Internal Migration and the Effective Price of State and Local Taxes

By AUSTIN J. DRUKKER*

This paper examines the mobility response of high-income households in the United States to a provision in a 2017 tax law that limited the federal deductibility of state and local taxes. The increase in the effective price of state and local taxes induced by the cap on deductibility caused high-income households to leave high-tax states in favor of low-tax states and to prefer low-tax states to high-tax states conditional on moving. The findings suggest that policymakers should take seriously the prospect that high-income taxpayers may flee states that tax them heavily, which could have long-lasting implications for states' fiscal positions.

Keywords: state and local taxes, deductibility, migration, Tax Cuts and Jobs Act

JEL Codes: H24, H31, H71, H73

"Tax the rich, tax the rich, tax the rich. We did that. God forbid the rich leave."

– *Andrew Cuomo, former governor of New York* [1]

Tax rates differ substantially across the United States, and states have substantial leeway to decide how to raise revenues. While federal revenues derive primarily from personal income and payroll taxes, states derive revenues from a variety of sources, including income taxes, property

* Drukker: Department of Economics, University of Arizona, 1130 E. Helen Street #401, Tucson, AZ 85721 (email: adrukker@email.arizona.edu). I am grateful to David Agarwal, Donald Bruce, Matthew Comey, Chase Eck, Naomi Feldman, Price Fishback, Dirk Foremny, Henrik Kleven, Ashley Langer, Adam Looney, Joan Monras, Mathilde Muñoz, Juan Pantano, Andrew Reschovsky, Harvey Rosen, Stefanie Stantcheva, and Evan Taylor for helpful comments.

[1] Tom Precious, "'Serious as a Heart Attack': Cuomo Warns of Falling State Revenue," *Buffalo News*, February 4, 2019.

taxes, sales taxes, and fees. An important question for policymakers is whether households choose where to live in response to tax differentials, which could reduce the ability of subnational governments to redistribute income and provide public goods. This question has become increasingly important due to the rapid decline of mobility costs.

Recent literature has studied the mobility response of star athletes (Kleven, Landais, and Saez, 2013), inventors (Akcigit, Baslandze, and Stantcheva, 2016), star scientists (Moretti and Wilson, 2017), and the ultra-wealthy (Moretti and Wilson, forthcoming), all finding large mobility responses to tax differentials. But these cases may feature particularly high cross-border mobility both because they involve little location-specific human capital and because the workers studied tend to be less tied to specific firms (Kleven et al., 2020). Furthermore, some of these examples reflect location responses to extreme top tax rates.

This paper contributes to the growing literature on the relationship between taxes and mobility for high-income individuals. The key question of this paper is whether the federal tax treatment of state and local taxes (SALT) distorts the location decisions of high-income households. To answer this question, I exploit state-level variation in the federal tax treatment of SALT brought about by a 2017 tax law commonly referred to as the Tax Cuts and Jobs Act (TCJA). Among other things, the law limited the deductibility of SALT to $10,000 per household per year. Although some feared that the provision would harm high-tax states, evidence of a migration response to the TCJA's SALT provision has thus far been anecdotal.

Despite being a central conceptual component in several strands of economics, direct empirical evidence on the responsiveness of households' location decisions to taxes has been scant. Kleven et al. (2020) point to two main challenges to explain the paucity of empirical research in the field: data limitations and identification challenges. Information on migration patterns combined with precise measures of earnings and tax rates in different locations is hard to come by, and traditional surveys either lack this type of information or are statistically underpowered due to small sample sizes. Where data on migration patterns are available, the second fundamental difficulty is to find tax variation that is orthogonal to all other factors affecting individual location choices, such as local labor market conditions, local amenities, and public goods. The most natural approach is to use variation stemming from a federal tax reform.

Much of the recent literature has focused on a specific segment of the labor market for which detailed migration information is available from external sources. But this approach may lack generalizability, especially if the sample of taxpayers studied has abnormally high incomes (Agarwal and Foremny, 2019), and such individuals may not be economically valuable (Moretti and Wilson, 2017). Alternatively, administrative data can be used in certain contexts when information on migration is available.

To study the effects of taxes on migration, I exploit exogenous variation in the federal tax price of SALT induced by the TCJA. The federal tax price of SALT refers to the effective net cost of paying $1 to the state or local government, which for certain taxpayers can be less than $1 because SALT is deductible from federal taxes (Feldstein and Metcalf, 1987). I primarily rely on data from the US Census Bureau's American Community Survey (ACS), a large, publicly available, nationally representative dataset that includes individual- and household-level information about several categories of earnings, which allows for the construction of tax rates, as well as households' state of residence in the previous year, which allows for the construction of migration rates. The 2017 tax law provides a unique opportunity to study SALT because it was the first tax reform in US history to put a cap on the federal deductibility of SALT, which introduced substantial state-level variation in the tax price of SALT. Consequently, this paper is the first to utilize the concept of tax price in the context of internal migration.

I formulate and estimate a structural model of internal migration that incorporates the tax price of SALT and its relationship to preferences for government services. I first use the model to analyze the short-term extensive and intensive margin migration effects of the SALT cap. I find that high-income households were highly responsive to SALT differentials following the 2017 tax law, both on the extensive and intensive margins. I then use my model to predict the long-run implications of this tax-induced migration on states' revenues and provide a ranking of the effects by state. In aggregate, the 10 most negatively affected states are predicted to lose $2.2 billion in SALT revenue due to out-migration of high-income households, and the 10 most positively affected states are predicted to gain $1.4 billion in SALT revenue due to in-migration of high-income households.

The paper proceeds as follows. In section I, I describe the relevant background of the 2017 tax law and its effect on SALT deductibility, and I provide summary statistics and graphical evidence of a migration response. Section II formally introduces the concept of tax price and its relevance for location decisions. In section III, I describe my model and section IV describes the data. In section V, I describe the estimation and identification strategy and present the results. In section VI, I formulate and calibrate a dynamic model to analyze the potential long-run revenue implications of the tax-induced migration response reported in the previous sections for each state. Section VII concludes.

