the compared units shows a booming California economy with the rise of Silicon Valley and social media companies, and its trends may outstrip Virginia's economic growth. Additionally, California, as a particularly relevant epicenter of cultural and economic strength since 2000, violates some of the assumptions made about 'ease of movement' – many, regardless of their wages, choose to move to California for its status in media, culture, and industry, and so analyzing population flows likely does not isolate high-income earners in the same way the change might in Virginia.

This does not necessarily discount the arguments of either proponents or opponents of instituting/increasing a graduated income tax system: the very richest may be motivated to move, but the impact of their move may be offset by increased revenue anyways. What further analysis of the California treatment shows is that a state's perceived relative cultural and economic importance can supersede changes in taxation, meaning that remaining in or moving to a state that offers such access is more important than paying additional taxes. As such, this review shows that this treatment's outcomes are a, somewhat caveated, piece of supporting evidence for proponent arguments.

Illinois 2011 flat rate increase

DiD Treatment: Treatment had a statistically significant positive impact on outflows.

Illinois also provides an interesting study of a tax rate increase, especially given its measured impact on outflows but lack of a causal impact on PIT revenue. In 2011, Illinois did implement this tax increase, the state government caveated this change as a temporary measure meant to alleviate economic pressures following the Great Recession, with the increase automatically expiring after three years and the rate decreasing back to original levels over the next decade (Crosby and Merriman 2014).

On their surfaces, Illinois and Colorado appear to have several baseline differences that make a strong claim of parallel trends somewhat complicated; however, political, social, and economic trends are somewhat matched (“State Comparisons,” Lang 2021, Medlin 2020). The states have a similar urban/rural divide in land, population, and political beliefs that create a tension in state-level policy implementations (Appendix C).

This qualitative review emphasizes the real impact of this implementation on population outflows, but also the lack of measurable impact on PIT revenue. This implies that, at the very least, the implementation of a rate increase can cause residents to leave (supporting opponent arguments) but does not necessarily lead to a reduction in the overall PIT revenue and can, in fact potentially make up for lost revenue from emigrants (somewhat supporting proponent arguments) (Appendix D).

Minnesota 2014 increase in rate and number of brackets

DiD Result: No statistically significant treatment effect on DVs.

Minnesota considered several tax reforms in 2013 to increase its overall operating revenue, before landing on increasing both the number of brackets and highest rate (Dornfeld 2013). This revenue was earmarked for “increase[d] primary and secondary education spending … some property tax relief to homeowners and renters,” and economic and infrastructure development (Reuters Staff 2013).

Given this large tax overhaul, the treatment having no effect is somewhat surprising. The lack of statistically significant treatment effects could be the result of many different issues, but likely is a function of the not sufficiently establishing parallel trends between Minnesota and Virginia in the DiD analysis. While Virginia shares more baseline similarities with Minnesota than the other control unit options, these states are highly dissimilar in geographic location and urban/rural divide. Therefore, this treatment could have an impact on the dependent variables, but because of baseline dissimilarities cannot be fully controlled and the lack of DiD result clarity, alternative indicators, such as continued economic growth and health, can be used as evidence for supporters and opponents of this paper's studied policy change (Albares 2014).

District of Columbia 2012 increase in all IVs

DiD Result: Treatment has a statistically significant negative impact on PIT revenue.

Washington D.C.'s tax system change provides a unique insight into impact of an increase in all DVs; not only did the treatment include an increase in all three studied variables which most closely model what an institution of a graduated rate system from a flat system would look like, it also has a particularly strong control unit; any changes affecting Virginia, as a neighboring state with a deeply interlinked economy, would affect Washington D.C. similar. Obviously, there are a few key differences that must be accounted for in this analysis; Virginia is a state and has considerably more land mass than D.C., a territory whose borders enclose a total of 68 square miles ("State Comparisons"). However, given that there has been little change in the relationship between these two types of systems since 2000, the parallel trends assumption does still hold well.

The DiD analysis finds that the treatment resulted in a statistically significant impact on PIT revenue but could not establish a statistically significant relationship in the outflows. Because of D.C.'s unique location and lack of suburban or rural areas, the city's population could not take part in the intrastate exodus from cities to the suburbs or rural communities that most states experienced during the Great Recession (Russell 2013). As such, there is a large influx in interstate migration, particularly to metro-state area states of West Virginia, Virginia, and Maryland in the time period immediately preceding the treatment, artificially inflating the trendlines. Therefore, the outflows experienced after the implementation of the treatment would likely have otherwise indicated causal impact on the outflows experienced in post-treatment D.C.

This re-evaluated treatment case study thus supports the arguments made by opponents of implementing a graduated income taxation system.

<u>Treatments In Comparison & Conclusions</u>

This qualitative review does emphasize that the different treatments cannot be compared on a large scale, but further result analysis and comparisons can provide useful indicators of broader trends for specific categories of treated units. The California and New York treatments highlighted the importance of industry preeminence and offering socioeconomic opportunities unable to be found elsewhere on the impact of changing taxation systems; California and New York offer unique cultural, social, and economic opportunities unable to be found in most other states in the country, particularly within its cities. The main industries are also robust, and able to survive or adapt themselves following recessions, unlike the more stable but less durable industries like agriculture and manufacturing. This is distinct from states like Illinois and Pennsylvania, which have similar urban/rural divides but have been less able to adapt their economies as the United States has shifted industrial output from being manufacturing-based to services-based (Medlin 2020). They also differ from the District of Columbia, which is only a city that offers little in the way of more rural and less expensive housing. While these treatments are fundamentally incomparable because of the differences in underlying trends, the backgrounds of the diverging results are therefore important as a powerful treatment comparative tool.

Secondly, both North Carolina and Utah, when switching to a flat income tax from a graduated rate, did not have a statistically significant decrease in PIT revenue. Utah's treatment effect did not have a statistically significant impact on population flows, and North Carolina's treatment had a significant negative impact on inflows. While these results say little about a system shift in the opposite direction, they are evidence that while population flows may be impacted, changes in PIT revenue cannot be definitively ascribed to a shift from a graduated income tax to a flat rate; the Utah treatment measurement studies this against a flat rate system, while the North Carolina studies this against a graduated rate system, but the lack of concrete impacts are similar. Therefore, this study cannot categorically describe these treatments as *causing* PIT decreases, though can be on immigration factors.

Lastly, Minnesota's review indicates that treatments can still be evaluated, even when the DiD results are inconclusive or too fraught with confounding variables to use a causal analysis. However, should a stakeholder use this form of policy analysis, they must stipulate that the causal impact of the treatments unclear, and that the resulting analyses are based on inferences.

Policy Implications and Recommendations

Current Evaluation Methods are Inadequate at Best, Inaccurate at Worst

As established in *Literature Review*, the current means for establishing causality is insufficient. Previous literature regarding graduated personal income taxation systems in comparison to a flat rate are largely not holistic, as the authors do not always include controls indicating parallel trends in a state's economy *and* quality of life, do not cover a wide cross-section of treatments, and are not attempting to find statistically significant causal impact. When making claims, the authors of these papers often do not also caveat their findings with their own limitations; for example, legislators and voters considering implementing a state-level graduated income tax must only consider of Rauh and Shyu (2019) as indicative of potential migration flows for states similar to California; however, policies and their effects do not exist in vacuums, and these stakeholders should be concerned with multiple variables, such as the need for immediate cash on hand for the next year's operating budget for which the relevance of long-term migration flows is not as pertinent.

This research emphasizes the need for a comprehensive evaluation approach for new graduated personal income tax policies, and given the relative lack of data and relevant policy changes in recent years, taking a monolithic view of a tax change as wholly beneficial or wholly detrimental to every state would lack the necessary nuance of not only the different reasons for moving, but also of the different roles a tax system is meant to fulfill state-to-state. This thorough quantitative and qualitative research shows that even with comprehensive panel data, establishing true causality can only be done for a handful of tax change 'treatments,' and the impact of treatments varies greatly if there is true statistical significance to the results at all.

Considering Implementation on Case-by-Case Basis

The logical recommendation from these findings is that stakeholders should not entirely discredit or embrace a graduated income tax based on previously written case studies and tax theory; these research studies often failed to study true causal mechanisms and failed to understand the interactions of tax law with the complex, overlapping patchwork of other state laws and societal structure, which all influence behavioral responses of all taxpayers. Instead, these stakeholders should weigh the following in their decision making:

(1) First and foremost, stakeholders need to consider the needs that their state-level tax system fulfills and the purposes of instituting such a change. Is this tax meant to temporarily shield the state from a decreasing budget because of a period of economic distress? Is this a long-term revenue-generation endeavor? Are the funds earmarked for specific purposes? The DiD analysis of 23 changes in tax systems showed a variety of

responses to unique tax changes, and the content and purpose of these tax changes likely impacted high-come earner behaviors.

(2) Consider the current economic health, social structure, and industries of the given state. Does the state offer unique access to and depth in high-growth industries, markets, cultural centers, etc.? How durable are existing top industries should an economic recession occur suddenly? Are there intrastate migration opportunities that offer cheaper lifestyles than those in high-priced urban centers? Larger states like New York and California appear to have less negative impact from their increased treatments (rates, number of brackets, and highest income bracket), and in fact receive statistically significant positive impacts on desired impact variables, in comparison to states that lack economic and structural social diversity (such as Washington D.C. and Pennsylvania).

(3) Lastly, are there case studies of very similar tax changes in states that share very strong similarities? While causal impact is still difficult to measure, and concrete prediction modeling is beyond the scope of this paper, regional similarities occur (Appendix D). Quantitative results on causal impact must be appropriately tempered with qualitative state structure review that may have broken parallel trends assumptions or otherwise artificially inflated/depressed trendlines in dependent variables chosen to study treatment impact.

Considering these three implications, stakeholders will find that in states with highly diversified economies preeminent in cutting-edge industries are more likely to have positive effects from implementing a marginal personal income tax from a flat rate or no individual income tax. However, the same change could have disastrous effects on less agile economies, such as those struggling with the new digital revolution. However, closer study of analogous states who have implemented similar taxation changes can provide greater evidence for or against such a change; additionally, given the unclear risks of changing a taxation system, it should only be done with great consideration and to fill a specific, quantifiable need.

Areas of Further Research

Ideally, but not feasible for the scope of this research paper, the mixed-methods case studies could extend to each state and Washington D.C. with extended data from the 2020 census. Given that taxation changes occur across a breadth of differing state cultural, political, and legal systems, having representative case studies for at least each type of state (for example, delimited by region) could be practical for consideration of implementation in the future. However, there are limits to the existing data that can be found, and no state has actually implemented a graduated income tax from either no taxation system or graduated income tax regime since reliable data has been collected and digitized. Massachusetts will provide an invaluable case study once reliable data can be published; the ballot question regarding the implementation of a graduated income tax from a flat tax passed in November of 2022, and the new system was implemented at the beginning of the 2023 tax year ("Massachusetts' Millionaires'" 2023).

Another area of further research includes a more rigorous quantitative causal analysis of tax rate shifts with multiple units and dosages that allows for quantitative difference between changes within and between each state over a long period of time and for multiple, unpredictable dose treatments. However, multivariate difference-in-differences designs with multiple dosage treatment variables and robust controls for parallel trends stretches the limits of accepted statistical practice, and as of yet the statistical research has not extended to allow for multiple, unaligned dosage treatments. Research is still being done on the difference between fixed effects and first differences in such a model (Mesquita and Fowler 2021), and so cannot be implemented in this paper at this time.

Further color could be added to the analysis of patchwork state-level tax systems by studying effects of federal and local personal income taxes, and sales taxes as well. The studies could analyze international and intrastate population flows accounting for these more intricate treatments and could provide a deeper understanding of regressive taxation's impact on this issue as well. Additionally, this research could extend to include greater distillation of the issue of high earners disguising their total income so that they do not have to pay a greater tax burden as a new system is implemented. This analysis touched on the issue by differentiating lack of population flows and finding statistically significant changes in overall PIT revenue, but greater analysis of this phenomenon would be fruitful and highly relevant to policymakers' considerations as they weigh implementation of a new tax system.

Conclusions

Politicians, policymakers, and academics can find great political and personal utility in providing absolute answers to complicated policy questions, particularly those regarding such controversial pieces of American governance as personal income taxation. The two arguments generally made about instituting a graduated individual income tax from a flat or no personal income tax are (1) proponents of such an implementation, who argue that the personal income tax revenue will increase and that population flows are minimal, and (2) opponents of such an implementation, who are that high-income population outflows will outstrip inflows, leading to a decrease in the real personal income tax revenue. These approaches are misguided, as they lack the necessary nuance and room for uncertainty. In fact, many of these stakeholders propose expected behavior of high-income earners but their analyses are not holistic, causal, and/or made with data relevant to the present day. Given the scarcity of existing relevant data, and given the dearth of relevant tax policy changes, it is impossible to give concrete answers on how instituting a graduated income tax will affect a state's high-income earning population. There does, however, remain a distinct need for this kind of evaluative framework, given the high activity in state-level personal income tax policy, so with this paper I sought to provide a greater understanding of the limitations and realistic outcomes of evaluative research, and to provide recommendations that are flexible for stakeholders.

I specifically investigated causal impacts of changes in individual income tax structure that would most likely impact the wealthiest, who are a state's most mobile demographic. These changes include adjusting the number of income tax brackets, adjusting the highest income tax bracket, and/or adjusting the taxation rate levied on the highest income bracket. After binarizing this treatment variable – all changes were weighted the same – I identified states within specific time periods that received 'treatment,' or a change in the taxation system and paired that treated unit with a control unit, or a state that did not experience any tax changes at the same time. I then ran a difference-in-difference linear regression analysis on trends in population inflows, population outflows, and overall individual income tax revenue, while controlling for covariates that could otherwise violate the parallel trends assumptions. Ultimately, I found that even of states that could be meaningfully evaluated for treatment, only a small handful had statistically significant results, and even fewer provided actual evidence supporting either the proponents or opponents.

The two-pronged research design in which I specifically investigated causal mechanisms showed how limited the existing scope of statistical evaluative frameworks measuring policy ('treatment') effects in natural experiments. Given the limits of this design, I then weighed DiD causal impact results against qualitative state characteristics that cannot be fully captured by regression-controlled covariates on select treatments; this includes an evaluation of potential social, political, and economic structural influences on the measured dependent variables. By conducting this quantitative analysis and subsequent qualitative review, I was able to extrapolate certain conditions that appear indicative of a given state's response to taxation changes, especially those considering implementing a progressive personal income tax. Stakeholders must weigh previous case studies, the intent of the tax change, and the existing structural qualities of their state before making this decision.

Taxation is a phenomenon that is unlikely to disappear any time soon; research regarding this topic will continue to grow as more states change their type of personal income tax methodology and will benefit from advances in econometric research breakthroughs for natural experiments. Future research could also include the multi-level stages of personal income taxation and could even extend to entire tax codes themselves. However, in the meantime, this paper provides a meaningful, empirically based framework in which stakeholders can estimate state-level tax policy change causal impacts, providing tangible solutions while not misleadingly portraying this issue as a binary one.

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Appendix A: Cleaning Process of Raw Datasets

1. Personal Income Tax Rates, 2. Number of Income Tax Brackets, 3. High and Low Taxable Income Brackets – Independent Variables

These variables indicate policy changes, which are changes in state-level taxation systems. I use these variables as benchmarks to identify changes, or lack thereof, in the dependent variables (explored below).

Source(s):

Primarily used data from the Tax Policy Center's State Individual Income Tax Rates from 2000-2023 dataset (Urban Institute and Brookings Institution). I occasionally supplemented these data with the Tax Foundation's State Individual Income Tax Rates 2000-2014 dataset (Tax Foundation 2013); for example, Rhode Island's specific rates and brackets were not included in the Tax Policy Center's dataset from 2000-2004, and so the Tax Foundation provided those datapoints. I chose to primarily use the Tax Policy Center's data as it covered the same years, ensuring as much consistency as possible.

Cleaning Process:

The initial Tax Policy Center downloadable Excel file consisted of yearly sheets recording the following variables for the fifty states and Washington D.C.: Tax Rate Range (in percentages, high and low), Number of Brackets, Income Brackets (Lowest and Highest), Personal Exemptions (Single, Married, and Dependents), Standard Deduction (Single and Married), and a binary representation of Federal Income Tax Deductibility. I first eliminated the 'Personal Exemptions' and 'Standard Deduction' metacolumns and their subdata, as their information was irrelevant to my study. I also eliminated the 'Federal Income Tax Deductible' variable as the answer was the same for all states and D.C. – ‘yes.’ After this, I then conducted some general data cleaning (such as unmerging cells, deleting empty columns, corrected spelling errors, data type validation corrections, etc.). I changed each ‘flat rate’ column in order for the ‘Tax Rate Range’ values each to represent the flat rate, and the ‘Number of Brackets’ column was 1. States that do not have a personal income tax are represented by ‘0’s in the same columns. For non-graduated income taxation regimes, the ‘Income Brackets’ columns have no entry. As a last structural change for each sheet, I added a column indicating if the personal income tax only represented a tax rate on dividends and/or capital gains earnings, not salary taxation.

As previously mentioned, for any data that was not available or incorrect in this dataset, I then substituted those points with the correct Tax Foundation data; this was only necessary for years prior to 2014, so I did not need to supplement using an additional dataset.

Lastly, I aggregated all of the sheets into one dataset by creating a ‘year’ column, which delimited the data from each sheet.

Summary Statistics:

Summary Table of Independent Variable Data (1-3)

```
> summary(tdComb)
    State                Year       Tax Rate Low    Tax Rate High    Number of Brackets Lowest Income Brackets Highest Income Brackets Taxed Income Type  changeLowRate changeHighRate
 Length:1341        Min.   :1980   Min.   :0.000   Min.   : 0.000   Min.   : 0.000     Min.   :    0          Min.   :    3000        Length:1341        Min.   : -1   Min.   : -1
 Class :character   1st Qu.:2004   1st Qu.:0.000   1st Qu.: 2.900   1st Qu.: 1.000     1st Qu.: 2330          1st Qu.:   16001        Class :character   1st Qu.:  0   1st Qu.:  0
 Mode  :character   Median :2010   Median :2.000   Median : 5.500   Median : 3.000     Median : 5000          Median :   50750        Mode  :character   Median :  0   Median :  0
                    Mean   :2009   Mean   :2.136   Mean   : 4.923   Mean   : 3.443     Mean   : 9347          Mean   :  211614                           Mean   :Inf   Mean   :Inf
                    3rd Qu.:2017   3rd Qu.:3.500   3rd Qu.: 6.990   3rd Qu.: 6.000     3rd Qu.:10171          3rd Qu.:  200000                           3rd Qu.:  0   3rd Qu.:  0
                    Max.   :2023   Max.   :6.000   Max.   :14.500   Max.   :12.000     Max.   :73450          Max.   :25000000                           Max.   :Inf   Max.   :Inf
                                                   NA's   :6        NA's   :1          NA's   :550            NA's   :549                                NA's   :340   NA's   :319
 changeBrackets     changeLowBracket  changeHighBracket
 Min.   :-5.00000   Min.   :-1.0000   Min.   : -0.9600
 1st Qu.: 0.00000   1st Qu.: 0.0000   1st Qu.:  0.0000
 Median : 0.00000   Median : 0.0000   Median :  0.0000
 Mean   :-0.02093   Mean   :    Inf   Mean   :  0.5053
 3rd Qu.: 0.00000   3rd Qu.: 0.0163   3rd Qu.:  0.0187
 Max.   : 3.00000   Max.   :    Inf   Max.   :165.6667
 NA's   :3          NA's   :552       NA's   :551
```

4. State-to-State Migration Flows – Dependent Variable

This is one of two dependent variables I study; I am looking for a tax policy change (the independent variables measurement) associated with a change in state-to-state migration flows outside of the parallel trends assumption.

Source(s):

The Internal Revenue Service provides expansive and well maintained datasets broken down by state level migration flows, and I use those for primary state-level analysis of the taxation status quo (US Census Bureau "State-to-State"). This data is ideal because it measures resident tax filers, which pure residency numbers do not address. However, as mentioned previously, I utilize the data on the number of personal returns filed, not total data on the number of migration flows. As such, I do make some previously established key assumptions about these data. I do this instead of utilizing exact changes in the number of filers as the latter only exists in datasets covering the years 2011-2020. The IRS maintains relatively standardized data on state-to-state migration for the years 1990-2021, and so is better for my analysis. This data does have some limitations; for example, those who do not file tax returns, or do not file taxes whatsoever, are not recorded in these data. However, given that my primary research focus aimed to study behavioral responses of the high-income earners generally targeted by the changes in graduated taxation systems, and sought to study changes in residency status in particular, these limitations do not greatly impact my study.

Cleaning Process:

The Internal Revenue Service provides its data in yearly downloadable Excel formats as a Gross Migration File, which records the inflows of each state in one file. I first renamed the columns such that they are more strongly descriptive of their contents, and I dropped all columns except for the state of origin name, state of destination name, and the number of filed returns. I then pivot the table such that the flows are measured between each state, the two axes are both all fifty states and D.C., and the contents of each cell are the flows. After this, for both types of datasets, I then conducted some general data cleaning (such as unmerging cells, deleting empty columns, corrected spelling errors, data type validation corrections, etc.).

I have kept each dataset separated by year; this is so that I can more easily measure across specific years and maintain the size and structure of the datasets.

Summary Statistics:

Summary Table of (Compiled) State-to-State Migration Flows Data (4):

```
> summary(totals)
   Origin            Destination              2020              2019              2018              2017              2016              2015              2014
 Length:2704        Length:2704        Min.   :     -1   Min.   :     -1   Min.   :     -1   Min.   :     10   Min.   :     -1   Min.   :     -1   Min.   :     -1
 Class :character   Class :character   1st Qu.:    167   1st Qu.:    155   1st Qu.:    156   1st Qu.:    203   1st Qu.:    152   1st Qu.:    111   1st Qu.:    156
 Mode  :character   Mode  :character   Median :    450   Median :    425   Median :    433   Median :    566   Median :    408   Median :    297   Median :    416
                                       Mean   :   5680   Mean   :   5256   Mean   :   5367   Mean   :   6771   Mean   :   5049   Mean   :   3767   Mean   :   4951
                                       3rd Qu.:   1599   3rd Qu.:   1455   3rd Qu.:   1512   3rd Qu.:   1949   3rd Qu.:   1419   3rd Qu.:    991   3rd Qu.:   1368
                                       Max.   :3767209   Max.   :3486294   Max.   :3559725   Max.   :4490887   Max.   :3348458   Max.   :2498444   Max.   :3283503
                                       NA's   :51        NA's   :51        NA's   :51        NA's   :51        NA's   :51        NA's   :51        NA's   :51
      2013              2012              2011              2010              2009              2008              2007              2006              2005
 Min.   :      3   Min.   :      5   Min.   :     -1   Min.   :      3   Min.   :      3   Min.   :      3   Min.   :      4   Min.   :     -1   Min.   :      3
 1st Qu.:    166   1st Qu.:    156   1st Qu.:    139   1st Qu.:    132   1st Qu.:    140   1st Qu.:    140   1st Qu.:    136   1st Qu.:    137   1st Qu.:    132
 Median :    449   Median :    437   Median :    398   Median :    381   Median :    399   Median :    412   Median :    390   Median :    406   Median :    382
 Mean   :   5269   Mean   :   5167   Mean   :   4484   Mean   :   4276   Mean   :   4562   Mean   :   4779   Mean   :   4675   Mean   :   4803   Mean   :   4533
 3rd Qu.:   1492   3rd Qu.:   1452   3rd Qu.:   1303   3rd Qu.:   1240   3rd Qu.:   1346   3rd Qu.:   1378   3rd Qu.:   1331   3rd Qu.:   1344   3rd Qu.:   1268
 Max.   :3494979   Max.   :3426795   Max.   :2973671   Max.   :2836418   Max.   :3026084   Max.   :3169383   Max.   :3100843   Max.   :3185678   Max.   :3006642
 NA's   :51        NA's   :51        NA's   :51        NA's   :51        NA's   :51        NA's   :51        NA's   :51        NA's   :51        NA's   :51
      2004              2003              2002              2001              2000
 Min.   :      4   Min.   :      4   Min.   :      5   Min.   :      5   Min.   :      4
 1st Qu.:    128   1st Qu.:    128   1st Qu.:    132   1st Qu.:    130   1st Qu.:    130
 Median :    374   Median :    370   Median :    386   Median :    374   Median :    381
 Mean   :   4351   Mean   :   4333   Mean   :   4467   Mean   :   4505   Mean   :   4445
 3rd Qu.:   1252   3rd Qu.:   1251   3rd Qu.:   1292   3rd Qu.:   1309   3rd Qu.:   1283
 Max.   :2885696   Max.   :2763215   Max.   :2844381   Max.   :2868661   Max.   :2832638
 NA's   :51        NA's   :153       NA's   :157       NA's   :157       NA's   :155
```

5. Personal Income Tax Revenue – Dependent Variable

This is one of two dependent variables I study; I am looking for a tax policy change (the independent variables measurement) associated with a change in personal income tax revenue outside of the parallel trends assumption. This variable has largely remained unstudied in previous research papers regarding state-level personal income tax revenue.

Source(s):

I am using data from the St. Louis Federal Reserve (US Census Bureau "State Tax Collections: T40"). These data cover the state-level personal income tax collections for each state from 1942 through 2021. Each dataset is downloadable as an Excel file for each state over the years. These datasets are comprehensive for the states, and do not require supplemental or otherwise additional data. I did need to find supplemental data, from the same datasets but only published in quarterly form, for Washington D.C., as it was not included with the previous datasets' collection and analysis procedures. I extracted and summed the relevant subcategories from a dataset that includes the total tax collections in Washington D.C. covering the same time periods.

Cleaning:

I conducted a simple full join operation for all of the files so that there is one aggregate file such that one observation is a state and year, with the value being the dollar amount of the collections, which should be measured in the thousands.

Summary Statistics:

Summary Table of Personal Income Tax Revenue Data (5):

```
   State                2000              2001              2002              2003              2004              2005
 Length:51          Min.   :       0   Min.   :       0   Min.   :       0   Min.   :       0   Min.   :       0   Min.   :       0
 Class :character   1st Qu.:  781191   1st Qu.:  775020   1st Qu.:  770084   1st Qu.:  767587   1st Qu.:  840576   1st Qu.:  940257
 Mode  :character   Median : 1890427   Median : 1988460   Median : 1854848   Median : 1867150   Median : 2192038   Median : 2392727
                    Mean   : 3956438   Mean   : 4236641   Mean   : 3774188   Mean   : 3699369   Mean   : 4007031   Mean   : 4532067
                    3rd Qu.: 5749814   3rd Qu.: 5527602   3rd Qu.: 5208485   3rd Qu.: 5313525   3rd Qu.: 5493714   3rd Qu.: 5885208
                    Max.   :39574649   Max.   :44614297   Max.   :33046665   Max.   :32709761   Max.   :36398983   Max.   :42992007
      2006              2007              2008              2009              2010              2011              2012
 Min.   :       0   Min.   :       0   Min.   :       0   Min.   :       0   Min.   :       0   Min.   :       0   Min.   :       0
 1st Qu.: 1019058   1st Qu.: 1055508   1st Qu.: 1049282   1st Qu.:  934596   1st Qu.:  881390   1st Qu.: 1061253   1st Qu.: 1097240
 Median : 2501120   Median : 2774851   Median : 2944851   Median : 2662759   Median : 2416324   Median : 2689843   Median : 2891743
 Mean   : 5022598   Mean   : 5442948   Mean   : 5698070   Mean   : 5030287   Mean   : 4849210   Mean   : 5303257   Mean   : 5719969
 3rd Qu.: 6188834   3rd Qu.: 6560923   3rd Qu.: 7060594   3rd Qu.: 6224706   3rd Qu.: 5996142   3rd Qu.: 6557104   3rd Qu.: 7243897
 Max.   :51219823   Max.   :53318287   Max.   :55745970   Max.   :44355959   Max.   :45646436   Max.   :50508441   Max.   :55024435
      2013              2014              2015              2016              2017              2018              2019
 Min.   :       0   Min.   :       0   Min.   :       0   Min.   :       0   Min.   :       0   Min.   :       0   Min.   :        0
 1st Qu.: 1109746   1st Qu.: 1086448   1st Qu.: 1197923   1st Qu.: 1146705   1st Qu.: 1180660   1st Qu.: 1316734   1st Qu.:  1501567
 Median : 2956588   Median : 2962128   Median : 3336587   Median : 3374535   Median : 3624543   Median : 3897236   Median :  4098020
 Mean   : 6310690   Mean   : 6343844   Mean   : 6858990   Mean   : 6975146   Mean   : 7159547   Mean   : 8013947   Mean   :  8330166
 3rd Qu.: 8025518   3rd Qu.: 7824242   3rd Qu.: 8585760   3rd Qu.: 8343363   3rd Qu.: 8722967   3rd Qu.: 9616112   3rd Qu.:  9957110
 Max.   :66809000   Max.   :67995659   Max.   :77929551   Max.   :80753345   Max.   :84196751   Max.   :95152230   Max.   :100079921
      2020              2021
 Min.   :       0   Min.   :        0
 1st Qu.: 1290296   1st Qu.:  1823561
 Median : 3916190   Median :  4617143
 Mean   : 7863194   Mean   : 10204999
 3rd Qu.: 8832580   3rd Qu.: 10959857
 Max.   :84412243   Max.   :146324579
```

The model also includes eight control variables, intending to ensure that the model maintains parallel trends (as described in the *Assumptions* section).

6. State Population Figures – Control

In addition to contributing to maintaining the parallel trends assumption, the state population control variable also provides further information for the migration flows data. Since flows are measured by return filings and not overall population change, this information controls for potential issues with unanticipated changes in overall state population within the model's data.

Source(s):

The Census Bureau maintains yearly population measurements and estimates between 1941 and 2022 (US Census Bureau "Release").

Cleaning:

This data was largely clean upon download. I did need to delete irrelevant rows for territories and larger geographic area measurements, but otherwise the data is fulsome.

Summary Statistics

Summary Table of State Population Data (6):

```
> summary(final_df)
      Year        Alabama            Alaska           Arizona           Arkansas          California          Colorado          Connecticut       District.of.Columbia    Delaware           Florida            Georgia             Hawaii             Idaho            Illinois            Indiana             Iowa
 Min.   :2000   Min.   :4452173   Min.   :627963   Min.   :5160586   Min.   :2678588   Min.   :33987977   Min.   :4326921   Min.   :3411777   Min.   :3949000   Min.   : 786373   Min.   :16047515   Min.   : 8227303   Min.   :1213519   Min.   :1299430   Min.   :12434161   Min.   :6091866   Min.   :2929067
 1st Qu.:2005   1st Qu.:4584599   1st Qu.:669035   1st Qu.:5886593   1st Qu.:2791263   1st Qu.:35876258   1st Qu.:4654022   1st Qu.:3509582   1st Qu.:4280500   1st Qu.: 848680   1st Qu.:17923276   1st Qu.: 8983395   1st Qu.:1296980   1st Qu.:1438348   1st Qu.:12618416   1st Qu.:6292129   1st Qu.:2969002
 Median :2010   Median :4792578   Median :718166   Median :6440379   Median :2931518   Median :37477930   Median :5084720   Median :3570292   Median :4640000   Median : 903618   Median :18950875   Median : 9757920   Median :1371783   Median :1577546   Median :12735862   Median :6503902   Median :3058796
 Mean   :2010   Mean   :4742701   Mean   :700990   Mean   :6371987   Mean   :2889522   Mean   :37294723   Mean   :5091762   Mean   :3545563   Mean   :4655409   Mean   : 898152   Mean   :19075795   Mean   : 9641016   Mean   :1353561   Mean   :1570543   Mean   :12717529   Mean   :6469858   Mean   :3053777
 3rd Qu.:2016   3rd Qu.:4863819   3rd Qu.:736014   3rd Qu.:6916778   3rd Qu.:2988794   3rd Qu.:39083317   3rd Qu.:5521465   3rd Qu.:3588614   3rd Qu.:5029750   3rd Qu.: 948008   3rd Qu.:20525206   3rd Qu.:10277170   3rd Qu.:1421153   3rd Qu.:1676151   3rd Qu.:12835836   3rd Qu.:6631284   3rd Qu.:3130543
 Max.   :2021   Max.   :5049846   Max.   :742575   Max.   :7291843   Max.   :3028122   Max.   :39501653   Max.   :5811297   Max.   :3623355   Max.   :5378000   Max.   :1004807   Max.   :21828069   Max.   :10788029   Max.   :1451043   Max.   :1904314   Max.   :12895778   Max.   :6813532   Max.   :3197689
     Kansas           Kentucky          Louisiana           Maine            Maryland        Massachusetts        Michigan          Minnesota        Mississippi          Missouri          Montana           Nebraska           Nevada         New.Hampshire       New.Jersey        New.Mexico          New.York
 Min.   :2693681   Min.   :4049021   Min.   :4302665   Min.   :1277072   Min.   :5311034   Min.   :6361104   Min.   : 9877597   Min.   :4933692   Min.   :2848353   Min.   :5607285   Min.   : 903773   Min.   :1713820   Min.   :2018741   Min.   :1239882   Min.   :8430621   Min.   :1821204   Min.   :19001780
 1st Qu.:2749707   1st Qu.:4191866   1st Qu.:4493053   1st Qu.:1319995   1st Qu.:5601126   1st Qu.:6418546   1st Qu.: 9932646   1st Qu.:5130587   1st Qu.:2905219   1st Qu.:5803401   1st Qu.: 943250   1st Qu.:1764296   1st Qu.:2454772   1st Qu.:1300966   1st Qu.:8654400   1st Qu.:1939740   1st Qu.:19146242
 Median :2863972   Median :4359640   Median :4576436   Median :1328508   Median :5814512   Median :6590329   Median : 9980774   Median :5328777   Median :2958458   Median :6003636   Median : 994124   Median :1835252   Median :2707798   Median :1318626   Median :8814002   Median :2072660   Median :19431544
 Mean   :2833886   Mean   :4315574   Mean   :4560039   Mean   :1326197   Mean   :5787688   Mean   :6628254   Mean   : 9974683   Mean   :5329387   Mean   :2941801   Mean   :5944995   Mean   : 994178   Mean   :1833929   Mean   :2667275   Mean   :1319220   Mean   :8787436   Mean   :2015526   Mean   :19412443
 3rd Qu.:2910848   3rd Qu.:4437511   3rd Qu.:4650232   3rd Qu.:1332065   3rd Qu.:6002392   3rd Qu.:6819831   3rd Qu.:10030988   3rd Qu.:5515020   3rd Qu.:2984169   3rd Qu.:6087391   3rd Qu.:1039476   3rd Qu.:1902877   3rd Qu.:2906799   3rd Qu.:1342140   3rd Qu.:8872766   3rd Qu.:2092764   3rd Qu.:19618328
 Max.   :2937922   Max.   :4507445   Max.   :4681346   Max.   :1377238   Max.   :6174610   Max.   :6995729   Max.   :10069577   Max.   :5711471   Max.   :2991892   Max.   :6169823   Max.   :1106227   Max.   :1963554   Max.   :3146402   Max.   :1387505   Max.   :9271689   Max.   :2118390   Max.   :20108296
 North.Carolina     North.Dakota         Ohio             Oklahoma           Oregon          Pennsylvania       Rhode.Island     South.Carolina     South.Dakota        Tennessee            Texas               Utah            Vermont           Virginia         Washington       West.Virginia        Wisconsin
 Min.   : 8081614   Min.   :638168   Min.   :11363543   Min.   :3454365   Min.   :3429708   Min.   :12284173   Min.   :1050268   Min.   :4024223   Min.   :755.0   Min.   :5703719   Min.   :20944499   Min.   :2244502   Min.   :609.0   Min.   :7105817   Min.   :5910512   Min.   :1785526   Min.   :5373999
 1st Qu.: 8758373   1st Qu.:646922   1st Qu.:11467793   1st Qu.:3559970   1st Qu.:3627622   1st Qu.:12465195   1st Qu.:1055142   1st Qu.:4292074   1st Qu.:777.0   1st Qu.:6015484   1st Qu.:22923487   1st Qu.:2474666   1st Qu.:621.2   1st Qu.:7601260   1st Qu.:6285667   1st Qu.:1806220   1st Qu.:5554038
 Median : 9616750   Median :680139   Median :11542592   Median :3774419   Median :3855143   Median :12729229   Median :1057228   Median :4654250   Median :819.5   Median :6377908   Median :25443700   Median :2795105   Median :624.0   Median :8063220   Median :6785244   Median :1824202   Median :5698189
 Mean   : 9465704   Mean   :697622   Mean   :11555678   Mean   :3742639   Mean   :3853253   Mean   :12649564   Mean   :1062417   Mean   :4628669   Mean   :821.0   Mean   :6342500   Mean   :25361385   Mean   :2771658   Mean   :623.9   Mean   :7986246   Mean   :6797468   Mean   :1825430   Mean   :5664273
 3rd Qu.:10130656   3rd Qu.:755970   3rd Qu.:11635624   3rd Qu.:3923737   3rd Qu.:4074589   3rd Qu.:12791754   3rd Qu.:1065270   3rd Qu.:4946275   3rd Qu.:860.8   3rd Qu.:6637296   3rd Qu.:27802681   3rd Qu.:3029087   3rd Qu.:625.0   3rd Qu.:8405064   3rd Qu.:7266792   3rd Qu.:1846664   3rd Qu.:5772109
 Max.   :10565885   Max.   :779518   Max.   :11797517   Max.   :3991225   Max.   :4256301   Max.   :13012059   Max.   :1096985   Max.   :5193266   Max.   :896.0   Max.   :6968351   Max.   :29558864   Max.   :3339113   Max.   :646.0   Max.   :8657365   Max.   :7740745   Max.   :1857446   Max.   :5896271
    Wyoming
 Min.   :494300
 1st Qu.:516284
 Median :566011
 Mean   :550976
 3rd Qu.:579866
 Max.   :586389
```

7. Unemployment Rates – Control

Unemployment rates provide information on the health of state-level economy, and inclusion of this variable helps the model control for state-level differences that may affect the personal income tax revenue collection (for example, if one state has a greater unemployment rate this year than the year previous, the change in tax revenue is likely *not* due to personal income tax policy changes).

Source(s):

The Bureau of Economic Analysis has collected data of the unemployment rates of each state since 1991, and I used their download tool to select the regional level and the exact columns from the survey datasets such that I isolated the state and unemployment rate by year alone (US Bureau of Economic Analysis "SAINC4").

Cleaning:

I largely did not need to clean the dataset, given the download tools. I did delete irrelevant rows, such as American territories and large continental region measurements.

Summary Statistics:

Summary Table of Unemployment Rates (7):

```
> summary(final_df)
      Year         Alabama          Alaska         Arizona          Arkansas       California        Colorado       Connecticut       Delaware      District.of.Colum
 Min.   :2000   Min.   : 3.200   Min.   :5.500   Min.   : 3.900   Min.   :3.500   Min.   : 4.100   Min.   :2.600   Min.   :2.400   Min.   :3.400   Min.   : 5.400  
 1st Qu.:2005   1st Qu.: 4.425   1st Qu.:6.525   1st Qu.: 4.825   1st Qu.:4.475   1st Qu.: 5.400   1st Qu.:3.725   1st Qu.:4.350   1st Qu.:3.850   1st Qu.: 6.100  
 Median :2010   Median : 5.750   Median :6.900   Median : 5.550   Median :5.400   Median : 6.450   Median :5.000   Median :5.250   Median :4.500   Median : 6.550  
 Mean   :2010   Mean   : 5.995   Mean   :6.964   Mean   : 6.177   Mean   :5.577   Mean   : 7.145   Mean   :5.164   Mean   :5.695   Mean   :5.173   Mean   : 7.091  
 3rd Qu.:2016   3rd Qu.: 6.725   3rd Qu.:7.450   3rd Qu.: 7.475   3rd Qu.:6.075   3rd Qu.: 8.550   3rd Qu.:6.675   3rd Qu.:7.500   3rd Qu.:6.450   3rd Qu.: 7.950  
 Max.   :2021   Max.   :11.000   Max.   :8.200   Max.   :10.400   Max.   :8.300   Max.   :12.200   Max.   :8.700   Max.   :9.100   Max.   :8.400   Max.   :10.200  
    Florida         Georgia          Hawaii          Idaho           Illinois          Indiana           Iowa           Kansas          Kentucky        Louisiana    
 Min.   : 3.200   Min.   : 3.60   Min.   :2.400   Min.   : 2.500   Min.   : 4.000   Min.   : 3.100   Min.   :2.500   Min.   :3.100   Min.   : 4.100   Min.   :4.300  
 1st Qu.: 4.050   1st Qu.: 4.55   1st Qu.:3.100   1st Qu.: 3.650   1st Qu.: 5.075   1st Qu.: 4.250   1st Qu.:3.625   1st Qu.:4.050   1st Qu.: 5.125   1st Qu.:5.150  
 Median : 5.000   Median : 5.15   Median :4.200   Median : 4.850   Median : 6.150   Median : 5.250   Median :4.200   Median :4.550   Median : 5.700   Median :6.100  
 Mean   : 5.845   Mean   : 6.00   Mean   :4.382   Mean   : 5.359   Mean   : 6.650   Mean   : 5.741   Mean   :4.159   Mean   :4.791   Mean   : 6.245   Mean   :6.105  
 3rd Qu.: 6.975   3rd Qu.: 6.95   3rd Qu.:5.500   3rd Qu.: 5.975   3rd Qu.: 8.525   3rd Qu.: 6.900   3rd Qu.:4.650   3rd Qu.:5.500   3rd Qu.: 6.475   3rd Qu.:6.775  
 Max.   :11.100   Max.   :10.50   Max.   :7.200   Max.   :12.000   Max.   :10.400   Max.   :10.400   Max.   :6.400   Max.   :7.100   Max.   :10.300   Max.   :8.700  
     Maine          Maryland      Massachusetts      Michigan        Minnesota      Mississippi        Missouri        Montana         Nebraska         Nevada      
 Min.   :2.800   Min.   :3.400   Min.   :2.700   Min.   : 3.600   Min.   :2.900   Min.   : 4.800   Min.   :3.100   Min.   :3.400   Min.   :2.500   Min.   : 4.000  
 1st Qu.:3.925   1st Qu.:4.025   1st Qu.:4.075   1st Qu.: 5.250   1st Qu.:3.725   1st Qu.: 5.650   1st Qu.:4.600   1st Qu.:3.950   1st Qu.:3.000   1st Qu.: 4.525  
 Median :4.650   Median :4.400   Median :5.200   Median : 7.000   Median :4.350   Median : 6.450   Median :5.400   Median :4.600   Median :3.300   Median : 5.650  
 Mean   :5.091   Mean   :5.064   Mean   :5.414   Mean   : 7.227   Mean   :4.668   Mean   : 6.936   Mean   :5.627   Mean   :4.809   Mean   :3.482   Mean   : 7.141  
 3rd Qu.:5.575   3rd Qu.:6.400   3rd Qu.:6.450   3rd Qu.: 8.600   3rd Qu.:5.300   3rd Qu.: 7.800   3rd Qu.:6.100   3rd Qu.:5.325   3rd Qu.:3.900   3rd Qu.: 9.175  
 Max.   :8.100   Max.   :7.700   Max.   :9.400   Max.   :13.700   Max.   :7.800   Max.   :10.400   Max.   :9.600   Max.   :7.300   Max.   :4.600   Max.   :13.500  
 New.Hampshire     New.Jersey      New.Mexico        New.York     North.Carolina     North.Dakota        Ohio           Oklahoma          Oregon        Pennsylvania  
 Min.   :2.500   Min.   :3.400   Min.   :3.800   Min.   :3.800   Min.   : 3.700   Min.   :2.100   Min.   : 4.000   Min.   :3.000   Min.   : 3.700   Min.   :4.100  
 1st Qu.:3.400   1st Qu.:4.525   1st Qu.:4.900   1st Qu.:4.725   1st Qu.: 4.725   1st Qu.:2.900   1st Qu.: 5.000   1st Qu.:3.850   1st Qu.: 5.200   1st Qu.:4.825  
 Median :3.700   Median :5.550   Median :5.900   Median :5.600   Median : 5.600   Median :3.150   Median : 5.750   Median :4.500   Median : 6.450   Median :5.400  
 Mean   :4.077   Mean   :6.095   Mean   :5.991   Mean   :6.109   Mean   : 6.305   Mean   :3.264   Mean   : 6.223   Mean   :4.641   Mean   : 6.714   Mean   :5.918  
 3rd Qu.:4.950   3rd Qu.:7.850   3rd Qu.:6.875   3rd Qu.:7.500   3rd Qu.: 6.975   3rd Qu.:3.650   3rd Qu.: 7.150   3rd Qu.:5.275   3rd Qu.: 7.825   3rd Qu.:7.125  
 Max.   :6.700   Max.   :9.500   Max.   :8.100   Max.   :9.900   Max.   :10.900   Max.   :5.100   Max.   :10.300   Max.   :6.800   Max.   :11.300   Max.   :9.100  
  Rhode.Island    South.Carolina    South.Dakota     Tennessee          Texas            Utah          Vermont         Virginia        Washington      West.Virginia  
 Min.   : 3.600   Min.   : 2.800   Min.   :2.500   Min.   : 3.400   Min.   :3.500   Min.   :2.600   Min.   :2.300   Min.   :2.300   Min.   : 4.300   Min.   :4.300  
 1st Qu.: 4.925   1st Qu.: 5.050   1st Qu.:3.100   1st Qu.: 4.625   1st Qu.:4.450   1st Qu.:3.300   1st Qu.:3.325   1st Qu.:3.300   1st Qu.: 5.200   1st Qu.:5.025  
 Median : 5.250   Median : 6.200   Median :3.200   Median : 5.450   Median :5.250   Median :3.950   Median :3.800   Median :4.000   Median : 5.850   Median :5.700  
 Mean   : 6.627   Mean   : 6.450   Mean   :3.518   Mean   : 5.945   Mean   :5.609   Mean   :4.382   Mean   :4.059   Mean   :4.400   Mean   : 6.414   Mean   :6.064  
 3rd Qu.: 8.850   3rd Qu.: 6.875   3rd Qu.:3.800   3rd Qu.: 7.200   3rd Qu.:6.625   3rd Qu.:5.300   3rd Qu.:4.625   3rd Qu.:5.575   3rd Qu.: 7.400   3rd Qu.:6.775  
 Max.   :11.200   Max.   :11.200   Max.   :5.000   Max.   :10.500   Max.   :8.100   Max.   :7.800   Max.   :6.600   Max.   :7.100   Max.   :10.000   Max.   :8.700  
   Wisconsin        Wyoming     
 Min.   :3.000   Min.   :2.800  
 1st Qu.:4.125   1st Qu.:3.800  
 Median :4.900   Median :4.150  
 Mean   :5.259   Mean   :4.409  
 3rd Qu.:6.150   3rd Qu.:5.150  
 Max.   :8.700   Max.   :6.400  
```

8. Corporate Income Tax Revenue - Control

Corporate income tax revenue data provide information on company behavior and response – some states that historically have a low personal income tax have a high corporate income tax (Fritts 2023), which may affect job movements across state lines. The inclusion of this variable helps the model control for state-level differences that may affect the personal income tax revenue collection.

Source(s):

I am using data from the St. Louis Federal Reserve (US Census Bureau "State Tax Collections: T41"). These data cover the state-level corporate income tax collections for each state and the District of Columbia from 1957 through 2021. Each dataset is downloadable as an Excel file for each state over the years. These datasets are comprehensive for my purposes, and do not require supplemental or otherwise additional data.

Cleaning:

I conducted a simple full join operation for all of the files so that there is one aggregate file such that one observation is a state and year, with the value being the dollar amount of the collections, which should be measured in the thousands.

Summary Table of Corporate Income Tax Revenue (8):

```
> summary(final_df)
      Year         Alabama            Alaska           Arizona          Arkansas         California          Colorado          Connecticut          Delaware        District.of.Columbia     Florida            Georgia            Hawaii
 Min.   :2000   Min.   :  67457   Min.   : 201533   Min.   :176874   Min.   :346280   Min.   : 5333036   Min.   : 199853   Min.   : 149454   Min.   :125000   Min.   :142417         Min.   :1182796   Min.   : 484139   Min.   : 30603
 1st Qu.:2005   1st Qu.: 212269   1st Qu.: 337528   1st Qu.:293616   1st Qu.:516464   1st Qu.: 7583750   1st Qu.: 336245   1st Qu.: 459984   1st Qu.:235250   1st Qu.:241468         1st Qu.:1787205   1st Qu.: 686394   1st Qu.: 68956
 Median :2010   Median : 404690   Median : 450990   Median :381120   Median :565392   Median : 9325134   Median : 485834   Median : 626339   Median :414500   Median :258590         Median :2057730   Median : 843994   Median : 90552
 Mean   :2010   Mean   : 459407   Mean   : 472342   Mean   :362546   Mean   :594767   Mean   : 9924791   Mean   : 517786   Mean   : 803204   Mean   :409182   Mean   :266617         Mean   :2065748   Mean   : 857249   Mean   :102247
 3rd Qu.:2016   3rd Qu.: 640332   3rd Qu.: 531392   3rd Qu.:403781   3rd Qu.:683726   3rd Qu.:10265480   3rd Qu.: 664836   3rd Qu.: 769579   3rd Qu.:520500   3rd Qu.:307062         3rd Qu.:2400343   3rd Qu.: 983316   3rd Qu.:125565
 Max.   :2021   Max.   :1297513   Max.   :1134256   Max.   :618457   Max.   :986170   Max.   :26097277   Max.   :1278046   Max.   :2607064   Max.   :902000   Max.   :400746         Max.   :3407190   Max.   :1750735   Max.   :191426
     Idaho           Illinois          Indiana             Iowa             Kansas          Kentucky           Louisiana          Maine              Maryland           Massachusetts       Michigan           Minnesota          Mississippi
 Min.   : 88310   Min.   : 76769   Min.   :1278538   Min.   : 597347   Min.   :121931   Min.   : 302129   Min.   :171579   Min.   : 812257   Min.   : 359420   Min.   : 77366   Min.   : 631895   Min.   : 533901   Min.   :205729
 1st Qu.:197755   1st Qu.:140935   1st Qu.:2191510   1st Qu.: 734961   1st Qu.:254172   1st Qu.: 385270   1st Qu.:252735   1st Qu.:1446985   1st Qu.: 738743   1st Qu.:138890   1st Qu.: 885925   1st Qu.: 785130   1st Qu.:268766
 Median :336162   Median :188792   Median :2774135   Median : 824910   Median :376074   Median : 554397   Median :322596   Median :1966676   Median : 863610   Median :175266   Median :1190484   Median :1068953   Median :326164
 Mean   :339006   Mean   :181584   Mean   :2884095   Mean   : 850705   Mean   :360547   Mean   : 582011   Mean   :380178   Mean   :1966102   Mean   : 876285   Mean   :170632   Mean   :1368083   Mean   :1134927   Mean   :328669
 3rd Qu.:431154   3rd Qu.:212566   3rd Qu.:3493826   3rd Qu.: 920841   3rd Qu.:436958   3rd Qu.: 730741   3rd Qu.:491844   3rd Qu.:2219654   3rd Qu.:1003174   3rd Qu.:187446   3rd Qu.:1842556   3rd Qu.:1349167   3rd Qu.:367872
 Max.   :793641   Max.   :351479   Max.   :5729501   Max.   :1385158   Max.   :727435   Max.   :1001619   Max.   :752773   Max.   :3672995   Max.   :1840705   Max.   :284317   Max.   :2382496   Max.   :2423383   Max.   :686857
    Missouri         Montana          Nebraska            Nevada         New.Hampshire      New.Jersey         New.Mexico          New.York        North.Carolina  North.Dakota          Ohio              Oklahoma            Oregon
 Min.   :195814   Min.   : 44137   Min.   : 662343   Min.   : 49807   Min.   :107628   Min.   : 312176   Min.   :1101296   Min.   : 89708   Min.   :0       Min.   :2044504   Min.   :   -118   Min.   :104448   Min.   : 196257
 1st Qu.:295666   1st Qu.:100746   1st Qu.: 836582   1st Qu.: 76432   1st Qu.:158066   1st Qu.: 480724   1st Qu.:2063088   1st Qu.:124520   1st Qu.:0       1st Qu.:3109851   1st Qu.:   8886   1st Qu.:178812   1st Qu.: 356528
 Median :376924   Median :141250   Median :1144620   Median :113695   Median :233574   Median : 542746   Median :2258854   Median :176586   Median :0       Median :4104082   Median : 249716   Median :303630   Median : 449000
 Mean   :370771   Mean   :138108   Mean   :1079158   Mean   :122851   Mean   :250538   Mean   : 560845   Mean   :2468769   Mean   :202486   Mean   :0       Mean   :3943438   Mean   : 435227   Mean   :310175   Mean   : 515096
 3rd Qu.:433412   3rd Qu.:170259   3rd Qu.:1292212   3rd Qu.:159344   3rd Qu.:307402   3rd Qu.: 591012   3rd Qu.:2561650   3rd Qu.:248076   3rd Qu.:0       3rd Qu.:4852338   3rd Qu.: 759446   3rd Qu.:381414   3rd Qu.: 630216
 Max.   :550199   Max.   :268444   Max.   :1565544   Max.   :250438   Max.   :571220   Max.   :1009975   Max.   :5959760   Max.   :459880   Max.   :0       Max.   :5416105   Max.   :1327484   Max.   :601224   Max.   :1223523
  Pennsylvania      Rhode.Island     South.Carolina    South.Dakota      Tennessee            Texas          Utah             Vermont            Virginia          Washington       West.Virginia       Wisconsin          Wyoming
 Min.   :1189314   Min.   : 28273   Min.   :148500   Min.   : 4334   Min.   : 502977   Min.   :0   Min.   :110989   Min.   : 308554   Min.   : 37306   Min.   :175353   Min.   : 445016   Min.   :110068   Min.   :0
 1st Qu.:1698458   1st Qu.:109704   1st Qu.:218852   1st Qu.:32716   1st Qu.: 808266   1st Qu.:0   1st Qu.:203104   1st Qu.: 612842   1st Qu.: 72562   1st Qu.:193782   1st Qu.: 707178   1st Qu.:183962   1st Qu.:0
 Median :2154187   Median :133503   Median :304328   Median :43682   Median :1091978   Median :0   Median :317251   Median : 788442   Median : 91669   Median :249758   Median : 891457   Median :216045   Median :0
 Mean   :2112716   Mean   :132777   Mean   :314045   Mean   :42434   Mean   :1153189   Mean   :0   Mean   :310250   Mean   : 793156   Mean   : 93695   Mean   :265901   Mean   : 938198   Mean   :268017   Mean   :0
 3rd Qu.:2428259   3rd Qu.:163865   3rd Qu.:384468   3rd Qu.:49050   3rd Qu.:1478904   3rd Qu.:0   3rd Qu.:366562   3rd Qu.: 857188   3rd Qu.:111094   3rd Qu.:320864   3rd Qu.: 975886   3rd Qu.:317185   3rd Qu.:0
 Max.   :4045313   Max.   :257943   Max.   :740197   Max.   :76665   Max.   :2564458   Max.   :0   Max.   :745673   Max.   :1579303   Max.   :166841   Max.   :438328   Max.   :2517169   Max.   :539136   Max.   :0
```

9. State Gross Domestic Product (GDP) – Control

GDP provides a measurement of a state's economic health, and controlling for differences between states and years helps the model compare between states of differing economic size and health that may impact personal income tax revenue.

Source(s):

The Bureau of Economic Analysis has collected data of Gross Domestic Product in each state from 1998 through 2021, and I used their download tool to select the regional level and the exact columns from the survey datasets such that I isolated the state and unemployment rate by year alone (US Bureau of Economic Analysis, "SASUMMARY").

Cleaning:

I largely did not need to clean the dataset, given the download tools. I did delete irrelevant rows, such as American territories and large continental region measurements.