I. Background

On November 2, 2017, the US House of Representatives introduced the TCJA. In contrast to the intense debate over health care reform that had dominated the Republican legislative agenda for much of 2017, the TCJA was met with little public debate, quickly passed by the House, rushed through the Senate, and signed into law on December 22, 2017. The law became effective January 1, 2018, for the start of the 2018 tax year. The TCJA was the largest US tax reform in 30 years and made significant changes to individual income taxation, including eliminating individual exemptions in place of expanded child tax credits and an increased standard deduction, capping the mortgage interest deduction, and capping the SALT deduction to $10,000. Table 1 shows the extent of SALT claims on federal income tax returns for 2017 by AGI. Individuals not subject to the alternative minimum tax (AMT) may claim a deduction for SALT paid on income, sales, and real estate.[2] Income and property taxes make up the vast majority of SALT claims, and it is clear from table 1 that the $10,000 SALT cap is binding even for modest levels of income. Table 2 shows which states are most likely to be affected by the $10,000 SALT cap based on the share of returns claiming SALT and average SALT claims. These descriptive data are consistent with the narrative that Democratic-leaning states are likely to be the most affected by the TCJA's SALT cap, as the top 10 states in terms of the share of taxpayers claiming SALT and average SALT claimed all voted for the Democratic presidential candidate in 2020.

Figure 1 shows the migration rate for different income groups. The migration rate for taxpayers with AGI between $100,000 and $500,000 is essentially flat over the entire sample period. But for

[2] Taxpayers may deduct real estate (property) taxes and either income taxes or general sales taxes (general sales taxes were not deductible in 2014). While income and property taxes represent the bulk of SALT nationally, sales taxes can be important in states with no income tax. Nine states currently do not levy an income tax (Alaska, Florida, New Hampshire, Nevada, South Dakota, Tennessee, Texas, Washington, and Wyoming). New Hampshire and Tennessee (through 2020) tax investment income and interest. Washington taxes investment income and capital gains for certain high earners.

TABLE 1—SALT CLAIMS ON FEDERAL TAX RETURNS, 2017

	Adjusted gross income			
	$100,000–$200,000	$200,000–$500,000	$500,000–$1 million	$1 million and above
Share claiming SALT	0.753	0.935	0.936	0.919
Average SALT claim (dollars)	11,399	23,386	56,152	280,991
Average income tax claim (dollars)	5,841	14,178	39,708	245,702
Average property tax claim (dollars)	4,823	8,227	15,079	32,162

Source: Statistics of Income.

Notes: The share of returns claiming SALT is as a share of all returns filed. Average SALT claims are conditional on itemizing.

TABLE 2—SALT CLAIMS ON FEDERAL TAX RETURNS, BY STATE, 2017

Top 10		Bottom 10		Top 10		Bottom 10	
State	Share claiming SALT	State	Share claiming SALT	State	Average SALT claim (dollars)	State	Average SALT claim (dollars)
MD*	0.991	NH*	0.841	NY*	84,609	AL	31,978
NJ*	0.991	ND	0.825	CA*	80,302	FL	28,071
CT*	0.991	TX	0.817	NJ*	74,707	TX	27,443
RI*	0.989	WA*	0.809	MN*	72,912	ND	27,218
DC*	0.989	TN	0.801	CT*	72,824	NV*	27,201
NY*	0.987	FL	0.797	OR*	71,166	WY	25,867
VA*	0.986	NV*	0.789	DC*	68,612	WA*	25,632
MA*	0.986	SD	0.721	MD*	68,090	SD	22,154
MN*	0.985	WY	0.712	VT*	67,898	TN	19,526
CA*	0.983	AK	0.665	ME*	65,439	AK	16,906

Source: Statistics of Income.

Notes: The sample is taxpayers with AGI between $500,000 and $1 million. The share of returns claiming SALT is as a share of all returns filed. Average SALT claims are conditional on itemizing. States marked with * voted for the Democratic presidential candidate in 2020.

taxpayers with AGI above $500,000 there is a clear rise in the migration rate immediately following the 2017 tax law, followed by an immediate drop back to pre-TCJA levels. Figure 2 shows the transition probability for individuals with AGI above $500,000. From 2012 to 2017, the share of high-income individuals moving between high-tax states was roughly constant. But in 2018, there is a clear drop in the probability of a high-income individual moving between high-tax states and a rise in the probability of a high-income individual moving from a high-tax state to a

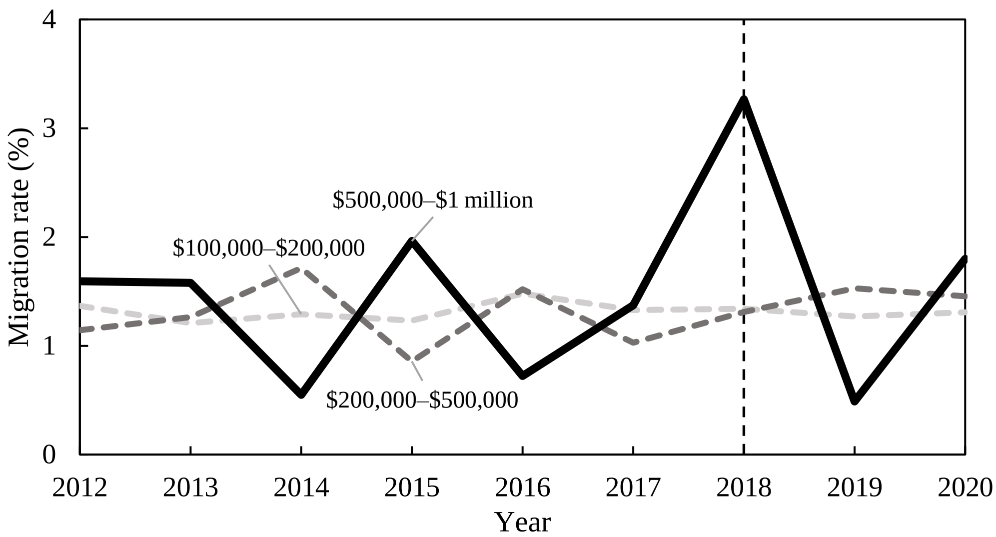


FIGURE 1. MIGRATION RATE BY ADJUSTED GROSS INCOME, 2012–20

Source: Current Population Survey, Annual Social and Economic Supplement.
Notes: Migration rate is the percentage of respondents who moved to a different state from a year ago.