Summary Table of State GDP (9):

```
> summary(final_df)
      Year        Alabama          Alaska         Arizona          Arkansas        California         Colorado        Connecticut       Delaware      District.of.Columbia
 Min.   :2000   Min.   :156853   Min.   :39406   Min.   :208439   Min.   : 89789   Min.   :1692324   Min.   :231589   Min.   :216157   Min.   :56534   Min.   : 85355
 1st Qu.:2005   1st Qu.:181622   1st Qu.:46540   1st Qu.:258200   1st Qu.:103662   1st Qu.:1943991   1st Qu.:253026   1st Qu.:235370   1st Qu.:59518   1st Qu.: 99561
 Median :2010   Median :188304   Median :52524   Median :273830   Median :108196   Median :2062732   Median :271340   Median :241808   Median :60600   Median :110816
 Mean   :2010   Mean   :185619   Mean   :50595   Mean   :273615   Mean   :107276   Mean   :2166658   Mean   :285599   Mean   :239185   Mean   :61039   Mean   :108438
 3rd Qu.:2016   3rd Qu.:193554   3rd Qu.:54520   3rd Qu.:289269   3rd Qu.:112686   3rd Qu.:2410284   3rd Qu.:317317   3rd Qu.:246915   3rd Qu.:62778   3rd Qu.:118935
 Max.   :2021   Max.   :209979   Max.   :58283   Max.   :347656   Max.   :123347   Max.   :2874730   Max.   :373763   Max.   :257953   Max.   :66793   Max.   :126983
    Florida           Georgia           Hawaii          Idaho           Illinois          Indiana            Iowa            Kansas          Kentucky         Louisiana          Maine
 Min.   : 642708   Min.   :389727   Min.   :55678   Min.   :46084   Min.   :640723   Min.   :259474   Min.   :120449   Min.   :114030   Min.   :151495   Min.   :205722   Min.   :48490
 1st Qu.: 769860   1st Qu.:429987   1st Qu.:67324   1st Qu.:56364   1st Qu.:687820   1st Qu.:288323   1st Qu.:144978   1st Qu.:125553   1st Qu.:167823   1st Qu.:223438   1st Qu.:53642
 Median : 815912   Median :450398   Median :70284   Median :58496   Median :711951   Median :300738   Median :152648   Median :139558   Median :175701   Median :232864   Median :54365
 Mean   : 820315   Mean   :465046   Mean   :69581   Mean   :60204   Mean   :712955   Mean   :302364   Mean   :153239   Mean   :138578   Mean   :175276   Mean   :230174   Mean   :54818
 3rd Qu.: 874215   3rd Qu.:502408   3rd Qu.:74288   3rd Qu.:64880   3rd Qu.:747298   3rd Qu.:318896   3rd Qu.:170762   3rd Qu.:152474   3rd Qu.:183815   3rd Qu.:236154   3rd Qu.:55536
 Max.   :1029575   Max.   :575292   Max.   :79845   Max.   :80093   Max.   :780060   Max.   :346240   Max.   :179753   Max.   :162290   Max.   :197818   Max.   :247773   Max.   :63594
    Maryland      Massachusetts       Michigan        Minnesota        Mississippi        Missouri          Montana          Nebraska          Nevada         New.Hampshire     New.Jersey
 Min.   :250771   Min.   :358121   Min.   :383140   Min.   :247599   Min.   : 87309   Min.   :243060   Min.   :31241   Min.   : 76368   Min.   :105635   Min.   :56779   Min.   :471426
 1st Qu.:302694   1st Qu.:388986   1st Qu.:426012   1st Qu.:279216   1st Qu.: 97115   1st Qu.:266010   1st Qu.:37674   1st Qu.: 89940   1st Qu.:128509   1st Qu.:65026   1st Qu.:507038
 Median :328903   Median :430143   Median :443742   Median :291102   Median :100247   Median :271134   Median :41334   Median :100026   Median :133622   Median :67342   Median :519046
 Mean   :322151   Mean   :432592   Mean   :439701   Mean   :296874   Mean   : 97932   Mean   :270136   Mean   :40809   Mean   : 99799   Mean   :133815   Mean   :68309   Mean   :518708
 3rd Qu.:351326   3rd Qu.:473527   3rd Qu.:451707   3rd Qu.:322751   3rd Qu.:100786   3rd Qu.:279087   3rd Qu.:45155   3rd Qu.:112308   3rd Qu.:143822   3rd Qu.:73190   3rd Qu.:534916
 Max.   :368571   Max.   :533102   Max.   :481778   Max.   :346204   Max.   :104353   Max.   :295687   Max.   :48976   Max.   :122136   Max.   :159567   Max.   :82986   Max.   :566893
   New.Mexico        New.York       North.Carolina    North.Dakota        Ohio            Oklahoma          Oregon         Pennsylvania     Rhode.Island    South.Carolina    South.Dakota
 Min.   :71652   Min.   :1092188   Min.   :356912   Min.   :24706   Min.   :502967   Min.   :124227   Min.   :136166   Min.   :538790   Min.   :45178   Min.   :150156   Min.   :29386
 1st Qu.:84540   1st Qu.:1174188   1st Qu.:414741   1st Qu.:29656   1st Qu.:526500   1st Qu.:145818   1st Qu.:160004   1st Qu.:595446   1st Qu.:50528   1st Qu.:169010   1st Qu.:35969
 Median :87601   Median :1278496   Median :444192   Median :40128   Median :545854   Median :164357   Median :173714   Median :633460   Median :51492   Median :177092   Median :41709
 Mean   :85804   Mean   :1283357   Mean   :443912   Mean   :41807   Mean   :554494   Mean   :166737   Mean   :176739   Mean   :634457   Mean   :51020   Mean   :181064   Mean   :40528
 3rd Qu.:89111   3rd Qu.:1395833   3rd Qu.:481000   3rd Qu.:53766   3rd Qu.:582672   3rd Qu.:192890   3rd Qu.:196046   3rd Qu.:682089   3rd Qu.:52656   3rd Qu.:196508   3rd Qu.:45747
 Max.   :94897   Max.   :1514779   Max.   :541933   Max.   :57790   Max.   :629287   Max.   :201161   Max.   :227979   Max.   :715060   Max.   :54606   Max.   :221045   Max.   :49557
   Tennessee          Texas              Utah           Vermont          Virginia         Washington      West.Virginia      Wisconsin         Wyoming
 Min.   :233362   Min.   : 995661   Min.   : 92498   Min.   :23016   Min.   :348327   Min.   :303673   Min.   :61665   Min.   :232411   Min.   :27435
 1st Qu.:265650   1st Qu.:1163166   1st Qu.:112155   1st Qu.:26913   1st Qu.:414030   1st Qu.:343637   1st Qu.:65974   1st Qu.:259995   1st Qu.:34180
 Median :275888   Median :1331781   Median :126108   Median :28542   Median :442765   Median :384517   Median :69582   Median :271373   Median :38134
 Mean   :284238   Mean   :1385928   Mean   :130627   Mean   :27776   Mean   :432836   Mean   :405552   Mean   :68207   Mean   :272464   Mean   :36703
 3rd Qu.:308728   3rd Qu.:1616441   3rd Qu.:146402   3rd Qu.:29210   3rd Qu.:458764   3rd Qu.:454185   3rd Qu.:70546   3rd Qu.:291209   3rd Qu.:39715
 Max.   :352461   Max.   :1815063   Max.   :186910   Max.   :30546   Max.   :505351   Max.   :575129   Max.   :73170   Max.   :306467   Max.   :42868
```

10. Per Capita Personal Income – Control

Inclusion of this variable in the model informs regression analysis by controlling for state-level differences in income – this helps provide a more accurate analysis of differences between states that have higher wages versus states that have lower wages (for example, being able to compare California tax policy and revenue more accurately to Oklahoma tax policy and revenue).

Source(s):

The Bureau of Economic Analysis has collected data of the per capita personal income in each state from 1932 through 2020, and I used their download tool to select the regional level and the exact columns from the survey datasets such that I isolated the state and unemployment rate by year alone (US Bureau of Economic Analysis “SAINC4”).

Cleaning:

I largely did not need to clean the dataset, given the download tools. I did delete irrelevant rows, such as American territories and large continental region measurements.

Summary Table of Per Capita Personal Income (10):

```
> summary(final_df)
      Year        Alabama         Alaska         Arizona        Arkansas       California       Colorado       Connecticut    District.of.Columbia    Delaware        Florida
 Min.   :2000   Min.   :24306   Min.   :32044   Min.   :26388   Min.   :22781   Min.   :33410   Min.   :34029   Min.   :43070   Min.   :33884         Min.   :43524   Min.   :29
 1st Qu.:2005   1st Qu.:30330   1st Qu.:39596   1st Qu.:32626   1st Qu.:28574   1st Qu.:39621   1st Qu.:38371   1st Qu.:50728   1st Qu.:39742         1st Qu.:53662   1st Qu.:36
 Median :2010   Median :34478   Median :51110   Median :35810   Median :33326   Median :44562   Median :43306   Median :62195   Median :42848         Median :65186   Median :40
 Mean   :2010   Mean   :34865   Mean   :48993   Mean   :37267   Mean   :34701   Mean   :48343   Mean   :46454   Mean   :60923   Mean   :44500         Mean   :65654   Mean   :41
 3rd Qu.:2016   3rd Qu.:38893   3rd Qu.:56961   3rd Qu.:41188   3rd Qu.:40647   3rd Qu.:56056   3rd Qu.:52377   3rd Qu.:68340   3rd Qu.:48518         3rd Qu.:77545   3rd Qu.:46
 Max.   :2021   Max.   :49769   Max.   :65813   Max.   :55487   Max.   :50625   Max.   :76614   Max.   :70706   Max.   :83294   Max.   :59931         Max.   :96477   Max.   :62
    Georgia         Hawaii          Idaho          Illinois        Indiana           Iowa           Kansas         Kentucky        Louisiana         Maine          Maryland
 Min.   :28851   Min.   :29319   Min.   :25183   Min.   :33212   Min.   :28153   Min.   :27390   Min.   :28253   Min.   :24868   Min.   :23997   Min.   :27491   Min.   :35591
 1st Qu.:33652   1st Qu.:36901   1st Qu.:29864   1st Qu.:38572   1st Qu.:31955   1st Qu.:33078   1st Qu.:33331   1st Qu.:29596   1st Qu.:31067   1st Qu.:33306   1st Qu.:44030
 Median :36261   Median :42389   Median :33210   Median :43827   Median :36747   Median :39870   Median :42136   Median :34104   Median :38823   Median :38898   Median :50756
 Mean   :38450   Mean   :43054   Mean   :35294   Mean   :45889   Mean   :38366   Mean   :40234   Mean   :41714   Mean   :35022   Mean   :38108   Mean   :39712   Mean   :50773
 3rd Qu.:42760   3rd Qu.:48786   3rd Qu.:39920   3rd Qu.:51888   3rd Qu.:43400   3rd Qu.:46244   3rd Qu.:47330   3rd Qu.:39620   3rd Qu.:43106   3rd Qu.:44473   3rd Qu.:57180
 Max.   :55786   Max.   :60947   Max.   :52369   Max.   :67244   Max.   :56497   Max.   :57163   Max.   :58924   Max.   :51266   Max.   :54217   Max.   :58484   Max.   :69817
 Massachusetts      Michigan       Minnesota      Mississippi       Missouri        Montana        Nebraska         Nevada       New.Hampshire     New.Jersey      New.Mexico
 Min.   :38594   Min.   :30344   Min.   :32448   Min.   :21681   Min.   :27941   Min.   :23081   Min.   :29039   Min.   :31986   Min.   :35335   Min.   :39216   Min.   :23102
 1st Qu.:45216   1st Qu.:33162   1st Qu.:38466   1st Qu.:27122   1st Qu.:32880   1st Qu.:30604   1st Qu.:35004   1st Qu.:36547   1st Qu.:41252   1st Qu.:45274   1st Qu.:29293
 Median :53853   Median :36875   Median :44242   Median :31916   Median :37922   Median :37476   Median :43461   Median :39716   Median :48114   Median :52363   Median :34378
 Mean   :55622   Mean   :39129   Mean   :46002   Mean   :31976   Mean   :39008   Mean   :37938   Mean   :43144   Mean   :41410   Mean   :49676   Mean   :53764   Mean   :34518
 3rd Qu.:63815   3rd Qu.:44252   3rd Qu.:52443   3rd Qu.:35899   3rd Qu.:44138   3rd Qu.:44032   3rd Qu.:49948   3rd Qu.:45211   3rd Qu.:55912   3rd Qu.:60194   3rd Qu.:38607
 Max.   :83653   Max.   :56494   Max.   :66280   Max.   :45881   Max.   :55325   Max.   :56949   Max.   :61205   Max.   :60213   Max.   :73200   Max.   :77016   Max.   :50311
    New.York     North.Carolina   North.Dakota        Ohio          Oklahoma         Oregon       Pennsylvania    Rhode.Island   South.Carolina   South.Dakota     Tennessee
 Min.   :36090   Min.   :27510   Min.   :25892   Min.   :28598   Min.   :24178   Min.   :28386   Min.   :30443   Min.   :30417   Min.   :25133   Min.   :26825   Min.   :27066
 1st Qu.:41695   1st Qu.:32855   1st Qu.:32314   1st Qu.:33009   1st Qu.:32606   1st Qu.:32901   1st Qu.:36835   1st Qu.:37495   1st Qu.:29710   1st Qu.:34166   1st Qu.:31927
 Median :49836   Median :37368   Median :46632   Median :38050   Median :39562   Median :37294   Median :43231   Median :43484   Median :33856   Median :43090   Median :36789
 Mean   :51672   Mean   :38300   Mean   :44604   Mean   :39584   Mean   :38689   Mean   :39871   Mean   :44388   Mean   :44150   Mean   :35630   Mean   :42642   Mean   :38171
 3rd Qu.:58830   3rd Qu.:42721   3rd Qu.:55272   3rd Qu.:45020   3rd Qu.:44776   3rd Qu.:45673   3rd Qu.:50868   3rd Qu.:49058   3rd Qu.:40897   3rd Qu.:49190   3rd Qu.:43258
 Max.   :76837   Max.   :56173   Max.   :64524   Max.   :56879   Max.   :53870   Max.   :61596   Max.   :64279   Max.   :64376   Max.   :52467   Max.   :64462   Max.   :56560
     Texas            Utah          Vermont         Virginia       Washington    West.Virginia     Wisconsin        Wyoming
 Min.   :28383   Min.   :24260   Min.   :29014   Min.   :32715   Min.   :32723   Min.   :22317   Min.   :29556   Min.   :29607
 1st Qu.:33864   1st Qu.:29527   1st Qu.:35410   1st Qu.:40722   1st Qu.:38045   1st Qu.:27412   1st Qu.:34920   1st Qu.:40662
 Median :40992   Median :34066   Median :42858   Median :46561   Median :44233   Median :33672   Median :40192   Median :50264
 Mean   :41568   Mean   :35974   Mean   :43291   Mean   :47174   Mean   :47280   Mean   :33475   Mean   :41645   Mean   :49095
 3rd Qu.:47441   3rd Qu.:41427   3rd Qu.:49435   3rd Qu.:53010   3rd Qu.:54459   3rd Qu.:37446   3rd Qu.:47041   3rd Qu.:57608
 Max.   :59865   Max.   :56019   Max.   :61882   Max.   :66305   Max.   :73775   Max.   :48488   Max.   :59626   Max.   :69666
```

11. Per Capita Personal Consumption Expenditure – Control

Per capita personal consumption expenditure data provide information on the health of state-level economies as well as indication of quality of life of state residents, and inclusion of this variable helps the model control for state-level differences that may affect the personal income tax revenue collection.

Source(s):

The Bureau of Economic Analysis has collected data of the per capita personal consumption expenditure in each state from 2000 through 2020, and I used their download tool to select the regional level and the exact columns from the survey datasets such that I isolated the state and unemployment rate by year alone (US Bureau of Economic Analysis, "SASUMMARY").

Cleaning:

I largely did not need to clean the dataset, given the download tools. I did delete irrelevant rows, such as American territories and large continental region measurements.

Summary Table of Per Capita Personal Consumption Expenditure (11):

```
> summary(final_df)
      Year         Alabama          Alaska          Arizona         Arkansas       California       Colorado       Connecticut       Delaware     District.of.Columbia    Florida
 Min.   :2000   Min.   :20199   Min.   :27199   Min.   :23507   Min.   :18936   Min.   :24661   Min.   :26946   Min.   :29557   Min.   :27049   Min.   :39154          Min.   :25
 1st Qu.:2005   1st Qu.:25355   1st Qu.:34956   1st Qu.:29091   1st Qu.:23646   1st Qu.:30892   1st Qu.:32006   1st Qu.:36880   1st Qu.:34126   1st Qu.:50683          1st Qu.:31
 Median :2010   Median :27769   Median :40051   Median :31542   Median :26615   Median :35148   Median :35273   Median :40946   Median :37541   Median :56910          Median :34
 Mean   :2010   Mean   :28074   Mean   :39974   Mean   :31828   Mean   :27060   Mean   :35826   Mean   :36347   Mean   :41093   Mean   :37584   Mean   :56154          Mean   :35
 3rd Qu.:2015   3rd Qu.:31123   3rd Qu.:45319   3rd Qu.:34980   3rd Qu.:30755   3rd Qu.:40584   3rd Qu.:40643   3rd Qu.:45966   3rd Qu.:41816   3rd Qu.:62416          3rd Qu.:39
 Max.   :2020   Max.   :35458   Max.   :51364   Max.   :40630   Max.   :34786   Max.   :48478   Max.   :47559   Max.   :51243   Max.   :46607   Max.   :71454          Max.   :45
    Georgia         Hawaii          Idaho          Illinois         Indiana           Iowa           Kansas         Kentucky       Louisiana         Maine          Maryland
 Min.   :22935   Min.   :25083   Min.   :20072   Min.   :25035   Min.   :21936   Min.   :21720   Min.   :22798   Min.   :20684   Min.   :19591   Min.   :24405   Min.   :26292
 1st Qu.:27684   1st Qu.:31370   1st Qu.:24646   1st Qu.:30426   1st Qu.:26977   1st Qu.:26774   1st Qu.:27938   1st Qu.:25350   1st Qu.:24190   1st Qu.:31274   1st Qu.:33143
 Median :29589   Median :35182   Median :27265   Median :34160   Median :29452   Median :30680   Median :31665   Median :28460   Median :29545   Median :35635   Median :37328
 Mean   :30574   Mean   :35412   Mean   :27655   Mean   :34682   Mean   :30214   Mean   :30600   Mean   :31387   Mean   :28761   Mean   :29308   Mean   :35545   Mean   :36930
 3rd Qu.:34040   3rd Qu.:39445   3rd Qu.:30724   3rd Qu.:38919   3rd Qu.:33629   3rd Qu.:34610   3rd Qu.:34840   3rd Qu.:32259   3rd Qu.:33688   3rd Qu.:39934   3rd Qu.:41162
 Max.   :39055   Max.   :45954   Max.   :35364   Max.   :44598   Max.   :38412   Max.   :38214   Max.   :39038   Max.   :36633   Max.   :37735   Max.   :45686   Max.   :45443
 Massachusetts      Michigan       Minnesota      Mississippi       Missouri        Montana         Nebraska         Nevada       New.Hampshire     New.Jersey      New.Mexico
 Min.   :29712   Min.   :23084   Min.   :27055   Min.   :17703   Min.   :23596   Min.   :21539   Min.   :22682   Min.   :25070   Min.   :27894   Min.   :28089   Min.   :20024
 1st Qu.:37934   1st Qu.:27552   1st Qu.:32915   1st Qu.:22443   1st Qu.:28643   1st Qu.:28094   1st Qu.:28330   1st Qu.:30648   1st Qu.:35750   1st Qu.:35815   1st Qu.:25090
 Median :42172   Median :31200   Median :36097   Median :26015   Median :32028   Median :32796   Median :32352   Median :32945   Median :40513   Median :39992   Median :28424
 Mean   :42333   Mean   :32090   Mean   :36690   Mean   :25853   Mean   :32462   Mean   :32799   Mean   :32516   Mean   :32896   Mean   :40594   Mean   :39767   Mean   :28475
 3rd Qu.:47657   3rd Qu.:36758   3rd Qu.:40777   3rd Qu.:29372   3rd Qu.:36365   3rd Qu.:37655   3rd Qu.:36944   3rd Qu.:35934   3rd Qu.:45795   3rd Qu.:44232   3rd Qu.:32254
 Max.   :53622   Max.   :41895   Max.   :46007   Max.   :32577   Max.   :40955   Max.   :42370   Max.   :41213   Max.   :40966   Max.   :52399   Max.   :49386   Max.   :35940
    New.York     North.Carolina  North.Dakota        Ohio          Oklahoma         Oregon       Pennsylvania    Rhode.Island   South.Carolina   South.Dakota     Tennessee
 Min.   :24595   Min.   :22491   Min.   :21761   Min.   :22970   Min.   :19583   Min.   :23590   Min.   :24923   Min.   :24132   Min.   :21375   Min.   :20577   Min.   :22127
 1st Qu.:31401   1st Qu.:26862   1st Qu.:28447   1st Qu.:27968   1st Qu.:24475   1st Qu.:28955   1st Qu.:31357   1st Qu.:31120   1st Qu.:26451   1st Qu.:26735   1st Qu.:26532
 Median :36768   Median :29424   Median :34946   Median :30898   Median :28064   Median :31860   Median :35845   Median :34773   Median :29654   Median :31869   Median :29379
 Mean   :37074   Mean   :30346   Mean   :35109   Mean   :31712   Mean   :28056   Mean   :32661   Mean   :35708   Mean   :34538   Mean   :30076   Mean   :31849   Mean   :29890
 3rd Qu.:42777   3rd Qu.:33909   3rd Qu.:43066   3rd Qu.:35922   3rd Qu.:31791   3rd Qu.:36523   3rd Qu.:40318   3rd Qu.:38716   3rd Qu.:34009   3rd Qu.:37108   3rd Qu.:33252
 Max.   :49963   Max.   :39244   Max.   :44800   Max.   :40261   Max.   :35199   Max.   :42766   Max.   :45640   Max.   :42976   Max.   :38665   Max.   :42486   Max.   :37910
     Texas            Utah          Vermont         Virginia       Washington    West.Virginia     Wisconsin        Wyoming
 Min.   :22536   Min.   :19969   Min.   :25735   Min.   :24737   Min.   :25689   Min.   :19492   Min.   :23284   Min.   :23182
 1st Qu.:27228   1st Qu.:24666   1st Qu.:33312   1st Qu.:31725   1st Qu.:31176   1st Qu.:24380   1st Qu.:28967   1st Qu.:29929
 Median :30592   Median :27691   Median :38362   Median :35817   Median :35251   Median :28759   Median :32497   Median :34788
 Mean   :31437   Mean   :28143   Mean   :38036   Mean   :35335   Mean   :35996   Mean   :28769   Mean   :32713   Mean   :34332
 3rd Qu.:35984   3rd Qu.:31585   3rd Qu.:43506   3rd Qu.:39392   3rd Qu.:40584   3rd Qu.:32997   3rd Qu.:36549   3rd Qu.:39446
 Max.   :40600   Max.   :37320   Max.   :47860   Max.   :43822   Max.   :47385   Max.   :37764   Max.   :41482   Max.   :43115
```

12. Health Coverage – Control

Health coverage data provide preliminary quality-of-life analysis for a state, and its inclusion helps control for differences in state-to-state migration that may impact tax revenue collection outside of tax policy.

Source(s):

The Census Bureau has a downloadable dataset that tracks health coverage for each state and the District of Columbia from the years 2000 through 2021 through the Annual Community Survey (US Census Bureau "American Community").

Cleaning:

I deleted all rows that broke down the data further than total percentage covered in a state (such as the public/private distinction) and then further deleted all columns that contained information other than that percentage of the population (such as the total number covered in a state). I did have to combine two datasets together, as one had data through 2008, and the other had data from 2008 through 2021.

Summary Table of Health Insurance Coverage (12):

```
> summary(final_df)
      Year         Alabama          Alaska          Arizona         Arkansas        California       Colorado       Connecticut    District.of.Columbia    Delaware         Florida
 Min.   :2000   Min.   :84.80   Min.   :78.90   Min.   :79.10   Min.   :81.10   Min.   :80.90   Min.   :82.80   Min.   :89.1   Min.   :86.70          Min.   :86.30   Min.   :78.70
 1st Qu.:2005   1st Qu.:86.40   1st Qu.:81.30   1st Qu.:82.50   1st Qu.:82.90   1st Qu.:81.80   1st Qu.:84.10   1st Qu.:90.5   1st Qu.:89.60          1st Qu.:87.90   1st Qu.:79.80
 Median :2010   Median :87.50   Median :82.80   Median :83.30   Median :84.00   Median :82.10   Median :85.10   Median :90.9   Median :90.90          Median :93.00   Median :82.50
 Mean   :2010   Mean   :87.78   Mean   :83.08   Mean   :84.54   Mean   :85.87   Mean   :85.13   Mean   :86.91   Mean   :91.7   Mean   :91.09          Mean   :91.91   Mean   :82.57
 3rd Qu.:2015   3rd Qu.:89.90   3rd Qu.:85.10   3rd Qu.:88.70   3rd Qu.:90.50   3rd Qu.:91.40   3rd Qu.:91.90   3rd Qu.:94.0   3rd Qu.:93.40          3rd Qu.:96.10   3rd Qu.:86.70
 Max.   :2020   Max.   :90.90   Max.   :88.60   Max.   :90.00   Max.   :92.10   Max.   :93.00   Max.   :92.50   Max.   :95.1   Max.   :94.60          Max.   :96.80   Max.   :87.90
    Georgia          Hawaii          Idaho          Illinois         Indiana           Iowa           Kansas          Kentucky        Louisiana          Maine          Maryland      Massachusetts
 Min.   :80.30   Min.   :90.20   Min.   :81.90   Min.   :86.00   Min.   :85.20   Min.   :89.10   Min.   :86.10   Min.   :84.00   Min.   :78.10   Min.   :88.80   Min.   :86.20   Min.   :88.7
 1st Qu.:81.70   1st Qu.:91.40   1st Qu.:83.80   1st Qu.:86.60   1st Qu.:86.20   1st Qu.:90.80   1st Qu.:87.70   1st Qu.:85.70   1st Qu.:82.20   1st Qu.:89.60   1st Qu.:87.70   1st Qu.:91.6
 Median :84.00   Median :92.90   Median :85.00   Median :87.00   Median :88.10   Median :91.60   Median :89.70   Median :86.90   Median :82.70   Median :89.90   Median :89.60   Median :95.7
 Mean   :83.76   Mean   :93.19   Mean   :85.73   Mean   :88.67   Mean   :88.37   Mean   :92.36   Mean   :89.14   Mean   :88.72   Mean   :84.61   Mean   :90.55   Mean   :89.93   Mean   :94.4
 3rd Qu.:86.10   3rd Qu.:95.80   3rd Qu.:88.90   3rd Qu.:92.60   3rd Qu.:90.40   3rd Qu.:95.00   3rd Qu.:90.80   3rd Qu.:93.60   3rd Qu.:88.10   3rd Qu.:91.60   3rd Qu.:93.40   3rd Qu.:97.0
 Max.   :87.40   Max.   :96.50   Max.   :91.20   Max.   :93.50   Max.   :92.50   Max.   :95.70   Max.   :91.30   Max.   :94.90   Max.   :92.40   Max.   :94.30   Max.   :94.00   Max.   :97.5
    Michigan       Minnesota      Mississippi      Missouri         Montana         Nebraska          Nevada       New.Hampshire     New.Jersey      New.Mexico        New.York     North.Carolina
 Min.   :87.60   Min.   :90.8   Min.   :79.2   Min.   :86.30   Min.   :81.10   Min.   :86.80   Min.   :77.40   Min.   :88.50   Min.   :84.20   Min.   :76.30   Min.   :84.00   Min.   :82.10
 1st Qu.:88.60   1st Qu.:91.5   1st Qu.:82.3   1st Qu.:87.00   1st Qu.:82.70   1st Qu.:88.60   1st Qu.:80.40   1st Qu.:89.50   1st Qu.:86.60   1st Qu.:79.40   1st Qu.:86.00   1st Qu.:83.60
 Median :89.70   Median :92.1   Median :83.3   Median :88.30   Median :84.40   Median :89.60   Median :82.80   Median :90.30   Median :87.30   Median :80.30   Median :88.60   Median :84.70
 Mean   :90.72   Mean   :92.9   Mean   :84.3   Mean   :88.68   Mean   :85.66   Mean   :89.94   Mean   :83.14   Mean   :91.16   Mean   :88.21   Mean   :82.62   Mean   :89.16   Mean   :85.76
 3rd Qu.:93.90   3rd Qu.:95.1   3rd Qu.:87.1   3rd Qu.:90.50   3rd Qu.:88.40   3rd Qu.:91.70   3rd Qu.:87.70   3rd Qu.:93.70   3rd Qu.:91.30   3rd Qu.:89.10   3rd Qu.:92.90   3rd Qu.:88.70
 Max.   :95.00   Max.   :95.9   Max.   :88.2   Max.   :91.10   Max.   :91.90   Max.   :92.90   Max.   :88.80   Max.   :94.90   Max.   :92.80   Max.   :90.90   Max.   :94.80   Max.   :89.60
  North.Dakota        Ohio          Oklahoma         Oregon       Pennsylvania    Rhode.Island   South.Carolina   South.Dakota     Tennessee          Texas            Utah          Vermont
 Min.   :87.80   Min.   :87.70   Min.   :80.0   Min.   :82.10   Min.   :89.10   Min.   :87.80   Min.   :82.50   Min.   :86.90   Min.   :84.90   Min.   :74.60   Min.   :82.6   Min.   :88.50
 1st Qu.:89.90   1st Qu.:88.50   1st Qu.:81.3   1st Qu.:83.70   1st Qu.:90.00   1st Qu.:88.90   1st Qu.:83.60   1st Qu.:88.30   1st Qu.:86.10   1st Qu.:76.00   1st Qu.:85.5   1st Qu.:90.80
 Median :90.20   Median :89.30   Median :82.3   Median :85.30   Median :90.30   Median :90.60   Median :86.30   Median :89.10   Median :87.30   Median :77.00   Median :87.2   Median :92.00
 Mean   :90.65   Mean   :90.27   Mean   :83.2   Mean   :87.25   Mean   :91.41   Mean   :91.51   Mean   :86.19   Mean   :89.22   Mean   :87.81   Mean   :78.24   Mean   :87.3   Mean   :92.59
 3rd Qu.:92.10   3rd Qu.:93.40   3rd Qu.:85.8   3rd Qu.:92.80   3rd Qu.:93.60   3rd Qu.:94.30   3rd Qu.:89.00   3rd Qu.:90.20   3rd Qu.:89.70   3rd Qu.:81.60   3rd Qu.:89.5   3rd Qu.:95.40
 Max.   :93.10   Max.   :94.40   Max.   :86.2   Max.   :93.90   Max.   :94.50   Max.   :95.90   Max.   :90.00   Max.   :91.30   Max.   :91.00   Max.   :83.40   Max.   :91.2   Max.   :96.30
    Virginia       Washington     West.Virginia     Wisconsin         Wyoming
 Min.   :85.20   Min.   :84.70   Min.   :83.10   Min.   :89.50   Min.   :83.20
 1st Qu.:87.30   1st Qu.:86.10   1st Qu.:85.40   1st Qu.:90.60   1st Qu.:84.90
 Median :87.70   Median :87.60   Median :86.00   Median :91.20   Median :86.40
 Mean   :88.77   Mean   :88.88   Mean   :88.08   Mean   :92.05   Mean   :86.29
 3rd Qu.:90.90   3rd Qu.:93.40   3rd Qu.:93.30   3rd Qu.:94.30   3rd Qu.:87.70
 Max.   :93.20   Max.   :94.00   Max.   :94.70   Max.   :94.70   Max.   :89.50
```

13. Public Education High School Graduation Rates – Control

Public education high school graduation rate data provide preliminary quality-of-life analysis for a state, and its inclusion helps control for differences in state-to-state migration that may impact tax revenue collection outside of tax policy.