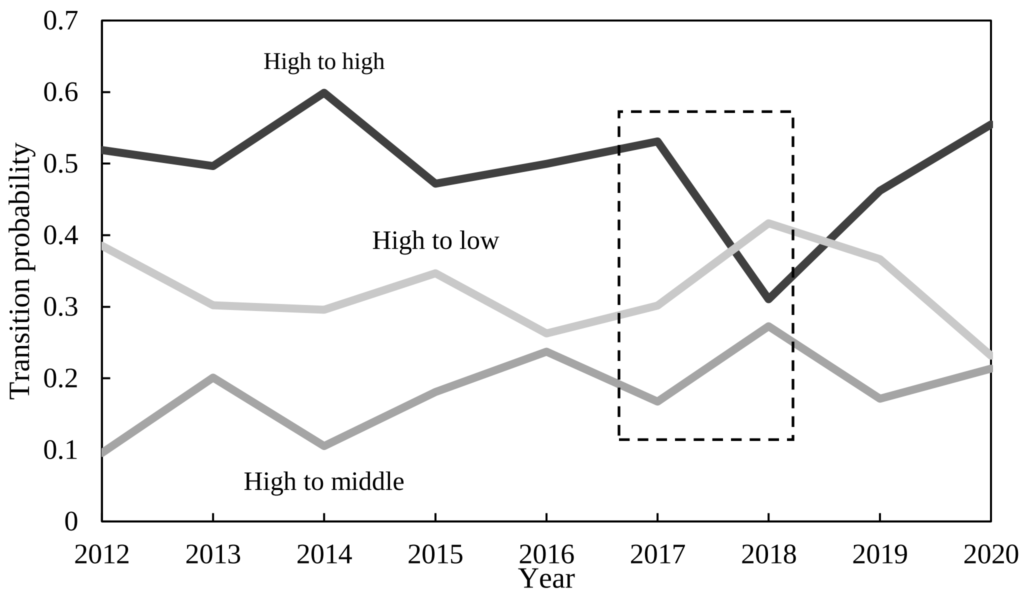


FIGURE 2. TRANSITION PROBABILITY FOR HIGH-INCOME HOUSEHOLDS MOVING FROM HIGH-TAX STATES, 2012–20

Source: American Community Survey.
Notes: The transition probability is the share of respondents with AGI above $500,000 who moved from a high-tax state to a different state from a year ago. High-, middle-, and low-tax states are the top, middle, and bottom 17 states in terms of average SALT claims in 2017 (see table 2).

middle- or low-tax state. Figures 1 and 2 are consistent with previous findings in the literature that higher-income taxpayers' location choices are responsive to tax changes. The figures also suggest that the migration response to the tax change was immediate, with large responses observed within the first year of the 2017 tax law coming into effect. In contrast, Moretti and Wilson's (2017) find that there is a delayed migration response to state tax differentials for star scientists.

II. Tax Price and Location Preferences

Almost all papers studying tax-induced migration have exploited variation in the net-of-tax rate—the share of each $1 that remains after paying state and federal taxes—induced by a tax reform (Agarwal and Foremny, 2019; Moretti and Wilson, 2017; Kleven, Landais, and Saez, 2013). In the context of the TCJA, however, it is inappropriate to study the effect of net-of-tax rate differentials on between-state migration because the TCJA had no direct effect on states' tax rates. US states have always had autonomy when it comes to setting tax policy, and large variation in net-of-tax rates between states existed before the TCJA.

According to Tiebout's (1956) pure theory of local expenditures, state and local taxes are the mechanism by which consumers register their preferences for public goods; consumers are, in a sense, surrounded by a government whose objective it is to ascertain their wants for public goods and to tax accordingly. Consumers' preferences over locations are thus revealed by their choices. Changing the price of SALT should therefore induce a behavioral response from households who pay said taxes. As with other extensive-margin decisions, location decisions depend on average rather than marginal taxes (Kleven et al., 2020).[3]

[3] From state and local governments' point of view, the average tax price in a region is the relevant determinant of fiscal outcomes (Feldstein and Metcalf, 1987; Coyne 2017).

The tax price of SALT can be thought of as the effective cost of $1 of state and local spending (Feldstein and Metcalf, 1987; Coyne, 2017). Fundamentally, the tax price of SALT is the amount by which SALT liability is offset by a decline in federal income tax liability caused by SALT. While the tax price does not change the amount of taxes residents actually pay, a lower tax price reflects the fact that SALT paid is deductible from federally taxable income. Under a tax regime where SALT is fully deductible, for a taxpayer who itemizes deductions and does not pay the AMT, the tax price of SALT is simply $1-\tau^F$, where τ^F is a taxpayer's federal marginal income tax rate. If a taxpayer pays the AMT or does not itemize, then the tax price of SALT is 1, since taxpayers must itemize deductions to claim the SALT deduction and SALT is not deductible from alternative minimum taxable income for purposes of calculating the AMT. When SALT is fully deductible, the *marginal* tax price is equal to the *average* tax price. When SALT is not fully deductible, the marginal tax price of SALT is 1 for amounts over the deductibility cap and the calculation of the average tax price of SALT must take this into account. For a taxpayer who itemizes and does not pay the AMT, the average tax price of SALT is $1-\tau^F(S'/S)$, where S is the total amount of SALT paid and S' is the deductible portion. When SALT is fully deductible, $S'=S$ and the formula simplifies to $1-\tau^F$. Appendix figure 1 shows average and marginal tax prices as a function of SALT paid in 2017 and 2018 for a hypothetical household.

I focus my analysis on households in the 99th percentile of the AGI distribution, since they were most affected by the TCJA's SALT cap. This impact is demonstrated in appendix figure 2, shows the average of absolute tax price differentials between all 1,275 = ½ × 50 × 51 state combinations from 2013 to 2020 for representative households in different percentiles of the AGI distribution (throughout the text, I refer to the District of Columbia as a State). Representative households are constructed by assigning the mean among households in a given percentile of the

AGI distribution of all dollar-denominated, tax-relevant variables and the median of all other tax-relevant variables, such as age, marital status, and number of dependents. Before the TCJA, households in all the AGI percentiles shown faced essentially constant average between-state tax price differential. After the TCJA, the average tax price differential for the household in the 99th percentile jumps up about 5 percentage points, while the tax price differential for the households in lower percentiles drop to 0, since these households switched to taking the now-doubled standard deduction. In other words, the TCJA's SALT cap erased between-state tax price differentials for households below the 99th percentile of the AGI distribution but dramatically increased between-state tax price differentials for households in the 99th percentile of the AGI distribution.

III. Model

Consider an economy with J states. A worker i living in state $j \in 1, \ldots, J$ receives flow utility in year t from local amenities A_j, consumption c_{ijt}, housing h_{ijt}, and government services g_{ijt} according to the Cobb–Douglas utility function

$$U_{ijt} = A_j c_{ijt}^{(1-\alpha^*-\beta^*)} h_{ijt}^{\alpha^*} g_{ijt}^{\beta^*}$$

Consumption goods are tradable with a price normalized to 1. Utility from housing services derives from the size of one's house, H_{ijt}, at a constant flow rate μ, such that $h_{ijt} = \mu H_{ijt}$, and the price of housing is P_{jt}.

Each worker supplies a fixed unit of labor and consumes all after-tax income. Wages, w_{ijt}, are subject to a state income (or sales) tax and a federal income tax. Let $\bar{\tau}_{ijt}^F$ denote an individual's federal average income tax rate and τ_{ijt}^F the federal marginal income tax rate. Let $\bar{\tau}_{ijt}^S$ denote an individual's state average income tax rate, or, in the case that the individual deducts state sales tax rather than state income tax, sales tax payments as a share of income. An individual's after-tax wage income thus equals $(1-\bar{\tau}_{ijt}^S-\bar{\tau}_{ijt}^F)w_{ijt}$. Housing is taxed at the property tax rate τ_{jt}^P, such that the individual's property tax bill is $\mu\tau_{jt}^P P_{jt}H_{ijt}$.

Total SALT paid, S_{ijt}, is comprised of state and local income (or sales) taxes and property taxes, so $S_{ijt}=\bar{\tau}_{ijt}^S w_{ijt}+\mu\tau_{jt}^P P_{jt}H_{ijt}$. Let S'_{ijt} denote the portion of SALT paid that is deductible from federal income taxes. In the United States, the extent of SALT deductibility depends on two main factors: itemization status and AMT liability. SALT can only be deducted if the taxpayer itemizes deductions and is not subject to the AMT, both of which are functions of the amount of SALT paid. In addition, prior to 2018, there was no limit on SALT deductibility; but starting in 2018, a \$10,000 limit per household was imposed. I compute S'_{ijt} using an algorithm to capture these and other nuances of the US tax system.

SALT is deductible from federally taxable income at a rate τ_{ijt}^F, which implies the average effective net cost of paying S_{ijt} dollars in SALT is $\tau_{ijt}=1-\tau_{ijt}^F(S'_{ijt}/S_{ijt})$, where $\tau_{ijt}\in[1-\tau_{ijt}^F,1]$ is the federal tax price of SALT. Prior to the 2017 tax law, when SALT was fully deductible, the average tax price of a dollar paid to the state and local government for an itemizer not subject to the AMT was $1-\tau_{ijt}^F$, corresponding to the case $S_{ijt}=S'_{ijt}$. For a taxpayer who pays the AMT or does not itemize, the tax price of SALT is 1, corresponding to the case $S'_{ijt}=0$.

State and local government services are financed through SALT and can be thought of as a non-tradable good whose price is proportional to τ_{ijt}. I constrain $\tau_{ijt}\in[1-\tau_{ijt}^F,1]$ by assuming utility from government services is proportional to SALT paid, $g_{ijt}=\omega S_{ijt}$, with $\omega>0$; $\omega<1$ corresponds to the case where there is a social cost of public funds.

A household's after-tax budget constraint is therefore

$$(1-\bar{\tau}_{ijt}^F)w_{ijt}=c_{ijt}+P_{jt}h_{ijt}+\tau_{ijt}\omega^{-1}g_{ijt}$$

The budget constraint simply says that all income net of federal taxes is spent on consumption, housing, and state and local government services. Alternatively, the budget constraint can be written in terms of all after-tax (state and federal) income going toward consumption and housing expenditures:

$$\underbrace{\left(1-\bar{\tau}_{ijt}^{S}-\bar{\tau}_{ijt}^{F}\right)w_{ijt}}_{\text{after-tax wage income}} \;-\; \underbrace{\mu\tau_{jt}^{P}P_{jt}H_{ijt}}_{\text{property taxes}} \;+\; \underbrace{\tau_{ijt}^{F}S_{ijt}'}_{\text{SALT deduction}} \;=\; c_{ijt}+P_{jt}h_{ijt}$$

The functional form of the utility function implies that households spend a constant share $1-\alpha^{*}-\beta^{*}$ of after-federal-tax income on consumption, α^{*} on housing, and β^{*} on government services. Since the price of consumption is 1, the price of housing is P_{jt}, and the price of government services is $\tau_{ijt}\omega^{-1}$, this implies

$$c_{ijt}=(1-\alpha^{*}-\beta^{*})\left(1-\bar{\tau}_{ijt}^{F}\right)w_{ijt},\;\; h_{ijt}=\alpha^{*}\left(1-\bar{\tau}_{ijt}^{F}\right)w_{ijt}P_{jt}^{-1},\;\; g_{ijt}=\beta^{*}\left(1-\bar{\tau}_{ijt}^{F}\right)w_{ijt}\omega\tau_{ijt}^{-1}$$