Source(s):

The Department of Education compiles data with the National Center on Education Statistics on the public high school graduation rate for each state and Washington D.C., with data ranging from 2002 to 2020.

Cleaning:

I selected data according to the specific graduation rate figures that I needed, rather than the overall graduation totals to compile my overall table; I was unable to download each file separately, so I went through each year to create one file with all rates per state, per year. Otherwise, the data did not need to be cleaned.

Summary Table of Health Public High School Graduation Rates (13):

```
> summary(final_df)
     Year         Alabama          Alaska          Arizona         Arkansas        California        Colorado       Connecticut    District.of.Columbia    Delaware         Florida          Georgia
 Min.   :2000   Min.   :84.80   Min.   :78.90   Min.   :79.10   Min.   :81.10   Min.   :80.90   Min.   :82.80   Min.   :89.1   Min.   :86.70          Min.   :86.30   Min.   :78.70   Min.   :80.30
 1st Qu.:2005   1st Qu.:86.40   1st Qu.:81.30   1st Qu.:82.50   1st Qu.:82.90   1st Qu.:81.80   1st Qu.:84.10   1st Qu.:90.5   1st Qu.:89.60          1st Qu.:87.90   1st Qu.:79.80   1st Qu.:81.70
 Median :2010   Median :87.50   Median :82.80   Median :83.30   Median :84.00   Median :82.10   Median :85.10   Median :90.9   Median :90.90          Median :93.00   Median :82.50   Median :84.00
 Mean   :2010   Mean   :87.78   Mean   :83.08   Mean   :84.54   Mean   :85.87   Mean   :85.13   Mean   :86.91   Mean   :91.7   Mean   :91.09          Mean   :91.91   Mean   :82.57   Mean   :83.76
 3rd Qu.:2015   3rd Qu.:89.90   3rd Qu.:85.10   3rd Qu.:88.70   3rd Qu.:90.50   3rd Qu.:91.40   3rd Qu.:91.90   3rd Qu.:94.0   3rd Qu.:93.40          3rd Qu.:96.10   3rd Qu.:86.70   3rd Qu.:86.10
 Max.   :2020   Max.   :90.90   Max.   :88.60   Max.   :90.00   Max.   :92.10   Max.   :93.00   Max.   :92.50   Max.   :95.1   Max.   :94.60          Max.   :96.80   Max.   :87.90   Max.   :87.40
     Hawaii          Idaho          Illinois         Indiana           Iowa            Kansas         Kentucky        Louisiana          Maine          Maryland      Massachusetts     Michigan
 Min.   :90.20   Min.   :81.90   Min.   :86.00   Min.   :85.20   Min.   :89.10   Min.   :86.10   Min.   :84.00   Min.   :78.10   Min.   :88.80   Min.   :86.20   Min.   :88.7   Min.   :87.60
 1st Qu.:91.40   1st Qu.:83.80   1st Qu.:86.60   1st Qu.:86.20   1st Qu.:90.80   1st Qu.:87.70   1st Qu.:85.70   1st Qu.:82.20   1st Qu.:89.60   1st Qu.:87.70   1st Qu.:91.6   1st Qu.:88.60
 Median :92.90   Median :85.00   Median :87.00   Median :88.10   Median :91.60   Median :89.70   Median :86.90   Median :82.70   Median :89.90   Median :89.60   Median :95.7   Median :89.70
 Mean   :93.19   Mean   :85.73   Mean   :88.67   Mean   :88.37   Mean   :92.36   Mean   :89.14   Mean   :88.72   Mean   :84.61   Mean   :90.55   Mean   :89.93   Mean   :94.4   Mean   :90.72
 3rd Qu.:95.80   3rd Qu.:88.90   3rd Qu.:92.60   3rd Qu.:90.40   3rd Qu.:95.00   3rd Qu.:90.80   3rd Qu.:93.60   3rd Qu.:88.10   3rd Qu.:91.60   3rd Qu.:93.40   3rd Qu.:97.0   3rd Qu.:93.90
 Max.   :96.50   Max.   :91.20   Max.   :93.50   Max.   :92.50   Max.   :95.70   Max.   :91.30   Max.   :94.90   Max.   :92.40   Max.   :94.30   Max.   :94.00   Max.   :97.5   Max.   :95.00
   Minnesota      Mississippi       Missouri         Montana         Nebraska         Nevada       New.Hampshire      New.Jersey       New.Mexico        New.York     North.Carolina   North.Dakota
 Min.   :90.8   Min.   :79.2   Min.   :86.30   Min.   :81.10   Min.   :86.80   Min.   :77.40   Min.   :88.50   Min.   :84.20   Min.   :76.30   Min.   :84.00   Min.   :82.10   Min.   :87.80
 1st Qu.:91.5   1st Qu.:82.3   1st Qu.:87.00   1st Qu.:82.70   1st Qu.:88.60   1st Qu.:80.40   1st Qu.:89.50   1st Qu.:86.60   1st Qu.:79.40   1st Qu.:86.00   1st Qu.:83.60   1st Qu.:89.90
 Median :92.1   Median :83.3   Median :88.30   Median :84.40   Median :89.60   Median :82.80   Median :90.30   Median :87.30   Median :80.30   Median :88.60   Median :84.70   Median :90.20
 Mean   :92.9   Mean   :84.3   Mean   :88.68   Mean   :85.66   Mean   :89.94   Mean   :83.14   Mean   :91.16   Mean   :88.21   Mean   :82.62   Mean   :89.16   Mean   :85.76   Mean   :90.65
 3rd Qu.:95.1   3rd Qu.:87.1   3rd Qu.:90.50   3rd Qu.:88.40   3rd Qu.:91.70   3rd Qu.:87.70   3rd Qu.:93.70   3rd Qu.:91.30   3rd Qu.:89.10   3rd Qu.:92.90   3rd Qu.:88.70   3rd Qu.:92.10
 Max.   :95.9   Max.   :88.2   Max.   :91.10   Max.   :91.90   Max.   :92.90   Max.   :88.80   Max.   :94.90   Max.   :92.80   Max.   :90.90   Max.   :94.80   Max.   :89.60   Max.   :93.10
      Ohio          Oklahoma         Oregon        Pennsylvania    Rhode.Island   South.Carolina   South.Dakota     Tennessee          Texas            Utah          Vermont         Virginia
 Min.   :87.70   Min.   :80.0   Min.   :82.10   Min.   :89.10   Min.   :87.80   Min.   :82.50   Min.   :86.90   Min.   :84.90   Min.   :74.60   Min.   :82.6   Min.   :88.50   Min.   :85.20
 1st Qu.:88.50   1st Qu.:81.3   1st Qu.:83.70   1st Qu.:90.00   1st Qu.:88.90   1st Qu.:83.60   1st Qu.:88.30   1st Qu.:86.10   1st Qu.:76.00   1st Qu.:85.5   1st Qu.:90.80   1st Qu.:87.30
 Median :89.30   Median :82.3   Median :85.30   Median :90.30   Median :90.60   Median :86.30   Median :89.10   Median :87.30   Median :77.00   Median :87.2   Median :92.00   Median :87.70
 Mean   :90.27   Mean   :83.2   Mean   :87.25   Mean   :91.41   Mean   :91.51   Mean   :86.19   Mean   :89.22   Mean   :87.81   Mean   :78.24   Mean   :87.3   Mean   :92.59   Mean   :88.77
 3rd Qu.:93.40   3rd Qu.:85.8   3rd Qu.:92.80   3rd Qu.:93.60   3rd Qu.:94.30   3rd Qu.:89.00   3rd Qu.:90.20   3rd Qu.:89.70   3rd Qu.:81.60   3rd Qu.:89.5   3rd Qu.:95.40   3rd Qu.:90.90
 Max.   :94.40   Max.   :86.2   Max.   :93.90   Max.   :94.50   Max.   :95.90   Max.   :90.00   Max.   :91.30   Max.   :91.00   Max.   :83.40   Max.   :91.2   Max.   :96.30   Max.   :93.20
   Washington     West.Virginia     Wisconsin         Wyoming
 Min.   :84.70   Min.   :83.10   Min.   :89.50   Min.   :83.20
 1st Qu.:86.10   1st Qu.:85.40   1st Qu.:90.60   1st Qu.:84.90
 Median :87.60   Median :86.00   Median :91.20   Median :86.40
 Mean   :88.88   Mean   :88.08   Mean   :92.05   Mean   :86.29
 3rd Qu.:93.40   3rd Qu.:93.30   3rd Qu.:94.30   3rd Qu.:87.70
 Max.   :94.00   Max.   :94.70   Max.   :94.70   Max.   :89.50
```

Appendix B: All State-Level Taxation System Changes (Number of Brackets, Highest Income Bracket, and Tax Rate High) 2000-2020 and Where Treatment is Set

State	***Type of Personal Income Taxation System***	***Summary identifying changes by year in Number of Brackets (NoB), Highest Income Bracket (HIB), and Tax Rate High (rate)***			***Treatment Year and Trendline Ends***
		NoB	***Rate***	***HIB***	
Alabama	Graduated	No change 2000-2020.	No change 2000-2020.	No change 2000-2020.	N/A
Alaska	None	No change 2000-2020.	No change 2000-2020.	No change 2000-2020.	N/A
Arizona	Graduated	No change 2000-2020.	-0.5% in 2006; -0.04% in 2020.	Originally fixed; gradual annual increases 2006-2020.	2000-2018 (treatment set at 2006); 2019 eliminated for comparison

					state
Arkansas	Graduated	No change 2000-2020.	Brief -0.5% in 2003, before returning to 2002 rate in 2004; -0.1% in 2015; -0.3% in 2020.	Originally fixed; Small, varied, increases (usually annually) 2003-2015. 2015-2019 fixed. 2020 dramatic increase	2005-2019 (treatment set in 2015)
California	Graduated	+3 brackets in 2013.	Impermanent +0.25% 2009-2010; +3% in 2013.	Slight annual increase every year 2000-2012. Significant jump in 2013, then continual trend of slight annual increase through 2020.	2000-2020 (treatment set in 2013) – 2009-2010 change is impermanent and I do not think would have a meaningful impact on trends
Colorado	Flat rate	+0.07% in 2000	N/A	N/A	Cannot measure trends before 2000.
Connecticut*	Graduated	+0.5% in 2004; +1.5% in 2009; +0.2% in 2012; +2.99% in 2016	+1 in 2009; +3 in 2012; +1 in 2016.	Stable 2000-2008; Dramatic increase in 2009, stable through 2011. Dramatic decrease 2012, stable through 2015. Dramatic increase to 2011 levels in 2016, holds	Too much variance in taxation system to establish large enough trendlines

				through 2020	
Delaware*	Graduated	-0.45% in 2001; +1.0% in 2010; -0.2% in 2012; -0.15% in 2014	-1 in 2007; +1 in 2015	Dramatic increase in 2001	Too volatile to establish trendlines
District of Columbia	Graduated	-0.5% in 2001; +0.3% in 2002; -0.6% in 2003; +0.8% in 2004; -0.5% in 2005; -0.3% in 2006; -0.2% in 2008; +0.45% in 2012	+1 in 2012; +1 in 2017; +1 in 2020	Dramatic variance; large increase in 2012 and 2017	2003-2016 (treatment set in 2012 – from a trend of decreasing tax rates to an increase and addition of a bracket) Not a long enough trendline for a 2017 treatment
Florida	None	No change 2000-2020	No change 2000-2020	No change 2000-2020	N/A
Georgia	Graduated	-0.25% in 2019	No change 2000-2020	No change 2000-2020	Not enough data to establish a trendline post 2019
Hawaii	Graduated	-0.25% in 2001; -0.2% in 2002; -0.05% in 2003; +3.75% in 2009; -3.75% in 2016; +0.05% in 2017; +3.70% in 2018	-1 in 2001; +1 in 2004; +3 in 2009; -3 in 2016; +3 in 2018	Slight increase in 2007; Dramatic increase in 2009; Dramatic decrease in 2016; dramatic increase in 2018	2003-2015 (treatment set in 2009) Treatments are too volatile outside of this period to establish accurate trendlines
Idaho	Graduated	-0.4% in 2002; -0.4% in 2013;	-1 in 2013	Gradual annual	2002-2018 (treatment set

		-0.475% in 2019		increase	in 2013)
Illinois	Flat	+2% in 2011; -1.25% in 2015; +1.2% in 2018	N/A	N/A	2001-2014 (treatment set in 2011); truncated at 2001 because of comparison state (not enough prior data to establish trendline for a 2015 treatment)
Indiana	Flat	-0.1% in 2015; -0.07% in 2017	N/A	N/A	Not enough time between treatments to establish a trendline
Iowa	Graduated	-0.45% in 2019	No change 2000-2020	Gradual annual increase	Not enough post-2019 data to establish a trendline
Kansas	Graduated	-1.55% in 2013; -0.1% in 2014; -0.2% in 2015; +1.10% in 2018	-1 in 2013; +1 in 2018	Dramatic decrease in 2013; increase to same level in 2018	2000-2017 (treatment set in 2013); post 2013 are predictable decreases in top rate; post 2018 comparisons difficult to establish trendlines for Kansas and comparison state
Kentucky	Graduated	-1% in 2019	+1 in 2005; -5	Dramatic	2000-2018

	to flat		in 2019	increase in 2005; eliminated in 2019	(treatment set in 2005); not enough post 2019 data to establish a trendline
Louisiana	Graduated	No change 2000-2020	No change 2000-2020	Dramatic decrease in 2004; return to same level in 2010.	1. 2000-2009 (treatment set in 2004) * not enough data to set trendlines, included as example 2. 2004-2020 (treatment set in 2010)
Maine*	Graduated	-0.5% in 2013; -0.05% in 2014; -0.8% in 2016	-1 in 2013; +1 2017; -1 2018	Began gradual annual increase from fixed in 2003; dramatic increase in 2017 before reverting back to similar levels to 2015 in 2018	Very volatile taxation system, too volatile to establish trendlines after initial tax decreases
Maryland*	Graduated	-0.05% in 2001; -0.05% in 2002; +0.75% in 2008; +0.75% in 2009; -0.75% in 2011; +0.25% in 2013	+3 in 2008; +1 in 2009; -1 in 2011; +1 in 2013	Extreme increase in 2008; extreme increase in 2009; decrease to 2008 levels in 2011; dramatic decrease in 2014;	Very volatile taxation system, too volatile to establish trendlines
Massachusetts *	Flat	-0.35% in 2001; -0.3% in 2002; -0.05% yearly 2012-	N/A	N/A	Too volatile to establish trendlines

		2016; -0.05% in 2019			
Michigan	Flat	-0.2% in 2001; -0.1% in 2002; -0.1% in 2003; -0.1% in 2005; +0.45% in 2008; -0.1% in 2013	N/A	N/A	2000-2012 (treatment set in 2008); small changes throughout early 2000s were predictable
Minnesota	Graduated	-0.15% in 2001; +2% in 2014	+1 in 2014	Gradual annual increase; dramatic increase in 2014, continue gradual annual increase	2001-2020 (treatment set in 2014)
Mississippi	Graduated	No change 2000-2020.	No change 2000-2020.	No change 2000-2020.	N/A
Missouri	Graduated	-0.1% in 2018; -0.5% in 2019	-1 in 2019	Slight increase from fixed in 2018; decrease in 2019	Policy change too late to collect fulsome trendline data
Montana	Graduated	-4.1% in 2005	-3 in 2005	Gradual annual increase 2000-2005; dramatic decrease in 2005, then gradual increase usually every year	2000-2018 (treatment set in 2005) Truncated at 2018 because of its comparison state
Nebraska	Graduated	+0.16% in 2003	No change 2000-2020.	Slight increase in 2006; began gradual annual increase in	1. 2003-2013 (treatment set in 2006) 2. 2006-2017

				2014	(treatment set at 2014) Truncating at 2017 because of comparison state
Nevada	None	No change 2000-2020	No change 2000-2020	No change 2000-2020	N/A
New Hampshire	Flat, dividends only	No change 2000-2020	N/A	N/A	N/A
New Jersey*	Graduated	+2.6% in 2005; +1.78% in 2009; -1.78% in 2011; +1.78% in 2019	+2 in 2009; -2 in 2011;	Dramatic increase in 2005; dramatic increase in 2009; decrease to 2008 levels in 2011; dramatic increase in 2019	Treatments too volatile to establish sufficient trendlines
New Mexico*	Graduated	-1.4% in 2004; -1.5% in 2005; -0.4% in 2009	-2 in 2004; -1 in 2005	Dramatic decrease in 2004; dramatic decrease in 2005	Treatments too volatile to establish sufficient trendlines
New York	Graduated	+0.85% in 2004; -0.85% in 2007; +2.12% in 2009; -0.15% in 2012	+2 in 2004; -2 in 2007; + 2 in 2009; +1 in 2012	Dramatic increase in 2004; decrease to 2003 levels in 2007; increase to 2006 levels in 2009; dramatic increase in 2012, which then started a gradual annual	2009-2020 (treatment set at 2012) (previous changes are too volatile)

				increase	
North Carolina	Graduated to flat	+0.5% in 2002; -0.25% in 2006; -0.25% in 2008; -1.95% in 2014; -0.05% in 2015; -0.25% in 2017; -0.25% in 2019	+1 in 2002; +1 in 2005; -1 in 2006; -1 in 2008; -2 in 2014 (to fixed)	Dramatic increase in 2002; significant increase in 2005; return to 2004 levels in 2006; dramatic decrease in 2008; N/A starting 2014	2009-2020 (treatment set at 2014 for the known passage of a law that sought to eliminate graduated in favor of fixed)
North Dakota*	Graduated	-6.46% in 2002; -0.68% in 2009; -0.87% in 2012; -0.77% in 2014; -0.32 in 2016;	-3 in 2002	Dramatic increase in 2002, then gradual annual increase until 2020.	High ‘volatility.’ Semiregular tax cuts since 2002 make it difficult to set a specific treatment; not using this data
Ohio*	Graduated	-0.248% in 2001; + 0.52% in 2002; -0.315% in 2006; -0.315% in 2007; -0.315% in 2008; -0.315% in 2011; -0.533% in 2014; -0.059% in 2015; -0.336% in 2016; -0.2% in 2020	-1 in 2018; -2 in 2020	Generally slight increases every other year 2011-2020.	High ‘volatility.’ Regular tax cuts since 2006 make it difficult to set a specific treatment; not using this data
Oklahoma*	Graduated	-0.1% in 2002; +0.35% in 2003; -0.250% in 2004; -0.5%	-1 in 2007; -1 in 2016	Slight increase in 2006 before returning to 2005 levels in	High ‘volatility’, many slight decreases in

		in 2005; -0.6% in 2007; -0.15 in 2008; -0.25% in 2012; -0.25 in 2016		2007; Decrease in 2008 and 2016	tax rate; am not including this data
Oregon	Graduated	+2% in 2009; -1.1% in 2012	+2 in 2009; -1 in 2012	Gradual annual increase 2000-2008; dramatic increase in 2009; dramatic decrease in 2012	2000-2011 (treatment set at 2009); Not enough data to establish meaningful trendlines of 2012 treatment
Pennsylvania	Flat	+0.27% in 2004	N/A	N/A	2001-2020 (treatment set at 2004) Truncated at 2001 for comparison state
Rhode Island	Graduated	-0.198% in 2002; -3.91% in 2011	-2 in 2011	Gradual annual increase 2000-2011; dramatic decrease then gradual annual increase 2011-2020	2002-2018 (treatment set at 2011); truncated at 2018 for comparison state
South Carolina	Graduated	No change 2000-2020	No change 2000-2020	Gradual annual increase 2000-2020	N/A
South Dakota	None	No change 2000-2020	No change 2000-2020	No change 2000-2020	N/A
Tennessee	Flat (only on capital gains)	-3% in 2018; -1% in 2019; -1% in 2020	N/A	N/A	Part of elimination altogether to

					no tax in 2021; am not including this since I cannot observe post-change trends.
Texas	None	No change 2000-2020	No change 2000-2020	No change 2000-2020	N/A
Utah	Graduated to Flat	-0.02% in 2007; -1.98% in 2008; -0.05% in 2019	-5 in 2008	Gradual annual increase 2000-2008; N/A 2009-2020	2000-2018 (treatment set at 2008); 2007-2008 treatment considered as one overall effect
Vermont	Graduated	-0.1% in 2009; -0.45% in 2010; -0.2% in 2019	-1 in 2020	Gradual annual increase 2000-2018; dramatic decrease in 2019 then gradual annual increase in 2020	2000-2018 (treatment set at 2009); 2009/2010 treatment considered as one
Virginia	Graduated	No change 2000-2020	No change 2000-2020	No change 2000-2020	N/A
Washington	None	No change 2000-2020	No change 2000-2020	No change 2000-2020	N/A
West Virginia	Graduated	No change 2000-2020	No change 2000-2020	No change 2000-2020	N/A
Wisconsin	Graduated	-0.02% in 2001; +1% in 2009; -0.1% in 2014	+1 in 2001; +1 in 2009; -1 in 2014	Dramatic increase in 2001 followed by gradual annual increase. Dramatic	2001-2013 (treatment set in 2009). Not enough data to establish trendlines for 2014

				increase in 2009, followed by gradual annual increase. Slight decrease in 2014, followed by gradual annual increase	treatment
Wyoming	None	No change 2000-2020	No change 2000-2020	No change 2000-2020	N/A

If not bolded but has a State taxation system contains changes in this time period, but the system is too volatile to conduct a DiD analysis on it; there are too many changes in the system to establish trendlines.

Bolded and italicized states indicate that they have personal income tax changes that were subject to my DiD analysis.

Appendix C: Matching Treated Units with Control Units for DiD Analysis

The following chart details reasoning behind each matched treated unit (a taxation change in a specific state) and corresponding control unit (a state with a similar taxation system and did not experience a taxation change in the same time period).

The following units represent control unit matching options for flat rate states: Colorado; New Hampshire (dividends only); Tennessee (capital gains only, through 2017); Indiana (through 2014).

The following units represent matching control unit options for marginal rate states: Alabama; Georgia (through 2018); Iowa* (through 2018); Mississippi; Missouri (through 2017); South Carolina*; Virginia; West Virginia.

*These states marked as controls have fixed annual changes to the highest income bracket, adjusting slightly for inflation every year. I do not consider these to be meaningful taxation system changes and regard these units as controls as I do states which do not annually adjust their highest income bracket. However, it is a factor I considered when matching units.