Substituting the above expressions into the utility function and taking the natural log gives the indirect flow utility function

$$\ln V_{ijt}'=\ln A_{j}+\ln\bar{w}_{ijt}-\alpha^{*}\ln P_{jt}-\beta^{*}\ln\tau_{ijt}+C_{1}$$

where C_1 is a function of the (constant) parameters α^{*}, β^{*}, and ω, and $\bar{w}_{ijt}=\left(1-\bar{\tau}_{ijt}\right)w_{ijt}$ is after-federal-tax wages. The indirect flow utility function says that households gain utility from better local amenities A_j and higher after-tax wages $\bar{w}_{ijt}$ and lose utility from higher local house prices P_{jt} and a higher local tax price τ_{ijt}.

Each state is assumed to have a perfectly competitive representative firm producing according to a production function with a constant elasticity of substitution

$$Q_{jt}=B_{j}\left[\theta K_{jt}^{\rho}+(1-\theta)N_{jt}^{\rho}\right]^{1/\rho}$$

where Q_{jt} is output, N_{jt} is labor, K_{jt} is capital, B_j is total factor productivity, θ is the weight of capital in the production process, and $\rho<1$ governs the elasticity of substitution between capital and labor. The labor market is perfectly competitive and workers inelastically supply all their labor in the state where they reside, so workers receive a wage w_{jt} equal to the value of their marginal product. Normalizing the price of output to 1,

$$w_{ijt} = \frac{dQ_{jt}}{dN_{jt}} = (1-\theta)B_j Q_{jt}^{1/\nu} N_{jt}^{-1/\nu}$$

where $\nu = 1/(1-\rho)$ is the elasticity of substitution between capital and labor. Taking the natural log of the wage equation and substituting the expression into the indirect flow utility function yields

$$\ln V'_{ijt} = \ln(A_j B_j) + \frac{1}{\nu}\ln Q_{jt} - \frac{1}{\nu}\ln N_{jt} - \alpha^* \ln P_{jt} - \beta^* \ln \tau_{ijt} + \ln(1 - \bar{\tau}_{ijt}^F) + C_2$$

where C_2 is a function of the (constant) parameters α^*, β^*, ω, and θ. Assuming perfectly elastic substitution between capital and labor, the equation can be simplified to

$$\ln V'_{ijt} = \ln(A_j B_j) - \alpha^* \ln P_{jt} - \beta^* \ln \tau_{ijt} + \ln(1 - \bar{\tau}_{ijt}^F) + C_2$$

I assume there is competition for land and an imperfectly elastic supply of housing. The local supply of housing is determined by an underlying state-specific (inverse) housing supply elasticity, ζ_j, which takes the following form and is microfounded (Monras, 2020b; Saiz, 2010): $\zeta_j = \ln P_{jt}/\ln N_{jt}$. Following Monras (2020a), I assume that the local labor demand elasticity is not a source of congestion, and that congestion forces are governed solely by ζ_j.

Substituting the expression for $\ln P_{jt}$ into the indirect flow utility function yields

$$\ln V'_{ijt} = \ln(A_j B_j) - \alpha^* \zeta_j \ln N_{jt} - \beta^* \ln \tau_{ijt} + \ln(1 - \bar{\tau}_{ijt}^F) + C_2$$

The indirect flow utility function implies that utility decreases with population size, but this effect is attenuated if a state has a more elastic housing supply. Since utility is assumed to decreases with population size, congestion forces dominate agglomeration forces.

IV. Data

The primary data source used for the analysis is the American Community Survey. To collect ACS data, the US Census Bureau mails questionnaires to approximately 295,000 addresses each month across the United States, which are used to construct one-year and five-year samples. One-year ACS samples for 2012–20 were downloaded from IPUMS-USA (Ruggles et al., 2021). Using detailed income information of the respondents, marginal tax rates and tax liabilities are determined using TAXSIM, a microsimulation function for calculating tax liabilities from individual data under US federal and state income tax laws (Feenberg and Coutts, 1993). Appendix A details the construction of the TAXSIM variables using the ACS data, which closely follows the procedure of Coyne (2017). I focus my analysis on the household unit.

The ACS provides rich income and demographic information, but two complications arise from the use of ACS data as it relates to itemized deductions. First, that the ACS does not ask about charitable contributions or deductible medical expenses. I therefore impute these deductions (conditional on imputed itemization status) based on data from the Internal Revenue Service's Statistics of Income, Historic [*sic*.] Table 2, which reports charitable contributions and deductible medical expenses by year, state, and AGI bucket. The second complication is that the ACS top codes property tax payments at $10,000. For households with top coded property tax payments, I assign the average of property taxes claimed on federal tax returns by itemizers by state and AGI bucket for 2017, adjusted for inflation.

I analyze the effect of SALT conditional on moving by exploiting the ACS question that asks whether a household lived in a different state one year prior to receiving the ACS questionnaire. An important caveat is that the US tax system is not purely residence-based: for most states, taxes are paid to the state of *employment* and taxpayers receive a tax credit from their state of *residence*.

Most of the literature studying US state taxes has assumed that taxpayers pay taxes in their state of residence, implying taxpayers live in the same state in which they work. The ACS asks respondents where they *currently* work but not where they worked a year ago. Because the ACS is mailed to specific *addresses* and not to specific *people*, by using state of residence to determine migration response, I implicitly assume that respondents receive and complete the ACS survey at their primary residence and that they live and work in the same state.

I use an algorithm in conjunction with TAXSIM to compute the tax price of SALT. The main idea is to determine the amount by which SALT liability is offset by a decline in federal income tax liability caused by SALT. This is done in five steps. First, taxes are calculated using TAXSIM for the representative household in each state j. Second, federal tax liability is recalculated assuming that property taxes and state income taxes (or state sales taxes) calculated in step 1 are deductible.[4] Third, federal tax liability is recalculated assuming that property taxes and state income taxes (or state sales taxes) calculated in step 1 are not deductible. Fourth, I construct a variable, ΔT_{ijt}, equal to the federal tax liability from step 3 minus the federal tax liability from step 2, which represents the federal tax savings caused by the deductibility of SALT. Finally, I compute the federal tax price of SALT for each state j as $\tau_{ijt} = 1 - \left(\Delta T_{ijt}/S_{ijt}\right)$. This algorithmic formulation for τ_{ijt} is equivalent to the equation $\tau_{ijt} = 1 - \tau_{ijt}^{F}\left(S'_{ijt}/S_{ijt}\right)$ presented in section III. An additional advantage of this algorithmic approach is that it appropriately accounts for many complications of how the tax system actually works that might be missed using other approaches.

[4] TAXSIM estimates a household's sales tax based on tables supplied by the Internal Revenue Service (2006) and deducts the larger of state income taxes or sales taxes.

Housing supply elasticities are taken from Saiz (2010), who estimates housing supply elasticities for metropolitan areas with populations above 500,000. I use the housing supply elasticity associated with the largest metropolitan area in each state; if a state does not have a metropolitan area with a population above 500,000, I use the population-weighted average elasticity for all the metropolitan areas. State-level economic variables include the unemployment rate and labor force participation rate (from Local Area Unemployment Statistics) and value added in outdoor recreation (from the Bureau of Economic Analysis). One-year ACS samples are used to construct state-level demographics.

Table 3 shows summary statistics for movers and stayers with AGI between $100,000 and $200,000 (approximately the 80th–95th percentile of the distribution) and with AGI above $500,000 (approximately the 99th percentile of the distribution) for 2017 and 2018. For households with AGI between $100,000 and $200,000, movers compared to stayers are, on average, about 6 years younger, 20 percent more likely to hold a bachelor’s degree, 10 percent less likely to be married, nearly half as likely to be homeowner, and have about 25 percent fewer children. The characteristics of movers and stayers are nearly identical in 2018 compared to in 2017. For households with AGI above $500,000, the same general differences between movers and stayers persist, though they are not as pronounced. On average, movers compared to stayers are about 2 years younger, 5 percent more likely to hold a bachelor’s degree, 7 percent less likely to be married, 30 percent less likely to be homeowners, and have 30 percent fewer children. The observable characteristics of movers and stayers with AGI above $500,000 are also very similar between 2017 and 2018.

TABLE 3—SUMMARY STATISTICS FOR MOVERS AND STAYERS IN 2017 AND 2018

	2017		2018	
	Movers	Stayers	Movers	Stayers
AGI between $100,000 and $200,000				
Age	43	49	43	49
Share with a bachelor's degree	0.73	0.62	0.76	0.62
Share married	0.75	0.82	0.73	0.81
Number of children	0.75	0.98	0.71	0.97
Share homeowners	0.47	0.85	0.45	0.85
No. of households	3,336	174,947	3,598	183,390
AGI above $500,000				
Age	48	51	49	50
Share with a bachelor's degree	0.92	0.88	0.92	0.88
Share married	0.82	0.90	0.84	0.89
Number of children	0.80	1.10	0.76	1.14
Share homeowners	0.62	0.91	0.66	0.89
No. of households	130	6,738	184	8,833

Sources: American Community Survey.
Notes: Sample means are calculated using household frequency weights. Number of households is the unweighted total.

V. Identification, Estimation, and Results

I study the short-term effect of the TCJA's change to SALT deductibility along two margins of migration: The extensive margin, which refers to the decision about *whether* to move; and the intensive margin, which refers to the decision about *where* to move conditional on moving.

A. *Aggregate Analysis and the Extensive Margin*

I first consider the extensive margin migration effects of the change in SALT deductibility. The approach analyzes the effect of relative tax price differences between states on states' relative population stocks of high-income households. Derivation of the estimating equations closely follows that of Moretti and Wilson (2017) and Agarwal and Foremny (2019), with a few key differences. First, the estimating equations are derived from a primitive utility specification, whereas Moretti and Wilson (2017) and Agarwal and Foremny (2019) specify reduced-form equations for utility not derived from primitives. Second, I explicitly incorporate housing markets by relating state populations and housing prices to underlying housing supply elasticities, whereas Agrawal and Foremny (2019) indirectly incorporate housing markets into their model by including a disutility term that depends on population size, implicitly assuming housing supply elasticities are constant across regions.

Indirect flow utility for household i in state j in year t that lived in state ℓ in year $t-1$ is

$$\ln V'_{ijt} + \varepsilon_{ij\ell t} = \ln\left(A_j B_j\right) - \alpha^* \zeta_j \ln N_{jt} - \beta^* \ln \tau_{ijt} + \ln\left(1 - \bar{\tau}^F_{ijt}\right) + C_2 + \varepsilon_{ij\ell t}$$

Imposing a spatial equilibrium condition requires $V'_{ijt} = V'_{ikt}$ for all states j and k, implying

$$\ln\left(N_{jt}^{\zeta_j} / N_{kt}^{\zeta_k}\right) = \beta \ln\left(\tau_{ijt}/\tau_{ikt}\right) + \xi_j + \xi_k + \varepsilon_{jkt}$$

where $\beta = -\beta^*/\alpha^*$, $\xi_j = \ln\left(A_j B_j\right)/\alpha^*$, $\xi_k = -\ln(A_k B_k)/\alpha^*$, $\varepsilon_{jkt} = \varepsilon_{ij\ell t} - \varepsilon_{ik\ell t}$, and $\ln\left[\left(1 - \bar{\tau}^F_{ijt}\right)/(1 - \bar{\tau}^F_{ikt})\right] \approx 0$ since $\bar{\tau}^F_{ijt} \approx \bar{\tau}^F_{ikt}$.