Treated Unit	***Control Unit***	***Type of Personal Income Taxation System***	***Time***	***Treat-ment***	***Match Reasoning*** *(compared against the other options for controls)*
Arizona	Georgia	Graduated	2000-2018	2006	Political leanings; demographic splits; manufacturing and engineering industries; regional importance
Arkansas	Alabama	Graduated	2005-2019	2015	Geographic proximity; political leanings; demographic splits; main contributors to food processing industries
California	Virginia	Graduated	2000-2020	2013	Coastal proximity; political leanings and demographic breakdowns (best option); diverse array of industries, with technology and agricultural sectors holding considerable weight
District of Columbia	Virginia	Graduated	2003-2016	2012	Geographic proximity and political leanings; demographic breakdown
Hawaii	South Carolina	Graduated	2003-2015	2009	Similar climate and have significant tourism industries (some manufacturing in both as well)
Idaho	Iowa	Graduated	2002-2018	2013	Similar demographic breakdown and political leanings; main

					industries are agriculture and food processing
Illinois	Colorado	Flat	2001-2014	2011	Colorado is the only control unit with the same sort of taxation system (including the income type); have some similarities of urban/rural divide and political leanings.
Kansas	Missouri	Graduated	2000-2017	2013	Geographic proximity; large manufacturing industries; similar political leanings and demographic breakdown
Kentucky	Mississippi	Graduated to flat	2000-2018	2005	Geographic proximity; demographic similarities
Louisiana (Treatment 1)	Mississippi	Graduated	2000-2009	2004	Geographic proximity; similar political leaning, demographic breakdowns, and urban/rural divide
Louisiana (Treatment 2)	Mississippi	Graduated	2004-2020	2010	See above. – Example of non-example
Michigan	Colorado	Flat	2000-2012	2008	Colorado is the only control unit with the same sort of taxation system (including the income type); have some similarities of urban/rural divide and political leanings.
Minnesota	Virginia	Graduated	2001-2020	2014	Main industries overlap (technology and agriculture); similar political leanings and demographic breakdown.
Montana	Iowa	Graduated	2000-2018	2005	Geographic proximity; similar main industry output of agriculture; similar political leanings and demographic breakdown; similar urban/rural divide
Nebraska (Treatment 1)	Missouri	Graduated	2003-2013	2006	Geographic proximity; similar main industries (agriculture and

					manufacturing); similar political leanings and demographic breakdown
Nebraska (Treatment 2)	Missouri	Graduated	2006-2017	2014	See above.
New York	Virginia	Graduated	2009-2020	2012	Geographic proximity; similar demographic breakdown and financial services output
North Carolina	Virginia	Graduated to fixed	2009-2020	2014	Geographic proximity, similar political leanings and demographic breakdown; similar agricultural industry output
Oregon	Iowa	Graduated	2000-2011	2009	Geographic proximity; some agricultural industry output in both; similar demographic breakdown
Pennsylvania	Colorado	Flat	2001-2020	2004	Colorado is the only control unit with the same sort of taxation system (including the income type); have some similarities of urban/rural divide and political leanings.
Rhode Island	Iowa	Graduated	2002-2018	2011	Similar lack of large urban center and general size; similar demographic breakdown
Utah	Colorado	Graduated to Flat	2000-2018	2008	Geographic proximity; similar urban/rural divide and demographic breakdown; main industries are manufacturing and energy/natural resources
Vermont	Iowa	Graduated	2000-2018	2009	Similar lack of urban center and demographic breakdown; main manufacturing industries
Wisconsin	Iowa	Graduated	2001-2013	2009	Geographic proximity and share main manufacturing and geographic industries; similar demographic breakdown and

					political leanings.

Appendix D: Difference-in-Differences Results

<table>
<tr><th>Studied Treatment</th><th>Modeled Dependent Variable</th><th>Regression Results</th></tr>
<tr><td rowspan="2">Arizona 2006 slight rate decrease compared against Georgia 2000-2018</td><td>PIT Revenue</td><td><pre>
Twoways effects Within Model

Call:
plm(formula = PIT ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_ArizonaComp, effect = "twoway")

Balanced Panel: n = 2, T = 19, N = 38

Residuals:
       Min.   1st Qu.   Median   3rd Qu.   Max.
-1.4087e+05 -4.1748e+04 7.2760e-12 4.1748e+04 1.4087e+05

Coefficients:
                         Estimate Std. Error t-value Pr(>|t|)
DID   -6.9461e+05 5.1165e+05 -1.3576 0.207651
GDP   3.9463e+01 8.7184e+00 4.5264 0.001434 **
Population   3.2833e+00 2.2889e+00 1.4344 0.185271
HealthCoverage   1.6012e+05 8.0909e+04 1.9790 0.079188 .
CIT   -1.1333e-01 9.1091e-01 -0.1244 0.903719
pcPersonalExpenditure -1.7205e+02 3.7984e+02 -0.4530 0.661303
pcInc   -2.2765e+02 2.5458e+02 -0.8942 0.394481
unemp   -4.5647e+05 1.3639e+05 -3.3469 0.008566 **
gradrate   -1.0727e+04 1.1839e+04 -0.9061 0.388482

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares: 6.8288e+12
Residual Sum of Squares: 1.696e+11
R-Squared: 0.97516
Adj. R-Squared: 0.8979
F-statistic: 39.265 on 9 and 9 DF, p-value: 3.6954e-06
</pre></td></tr>
<tr><td>Inflows</td><td><pre>
Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_ArizonaComp, effect = "twoway")

Balanced Panel: n = 2, T = 19, N = 38

Residuals:
       Min.   1st Qu.   Median   3rd Qu.   Max.
-1.8467e+03 -5.5540e+02 1.4211e-12 5.5540e+02 1.8467e+03

Coefficients:
                         Estimate Std. Error t-value Pr(>|t|)
DID   -1.6731e+04 6.3383e+03 -2.6397 0.0269251 *
GDP   -2.8926e-01 1.0800e-01 -2.6782 0.0252798 *
Population   7.9069e-02 2.8355e-02 2.7885 0.0211056 *
HealthCoverage   5.2564e+03 1.0023e+03 5.2443 0.0005317 ***
CIT   -9.6068e-04 1.1284e-02 -0.0851 0.9340191
pcPersonalExpenditure 2.4337e+00 4.7055e+00 0.5172 0.6174779
pcInc   9.7627e+00 3.1537e+00 3.0956 0.0128130 *
unemp   7.9529e+03 1.6896e+03 4.7071 0.0011091 **
gradrate   5.9651e+02 1.4666e+02 4.0674 0.0028105 **

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares: 886140000
Residual Sum of Squares: 26027000
R-Squared: 0.97063
Adj. R-Squared: 0.87925
F-statistic: 33.047 on 9 and 9 DF, p-value: 7.7577e-06
</pre></td></tr>
</table>

<table>
<tr><td rowspan="2"></td><td>Outflows</td><td>Twoways effects Within Model

Call:
plm(formula = Outflow ~ Time + Treatment + DID + GDP + Population +
HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
gradrate, data = df_ArizonaComp, effect = "twoway")

Balanced Panel: n = 2, T = 19, N = 38

Residuals:
Min. 1st Qu. Median 3rd Qu. Max.
-4.0406e+03 -1.5551e+03 -4.2064e-12 1.5551e+03 4.0406e+03

Coefficients:
Estimate Std. Error t-value Pr(>|t|)
DID -1.6356e+04 1.3566e+04 -1.2057 0.25869
GDP 4.0064e-01 2.3115e-01 1.7332 0.11710
Population 2.9237e-02 6.0688e-02 0.4818 0.64147
HealthCoverage 4.6876e+03 2.1452e+03 2.1852 0.05669 .
CIT -5.2231e-02 2.4151e-02 -2.1627 0.05881 .
pcPersonalExpenditure 1.4533e+01 1.0071e+01 1.4431 0.18289
pcInc -3.9108e+00 6.7498e+00 -0.5794 0.57654
unemp 1.7928e+03 3.6161e+03 0.4958 0.63193
gradrate -2.6180e+02 3.1388e+02 -0.8341 0.42583

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares: 558350000
Residual Sum of Squares: 119220000
R-Squared: 0.78648
Adj. R-Squared: 0.12218
F-statistic: 3.68332 on 9 and 9 DF, p-value: 0.032706</td></tr>
<tr><td colspan="2">DiD estimator has a statistically significant negative impact on inflows</td></tr>
<tr><td>Arkansas 2015 slight rate decrease compared against Alabama 2005-2019</td><td>PIT Revenue</td><td>Twoways effects Within Model

Call:
plm(formula = PIT ~ Time + Treatment + DID + GDP + Population +
HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
gradrate, data = df_ArkansasComp, effect = "twoways")

Balanced Panel: n = 2, T = 15, N = 30

Residuals:
1 2 3 4 5 6 7 8 9
10 11 12 13 14
-11915.3 2862.5 13740.0 8356.0 -28080.2 22619.5 2400.2 2019.0 -28250.6
16249.1 -6207.7 25961.3 -9118.3 -9040.0
15 16 17 18 19 20 21 22 23
24 25 26 27 28
-1595.4 11915.3 -2862.5 -13740.0 -8356.0 28080.2 -22619.5 -2400.2 -2019.0
28250.6 -16249.1 6207.7 -25961.3 9118.3
29 30
9040.0 1595.4

Coefficients:
Estimate Std. Error t-value Pr(>|t|)
DID -3.2563e+05 1.0870e+05 -2.9957 0.03025 *
GDP 3.5504e+01 1.5522e+01 2.2874 0.07088 .
Population 1.2048e+00 2.1812e+00 0.5523 0.60450
HealthCoverage -2.5478e+04 2.0100e+04 -1.2676 0.26077
CIT 1.3872e-01 1.2086e-01 1.1478 0.30299
pcPersonalExpenditure 5.6331e+02 1.8147e+02 3.1041 0.02673 *
pcInc -1.3298e+02 5.8228e+01 -2.2839 0.07119 .
unemp -5.3084e+02 3.0472e+04 -0.0174 0.98677
gradrate -1.1128e+04 9.0335e+03 -1.2318 0.27279

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares: 2.9705e+11
Residual Sum of Squares: 7321600000
R-Squared: 0.97535
Adj. R-Squared: 0.85704
F-statistic: 21.9842 on 9 and 5 DF, p-value: 0.0016696</td></tr>
</table>

Inflows

```
Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_ArkansasComp, effect = "twoways")

Balanced Panel: n = 2, T = 15, N = 30

Residuals:
         1          2          3          4          5          6          7
8          9         10         11         12
  387.1874  -601.3847   154.2408   -12.9319  -764.4959   193.8653  1001.0147
2.3432  -416.4100    56.5711   358.4799   669.5794
        13         14         15         16         17         18         19
20         21         22         23         24
-1737.6265   470.1804   239.3868  -387.1874   601.3847  -154.2408    12.9319
764.4959  -193.8653 -1001.0147    -2.3432   416.4100
        25         26         27         28         29         30
  -56.5711  -358.4799  -669.5794  1737.6265  -470.1804  -239.3868

Coefficients:
                         Estimate  Std. Error t-value Pr(>|t|)
DID                   -2.1468e+03  4.4772e+03 -0.4795   0.6518
GDP                   -7.7051e-01  6.3932e-01 -1.2052   0.2821
Population            -6.8684e-03  8.9844e-02 -0.0764   0.9420
HealthCoverage        -3.2131e+01  8.2789e+02 -0.0388   0.9705
CIT                   -7.1563e-04  4.9782e-03 -0.1438   0.8913
pcPersonalExpenditure -8.0297e-01  7.4748e+00 -0.1074   0.9186
pcInc                  1.4961e+00  2.3984e+00  0.6238   0.5601
unemp                 -4.7653e+02  1.2551e+03 -0.3797   0.7198
gradrate               2.4528e+02  3.7208e+02  0.6592   0.5389

Total Sum of Squares:    37013000
Residual Sum of Squares: 12422000
R-Squared:      0.6644
Adj. R-Squared: -0.94649
F-statistic: 1.09985 on 9 and 5 DF, p-value: 0.48433
```

Outflows

```
Twoways effects Within Model

Call:
plm(formula = Outflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_ArkansasComp, effect = "twoways")

Balanced Panel: n = 2, T = 15, N = 30

Residuals:
       1        2        3        4        5        6        7        8        9
10       11       12       13       14
 -33.737 -143.264  224.368  110.987 -430.461  293.501  181.747 -244.783  -13.587
55.229  -17.272  526.649 -648.736  321.568
      15       16       17       18       19       20       21       22       23
24       25       26       27       28
-182.210   33.737  143.264 -224.368 -110.987  430.461 -293.501 -181.747  244.783
13.587  -55.229   17.272 -526.649  648.736
      29       30
-321.568  182.210

Coefficients:
                        Estimate  Std. Error t-value Pr(>|t|)
DID                   -6.3238e+03  2.0381e+03 -3.1028  0.02677 *
GDP                   -8.2163e-01  2.9104e-01 -2.8231  0.03697 *
Population             5.3344e-02  4.0899e-02  1.3043  0.24895
HealthCoverage        -1.0022e+02  3.7688e+02 -0.2659  0.80091
CIT                    8.2454e-04  2.2662e-03  0.3638  0.73085
pcPersonalExpenditure  8.2419e+00  3.4027e+00  2.4222  0.05996 .
pcInc                 -2.2967e-01  1.0918e+00 -0.2104  0.84169
unemp                 -1.1990e+02  5.7136e+02 -0.2099  0.84206
gradrate              -1.4823e+01  1.6938e+02 -0.0875  0.93366
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    34497000
Residual Sum of Squares: 2574100
R-Squared:      0.92538
Adj. R-Squared: 0.5672
F-statistic: 6.88958 on 9 and 5 DF, p-value: 0.023417
```

DiD estimator has a statistically significant negative impact on PIT revenue and outflows

<table>
<tr>
<td rowspan="2">California 2013 increased all IVs compared against Virginia 2000-2020</td>
<td>PIT Revenue</td>
<td><pre>
Twoways effects Within Model

Call:
plm(formula = PIT ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_CaliComp, effect = "twoways")

Balanced Panel: n = 2, T = 21, N = 42

Residuals:
    Min. 1st Qu.   Median   Mean 3rd Qu.   Max.
-1806198 -586048   0   0   586048 1806198

Coefficients:
                         Estimate Std. Error t-value Pr(>|t|)
DID   9.6620e+06 4.1857e+06 2.3084 0.04142 *
GDP   -5.2444e+01 3.5864e+01 -1.4623 0.17163
Population   1.2731e+01 4.7510e+00 2.6797 0.02142 *
HealthCoverage   -1.5755e+06 5.6938e+05 -2.7671 0.01832 *
CIT   3.4543e+00 1.1133e+00 3.1029 0.01005 *
pcPersonalExpenditure 3.2131e+03 2.2279e+03 1.4422 0.17711
pcInc   2.3170e+03 1.5822e+03 1.4644 0.17106
unemp   -2.1308e+06 9.9823e+05 -2.1346 0.05613 .
gradrate   1.2776e+06 6.0822e+05 2.1006 0.05954 .

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares: 3.2946e+15
Residual Sum of Squares: 3.7615e+13
R-Squared: 0.98858
Adj. R-Squared: 0.95745
F-statistic: 105.829 on 9 and 11 DF, p-value: 2.1713e-09
</pre></td>
</tr>
<tr>
<td>Inflows</td>
<td><pre>
Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_CaliComp, effect = "twoways")

Balanced Panel: n = 2, T = 21, N = 42

Residuals:
    Min. 1st Qu.   Median 3rd Qu.   Max.
-11230.2 -3519.2   0.0   3519.2 11230.2

Coefficients:
                         Estimate Std. Error t-value Pr(>|t|)
DID   9.8112e+03 2.3011e+04 0.4264   0.6781
GDP   -1.3701e-01 1.9716e-01 -0.6949   0.5015
Population   3.2706e-02 2.6119e-02 1.2522   0.2365
HealthCoverage   -5.0956e+03 3.1302e+03 -1.6279   0.1318
CIT   -3.5775e-03 6.1203e-03 -0.5845   0.5707
pcPersonalExpenditure 2.6099e+01 1.2248e+01 2.1308   0.0565 .
pcInc   -6.4639e+00 8.6983e+00 -0.7431   0.4730
unemp   -4.6719e+03 5.4879e+03 -0.8513   0.4127
gradrate   -6.4248e+02 3.3438e+03 -0.1921   0.8511

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares: 4231400000
Residual Sum of Squares: 1136900000
R-Squared: 0.73133
Adj. R-Squared: -0.0014108
F-statistic: 3.32692 on 9 and 11 DF, p-value: 0.032186
</pre></td>
</tr>
</table>

Outflows

```
Twoways effects Within Model

Call:
plm(formula = Outflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_CaliComp, effect = "twoways")

Balanced Panel: n = 2, T = 21, N = 42

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-1.5727e+04 -3.3485e+03 -7.9581e-13  3.3485e+03  1.5727e+04

Coefficients:
                        Estimate  Std. Error t-value Pr(>|t|)
DID                  -4.6870e+04  2.6123e+04 -1.7942 0.100288
GDP                   8.3720e-01  2.2383e-01  3.7403 0.003264 **
Population           -8.1025e-02  2.9652e-02 -2.7326 0.019489 *
HealthCoverage       -3.4475e+03  3.5536e+03 -0.9702 0.352819
CIT                  -1.9516e-02  6.9481e-03 -2.8088 0.017006 *
pcPersonalExpenditure -2.1123e+01  1.3905e+01 -1.5191 0.156946
pcInc                -9.3665e+00  9.8748e+00 -0.9485 0.363236
unemp                -9.6499e+03  6.2301e+03 -1.5489 0.149677
gradrate             -6.0271e+03  3.7960e+03 -1.5877 0.140656
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    1.1814e+10
Residual Sum of Squares: 1465200000
R-Squared:      0.87598
Adj. R-Squared: 0.53775
F-statistic: 8.63301 on 9 and 11 DF, p-value: 0.00076065
```

DiD estimator has a statistically significant positive impact on PIT revenue

District of Columbia 2012 increase in all IVs compared against Virginia 2003-2016

PIT Revenue

```
Twoways effects Within Model

Call:
plm(formula = PIT ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_DCComp, effect = "twoway")

Balanced Panel: n = 2, T = 14, N = 28

Residuals:
      1       2       3       4       5       6       7       8       9
10      11      12      13      14      15      16
 -54211   43010   10600   24144   94481   49460 -115909   42567  -94142
-21067  100069   20685  -41182  -58505   54211  -43010
     17      18      19      20      21      22      23      24      25
26      27      28
 -10600  -24144  -94481  -49460  115909  -42567   94142   21067 -100069
-20685   41182   58505

Coefficients:
                        Estimate  Std. Error t-value Pr(>|t|)
DID                  -8.1295e+05  2.1551e+05 -3.7722  0.01957 *
GDP                   9.6847e+00  3.8703e+01  0.2502  0.81473
Population           -5.3438e+00  7.0494e+00 -0.7581  0.49063
HealthCoverage       -2.9562e+05  1.7560e+05 -1.6835  0.16757
CIT                   4.3055e+00  1.6918e+00  2.5449  0.06365 .
pcPersonalExpenditure -7.9087e+00  1.8506e+02 -0.0427  0.96796
pcInc                -2.3793e+02  1.6628e+02 -1.4309  0.22570
unemp                -7.5591e+05  2.3298e+05 -3.2445  0.03154 *
gradrate             -1.0869e+04  4.0326e+04 -0.2695  0.80085
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    2.6234e+12
Residual Sum of Squares: 1.1394e+11
R-Squared:      0.95657
Adj. R-Squared: 0.70683
F-statistic: 9.78861 on 9 and 4 DF, p-value: 0.021073
```

<table>
<tr>
<td rowspan="3"></td>
<td>Inflows</td>
<td><pre>
Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_DCComp, effect = "twoway")

Balanced Panel: n = 2, T = 14, N = 28

Residuals:
       1   2   3   4   5   6   7   8   9   10
11   12   13   14
 1886.46 -216.45 1268.12 -2604.46 -5433.21 -1012.80 -311.44 3954.39 2469.38 -2527.73
-2772.41   179.71 6699.67 -1579.25
      15   16   17   18   19   20   21   22   23   24
25   26   27   28
-1886.46   216.45 -1268.12 2604.46 5433.21 1012.80   311.44 -3954.39 -2469.38 2527.73
2772.41 -179.71 -6699.67 1579.25

Coefficients:
                         Estimate Std. Error t-value Pr(>|t|)
DID   -8.1661e+01 1.0130e+04 -0.0081   0.9940
GDP   1.4845e+00 1.8191e+00 0.8160   0.4603
Population   -1.6685e-01 3.3134e-01 -0.5036   0.6410
HealthCoverage   8.2377e+03 8.2537e+03 0.9981   0.3747
CIT   4.2783e-02 7.9518e-02 0.5380   0.6191
pcPersonalExpenditure 6.6394e+00 8.6981e+00 0.7633   0.4878
pcInc   -1.9223e+00 7.8157e+00 -0.2460   0.8178
unemp   1.3860e+03 1.0951e+04 0.1266   0.9054
gradrate   1.6412e+03 1.8954e+03 0.8659   0.4354

Total Sum of Squares: 505170000
Residual Sum of Squares: 251720000
R-Squared: 0.50171
Adj. R-Squared: -2.3635
F-statistic: 0.447491 on 9 and 4 DF, p-value: 0.85449
</pre></td>
</tr>
<tr>
<td>Outflows</td>
<td><pre>
Twoways effects Within Model

Call:
plm(formula = Outflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_DCComp, effect = "twoway")

Balanced Panel: n = 2, T = 14, N = 28

Residuals:
        1   2   3   4   5   6   7   8
9   10   11   12   13
 2201.429   37.489 1636.069 -4260.022 -6153.236 -1101.850   263.589 4776.252
2600.280 -3634.094 -1495.909 -1288.221 8209.445
       14   15   16   17   18   19   20   21
22   23   24   25   26
-1791.220 -2201.429   -37.489 -1636.069 4260.022 6153.236 1101.850 -263.589
-4776.252 -2600.280 3634.094 1495.909 1288.221
       27   28
-8209.445 1791.220

Coefficients:
                         Estimate Std. Error t-value Pr(>|t|)
DID   -5.5071e+02 1.2184e+04 -0.0452   0.9661
GDP   1.3198e+00 2.1881e+00 0.6032   0.5789
Population   -1.6081e-02 3.9855e-01 -0.0403   0.9697
HealthCoverage   1.0463e+04 9.9279e+03 1.0539   0.3514
CIT   3.8251e-02 9.5647e-02 0.3999   0.7097
pcPersonalExpenditure 7.9236e-01 1.0462e+01 0.0757   0.9433
pcInc   -6.0629e+00 9.4010e+00 -0.6449   0.5541
unemp   5.5213e+03 1.3172e+04 0.4192   0.6966
gradrate   2.1828e+03 2.2799e+03 0.9574   0.3926

Total Sum of Squares: 561440000
Residual Sum of Squares: 364200000
R-Squared: 0.35131
Adj. R-Squared: -3.3786
F-statistic: 0.2407 on 9 and 4 DF, p-value: 0.96462
</pre></td>
</tr>
<tr>
<td colspan="2">DiD estimator has a statistically significant negative impact on PIT revenue</td>
</tr>
</table>

<table>
<tr>
<td rowspan="2">Hawaii 2009 with steadily increasing all IVs compared against South Carolina 2003-2015</td>
<td>PIT Revenue</td>
<td>Twoways effects Within Model

Call:
plm(formula = PIT ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_HIComp, effect = "twoway")

Balanced Panel: n = 2, T = 13, N = 26

Residuals:
         1   2   3   4   5   6   7   8
9   10
 -18988.98   23638.53   4191.15   175.09   14177.65 -23193.44   15846.90   54369.16
-103691.62 -12231.20
        11   12   13   14   15   16   17   18
19   20
  19094.30   21188.82   5423.65   18988.98 -23638.53   -4191.15   -175.09 -14177.65
23193.44 -15846.90
        21   22   23   24   25   26
 -54369.16 103691.62   12231.20 -19094.30 -21188.82   -5423.65

Coefficients:
                        Estimate Std. Error t-value Pr(>|t|)
DID   -3.1208e+05 8.3494e+05 -0.3738   0.7334
GDP   -1.5786e+01 4.3555e+01 -0.3624   0.7411
Population   7.4353e-01 3.4156e+00 0.2177   0.8416
HealthCoverage   -5.9719e+04 5.7671e+04 -1.0355   0.3766
CIT   2.1251e+00 1.7112e+00 1.2418   0.3025
pcPersonalExpenditure 4.2527e+02 6.1374e+02 0.6929   0.5382
pcInc   -1.4204e+02 1.7636e+02 -0.8054   0.4795
unemp   -3.0933e+05 2.3481e+05 -1.3174   0.2793
gradrate   -4.6957e+04 1.1348e+05 -0.4138   0.7068

Total Sum of Squares: 3.2483e+11
Residual Sum of Squares: 3.3255e+10
R-Squared: 0.89762
Adj. R-Squared: 0.14687
F-statistic: 2.92265 on 9 and 3 DF, p-value: 0.20436</td>
</tr>
<tr>
<td>Inflows</td>
<td>Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_HIComp, effect = "twoway")

Balanced Panel: n = 2, T = 13, N = 26

Residuals:
       1   2   3   4   5   6   7   8
9   10   11   12   13
  279.56 -326.09   697.37 -778.83 -270.51   398.49   423.66 -625.24
211.08 1059.73 -1288.79 -590.49   810.06
      14   15   16   17   18   19   20   21
22   23   24   25   26
 -279.56   326.09 -697.37   778.83   270.51 -398.49 -423.66   625.24
-211.08 -1059.73 1288.79   590.49 -810.06

Coefficients:
                        Estimate Std. Error t-value Pr(>|t|)
DID   9.8081e+03 1.5745e+04 0.6229 0.57748
GDP   -1.4712e-01 8.2135e-01 -0.1791 0.86926
Population   -3.1956e-02 6.4412e-02 -0.4961 0.65388
HealthCoverage   -2.7822e+03 1.0876e+03 -2.5582 0.08334 .
CIT   -1.1778e-02 3.2271e-02 -0.3650 0.73935
pcPersonalExpenditure -2.0090e+01 1.1574e+01 -1.7358 0.18100
pcInc   5.0654e+00 3.3259e+00 1.5230 0.22513
unemp   -4.5696e+03 4.4280e+03 -1.0320 0.37799
gradrate   1.1333e+03 2.1400e+03 0.5296 0.63310

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares: 192840000
Residual Sum of Squares: 11826000
R-Squared: 0.93867
Adj. R-Squared: 0.48893
F-statistic: 5.10192 on 9 and 3 DF, p-value: 0.1035</td>
</tr>
</table>

<table>
<tr>
<td rowspan="2"></td>
<td>Outflows</td>
<td>

```
Twoways effects Within Model

Call:
plm(formula = Outflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_HIComp, effect = "twoway")

Balanced Panel: n = 2, T = 13, N = 26

Residuals:
       1        2        3        4        5        6        7        8
9       10       11       12       13
-157.567  309.904  197.532 -348.495   88.809  -90.183  405.643  224.998
-979.328  475.837 -546.064  -22.563  441.477
      14       15       16       17       18       19       20       21
22       23       24       25       26
 157.567 -309.904 -197.532  348.495  -88.809   90.183 -405.643 -224.998
979.328 -475.837  546.064   22.563 -441.477

Coefficients:
                         Estimate  Std. Error t-value Pr(>|t|)
DID                    1.0358e+04  9.5857e+03  1.0806   0.3590
GDP                   -7.4880e-01  5.0004e-01 -1.4975   0.2312
Population             1.7098e-02  3.9214e-02  0.4360   0.6923
HealthCoverage        -2.1071e+03  6.6210e+02 -3.1825   0.0500 *
CIT                   -3.0464e-02  1.9646e-02 -1.5506   0.2188
pcPersonalExpenditure -1.1142e+01  7.0461e+00 -1.5814   0.2119
pcInc                  7.1580e+00  2.0248e+00  3.5352   0.0385 *
unemp                 -1.7136e+03  2.6958e+03 -0.6357   0.5702
gradrate               1.0818e+03  1.3028e+03  0.8304   0.4672
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    78063000
Residual Sum of Squares: 4383200
R-Squared:      0.94385
Adj. R-Squared: 0.53208
F-statistic: 5.60312 on 9 and 3 DF, p-value: 0.091681
```

</td>
</tr>
<tr>
<td colspan="2">DiD estimator has no statistically significant impacts</td>
</tr>
<tr>
<td>Idaho 2013 decrease in rate and number of brackets compared against Iowa 2002-2018</td>
<td>PIT Revenue</td>
<td>

```
Twoways effects Within Model

Call:
plm(formula = PIT ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_IDComp, effect = "twoway")

Balanced Panel: n = 2, T = 17, N = 34

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-5.9848e+04 -1.4291e+04 -7.4579e-11  1.4291e+04  5.9848e+04

Coefficients:
                         Estimate  Std. Error t-value Pr(>|t|)
DID                    4.1020e+05  1.1118e+05  3.6895 0.007762 **
GDP                    6.9600e+00  1.5118e+01  0.4604 0.659197
Population            -2.8054e+00  1.1124e+00 -2.5220 0.039696 *
HealthCoverage         4.8034e+04  4.5778e+04  1.0493 0.328914
CIT                    8.2821e-02  3.1619e-01  0.2619 0.800911
pcPersonalExpenditure  4.3458e+01  1.9048e+02  0.2282 0.826047
pcInc                  4.3435e+01  6.6680e+01  0.6514 0.535587
unemp                  4.1211e+04  7.5798e+04  0.5437 0.603527
gradrate              -1.8481e+04  1.0594e+04 -1.7444 0.124603
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    1.3832e+12
Residual Sum of Squares: 2.0462e+10
R-Squared:      0.98521
Adj. R-Squared: 0.93026
F-statistic: 51.8003 on 9 and 7 DF, p-value: 1.4085e-05
```

</td>
</tr>
</table>

Inflows

```
Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_IDComp, effect = "twoway")

Balanced Panel: n = 2, T = 17, N = 34

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-6.7486e+02 -3.1049e+02  2.2027e-13  3.1049e+02  6.7486e+02

Coefficients:
                         Estimate  Std. Error t-value Pr(>|t|)
DID                   -4.8088e+03  1.6420e+03 -2.9285  0.02207 *
GDP                   -2.5853e-01  2.2327e-01 -1.1579  0.28488
Population             3.4257e-02  1.6429e-02  2.0851  0.07551 .
HealthCoverage        -3.3887e+02  6.7609e+02 -0.5012  0.63159
CIT                    1.7029e-03  4.6698e-03  0.3647  0.72613
pcPersonalExpenditure  7.9250e-01  2.8132e+00  0.2817  0.78631
pcInc                  2.1722e+00  9.8481e-01  2.2057  0.06320 .
unemp                 -9.0428e+02  1.1195e+03 -0.8078  0.44580
gradrate               4.3147e+02  1.5647e+02  2.7575  0.02820 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    93232000
Residual Sum of Squares: 4463300
R-Squared:      0.95213
Adj. R-Squared: 0.77432
F-statistic: 15.4691 on 9 and 7 DF, p-value: 0.00078328
```

Outflows

```
Twoways effects Within Model

Call:
plm(formula = Outflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_IDComp, effect = "twoway")

Balanced Panel: n = 2, T = 17, N = 34

Residuals:
    Min.  1st Qu.   Median  3rd Qu.     Max.
-1587.02  -349.53     0.00   349.53  1587.02

Coefficients:
                         Estimate  Std. Error t-value Pr(>|t|)
DID                    3.7124e+03  2.8718e+03  1.2927   0.2371
GDP                   -2.9600e-01  3.9049e-01 -0.7580   0.4732
Population            -3.3917e-02  2.8733e-02 -1.1804   0.2764
HealthCoverage        -3.2017e+02  1.1824e+03 -0.2708   0.7944
CIT                    6.5997e-03  8.1671e-03  0.8081   0.4456
pcPersonalExpenditure  1.7030e+00  4.9200e+00  0.3461   0.7394
pcInc                 -1.1563e+00  1.7223e+00 -0.6714   0.5235
unemp                  3.2046e+02  1.9579e+03  0.1637   0.8746
gradrate              -2.2628e+02  2.7365e+02 -0.8269   0.4356

Total Sum of Squares:    36523000
Residual Sum of Squares: 13652000
R-Squared:      0.62622
Adj. R-Squared: -0.76209
F-statistic: 1.30308 on 9 and 7 DF, p-value: 0.37169
```

DiD estimator has a statistically significant positive impact on PIT revenue and a statistically significant decrease in inflows

<table>
<tr>
<td rowspan="2">Illinois 2011 rate increase compared against Colorado 2001-2014</td>
<td>PIT Revenue</td>
<td><pre>
Twoways effects Within Model

Call:
plm(formula = Outflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_IL1Comp, effect = "twoway")

Balanced Panel: n = 2, T = 15, N = 30

Residuals:
       1   2   3   4   5   6   7   8
9   10   11   12   13   14
 -150.65   712.10   231.48 -1725.86   403.04   469.97 1437.22 -1739.81
-310.86   938.01 -264.63 -759.23   741.21   517.83
      15   16   17   18   19   20   21   22
23   24   25   26   27   28
 -499.81   150.65 -712.10 -231.48 1725.86 -403.04 -469.97 -1437.22
1739.81   310.86 -938.01   264.63   759.23 -741.21
      29   30
 -517.83   499.81

Coefficients:
                        Estimate Std. Error t-value Pr(>|t|)
DID   4.1853e+02 6.9130e+03 0.0605   0.9541
GDP   -2.4620e-01 1.8681e-01 -1.3179   0.2447
Population   -3.9431e-02 2.5988e-02 -1.5173   0.1896
HealthCoverage   -9.0235e+02 2.5746e+03 -0.3505   0.7403
CIT   2.5675e-02 2.6802e-02 0.9579   0.3821
pcPersonalExpenditure -3.4555e+00 8.4090e+00 -0.4109   0.6981
pcInc   3.1971e+00 4.8657e+00 0.6571   0.5402
unemp   -4.0793e+03 2.5898e+03 -1.5752   0.1760
gradrate   -5.9283e+02 6.2757e+02 -0.9446   0.3882

Total Sum of Squares: 123490000
Residual Sum of Squares: 23456000
R-Squared: 0.81006
Adj. R-Squared: -0.10166
F-statistic: 2.36932 on 9 and 5 DF, p-value: 0.17752
</pre></td>
</tr>
<tr>
<td>Inflows</td>
<td><pre>
Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_IL1Comp, effect = "twoway")

Balanced Panel: n = 2, T = 15, N = 30

Residuals:
        1   2   3   4   5   6   7   8
9   10   11   12   13
  474.767 -1726.515 1207.700   388.714 -455.476   -12.206   -68.730 -461.546
1404.804   350.233 -1101.747 -401.008   270.636
       14   15   16   17   18   19   20   21
22   23   24   25   26
  353.250 -222.878 -474.767 1726.515 -1207.700 -388.714   455.476   12.206
68.730   461.546 -1404.804 -350.233 1101.747
       27   28   29   30
  401.008 -270.636 -353.250   222.878

Coefficients:
                        Estimate Std. Error t-value Pr(>|t|)
DID   -9.8710e+02 6.0422e+03 -0.1634 0.87663
GDP   -3.7357e-01 1.6328e-01 -2.2880 0.07083 .
Population   -5.5191e-02 2.2714e-02 -2.4298 0.05940 .
HealthCoverage   -3.6679e+03 2.2503e+03 -1.6300 0.16404
CIT   1.0795e-03 2.3426e-02 0.0461 0.96503
pcPersonalExpenditure -6.9573e+00 7.3498e+00 -0.9466 0.38731
pcInc   7.8169e-01 4.2529e+00 0.1838 0.86139
unemp   -3.7033e+03 2.2636e+03 -1.6361 0.16276
gradrate   2.0625e+02 5.4853e+02 0.3760 0.72233

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares: 304260000
Residual Sum of Squares: 17919000
R-Squared: 0.9411
Adj. R-Squared: 0.65841
F-statistic: 8.87741 on 9 and 5 DF, p-value: 0.013499
</pre></td>
</tr>
</table>

<table>
<tr><td rowspan="2"></td><td>Outflows</td><td><pre>
Twoways effects Within Model

Call:
plm(formula = PIT ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_IL1Comp, effect = "twoway")

Balanced Panel: n = 2, T = 15, N = 30

Residuals:
      1   2   3   4   5   6   7   8
9   10   11   12   13   14   15   16
  29286   48802 -205044 150816 -58640 -89643 133255 172845
-284100 -66766 169188 263315 -362510   87489   11706 -29286
     17   18   19   20   21   22   23   24
25   26   27   28   29   30
 -48802 205044 -150816   58640   89643 -133255 -172845 284100
66766 -169188 -263315 362510 -87489 -11706

Coefficients:
                         Estimate Std. Error t-value Pr(>|t|)
DID   5.0359e+06 1.3533e+06 3.7211 0.01370 *
GDP   -1.4461e+01 3.6570e+01 -0.3954 0.70884
Population   -1.5592e+00 5.0875e+00 -0.3065 0.77159
HealthCoverage   -9.5823e+03 5.0402e+05 -0.0190 0.98557
CIT   -1.0560e+01 5.2470e+00 -2.0125 0.10032
pcPersonalExpenditure 9.4988e+02 1.6462e+03 0.5770 0.58893
pcInc   -9.3607e+01 9.5254e+02 -0.0983 0.92554
unemp   -5.3399e+05 5.0699e+05 -1.0533 0.34044
gradrate   -3.4981e+05 1.2286e+05 -2.8473 0.03594 *

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares: 5.2128e+13
Residual Sum of Squares: 8.9894e+11
R-Squared: 0.98276
Adj. R-Squared: 0.89998
F-statistic: 31.6604 on 9 and 5 DF, p-value: 0.00069653
</pre></td></tr>
<tr><td colspan="2">DiD estimator has a statistically significant positive impact on outflows</td></tr>
<tr><td>Kansas 2013 start of decreasing rate and a decrease in the number of brackets compared against Missouri 2000-2017</td><td>PIT Revenue</td><td><pre>
Twoways effects Within Model

Call:
plm(formula = PIT ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_KSComp, effect = "twoway")

Balanced Panel: n = 2, T = 18, N = 36

Residuals:
   Min. 1st Qu. Median 3rd Qu.   Max.
-164334 -28179   0   28179 164334

Coefficients:
                         Estimate Std. Error t-value Pr(>|t|)
DID   -5.1718e+05 2.7902e+05 -1.8535 0.10093
GDP   -4.0449e+01 1.9307e+01 -2.0951 0.06947 .
Population   4.2633e+00 1.5524e+00 2.7463 0.02520 *
HealthCoverage   1.4292e+04 1.2030e+05 0.1188 0.90836
CIT   -6.2951e-01 1.2481e+00 -0.5044 0.62760
pcPersonalExpenditure 2.8071e+02 2.4946e+02 1.1253 0.29310
pcInc   4.7720e+01 7.4527e+01 0.6403 0.53987
unemp   -2.3550e+05 1.3185e+05 -1.7862 0.11189
gradrate   1.0132e+05 5.6456e+04 1.7946 0.11045

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares: 4.4643e+12
Residual Sum of Squares: 1.6377e+11
R-Squared: 0.96332
Adj. R-Squared: 0.8395
F-statistic: 23.3417 on 9 and 8 DF, p-value: 8.2048e-05
</pre></td></tr>
</table>

Inflows

```
Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_KSComp, effect = "twoway")

Balanced Panel: n = 2, T = 18, N = 36

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-4.2663e+03 -5.4252e+02  1.4211e-14  5.4252e+02  4.2663e+03

Coefficients:
                         Estimate  Std. Error t-value Pr(>|t|)
DID                    6.9619e+02  5.6465e+03  0.1233   0.9049
GDP                   -3.9572e-02  3.9071e-01 -0.1013   0.9218
Population             3.2354e-02  3.1415e-02  1.0299   0.3332
HealthCoverage        -9.2803e+02  2.4345e+03 -0.3812   0.7130
CIT                   -2.1917e-02  2.5258e-02 -0.8677   0.4108
pcPersonalExpenditure  1.7785e+00  5.0483e+00  0.3523   0.7337
pcInc                  9.3719e-01  1.5082e+00  0.6214   0.5516
unemp                 -3.0094e+03  2.6681e+03 -1.1279   0.2921
gradrate              -3.3225e+02  1.1425e+03 -0.2908   0.7786

Total Sum of Squares:    127310000
Residual Sum of Squares: 67069000
R-Squared:      0.47319
Adj. R-Squared: -1.3048
F-statistic: 0.79843 on 9 and 8 DF, p-value: 0.63011
```

Outflows

```
Twoways effects Within Model

Call:
plm(formula = Outflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_KSComp, effect = "twoway")

Balanced Panel: n = 2, T = 18, N = 36

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-2.2506e+03 -4.4635e+02 -1.4921e-13  4.4635e+02  2.2506e+03

Coefficients:
                         Estimate  Std. Error t-value Pr(>|t|)
DID                    3.2521e+03  3.7906e+03  0.8579   0.4159
GDP                   -1.2841e-01  2.6229e-01 -0.4896   0.6376
Population             8.3061e-03  2.1090e-02  0.3938   0.7040
HealthCoverage        -8.9855e+02  1.6343e+03 -0.5498   0.5975
CIT                   -1.9369e-02  1.6956e-02 -1.1423   0.2864
pcPersonalExpenditure  3.4056e+00  3.3890e+00  1.0049   0.3444
pcInc                 -5.2504e-01  1.0125e+00 -0.5186   0.6181
unemp                 -8.3789e+02  1.7912e+03 -0.4678   0.6524
gradrate               1.1736e+02  7.6697e+02  0.1530   0.8822

Total Sum of Squares:    61067000
Residual Sum of Squares: 30226000
R-Squared:      0.50504
Adj. R-Squared: -1.1655
F-statistic: 0.906978 on 9 and 8 DF, p-value: 0.56031
```

DiD estimator has no statistically significant impacts

<table>
<tr>
<td rowspan="3">Kentucky 2005 increase in the number of brackets compared against Mississippi 2000-2018</td>
<td>PIT Revenue</td>
<td>

```
Twoways effects Within Model

Call:
plm(formula = PIT ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_KYComp, effect = "twoway")

Balanced Panel: n = 2, T = 19, N = 38

Residuals:
   Min. 1st Qu.  Median 3rd Qu.    Max.
 -64550  -13529       0   13529   64550

Coefficients:
                         Estimate  Std. Error t-value Pr(>|t|)
GDP                       7.89181    14.54773  0.5425  0.59937
Population                1.96871     0.98581  1.9970  0.07375 .
HealthCoverage         4826.94216 15113.50099  0.3194  0.75601
CIT                      -0.33443     0.14940 -2.2386  0.04912 *
pcPersonalExpenditure   189.21243    98.95399  1.9121  0.08491 .
pcInc                    84.00323    64.90050  1.2943  0.22464
unemp                 -7290.59697 58803.68469 -0.1240  0.90379
gradrate              -8533.35586  5109.45155 -1.6701  0.12585
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    9.2199e+11
Residual Sum of Squares: 2.1225e+10
R-Squared:      0.97698
Adj. R-Squared: 0.91482
F-statistic: 53.0491 on 8 and 10 DF, p-value: 3.4163e-07
```

</td>
</tr>
<tr>
<td>Inflows</td>
<td>

```
Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_KYComp, effect = "twoway")

Balanced Panel: n = 2, T = 19, N = 38

Residuals:
   Min. 1st Qu.  Median 3rd Qu.    Max.
-1566.6  -551.9     0.0   551.9  1566.6

Coefficients:
                        Estimate  Std. Error t-value Pr(>|t|)
GDP                    3.8065e-01  4.4802e-01  0.8496  0.41541
Population            -1.9359e-02  3.0360e-02 -0.6377  0.53802
HealthCoverage        -4.0822e+01  4.6545e+02 -0.0877  0.93184
CIT                   -5.3430e-03  4.6009e-03 -1.1613  0.27249
pcPersonalExpenditure  6.1212e+00  3.0475e+00  2.0086  0.07234 .
pcInc                 -3.0954e+00  1.9987e+00 -1.5487  0.15250
unemp                  2.1501e+03  1.8110e+03  1.1873  0.26255
gradrate              -5.9630e+00  1.5735e+02 -0.0379  0.97052
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    63908000
Residual Sum of Squares: 20130000
R-Squared:      0.68501
Adj. R-Squared: -0.16546
F-statistic: 2.71839 on 8 and 10 DF, p-value: 0.070432
```

</td>
</tr>
<tr>
<td>Outflows</td>
<td>

```
Twoways effects Within Model

Call:
plm(formula = Outflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_KYComp, effect = "twoway")

Balanced Panel: n = 2, T = 19, N = 38

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-1.3621e+03 -5.5186e+02  1.9895e-13  5.5186e+02  1.3621e+03

Coefficients:
                        Estimate  Std. Error t-value Pr(>|t|)
GDP                   -2.5017e-02  4.1781e-01 -0.0599  0.95343
Population             1.7726e-02  2.8312e-02  0.6261  0.54527
HealthCoverage         1.2668e+02  4.3406e+02  0.2919  0.77637
CIT                   -1.0202e-02  4.2906e-03 -2.3777  0.03876 *
pcPersonalExpenditure  6.6811e+00  2.8419e+00  2.3509  0.04058 *
pcInc                 -3.7275e+00  1.8639e+00 -1.9998  0.07341 .
unemp                 -6.3813e+02  1.6888e+03 -0.3779  0.71344
gradrate              -1.3303e+02  1.4674e+02 -0.9066  0.38596
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    87364000
Residual Sum of Squares: 17507000
R-Squared:      0.79961
Adj. R-Squared: 0.25856
F-statistic: 4.9879 on 8 and 10 DF, p-value: 0.010496
```

</td>
</tr>
</table>

	DiD estimator has no statistically significant impacts
Louisiana 2004 increase in the highest bracket compared against Mississippi 2000-2009	

PIT Revenue

```
Twoways effects Within Model

Call:
plm(formula = PIT ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_LA1Comp, effect = "twoway")

Balanced Panel: n = 2, T = 10, N = 20

Residuals:
ALL 9 residuals are 0: no residual degrees of freedom!

Coefficients:
                        Estimate  Std. Error t-value Pr(>|t|)
DID                    4.7020e+05        Inf       0      NaN
GDP                   -1.6338e+01        Inf       0      NaN
Population             2.5178e+00        Inf       0      NaN
HealthCoverage         9.7698e+04        Inf       0      NaN
CIT                    1.8133e-01        Inf       0      NaN
pcPersonalExpenditure  8.1268e+01        Inf       0      NaN
pcInc                  8.8257e+01        Inf       0      NaN
unemp                 -1.8581e+04        Inf       0      NaN
gradrate              -5.9987e+04        Inf       0      NaN

Total Sum of Squares:    7.4721e+11
Residual Sum of Squares: 5.1273e-20
R-Squared:      1
Adj. R-Squared: NaN
F-statistic: NaN on 9 and 0 DF, p-value: NA
```

Inflows

```
Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_LA1Comp, effect = "twoway")

Balanced Panel: n = 2, T = 10, N = 20

Residuals:
ALL 9 residuals are 0: no residual degrees of freedom!

Coefficients:
                        Estimate  Std. Error t-value Pr(>|t|)
DID                    4.0015e+03        Inf       0      NaN
GDP                   -6.3667e-01        Inf       0      NaN
Population             1.0293e-01        Inf       0      NaN
HealthCoverage         1.8357e+03        Inf       0      NaN
CIT                    2.4946e-02        Inf       0      NaN
pcPersonalExpenditure  3.2246e+00        Inf       0      NaN
pcInc                 -3.3916e-01        Inf       0      NaN
unemp                 -3.8397e+03        Inf       0      NaN
gradrate              -1.4601e+03        Inf       0      NaN

Total Sum of Squares:    158430000
Residual Sum of Squares: 3.2457e-23
R-Squared:      1
Adj. R-Squared: NaN
F-statistic: NaN on 9 and 0 DF, p-value: NA
```

Outflows

```
Twoways effects Within Model

Call:
plm(formula = Outflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_LA1Comp, effect = "twoway")

Balanced Panel: n = 2, T = 10, N = 20

Residuals:
ALL 9 residuals are 0: no residual degrees of freedom!

Coefficients:
                        Estimate  Std. Error t-value Pr(>|t|)
DID                   -1.1705e+04        Inf       0      NaN
GDP                    1.4746e+00        Inf       0      NaN
Population            -3.6838e-01        Inf       0      NaN
HealthCoverage        -2.4538e+03        Inf       0      NaN
CIT                   -3.9870e-02        Inf       0      NaN
pcPersonalExpenditure -9.2578e+00        Inf       0      NaN
pcInc                 -1.4667e+00        Inf       0      NaN
unemp                  5.4900e+03        Inf       0      NaN
gradrate               2.2869e+03        Inf       0      NaN

Total Sum of Squares:    1374500000
Residual Sum of Squares: 3.2536e-22
R-Squared:      1
Adj. R-Squared: NaN
F-statistic: NaN on 9 and 0 DF, p-value: NA
```

	Included as example; insufficient sample size

Louisiana 2010 decrease in the highest bracket compared against Mississippi 2004-2020

PIT Revenue

```
Twoways effects Within Model

Call:
plm(formula = PIT ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_LA2Comp, effect = "twoway")

Balanced Panel: n = 2, T = 17, N = 34

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-1.4581e+05 -4.4385e+04  1.2278e-11  4.4385e+04  1.4581e+05

Coefficients:
                         Estimate  Std. Error t-value Pr(>|t|)
DID                   -4.7764e+05  4.0945e+05 -1.1665   0.2816
GDP                   -1.0430e+01  1.0174e+01 -1.0252   0.3394
Population             1.5256e-01  1.5604e+00  0.0978   0.9249
HealthCoverage         1.0389e+05  8.8205e+04  1.1778   0.2773
CIT                    7.4812e-01  8.6648e-01  0.8634   0.4165
pcPersonalExpenditure -1.2388e+02  3.7807e+02 -0.3277   0.7527
pcInc                  1.2925e+02  2.1396e+02  0.6041   0.5648
unemp                  5.5048e+04  1.0227e+05  0.5383   0.6071
gradrate              -1.5563e+04  2.0167e+04 -0.7717   0.4655

Total Sum of Squares:    9.4109e+11
Residual Sum of Squares: 1.5958e+11
R-Squared:      0.83043
Adj. R-Squared: 0.20062
F-statistic: 3.80909 on 9 and 7 DF, p-value: 0.045831
```

Inflows

```
Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_LA2Comp, effect = "twoway")

Balanced Panel: n = 2, T = 17, N = 34

Residuals:
    Min.  1st Qu.   Median  3rd Qu.     Max.
-3152.05  -766.23     0.00   766.23  3152.05

Coefficients:
                         Estimate  Std. Error t-value Pr(>|t|)
DID                    4.7737e+03  7.7516e+03  0.6158  0.55748
GDP                   -3.7383e-01  1.9261e-01 -1.9409  0.09341 .
Population             2.0201e-02  2.9541e-02  0.6838  0.51608
HealthCoverage        -5.1569e+02  1.6698e+03 -0.3088  0.76644
CIT                    1.5417e-02  1.6404e-02  0.9398  0.37859
pcPersonalExpenditure -1.7007e+00  7.1574e+00 -0.2376  0.81898
pcInc                  5.5015e-01  4.0505e+00  0.1358  0.89578
unemp                 -2.5454e+03  1.9361e+03 -1.3147  0.23003
gradrate               2.4099e+02  3.8180e+02  0.6312  0.54796
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    173790000
Residual Sum of Squares: 57192000
R-Squared:      0.6709
Adj. R-Squared: -0.55145
F-statistic: 1.5856 on 9 and 7 DF, p-value: 0.27818
```

<table>
<tr>
<td rowspan="2"></td>
<td>Outflows</td>
<td>
<pre>
Twoways effects Within Model

Call:
plm(formula = Outflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_LA2Comp, effect = "twoway")

Balanced Panel: n = 2, T = 17, N = 34

Residuals:
   Min. 1st Qu. Median 3rd Qu.   Max.
-5880.3 -1670.4   0.0 1670.4 5880.3

Coefficients:
                         Estimate Std. Error t-value Pr(>|t|)
DID   1.0610e+03 1.7842e+04 0.0595 0.95424
GDP   7.4182e-01 4.4333e-01 1.6733 0.13818
Population   -1.7082e-01 6.7996e-02 -2.5122 0.04027 *
HealthCoverage   -1.0557e+02 3.8435e+03 -0.0275 0.97885
CIT   -2.4995e-02 3.7757e-02 -0.6620 0.52915
pcPersonalExpenditure 1.0562e+01 1.6474e+01 0.6411 0.54185
pcInc   -5.3816e+00 9.3231e+00 -0.5772 0.58186
unemp   6.0929e+03 4.4563e+03 1.3673 0.21382
gradrate   -1.0702e+03 8.7879e+02 -1.2178 0.26273

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares: 1444400000
Residual Sum of Squares: 302990000
R-Squared: 0.79023
Adj. R-Squared: 0.0111
F-statistic: 2.93005 on 9 and 7 DF, p-value: 0.085172
</pre>
</td>
</tr>
<tr>
<td colspan="2">DiD estimator has no statistically significant impacts</td>
</tr>
<tr>
<td>Michigan 2008 slight increase in a tax rate compared against Colorado 2000-2012</td>
<td>PIT Revenue</td>
<td>
<pre>
Twoways effects Within Model

Call:
plm(formula = PIT ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_MIComp, effect = "twoway")

Balanced Panel: n = 2, T = 13, N = 26

Residuals:
        1   2   3   4   5   6   7   8
9   10   11   12   13
 -21472.3   46418.0   32846.3 -108515.2 -68532.4 197354.5 -51110.6 -26988.4
-15697.6   -1422.1   28878.4 -10533.4   -1225.2
       14   15   16   17   18   19   20   21
22   23   24   25   26
  21472.3 -46418.0 -32846.3 108515.2   68532.4 -197354.5   51110.6   26988.4
15697.6   1422.1 -28878.4   10533.4   1225.2

Coefficients:
                        Estimate Std. Error t-value Pr(>|t|)
DID   4.7234e+06 2.2214e+06 2.1263   0.1234
GDP   1.0673e+02 5.8054e+01 1.8385   0.1633
Population   1.0639e+01 7.2054e+00 1.4766   0.2363
HealthCoverage   -3.3604e+05 2.6342e+05 -1.2757   0.2919
CIT   -4.2863e+00 2.8674e+00 -1.4949   0.2318
pcPersonalExpenditure 3.9490e+02 6.9674e+02 0.5668   0.6105
pcInc   -5.9037e+02 6.3743e+02 -0.9262   0.4227
unemp   3.3114e+05 4.4617e+05 0.7422   0.5118
gradrate   1.7245e+05 1.0117e+05 1.7045   0.1868

Total Sum of Squares: 3.0055e+12
Residual Sum of Squares: 1.273e+11
R-Squared: 0.95764
Adj. R-Squared: 0.64703
F-statistic: 7.53636 on 9 and 3 DF, p-value: 0.061858
</pre>
</td>
</tr>
</table>

Inflows

```
Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_MIComp, effect = "twoway")

Balanced Panel: n = 2, T = 13, N = 26

Residuals:
       1        2        3        4        5        6        7        8
9       10       11       12       13       14
 -688.07  -256.03   129.75  1299.01   291.16  -823.50  -257.37   305.05
250.66   228.98  -748.80   387.28  -118.13   688.07
      15       16       17       18       19       20       21       22
23       24       25       26
  256.03  -129.75 -1299.01  -291.16   823.50   257.37  -305.05  -250.66
-228.98   748.80  -387.28   118.13

Coefficients:
                        Estimate  Std. Error t-value Pr(>|t|)
DID                   -3.2970e+04  1.7622e+04 -1.8710  0.15810
GDP                   -1.1455e+00  4.6053e-01 -2.4874  0.08869 .
Population            -3.3972e-02  5.7158e-02 -0.5944  0.59412
HealthCoverage         2.4385e+03  2.0896e+03  1.1670  0.32755
CIT                    2.5673e-02  2.2746e-02  1.1287  0.34113
pcPersonalExpenditure -8.8024e+00  5.5270e+00 -1.5926  0.20949
pcInc                  4.2036e+00  5.0565e+00  0.8313  0.46678
unemp                 -5.9225e+03  3.5393e+03 -1.6734  0.19285
gradrate              -1.0735e+03  8.0256e+02 -1.3376  0.27338
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    154960000
Residual Sum of Squares: 8010700
R-Squared:      0.94831
Adj. R-Squared: 0.56921
F-statistic: 6.11483 on 9 and 3 DF, p-value: 0.081761
```

Outflows

```
Twoways effects Within Model

Call:
plm(formula = Outflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_MIComp, effect = "twoway")

Balanced Panel: n = 2, T = 13, N = 26

Residuals:
       1        2        3        4        5        6        7        8
9       10       11       12       13       14
  938.38   220.45  -305.27 -1304.06  -146.20   405.77   465.60  -274.66
-245.07  -338.74   984.52  -648.37   247.65  -938.38
      15       16       17       18       19       20       21       22
23       24       25       26
 -220.45   305.27  1304.06   146.20  -405.77  -465.60   274.66   245.07
338.74  -984.52   648.37  -247.65

Coefficients:
                        Estimate  Std. Error t-value Pr(>|t|)
DID                    3.0716e+02  1.9345e+04  0.0159   0.9883
GDP                    3.5791e-01  5.0555e-01  0.7080   0.5300
Population             1.4246e-02  6.2747e-02  0.2270   0.8350
HealthCoverage        -1.6737e+02  2.2939e+03 -0.0730   0.9464
CIT                   -1.2316e-02  2.4970e-02 -0.4932   0.6557
pcPersonalExpenditure  1.1130e+01  6.0674e+00  1.8344   0.1639
pcInc                  5.4013e-01  5.5509e+00  0.0973   0.9286
unemp                  7.2211e+02  3.8853e+03  0.1859   0.8644
gradrate               4.9745e+02  8.8103e+02  0.5646   0.6118

Total Sum of Squares:    681750000
Residual Sum of Squares: 9653900
R-Squared:      0.98584
Adj. R-Squared: 0.882
F-statistic: 23.2065 on 9 and 3 DF, p-value: 0.012693
```