Using observed, state-level tax rates to estimate the model would introduce a selection issue, since the choice of state might systematically differ with income. In order to isolate the variation in the tax rate due only to statutory changes, I follow Moretti and Wilson (2017) and Agarwal and Foremny (2019) and estimate the equation for a representative household, holding income fixed across states. As described above, I construct the representative household by assigning the national mean of all dollar-denominated, tax-relevant variables and the national median of all other tax-relevant variables—namely, age, marital status, and number of dependents.

Since property taxes vary by state and are an important component of the SALT deduction, assuming the representative household's property taxes are constant across states would introduce bias. Therefore, following the same procedure as Bakija and Gentry (2014) and Moretti and Wilson (2017), I compute state-specific property tax multipliers relative to the national average property tax deduction. The numerator of the multiplier is calculated as total statewide property tax revenues divided by state personal income; property tax revenues come from the Annual Survey of State and Local Government Finances and personal income comes from the Bureau of Economic Analysis. The denominator of the multiplier is computed as the population-weighted average of this ratio across the 51 states.

The structural parameter of interest is β, which can be interpreted as the elasticity of relative population stocks (adjusted for underlying housing supply elasticities) with respect to relative tax prices for a representative household. However, given the relatively large number of states, β can alternatively be interpreted as approximately the elasticity of a state's own population (adjusted for its own underlying housing supply elasticity) with respect to its own tax price for a representative household. This is seen by differentiating the estimating equation with respect to $\ln(\tau_{ijt})$: $\beta = \zeta_j \cdot d\ln(N_{jt})/d\ln(\tau_{ijt}) - \zeta_k \cdot d\ln(N_{kt})/d\ln(\tau_{ijt})$. Although the model implies that state k's population will depend on state j's tax price, this dependence becomes small as the number of states becomes large—in other words, as the number of substitutes increases. With 51 states, the cross-tax-price elasticity term is approximately 0, so $\beta \approx \zeta_j \cdot d\ln(N_{jt})/d\ln(\tau_{ijt})$.

I employ a difference-in-differences strategy to estimate β for a representative household in the 99th percentile of the AGI distribution. Using the terminology of design-based approaches, this household acts as the "treated" group because relative differences in the tax price between states for this household diverged substantially after the TCJA imposed the SALT cap; a representative household in the 85th percentile of the AGI distribution acts as the "control" group, since relative differences in the tax price between states for this household were completely eradicated after the TCJA (see appendix figure 2). This household also serves as a good control group because its observable characteristics are very similar to those of the treated group, as shown in table 3.

I modify the estimating equation slightly so that β can be interpreted in a difference-in-differences framework:

$$\ln\left(N_{ijt}^{\zeta_j}/N_{ikt}^{\zeta_k}\right) = \beta \ln\left(\tau_{ijt}/\tau_{ikt}\right) \times \mathrm{treated}_i \times \mathrm{post}_t + \gamma\, \mathrm{treated}_i + \xi_j + \xi_k + \xi_t + \boldsymbol{\phi}\mathbf{X}_{jkt} + \varepsilon_{ijkt}$$

where post_t indicates whether t is after 2017 and $\mathrm{treated}_i$ indicates whether household i is in the 99th percentile of the AGI distribution. The dependent variable has an i subscript, to denote the two representative households.

Identification of β requires that the tax variation induced by the TCJA's SALT provision is orthogonal to all other factors affecting individual location choices; in other words, differences in population stocks vary over time for reasons that are not correlated with the passage of the TCJA. For this reason, I include a vector of covariates $\mathbf{X}_{jkt}$ to control for states' economic and demographic characteristics. State fixed effects ξ_j and ξ_k are included to capture the effect of amenity-productivity levels and any other time-invariant, state-level policies, and year fixed effects ξ_t capture macroeconomic factors that affect all states in a particular year. After controlling for these potential confounding factors, the remaining identifying variation should come solely from changes to federal tax policy and non-linearities in the mapping from smooth changes in the income distribution and federal marginal tax rates (Coyne, 2017).

As shown by Callaway, Goodman-Bacon, and Sant'Anna (2021), identification of β as the average causal response of states' relative population stocks to a change in relative tax prices for high-income households requires that the evolution of relative population stocks for the treated group is the same as for the control group absent the TCJA (so called *standard* parallel trends) and that the evolution of relative population stocks for the treated group at different levels of treatment—that is, for state pairs with large and small tax price differentials—is the same absent the TCJA (so called *strong* parallel trends). Since the TCJA was a federal tax law, estimation does not suffer from identification issues related to staggered treatment (Goodman-Bacon, 2021) and there is a strong case against "selection bias" into different levels of treatment (Callaway, Goodman-Bacon, and Sant'Anna, 2021).

A possible threat to identification is that state legislators changed their tax policies in anticipation of or in reaction to the TCJA. It is unlikely that states changed their regimes in anticipation of the TCJA since the bill moved through Congress at an exceptionally fast pace, from inception to law in less than 2 months. It is also unlikely that states reacted to the TCJA in a way that would taint the interpretation of β. While some states initially sought workarounds to the SALT cap soon after the TCJA's passage—for example, by implementing a payroll tax credit or by allowing SALT to be classified as charitable contributions to the state—the Internal Revenue Service dramatically curbed the charitable deduction scheme with Treasury Decision 9864 (84 *Fed. Reg.* 27513), and the payroll tax credit did not get much traction with businesses. Hence, non-random, state-level anticipatory or reactionary tax changes are unlikely to be a threat to identification.

To formally check for the existence of pretrends, I implement an event study approach in the spirit of Agarwal and Foremny (2019) by estimating the following regression:

$$\ln\left(N_{ijt}^{\zeta_j}/N_{ikt}^{\zeta_k}\right) = \overline{\ln}\left(\tau_j/\tau_k\right) \sum_{\substack{y=-6 \\ y\neq -1}}^{2} \beta_y \left(\mathbf{1}_y \times \text{treated}_i\right) + \gamma \text{ treated}_i + \xi_j + \xi_k + \xi_t + \mathbf{X}_{jkt}\boldsymbol{\phi} + \varepsilon_{ijkt}$$

where $\mathbf{1}_y$ are indicators for the years before and after the tax law and $\overline{\ln}\left(\tau_j/\tau_k\right)$ is the average natural log of the tax price ratios between state j and k after 2017 for the representative household in the 99th percentile of the AGI distribution, which captures the intensity of the treatment and allows for joint estimation of relative increases and decreases.