DiD estimator has no statistically significant impacts

<table>
<tr>
<td rowspan="3">Minnesota 2014 increase in rate and number of brackets compared against Virginia 2001-2020</td>
<td>PIT Revenue</td>
<td><pre>
Twoways effects Within Model

Call:
plm(formula = PIT ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_MNComp, effect = "twoway")

Balanced Panel: n = 2, T = 21, N = 42

Residuals:
       Min.   1st Qu.   Median   3rd Qu.   Max.
-3.6013e+05 -8.3315e+04 -1.0914e-10 8.3315e+04 3.6013e+05

Coefficients:
                         Estimate Std. Error t-value Pr(>|t|)
DID   -3.1273e+05 6.4411e+05 -0.4855 0.63683
GDP   9.6055e+01 3.4677e+01 2.7700 0.01823 *
Population   -4.9550e+00 2.9806e+00 -1.6624 0.12463
HealthCoverage   -1.5969e+05 1.2473e+05 -1.2804 0.22676
CIT   -6.7353e-01 6.9098e-01 -0.9747 0.35063
pcPersonalExpenditure 3.0149e+02 3.3967e+02 0.8876 0.39375
pcInc   -6.7676e+02 2.9728e+02 -2.2766 0.04380 *
unemp   -4.9134e+05 2.9883e+05 -1.6442 0.12838
gradrate   2.9461e+04 4.8972e+04 0.6016 0.55964

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares: 4.4624e+12
Residual Sum of Squares: 9.2033e+11
R-Squared: 0.79376
Adj. R-Squared: 0.23128
F-statistic: 4.70394 on 9 and 11 DF, p-value: 0.0094309
</pre></td>
</tr>
<tr>
<td>Inflows</td>
<td><pre>
Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_MNComp, effect = "twoway")

Balanced Panel: n = 2, T = 21, N = 42

Residuals:
       Min.   1st Qu.   Median   3rd Qu.   Max.
-7.3511e+03 -1.2007e+03 2.8706e-12 1.2007e+03 7.3511e+03

Coefficients:
                         Estimate Std. Error t-value Pr(>|t|)
DID   5.1266e+03 1.2612e+04 0.4065   0.6922
GDP   -6.9631e-02 6.7899e-01 -0.1026   0.9202
Population   4.5437e-02 5.8361e-02 0.7785   0.4527
HealthCoverage   2.4327e+02 2.4422e+03 0.0996   0.9224
CIT   1.3096e-02 1.3530e-02 0.9679   0.3539
pcPersonalExpenditure -7.1977e+00 6.6509e+00 -1.0822   0.3023
pcInc   2.5972e+00 5.8208e+00 0.4462   0.6641
unemp   -5.8493e+03 5.8512e+03 -0.9997   0.3389
gradrate   -8.4552e+01 9.5890e+02 -0.0882   0.9313

Total Sum of Squares: 537760000
Residual Sum of Squares: 352850000
R-Squared: 0.34386
Adj. R-Squared: -1.4456
F-statistic: 0.640521 on 9 and 11 DF, p-value: 0.74358
</pre></td>
</tr>
<tr>
<td>Outflows</td>
<td><pre>
Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_MNComp, effect = "twoway")

Balanced Panel: n = 2, T = 21, N = 42

Residuals:
       Min.   1st Qu.   Median   3rd Qu.   Max.
-7.3511e+03 -1.2007e+03 2.8706e-12 1.2007e+03 7.3511e+03

Coefficients:
                         Estimate Std. Error t-value Pr(>|t|)
DID   5.1266e+03 1.2612e+04 0.4065   0.6922
GDP   -6.9631e-02 6.7899e-01 -0.1026   0.9202
Population   4.5437e-02 5.8361e-02 0.7785   0.4527
HealthCoverage   2.4327e+02 2.4422e+03 0.0996   0.9224
CIT   1.3096e-02 1.3530e-02 0.9679   0.3539
pcPersonalExpenditure -7.1977e+00 6.6509e+00 -1.0822   0.3023
pcInc   2.5972e+00 5.8208e+00 0.4462   0.6641
unemp   -5.8493e+03 5.8512e+03 -0.9997   0.3389
gradrate   -8.4552e+01 9.5890e+02 -0.0882   0.9313

Total Sum of Squares: 537760000
Residual Sum of Squares: 352850000
R-Squared: 0.34386
Adj. R-Squared: -1.4456
F-statistic: 0.640521 on 9 and 11 DF, p-value: 0.74358
</pre></td>
</tr>
</table>

	DiD estimator has no statistically significant impacts	
Montana 2005 decrease in rate and number of brackets compared against Iowa 2000-2018	PIT Revenue	
	Inflows	

PIT Revenue:

```
Twoways effects Within Model

Call:
plm(formula = PIT ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_MTComp, effect = "twoway")

Balanced Panel: n = 2, T = 19, N = 38

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-9.0443e+04 -1.9121e+04  9.0949e-12  1.9121e+04  9.0443e+04

Coefficients:
                         Estimate  Std. Error t-value Pr(>|t|)
DID                   -1.4619e+05  1.3354e+05 -1.0948  0.30205
GDP                    2.1385e+00  8.0115e+00  0.2669  0.79554
Population             6.0081e+00  2.2778e+00  2.6377  0.02702 *
HealthCoverage        -1.1383e+04  1.6611e+04 -0.6853  0.51044
CIT                    1.0111e-01  2.8021e-01  0.3609  0.72654
pcPersonalExpenditure -2.1822e+02  9.2466e+01 -2.3600  0.04260 *
pcInc                  4.4017e+01  6.5681e+01  0.6702  0.51958
unemp                 -1.1767e+05  5.3119e+04 -2.2152  0.05399 .
gradrate              -1.8286e+00  3.6681e+04  0.0000  0.99996
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    1.745e+12
Residual Sum of Squares: 3.8934e+10
R-Squared:      0.97769
Adj. R-Squared: 0.90828
F-statistic: 43.8201 on 9 and 9 DF, p-value: 2.2983e-06
```

Inflows:

```
Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_MTComp, effect = "twoway")

Balanced Panel: n = 2, T = 19, N = 38

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-1.4717e+03 -3.2530e+02  2.5580e-13  3.2530e+02  1.4717e+03

Coefficients:
                         Estimate  Std. Error t-value Pr(>|t|)
DID                    6.5620e+02  2.5747e+03  0.2549  0.80456
GDP                    2.9204e-01  1.5447e-01  1.8906  0.09125 .
Population            -1.2029e-02  4.3918e-02 -0.2739  0.79034
HealthCoverage        -2.1161e+02  3.2028e+02 -0.6607  0.52537
CIT                   -4.9625e-03  5.4027e-03 -0.9185  0.38230
pcPersonalExpenditure  2.4393e+00  1.7828e+00  1.3682  0.20444
pcInc                  1.3750e+00  1.2664e+00  1.0857  0.30582
unemp                  1.5059e+03  1.0242e+03  1.4704  0.17553
gradrate              -1.6122e+02  7.0723e+02 -0.2280  0.82477
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    34038000
Residual Sum of Squares: 14474000
R-Squared:      0.57477
Adj. R-Squared: -0.74815
F-statistic: 1.3517 on 9 and 9 DF, p-value: 0.33038
```

<table>
<tr>
<td rowspan="2"></td>
<td>Outflows</td>
<td><pre>
Twoways effects Within Model

Call:
plm(formula = Outflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_MTComp, effect = "twoway")

Balanced Panel: n = 2, T = 19, N = 38

Residuals:
       Min.   1st Qu.   Median   3rd Qu.   Max.
-1.9478e+03 -3.8154e+02 3.8369e-13 3.8154e+02 1.9478e+03

Coefficients:
                         Estimate Std. Error t-value Pr(>|t|)
DID   -3.1451e+03 3.2537e+03 -0.9666   0.3590
GDP   2.6947e-01 1.9521e-01 1.3804   0.2008
Population   -1.6280e-02 5.5501e-02 -0.2933   0.7759
HealthCoverage   2.5038e+02 4.0475e+02 0.6186   0.5515
CIT   -1.0748e-02 6.8275e-03 -1.5742   0.1499
pcPersonalExpenditure 1.4144e+00 2.2530e+00 0.6278   0.5457
pcInc   2.4422e+00 1.6004e+00 1.5261   0.1613
unemp   1.2683e+03 1.2943e+03 0.9799   0.3527
gradrate   -6.1120e+02 8.9375e+02 -0.6839   0.5113

Total Sum of Squares: 47406000
Residual Sum of Squares: 23115000
R-Squared: 0.51241
Adj. R-Squared: -1.0045
F-statistic: 1.0509 on 9 and 9 DF, p-value: 0.47113
</pre></td>
</tr>
<tr>
<td colspan="2">DiD estimator has no statistically significant impacts</td>
</tr>
<tr>
<td>Nebraska 2006 increase in highest income bracket compared against Missouri 2003-2013</td>
<td>PIT Revenue</td>
<td><pre>
Twoways effects Within Model

Call:
plm(formula = PIT ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_NEComp, effect = "twoway")

Balanced Panel: n = 2, T = 11, N = 22

Residuals:
        1   2   3   4   5   6   7   8
9   10   11   12   13
 -4193.76 18481.85 -14288.09 -10885.91 12505.27   -841.58 -5252.14   8077.73
-14688.15 29489.17 -18404.40   4193.76 -18481.85
       14   15   16   17   18   19   20   21
22
 14288.09 10885.91 -12505.27   841.58   5252.14 -8077.73 14688.15 -29489.17
18404.40

Coefficients:
                         Estimate Std. Error t-value Pr(>|t|)
DID   5.5263e+04 2.7211e+05 0.2031   0.8724
GDP   1.6355e+01 2.2791e+01 0.7176   0.6037
Population   1.2842e+01 5.3200e+00 2.4140   0.2500
HealthCoverage   1.5493e+05 8.0903e+04 1.9150   0.3064
CIT   7.4765e-01 3.4039e-01 2.1964   0.2720
pcPersonalExpenditure 3.2585e+02 4.8449e+02 0.6726   0.6231
pcInc   9.2280e+01 8.5850e+01 1.0749   0.4770
unemp   -2.5233e+05 6.7726e+04 -3.7257   0.1669
gradrate   -2.8617e+04 6.1383e+04 -0.4662   0.7223

Total Sum of Squares: 5.9976e+11
Residual Sum of Squares: 4711600000
R-Squared: 0.99214
Adj. R-Squared: 0.83503
F-statistic: 14.0327 on 9 and 1 DF, p-value: 0.20448
</pre></td>
</tr>
</table>

<table>
<tr><td rowspan="3"></td><td>Inflows</td><td><pre>
Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_NEComp, effect = "twoway")

Balanced Panel: n = 2, T = 11, N = 22

Residuals:
        1   2   3   4   5   6   7   8
9   10   11   12   13
 -41.8418 184.3967 -142.5548 -108.6106 124.7673   -8.3966 -52.4015   80.5929
-146.5462 294.2187 -183.6239   41.8418 -184.3967
       14   15   16   17   18   19   20   21
22
 142.5548 108.6106 -124.7673   8.3966   52.4015 -80.5929 146.5462 -294.2187
183.6239

Coefficients:
                         Estimate Std. Error t-value Pr(>|t|)
DID   -1.3146e+03 2.7149e+03 -0.4842   0.7129
GDP   4.0338e-01 2.2739e-01 1.7739   0.3268
Population   -3.5253e-02 5.3079e-02 -0.6642   0.6268
HealthCoverage   6.4224e+02 8.0718e+02 0.7957   0.5721
CIT   -2.9102e-03 3.3961e-03 -0.8569   0.5490
pcPersonalExpenditure 3.1087e+00 4.8338e+00 0.6431   0.6362
pcInc   -1.7232e+00 8.5654e-01 -2.0118   0.2937
unemp   3.9285e+03 6.7572e+02 5.8138   0.1084
gradrate   -8.6566e+02 6.1243e+02 -1.4135   0.3920

Total Sum of Squares: 26894000
Residual Sum of Squares: 469020
R-Squared: 0.98256
Adj. R-Squared: 0.63378
F-statistic: 6.2602 on 9 and 1 DF, p-value: 0.30128
</pre></td></tr>
<tr><td>Outflows</td><td><pre>
Twoways effects Within Model

Call:
plm(formula = Outflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_NEComp, effect = "twoway")

Balanced Panel: n = 2, T = 11, N = 22

Residuals:
       1   2   3   4   5   6   7   8
9   10   11   12   13   14
 -6.7984 29.9604 -23.1620 -17.6468 20.2719 -1.3643 -8.5141 13.0946
-23.8105 47.8040 -29.8348   6.7984 -29.9604 23.1620
      15   16   17   18   19   20   21   22
 17.6468 -20.2719   1.3643   8.5141 -13.0946 23.8105 -47.8040 29.8348

Coefficients:
                         Estimate Std. Error t-value Pr(>|t|)
DID   2.2618e+02 4.4111e+02 0.5127 0.69837
GDP   -1.1897e-01 3.6946e-02 -3.2202 0.19168
Population   -8.2319e-02 8.6241e-03 -9.5451 0.06645 .
HealthCoverage   2.7134e+02 1.3115e+02 2.0689 0.28663
CIT   -4.6703e-03 5.5180e-04 -8.4638 0.07487 .
pcPersonalExpenditure -5.8245e+00 7.8539e-01 -7.4160 0.08533 .
pcInc   6.2543e-01 1.3917e-01 4.4940 0.13939
unemp   2.7289e+03 1.0979e+02 24.8563 0.02560 *
gradrate   -2.1462e+02 9.9507e+01 -2.1568 0.27638

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares: 48835000
Residual Sum of Squares: 12382
R-Squared: 0.99975
Adj. R-Squared: 0.99468
F-statistic: 438.128 on 9 and 1 DF, p-value: 0.037061
</pre></td></tr>
<tr><td colspan="2">DiD estimator has no statistically significant impacts</td></tr>
</table>

Nebraska 2014 change in highest income bracket structure compared against Missouri 2006-2017

PIT Revenue

```
Twoways effects Within Model

Call:
plm(formula = PIT ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_NE2Comp, effect = "twoway")

Balanced Panel: n = 2, T = 12, N = 24

Residuals:
        1         2         3         4         5         6         7         8
9        10        11        12        13
 -4258.94  -6148.08  10076.70   4210.84  -8936.92  -8893.24  38693.63 -24743.99
-920.87  -5813.19  34970.90 -28236.84   4258.94
       14        15        16        17        18        19        20        21
22        23        24
  6148.08 -10076.70  -4210.84   8936.92   8893.24 -38693.63  24743.99    920.87
5813.19 -34970.90  28236.84

Coefficients:
                        Estimate  Std. Error t-value Pr(>|t|)
DID                   1.3901e+03  1.9621e+05  0.0071  0.99499
GDP                   8.1818e+00  1.9766e+01  0.4139  0.71909
Population            5.3134e+00  5.9262e+00  0.8966  0.46455
HealthCoverage        1.3782e+05  7.6998e+04  1.7899  0.21535
CIT                   1.9012e-01  3.2510e-01  0.5848  0.61787
pcPersonalExpenditure  9.2475e+02  6.1156e+02  1.5121  0.26965
pcInc                -8.4356e+01  6.3775e+01 -1.3227  0.31691
unemp                -2.4403e+05  5.3158e+04 -4.5906  0.04432 *
gradrate              4.9238e+04  6.1020e+04  0.8069  0.50442
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    6.7876e+11
Residual Sum of Squares: 8997100000
R-Squared:      0.98674
Adj. R-Squared: 0.84757
F-statistic: 16.5427 on 9 and 2 DF, p-value: 0.05828
```

Inflows

```
Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_NE2Comp, effect = "twoway")

Balanced Panel: n = 2, T = 12, N = 24

Residuals:
        1         2         3         4         5         6         7         8
9        10        11        12        13        14
 -138.91  -320.16   664.92  -460.88   570.86   205.13  2040.80 -2561.75
-1591.21  1117.58  1370.42  -896.79   138.91   320.16
      15        16        17        18        19        20        21        22
23        24
 -664.92   460.88  -570.86  -205.13 -2040.80  2561.75  1591.21 -1117.58
-1370.42   896.79

Coefficients:
                        Estimate  Std. Error t-value Pr(>|t|)
DID                   6.0572e+03  1.2526e+04  0.4836   0.6765
GDP                  -1.1241e+00  1.2619e+00 -0.8908   0.4670
Population           -6.0979e-01  3.7834e-01 -1.6118   0.2483
HealthCoverage       -7.4807e+02  4.9157e+03 -0.1522   0.8930
CIT                  -2.0970e-04  2.0755e-02 -0.0101   0.9929
pcPersonalExpenditure -1.7736e+01  3.9043e+01 -0.4543   0.6942
pcInc                -7.6107e+00  4.0715e+00 -1.8693   0.2025
unemp                 1.5536e+03  3.3937e+03  0.4578   0.6920
gradrate              5.9548e+03  3.8956e+03  1.5286   0.2660

Total Sum of Squares:    238840000
Residual Sum of Squares: 36670000
R-Squared:      0.84647
Adj. R-Squared: -0.76562
F-statistic: 1.22518 on 9 and 2 DF, p-value: 0.52767
```

Outflows

```
Twoways effects Within Model

Call:
plm(formula = Outflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_NE2Comp, effect = "twoway")

Balanced Panel: n = 2, T = 12, N = 24

Residuals:
        1         2         3         4         5         6         7         8
9        10        11        12        13
  -38.331  -176.500   431.246  -567.971   792.938   421.484  1136.967 -1999.833
-1589.423  1271.574   547.494  -229.645    38.331
       14        15        16        17        18        19        20        21
22        23        24
  176.500  -431.246   567.971  -792.938  -421.484 -1136.967  1999.833  1589.423
-1271.574  -547.494   229.645

Coefficients:
                         Estimate  Std. Error t-value Pr(>|t|)
DID                    5.3295e+03  9.7620e+03  0.5459   0.6399
GDP                   -1.3639e+00  9.8341e-01 -1.3869   0.2998
Population            -5.7739e-01  2.9484e-01 -1.9583   0.1893
HealthCoverage        -9.3440e+02  3.8309e+03 -0.2439   0.8300
CIT                   -6.4982e-03  1.6175e-02 -0.4018   0.7267
pcPersonalExpenditure -1.1204e+01  3.0427e+01 -0.3682   0.7480
pcInc                 -5.7558e+00  3.1730e+00 -1.8140   0.2113
unemp                  4.0220e+02  2.6447e+03  0.1521   0.8931
gradrate               5.7022e+03  3.0359e+03  1.8783   0.2011

Total Sum of Squares:    193150000
Residual Sum of Squares: 22271000
R-Squared:      0.8847
Adj. R-Squared: -0.32596
F-statistic: 1.7051 on 9 and 2 DF, p-value: 0.42379
```

DiD estimator has no statistically significant impacts

New York 2012 decrease in rate and increase in number of brackets and the highest bracket compared against Virginia 2009-2020

PIT Revenue

```
Twoways effects Within Model

Call:
plm(formula = Outflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_NY2Comp, effect = "twoway")

Balanced Panel: n = 2, T = 12, N = 24

Residuals:
        1         2         3         4         5         6         7         8
9        10        11        12        13
  -10.411 -1524.196  1534.607   289.531  -844.604  2121.518 -1971.800   130.093
1568.465 -2133.597   926.970   -86.576    10.411
       14        15        16        17        18        19        20        21
22        23        24
 1524.196 -1534.607  -289.531   844.604 -2121.518  1971.800  -130.093 -1568.465
2133.597  -926.970    86.576

Coefficients:
                         Estimate  Std. Error t-value Pr(>|t|)
DID                    2.7269e+04  1.8328e+04  1.4878   0.2752
GDP                    1.2786e-01  3.9773e-01  0.3215   0.7783
Population             6.2856e-02  6.4460e-02  0.9751   0.4323
HealthCoverage        -5.4623e+03  1.0751e+04 -0.5081   0.6619
CIT                   -5.8468e-02  5.6043e-02 -1.0433   0.4064
pcPersonalExpenditure -1.1258e+01  1.7704e+01 -0.6359   0.5899
pcInc                  1.5135e+01  1.0267e+01  1.4742   0.2784
unemp                  3.7586e+03  9.8114e+03  0.3831   0.7385
gradrate               1.0342e+04  5.9544e+03  1.7369   0.2245

Total Sum of Squares:    3201700000
Residual Sum of Squares: 43521000
R-Squared:      0.98641
Adj. R-Squared: 0.84368
F-statistic: 16.1261 on 9 and 2 DF, p-value: 0.05973
```

<table>
<tr><td rowspan="3"></td><td>Inflows</td><td><pre>
Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_NY2Comp, effect = "twoway")

Balanced Panel: n = 2, T = 12, N = 24

Residuals:
       1   2   3   4   5   6   7   8
9   10   11   12   13   14
-107.918 -179.585 287.503 -252.092 542.348 -539.629   51.900 411.841
-247.533 192.743 -119.322 -40.256 107.918 179.585
      15   16   17   18   19   20   21   22
23   24
-287.503 252.092 -542.348 539.629 -51.900 -411.841 247.533 -192.743
119.322   40.256

Coefficients:
                         Estimate Std. Error t-value Pr(>|t|)
DID   1.1954e+04 4.0491e+03 2.9523 0.09813 .
GDP   -2.0603e-01 8.7867e-02 -2.3448 0.14369
Population   -2.3399e-02 1.4241e-02 -1.6431 0.24207
HealthCoverage   8.0672e+03 2.3752e+03 3.3964 0.07683 .
CIT   5.0125e-02 1.2381e-02 4.0486 0.05594 .
pcPersonalExpenditure 1.3103e+01 3.9111e+00 3.3501 0.07872 .
pcInc   -1.1007e+01 2.2681e+00 -4.8530 0.03993 *
unemp   1.0521e+04 2.1675e+03 4.8538 0.03992 *
gradrate   6.2871e+02 1.3155e+03 0.4779 0.67983

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares: 359710000
Residual Sum of Squares: 2124100
R-Squared: 0.9941
Adj. R-Squared: 0.93209
F-statistic: 37.4113 on 9 and 2 DF, p-value: 0.026299
</pre></td></tr>
<tr><td>Outflows</td><td><pre>
Twoways effects Within Model

Call:
plm(formula = PIT ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_NY2Comp, effect = "twoway")

Balanced Panel: n = 2, T = 12, N = 24

Residuals:
      1   2   3   4   5   6   7   8
9   10   11   12   13   14   15   16
 -14464 255637 -241173 -92044 239176 -475784 373892   38424
-328747 425323 -190193   9954   14464 -255637 241173   92044
     17   18   19   20   21   22   23   24
-239176 475784 -373892 -38424 328747 -425323 190193   -9954

Coefficients:
                         Estimate Std. Error t-value Pr(>|t|)
DID   5.4421e+06 3.6906e+06 1.4746 0.27827
GDP   -2.0483e+02 8.0087e+01 -2.5575 0.12488
Population   -8.4623e+00 1.2980e+01 -0.6520 0.58134
HealthCoverage   4.9842e+06 2.1649e+06 2.3023 0.14792
CIT   -2.6143e+01 1.1285e+01 -2.3166 0.14647
pcPersonalExpenditure 1.1249e+04 3.5648e+03 3.1556 0.08745 .
pcInc   -5.5081e+03 2.0673e+03 -2.6644 0.11671
unemp   5.1355e+06 1.9756e+06 2.5994 0.12158
gradrate   -1.4489e+06 1.1990e+06 -1.2084 0.35037

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares: 8.8816e+13
Residual Sum of Squares: 1.7646e+12
R-Squared: 0.98013
Adj. R-Squared: 0.77152
F-statistic: 10.9628 on 9 and 2 DF, p-value: 0.086348
</pre></td></tr>
<tr><td colspan="2">DiD estimator had a statistically significant positive impact on inflows</td></tr>
</table>

<table>
<tr>
<td rowspan="2">North Carolina 2014 start of eliminating graduated income tax in favor of flat compared against Virginia 2009-2020</td>
<td>PIT Revenue</td>
<td>

```
Twoways effects Within Model

Call:
plm(formula = PIT ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_NCComp, effect = "twoway")

Balanced Panel: n = 2, T = 12, N = 24

Residuals:
        1         2         3         4         5         6         7         8
9        10
-34618.76  90068.10 -59431.36  12979.84  -8997.82 -17274.62  -9633.89  25167.36
62169.71 -78260.66
       11        12        13        14        15        16        17        18
19        20
 18552.44   -720.34  34618.76 -90068.10  59431.36 -12979.84   8997.82  17274.62
9633.89 -25167.36
       21        22        23        24
-62169.71  78260.66 -18552.44    720.34

Coefficients:
                        Estimate  Std. Error t-value Pr(>|t|)
DID                  -1.1876e+06  7.4281e+05 -1.5988   0.2510
GDP                   2.5011e+01  4.0661e+01  0.6151   0.6011
Population           -1.5073e+00  1.1503e+00 -1.3103   0.3203
HealthCoverage        1.1357e+05  3.8299e+05  0.2965   0.7948
CIT                  -1.9930e+01  9.1244e+00 -2.1843   0.1606
pcPersonalExpenditure -1.5518e+03  7.4778e+02 -2.0753   0.1736
pcInc                 1.6025e+02  1.8725e+02  0.8558   0.4823
unemp                -3.5993e+05  5.7207e+05 -0.6292   0.5935
gradrate             -8.7618e+04  1.7046e+05 -0.5140   0.6584

Total Sum of Squares:    4.9629e+12
Residual Sum of Squares: 4.8903e+10
R-Squared:      0.99015
Adj. R-Squared: 0.88668
F-statistic: 22.33 on 9 and 2 DF, p-value: 0.043583
```

</td>
</tr>
<tr>
<td>Inflows</td>
<td>

```
Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_NCComp, effect = "twoway")

Balanced Panel: n = 2, T = 12, N = 24

Residuals:
       1        2        3        4        5        6        7        8
9       10       11
 -23.313    0.927 -153.857  258.258  -82.015 -137.195   86.057  149.579
-124.663   66.841  -69.240
      12       13       14       15       16       17       18       19
20       21       22
  28.622   23.313   -0.927  153.857 -258.258   82.015  137.195  -86.057
-149.579  124.663  -66.841
      23       24
  69.240  -28.622

Coefficients:
                         Estimate  Std. Error  t-value Pr(>|t|)
DID                   -4.1978e+04  1.9693e+03 -21.3159 0.002194 **
GDP                    2.3254e+00  1.0780e-01  21.5719 0.002142 **
Population             6.9264e-03  3.0497e-03   2.2712 0.151115
HealthCoverage        -1.2470e+04  1.0154e+03 -12.2814 0.006565 **
CIT                    7.8653e-02  2.4190e-02   3.2514 0.082987 .
pcPersonalExpenditure -2.6621e+01  1.9825e+00 -13.4282 0.005500 **
pcInc                 -9.6912e-01  4.9642e-01  -1.9522 0.190166
unemp                 -2.7474e+04  1.5167e+03 -18.1146 0.003034 **
gradrate              -6.2735e+03  4.5192e+02 -13.8818 0.005149 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    554520000
Residual Sum of Squares: 343730
R-Squared:      0.99938
Adj. R-Squared: 0.99287
F-statistic: 358.279 on 9 and 2 DF, p-value: 0.0027864
```

</td>
</tr>
</table>

Outflows

```
Twoways effects Within Model

Call:
plm(formula = Outflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_NCComp, effect = "twoway")

Balanced Panel: n = 2, T = 12, N = 24

Residuals:
       1        2        3        4        5        6        7        8
9      10       11
  200.06  -784.05  -158.85  1026.00  -283.16  -454.22   464.03   439.80
-1094.10   979.76  -467.87
      12       13       14       15       16       17       18       19
20       21       22
  132.60  -200.06   784.05   158.85 -1026.00   283.16   454.22  -464.03
-439.80  1094.10  -979.76
      23       24
  467.87  -132.60

Coefficients:
                         Estimate  Std. Error t-value Pr(>|t|)
DID                    2.6348e+04  1.0431e+04  2.5260   0.1274
GDP                   -1.2865e+00  5.7097e-01 -2.2532   0.1530
Population            -3.9936e-03  1.6153e-02 -0.2472   0.8278
HealthCoverage         3.8460e+03  5.3779e+03  0.7151   0.5487
CIT                    1.6020e-02  1.2813e-01  0.1250   0.9119
pcPersonalExpenditure  2.0014e+01  1.0500e+01  1.9060   0.1969
pcInc                 -1.4890e+00  2.6293e+00 -0.5663   0.6283
unemp                  1.7542e+04  8.0332e+03  2.1837   0.1606
gradrate               6.1340e+03  2.3936e+03  2.5626   0.1245

Total Sum of Squares:    92673000
Residual Sum of Squares: 9642800
R-Squared:      0.89595
Adj. R-Squared: -0.1966
F-statistic: 1.91346 on 9 and 2 DF, p-value: 0.39008
```

DiD estimator has statistically significant negative impact on inflows.

Oregon 2009 increase in all IVs compared against Iowa 2000-2011

PIT Revenue

```
Twoways effects Within Model

Call:
plm(formula = PIT ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_OR1Comp, effect = "twoway")

Balanced Panel: n = 2, T = 12, N = 24

Residuals:
        1         2         3         4         5         6         7         8
9        10        11        12        13
  -3597.3  -61920.8   71319.5  -11544.1  -47758.4  112317.1   13376.5  -76306.3
4113.8    2161.3   -8567.7    6406.4    3597.3
       14        15        16        17        18        19        20        21
22        23        24
  61920.8  -71319.5   11544.1   47758.4 -112317.1  -13376.5   76306.3   -4113.8
-2161.3    8567.7   -6406.4

Coefficients:
                        Estimate  Std. Error t-value Pr(>|t|)
DID                   1.2686e+05  7.3810e+05  0.1719   0.8794
GDP                  -2.1084e+01  6.9711e+01 -0.3024   0.7909
Population            2.3953e+00  6.1128e+00  0.3919   0.7330
HealthCoverage       -1.6812e+05  2.0722e+05 -0.8113   0.5024
CIT                  -1.0125e+00  1.2862e+00 -0.7872   0.5136
pcPersonalExpenditure -5.5471e+02  1.0909e+03 -0.5085   0.6617
pcInc                 2.7249e+02  3.1619e+02  0.8618   0.4796
unemp                -2.4735e+05  2.8871e+05 -0.8567   0.4819
gradrate             -6.5075e+04  4.5447e+04 -1.4319   0.2885

Total Sum of Squares:    5.5894e+11
Residual Sum of Squares: 6.0201e+10
R-Squared:      0.89229
Adj. R-Squared: -0.23861
F-statistic: 1.84102 on 9 and 2 DF, p-value: 0.40119
```

Inflows

```
Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_OR1Comp, effect = "twoway")

Balanced Panel: n = 2, T = 12, N = 24

Residuals:
       1        2        3        4        5        6        7        8
9       10       11       12       13       14
-227.935  124.155  399.596 -202.880 -599.557  912.661 -208.923 -294.128
97.012  -50.821   99.208  -48.388  227.935 -124.155
      15       16       17       18       19       20       21       22
23       24
-399.596  202.880  599.557 -912.661  208.923  294.128  -97.012   50.821
-99.208   48.388

Coefficients:
                         Estimate  Std. Error t-value Pr(>|t|)
DID                    7.9361e+03  5.4064e+03  1.4679   0.2798
GDP                   -3.0161e-01  5.1062e-01 -0.5907   0.6146
Population            -4.0116e-04  4.4775e-02 -0.0090   0.9937
HealthCoverage         1.4067e+03  1.5178e+03  0.9268   0.4519
CIT                    1.2117e-02  9.4212e-03  1.2861   0.3272
pcPersonalExpenditure -1.2052e+00  7.9906e+00 -0.1508   0.8940
pcInc                 -3.5077e-01  2.3160e+00 -0.1515   0.8935
unemp                 -1.4460e+03  2.1148e+03 -0.6838   0.5647
gradrate               8.5527e+02  3.3289e+02  2.5693   0.1239

Total Sum of Squares:    54867000
Residual Sum of Squares: 3229900
R-Squared:      0.94113
Adj. R-Squared: 0.32302
F-statistic: 3.5527 on 9 and 2 DF, p-value: 0.23893
```

Outflows

```
Twoways effects Within Model

Call:
plm(formula = Outflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_OR1Comp, effect = "twoway")

Balanced Panel: n = 2, T = 12, N = 24

Residuals:
        1         2         3         4         5         6         7         8
9        10        11        12        13
 329.6778 -556.5623 -194.2892  244.2080  641.1773 -742.2096  400.5799    2.4914
-125.0733   90.9937 -203.2947  112.3010 -329.6778
       14        15        16        17        18        19        20        21
22        23        24
 556.5623  194.2892 -244.2080 -641.1773  742.2096 -400.5799   -2.4914  125.0733
-90.9937  203.2947 -112.3010

Coefficients:
                        Estimate  Std. Error t-value Pr(>|t|)
DID                  -3.9408e+02  5.5733e+03 -0.0707   0.9501
GDP                   1.3979e-01  5.2637e-01  0.2656   0.8154
Population            1.1847e-02  4.6156e-02  0.2567   0.8214
HealthCoverage        7.4522e+02  1.5646e+03  0.4763   0.6808
CIT                  -1.4828e-03  9.7119e-03 -0.1527   0.8927
pcPersonalExpenditure  5.5649e+00  8.2371e+00  0.6756   0.5690
pcInc                 1.4801e-01  2.3875e+00  0.0620   0.9562
unemp                 2.4799e+03  2.1800e+03  1.1376   0.3732
gradrate             -3.8709e+02  3.4316e+02 -1.1280   0.3764

Total Sum of Squares:    10107000
Residual Sum of Squares: 3432300
R-Squared:      0.6604
Adj. R-Squared: -2.9054
F-statistic: 0.432144 on 9 and 2 DF, p-value: 0.84543
```

DiD estimator has no statistically significant impacts

Pennsylvania 2004 rate increase compared against Colorado 2001-2020

PIT Revenue

```
Twoways effects Within Model

Call:
plm(formula = PIT ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_PAComp, effect = "twoway")

Balanced Panel: n = 2, T = 21, N = 42

Residuals:
   Min. 1st Qu.  Median 3rd Qu.    Max.
-170864  -39421       0   39421  170864

Coefficients:
                         Estimate  Std. Error t-value Pr(>|t|)
DID                   -5.4199e+05  2.6092e+05 -2.0772 0.061998 .
GDP                    5.0270e+00  7.9649e+00  0.6311 0.540838
Population            -1.8916e+00  4.5879e-01 -4.1231 0.001692 **
HealthCoverage         1.7516e+05  5.6870e+04  3.0799 0.010473 *
CIT                    3.8777e-01  3.8951e-01  0.9955 0.340878
pcPersonalExpenditure  2.4907e+02  1.2994e+02  1.9168 0.081588 .
pcInc                  5.3695e+01  6.6040e+01  0.8131 0.433427
unemp                  2.1488e+05  1.1237e+05  1.9122 0.082234 .
gradrate               1.4250e+04  2.9835e+04  0.4776 0.642256
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    6.4417e+12
Residual Sum of Squares: 1.85e+11
R-Squared:      0.97128
Adj. R-Squared: 0.89296
F-statistic: 41.3366 on 9 and 11 DF, p-value: 3.2917e-07
```

Inflows

```
Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_PAComp, effect = "twoway")

Balanced Panel: n = 2, T = 21, N = 42

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-3.8996e+03 -7.6625e+02  1.1369e-13  7.6625e+02  3.8996e+03

Coefficients:
                         Estimate  Std. Error t-value Pr(>|t|)
DID                    1.1048e+04  6.5640e+03  1.6830 0.120500
GDP                   -2.5709e-02  2.0037e-01 -0.1283 0.900223
Population            -1.3430e-02  1.1542e-02 -1.1636 0.269188
HealthCoverage        -1.5858e+03  1.4307e+03 -1.1084 0.291319
CIT                   -3.3756e-03  9.7990e-03 -0.3445 0.736978
pcPersonalExpenditure  4.5973e+00  3.2688e+00  1.4064 0.187218
pcInc                 -3.7422e-01  1.6614e+00 -0.2252 0.825917
unemp                  1.1153e+04  2.8269e+03  3.9454 0.002291 **
gradrate              -3.9292e+01  7.5056e+02 -0.0523 0.959189
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    1.405e+09
Residual Sum of Squares: 117080000
R-Squared:      0.91667
Adj. R-Squared: 0.68941
F-statistic: 13.445 on 9 and 11 DF, p-value: 9.7372e-05
```

Outflows

```
Twoways effects Within Model

Call:
plm(formula = Outflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_PAComp, effect = "twoway")

Balanced Panel: n = 2, T = 21, N = 42

Residuals:
    Min.  1st Qu.   Median  3rd Qu.     Max.
-2732.55  -814.32     0.00   814.32  2732.55

Coefficients:
                         Estimate  Std. Error t-value Pr(>|t|)
DID                    5.5366e+03  4.9106e+03  1.1275 0.283536
GDP                   -2.9640e-01  1.4990e-01 -1.9773 0.073606 .
Population            -2.8594e-02  8.6344e-03 -3.3116 0.006934 **
HealthCoverage        -2.1933e+03  1.0703e+03 -2.0492 0.065066 .
CIT                    3.4759e-03  7.3307e-03  0.4741 0.644666
pcPersonalExpenditure -2.1549e+00  2.4454e+00 -0.8812 0.397045
pcInc                  1.4871e+00  1.2429e+00  1.1965 0.256658
unemp                 -6.8008e+03  2.1149e+03 -3.2157 0.008221 **
gradrate              -7.5574e+02  5.6150e+02 -1.3459 0.205411
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    537870000
Residual Sum of Squares: 65525000
R-Squared:      0.87818
Adj. R-Squared: 0.54593
F-statistic: 8.81047 on 9 and 11 DF, p-value: 0.00069451
```

DiD estimator has a statistically significant negative impact on PIT revenue

Rhode Island 2011 decrease in all IVs compared against Iowa 2002-2018 — **PIT Revenue**

```
Twoways effects Within Model

Call:
plm(formula = PIT ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_RIComp, effect = "twoway")

Balanced Panel: n = 2, T = 17, N = 34

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-8.5842e+04 -2.4403e+04 -3.6380e-12  2.4403e+04  8.5842e+04

Coefficients:
                         Estimate  Std. Error t-value Pr(>|t|)
DID                   -6.8474e+04  2.3425e+05 -0.2923  0.77852
GDP                   -6.0027e+00  1.5105e+01 -0.3974  0.70291
Population             6.6521e+00  2.3904e+00  2.7828  0.02719 *
HealthCoverage         2.1544e+04  3.2368e+04  0.6656  0.52698
CIT                   -1.3506e-01  3.2101e-01 -0.4207  0.68657
pcPersonalExpenditure -2.0116e+02  1.8398e+02 -1.0934  0.31042
pcInc                  9.6551e+01  6.9956e+01  1.3802  0.21000
unemp                  2.7731e+04  6.7745e+04  0.4093  0.69453
gradrate              -2.2137e+03  5.8442e+04 -0.0379  0.97084
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    2.1691e+12
Residual Sum of Squares: 4.3537e+10
R-Squared:      0.97993
Adj. R-Squared: 0.90538
F-statistic: 37.9732 on 9 and 7 DF, p-value: 4.0388e-05
```

Inflows

```
Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_RIComp, effect = "twoway")

Balanced Panel: n = 2, T = 17, N = 34

Residuals:
   Min. 1st Qu.  Median 3rd Qu.    Max.
-1495.9  -359.7     0.0   359.7  1495.9

Coefficients:
                         Estimate  Std. Error t-value Pr(>|t|)
DID                    1.1672e+03  4.6567e+03  0.2506  0.80929
GDP                    3.3415e-01  3.0027e-01  1.1128  0.30254
Population            -7.3902e-02  4.7519e-02 -1.5552  0.16385
HealthCoverage        -9.6097e+02  6.4344e+02 -1.4935  0.17895
CIT                   -1.3185e-02  6.3813e-03 -2.0661  0.07766 .
pcPersonalExpenditure  3.2800e+00  3.6573e+00  0.8969  0.39959
pcInc                  1.2791e+00  1.3907e+00  0.9198  0.38829
unemp                 -5.0459e+02  1.3467e+03 -0.3747  0.71899
gradrate              -1.2413e+03  1.1618e+03 -1.0684  0.32078
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    64584000
Residual Sum of Squares: 17205000
R-Squared:      0.73361
Adj. R-Squared: -0.25585
F-statistic: 2.1419 on 9 and 7 DF, p-value: 0.16385
```

Outflows

```
Twoways effects Within Model

Call:
plm(formula = Outflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_RIComp, effect = "twoway")

Balanced Panel: n = 2, T = 17, N = 34

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-1.8110e+03 -6.2604e+02  2.5580e-13  6.2604e+02  1.8110e+03

Coefficients:
                         Estimate  Std. Error t-value Pr(>|t|)
DID                    7.6404e+00  4.9792e+03  0.0015  0.99882
GDP                    5.3541e-01  3.2107e-01  1.6676  0.13934
Population            -1.1375e-01  5.0811e-02 -2.2388  0.06018 .
HealthCoverage        -6.8340e+02  6.8802e+02 -0.9933  0.35365
CIT                   -1.0908e-02  6.8234e-03 -1.5986  0.15395
pcPersonalExpenditure -2.0586e+00  3.9106e+00 -0.5264  0.61485
pcInc                  1.9973e+00  1.4870e+00  1.3432  0.22112
unemp                 -1.1536e+03  1.4400e+03 -0.8011  0.44940
gradrate              -2.9516e+02  1.2422e+03 -0.2376  0.81899
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    58282000
Residual Sum of Squares: 19671000
R-Squared:      0.66249
Adj. R-Squared: -0.59114
F-statistic: 1.52665 on 9 and 7 DF, p-value: 0.29521
```

DiD estimator has no statistically significant impacts

<table>
<tr>
<td rowspan="3">Utah 2008 moving graduated to flat system compared against Colorado 2000-2018</td>
<td>PIT Revenue</td>
<td>Twoways effects Within Model

Call:
plm(formula = PIT ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_UTComp, effect = "twoway")

Balanced Panel: n = 2, T = 19, N = 38

Residuals:
   Min. 1st Qu. Median 3rd Qu.   Max.
-140278 -59104   0   59104 140278

Coefficients:
                         Estimate Std. Error t-value Pr(>|t|)
DID   -2.0565e+05 2.2184e+05 -0.9270 0.37811
GDP   5.2614e+01 2.5714e+01 2.0461 0.07106 .
Population   -1.1441e+00 2.7066e+00 -0.4227 0.68241
HealthCoverage   2.2404e+04 5.5288e+04 0.4052 0.69478
CIT   1.1434e+00 1.6841e+00 0.6789 0.51425
pcPersonalExpenditure -2.1706e+02 3.1819e+02 -0.6822 0.51232
pcInc   -7.4232e+01 1.2341e+02 -0.6015 0.56235
unemp   4.8889e+04 1.0794e+05 0.4529 0.66133
gradrate   4.2028e+03 3.1931e+04 0.1316 0.89818

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares: 2.0719e+12
Residual Sum of Squares: 1.9921e+11
R-Squared: 0.90385
Adj. R-Squared: 0.60473
F-statistic: 9.40072 on 9 and 9 DF, p-value: 0.0013188</td>
</tr>
<tr>
<td>Inflows</td>
<td>Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_UTComp, effect = "twoway")

Balanced Panel: n = 2, T = 19, N = 38

Residuals:
       Min.   1st Qu.   Median   3rd Qu.   Max.
-7.4026e+03 -2.2788e+03 5.4854e-12 2.2788e+03 7.4026e+03

Coefficients:
                         Estimate Std. Error t-value Pr(>|t|)
DID   6.7892e+03 1.0232e+04 0.6635   0.5236
GDP   9.8861e-01 1.1860e+00 0.8335   0.4261
Population   2.2834e-02 1.2484e-01 0.1829   0.8589
HealthCoverage   2.6270e+03 2.5501e+03 1.0301   0.3298
CIT   1.4782e-02 7.7679e-02 0.1903   0.8533
pcPersonalExpenditure -2.2233e+01 1.4676e+01 -1.5149   0.1641
pcInc   -5.1190e+00 5.6922e+00 -0.8993   0.3919
unemp   2.6593e+03 4.9787e+03 0.5341   0.6062
gradrate   1.5002e+03 1.4728e+03 1.0186   0.3350

Total Sum of Squares: 1785300000
Residual Sum of Squares: 423800000
R-Squared: 0.76261
Adj. R-Squared: 0.024064
F-statistic: 3.21248 on 9 and 9 DF, p-value: 0.048551</td>
</tr>
<tr>
<td>Outflows</td>
<td>Twoways effects Within Model

Call:
plm(formula = Outflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_UTComp, effect = "twoway")

Balanced Panel: n = 2, T = 19, N = 38

Residuals:
   Min. 1st Qu. Median 3rd Qu.   Max.
-6978.9 -1598.2   0.0 1598.2 6978.9

Coefficients:
                         Estimate Std. Error t-value Pr(>|t|)
DID   -1.2808e+03 8.0860e+03 -0.1584   0.8776
GDP   8.5182e-01 9.3727e-01 0.9088   0.3871
Population   -1.5542e-02 9.8653e-02 -0.1575   0.8783
HealthCoverage   3.3802e+03 2.0152e+03 1.6774   0.1278
CIT   6.0226e-02 6.1385e-02 0.9811   0.3522
pcPersonalExpenditure -1.9197e+01 1.1598e+01 -1.6552   0.1323
pcInc   -4.8013e+00 4.4983e+00 -1.0674   0.3136
unemp   -4.7322e+02 3.9344e+03 -0.1203   0.9069
gradrate   1.5661e+03 1.1639e+03 1.3456   0.2114

Total Sum of Squares: 994180000
Residual Sum of Squares: 264660000
R-Squared: 0.73379
Adj. R-Squared: -0.094427
F-statistic: 2.75641 on 9 and 9 DF, p-value: 0.073501</td>
</tr>
</table>

<table>
<tr><td></td><td colspan="2">DiD estimator has no statistically significant impacts</td></tr>
<tr><td rowspan="2">Vermont 2009 decrease in rates compared against Iowa 2000-2018</td><td>PIT Revenue</td><td>

```
Twoways effects Within Model

Call:
plm(formula = PIT ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_VTComp, effect = "twoway")

Balanced Panel: n = 2, T = 19, N = 38

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-7.4960e+04 -1.3149e+04  5.4570e-12  1.3149e+04  7.4960e+04

Coefficients:
                        Estimate  Std. Error t-value Pr(>|t|)
DID                   1.3455e+05  1.7170e+05  0.7836 0.453403
GDP                  -3.1826e+00  9.2735e+00 -0.3432 0.739331
Population            8.3100e+00  2.3744e+00  3.4998 0.006726 **
HealthCoverage        3.6441e+04  2.2166e+04  1.6440 0.134595
CIT                  -7.2164e-02  1.4478e-01 -0.4984 0.630121
pcPersonalExpenditure -4.7810e+01  6.6875e+01 -0.7149 0.492788
pcInc                 1.3088e+02  5.9186e+01  2.2113 0.054331 .
unemp                -1.1539e+05  9.1428e+04 -1.2621 0.238648
gradrate             -2.1858e+03  1.1157e+04 -0.1959 0.849035
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    2.8875e+12
Residual Sum of Squares: 3.5564e+10
R-Squared:      0.98768
Adj. R-Squared: 0.94937
F-statistic: 80.1919 on 9 and 9 DF, p-value: 1.6324e-07
```

</td></tr>
<tr><td>Inflows</td><td>

```
Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_VTComp, effect = "twoway")

Balanced Panel: n = 2, T = 19, N = 38

Residuals:
    Min.  1st Qu.   Median  3rd Qu.     Max.
-2800.83  -471.97     0.00   471.97  2800.83

Coefficients:
                        Estimate  Std. Error t-value Pr(>|t|)
DID                  -4.7659e+03  5.3646e+03 -0.8884   0.3974
GDP                   2.9153e-01  2.8974e-01  1.0062   0.3406
Population           -1.0421e-01  7.4185e-02 -1.4047   0.1937
HealthCoverage       -4.2384e+02  6.9255e+02 -0.6120   0.5557
CIT                   2.3488e-05  4.5233e-03  0.0052   0.9960
pcPersonalExpenditure  2.6046e-01  2.0894e+00  0.1247   0.9035
pcInc                 1.0729e-01  1.8492e+00  0.0580   0.9550
unemp                 8.7241e+02  2.8565e+03  0.3054   0.7670
gradrate              5.3217e+02  3.4860e+02  1.5266   0.1612

Total Sum of Squares:    77921000
Residual Sum of Squares: 34716000
R-Squared:      0.55447
Adj. R-Squared: -0.83161
F-statistic: 1.24454 on 9 and 9 DF, p-value: 0.37491
```

</td></tr>
</table>

Outflows

```
Twoways effects Within Model

Call:
plm(formula = Outflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_VTComp, effect = "twoway")

Balanced Panel: n = 2, T = 19, N = 38

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-2.7497e+03 -3.0629e+02 -5.7554e-13  3.0629e+02  2.7497e+03

Coefficients:
                         Estimate  Std. Error t-value Pr(>|t|)
DID                   -5.2926e+03  5.3531e+03 -0.9887  0.34864
GDP                    3.7394e-01  2.8911e-01  1.2934  0.22808
Population            -1.3921e-01  7.4026e-02 -1.8805  0.09273 .
HealthCoverage        -7.8282e+02  6.9107e+02 -1.1328  0.28659
CIT                   -7.9431e-04  4.5137e-03 -0.1760  0.86421
pcPersonalExpenditure -1.6772e+00  2.0849e+00 -0.8044  0.44188
pcInc                  1.1644e+00  1.8452e+00  0.6310  0.54370
unemp                  5.7182e+01  2.8504e+03  0.0201  0.98443
gradrate               1.4470e+02  3.4785e+02  0.4160  0.68717
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    73354000
Residual Sum of Squares: 34567000
R-Squared:      0.52876
Adj. R-Squared: -0.93732
F-statistic: 1.12206 on 9 and 9 DF, p-value: 0.4333
```

DiD estimator has no statistically significant impacts

Wisconsin 2009 increase in all IVs compared against Iowa 2001-2013

PIT Revenue

```
Twoways effects Within Model

Call:
plm(formula = PIT ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_WIComp, effect = "twoway")

Balanced Panel: n = 2, T = 13, N = 26

Residuals:
        1        2        3        4        5        6        7        8
9       10       11       12       13       14
 19690.6  11177.8 -69121.6  10838.5   9564.6  43511.2 -29363.7   3702.6
-25658.8  64612.2 -55133.8  11931.0   4249.5 -19690.6
      15       16       17       18       19       20       21       22
23       24       25       26
-11177.8  69121.6 -10838.5  -9564.6 -43511.2  29363.7  -3702.6  25658.8
-64612.2  55133.8 -11931.0  -4249.5

Coefficients:
                        Estimate  Std. Error t-value Pr(>|t|)
DID                  -4.3663e+05  6.6041e+05 -0.6611   0.5558
GDP                   2.0588e+01  2.4956e+01  0.8250   0.4699
Population            8.7313e-01  4.9138e+00  0.1777   0.8703
HealthCoverage       -1.4565e+03  1.2418e+05 -0.0117   0.9914
CIT                  -1.5204e+00  9.0875e-01 -1.6730   0.1929
pcPersonalExpenditure  5.8389e+01  7.2231e+02  0.0808   0.9407
pcInc                -2.4303e+02  2.1122e+02 -1.1506   0.3333
unemp                 1.1203e+05  2.7620e+05  0.4056   0.7122
gradrate              3.5930e+03  2.4099e+04  0.1491   0.8909

Total Sum of Squares:    2.9747e+11
Residual Sum of Squares: 3.2604e+10
R-Squared:      0.8904
Adj. R-Squared: 0.086654
F-statistic: 2.70799 on 9 and 3 DF, p-value: 0.22286
```

Inflows

```
Twoways effects Within Model

Call:
plm(formula = Inflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_WIComp, effect = "twoway")

Balanced Panel: n = 2, T = 13, N = 26

Residuals:
       1        2        3        4        5        6        7        8
9       10       11       12       13       14
 -51.082   66.897   17.485 -183.277  248.636 -314.913  634.996 -418.743
165.599 -501.029  341.606   34.757  -40.934   51.082
      15       16       17       18       19       20       21       22
23       24       25       26
 -66.897  -17.485  183.277 -248.636  314.913 -634.996  418.743 -165.599
501.029 -341.606  -34.757   40.934

Coefficients:
                        Estimate  Std. Error t-value Pr(>|t|)
DID                   1.3347e+03  5.6153e+03  0.2377  0.82743
GDP                  -5.0195e-01  2.1220e-01 -2.3655  0.09891 .
Population            3.3984e-02  4.1780e-02  0.8134  0.47555
HealthCoverage        1.5759e+03  1.0559e+03  1.4925  0.23238
CIT                   2.2382e-02  7.7268e-03  2.8967  0.06267 .
pcPersonalExpenditure -6.2589e+00  6.1416e+00 -1.0191  0.38318
pcInc                 1.4595e+00  1.7959e+00  0.8127  0.47590
unemp                -5.7051e+02  2.3485e+03 -0.2429  0.82372
gradrate             -7.3148e+01  2.0491e+02 -0.3570  0.74474
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    43278000
Residual Sum of Squares: 2357100
R-Squared:      0.94554
Adj. R-Squared: 0.54613
F-statistic: 5.78682 on 9 and 3 DF, p-value: 0.0879
```

Outflows

```
Twoways effects Within Model

Call:
plm(formula = Outflow ~ Time + Treatment + DID + GDP + Population +
    HealthCoverage + CIT + pcPersonalExpenditure + pcInc + unemp +
    gradrate, data = df_WIComp, effect = "twoway")

Balanced Panel: n = 2, T = 13, N = 26

Residuals:
        1         2         3         4         5         6         7         8
9        10        11        12        13
 153.0252 -120.5843 -194.0688  -32.0032  206.2395   -4.8129  162.5967 -170.3922
-131.4149  236.2935 -195.2498  -17.1051  107.4762
       14        15        16        17        18        19        20        21
22        23        24        25        26
-153.0252  120.5843  194.0688   32.0032 -206.2395    4.8129 -162.5967  170.3922
131.4149 -236.2935  195.2498   17.1051 -107.4762

Coefficients:
                        Estimate  Std. Error t-value Pr(>|t|)
DID                  -3.5999e+03  2.8224e+03 -1.2755  0.29194
GDP                  -2.3056e-01  1.0666e-01 -2.1617  0.11938
Population            5.5220e-03  2.1000e-02  0.2630  0.80961
HealthCoverage        3.0474e+02  5.3071e+02  0.5742  0.60605
CIT                   1.3234e-02  3.8837e-03  3.4076  0.04222 *
pcPersonalExpenditure -8.2286e+00  3.0869e+00 -2.6656  0.07597 .
pcInc                 2.7650e+00  9.0267e-01  3.0631  0.05486 .
unemp                 1.6919e+03  1.1804e+03  1.4333  0.24722
gradrate             -2.6635e+02  1.0299e+02 -2.5861  0.08135 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    33665000
Residual Sum of Squares: 595490
R-Squared:      0.98231
Adj. R-Squared: 0.8526
F-statistic: 18.5113 on 9 and 3 DF, p-value: 0.01759
```

DiD estimator has no statistically significant impacts