Appendix figure 3 shows the estimates of the β_y coefficients along with 90 percent confidence intervals. The results show that there do not appear to be pretrends, as the estimated coefficients for the period before the tax law are relatively flat and cannot be distinguished from 0. At the passage of the law (period 0) there is a sharp jump down to a value that is statistically different than 0, suggesting that increases in relative tax prices after the passage of the law decreased relative population stocks for households in the 99th percentile of the AGI distribution. The event study is reassuring because it is evidence that population changes did not predate the tax reform, bolstering the validity of the identifying assumption.

Regarding inference, there are two main issues related to computation of the standard errors. First, the errors might be correlated within a given year across origin states because taxes in the origin state are constant across the 51 observations that involve that origin state in that year; likewise, errors could be correlated across observations within a given year that share the same destination state (Moulton, 1990). Second, errors might be correlated over time within the panel dimension (Bertrand, Duflo, and Mullainathan, 2004). For these reasons, I compute standard errors that are robust to heteroskedasticity and allow for three-way clustering by origin-year, destination-year, and origin-destination, following Moretti and Wilson (2017) and Agarwal and Foremny (2019). This clustering scheme alleviates the first issue because it includes clustering at the origin-year and destination-year levels. It alleviates the second issue because it allows unrestricted serial correlation over time within each origin-destination pair, which is the cross-sectional unit in the panel. Specifically, it rules out correlation in the residual between origin-destination pairs in a particular year and a different pair in a different year, meaning the unobserved determinants of the relative population stocks between a pair of states in a given year is assumed to be uncorrelated with unobserved determinants of the relative population stocks between a different pair of states in a different year.

Table 4 shows the results of the difference-in-differences estimation using a representative household in the 99th percentile of the AGI distribution as the treated group and a representative household in the 85th percentile of the AGI distribution as the control group, both for housing elasticity–adjusted population stocks (column 1) and for unadjusted population stocks (column 2)—that is, where housing supply elasticities are equal to 1 for all states. The number of observations is 22,950 = ½ × (50 × 51) × 9 × 2, representing all possible origin–destination combinations for the 9 years of data for the 2 groups.

TABLE 4—DIFFERENCE-IN-DIFFERENCES AGGREGATE REGRESSION RESULTS, 2012–20

Log population ratio	(1)	(2)
Log tax price ratio	–0.642**	–1.014**
	(0.257)	(0.403)
Housing elasticity	Yes	No
Control group	85th	85th
No. of observations	22,950	22,950
R^2	0.992	0.880

Sources: Author's calculations using TAXSIM and the American Community Survey.

Notes: Housing elasticity indicates whether the population ratio was adjusted for local housing supply elasticities, as explained in the text. The treatment group is a representative household in the 99th percentile of the AGI distribution. The control group is a representative household in the indicated percentile of the AGI distribution. The regressions include origin fixed effects, destination fixed effects, year fixed, and economic and demographic controls, including: unemployment rate, labor force participation rate, share white, share age 25 and younger, share age 65 and older, and share with a bachelor's degree or more. Robust standard errors clustered at the origin-year, destination-year, and origin-destination levels are shown in parentheses. Statistical significance is indicated at the **5 percent level.

The results suggest that households in the 99th percentile of the AGI distribution are responsive to changes in the tax price of SALT: A 1 percent increase in the relative (own) tax price decreases the relative (own) population stock by 0.64 percent when adjusted for housing supply elasticities.

Comparing column 2 with column 1, the estimate that adjusts the relative population stocks for housing supply elasticities is smaller in magnitude than the unadjusted estimate, and the model using the adjusted population stocks has a higher R^2, which suggests that neglecting regional heterogeneity in housing supply elasticities will tend to overstate the effect of tax policies on migration. As shown in appendix table 1, the results are not sensitive to the choice of the 85th percentile of the AGI distribution as the control group; using a representative household from the 90th, 85th, 80th, 75th, or 70th percentile of the AGI distribution as the control group does not meaningfully change the results.

B. *Disaggregate Analysis and the Intensive Margin*

I next consider the intensive margin migration effects of the change in SALT deductibility. To do so, I take a disaggregate approach similar to Bakija and Slemrod (2004) and Agarwal and Foremny (2019). The approach analyzes the effect of tax price differences between states on a household's decision about where to move conditional on moving. One justification for focusing on the sample of movers is that tax rates are likely a function of all households' location decisions, and because movers are a relatively small share of the population it is likely that the equilibrium tax rates selected are driven by the large share of stayers, reducing endogeneity concerns (Schmidheiny, 2006; Agrawal and Foremny, 2019).

To derive the main estimating equation, I assume a moving household chooses to live in state j if the utility they receive in state j exceeds the utility they would receive in any other state $k \neq j$: $\ln V'_{ijt} + \varepsilon_{ijt} > \ln V'_{ikt} + \varepsilon_{ikt}$. I assume ε_{ijt} is drawn from a type-I extreme value distribution with scale parameter σ, so that the probability an individual mover i is observed in state j has the familiar closed form $\Pr_{ijt} = V'_{ijt}/\sum_{\ell} V'_{i\ell t}$.

Estimation proceeds by finding the vector of parameters that maximizes the probability that households in the sample choose their observed locations. This maximization procedure produces an estimate of $-\beta^*/\sigma$, which when multiplied by $1 - \overline{\Pr}_{jt}$ can be interpreted as approximately the elasticity of the choice probability with respect to the tax price, where $\overline{\Pr}_{jt} = 1/51$ is the probability of choosing a state at random. Note that β^* and σ cannot be separately identified unless σ is normalized.

Several issues arise that make standard maximum likelihood estimation challenging in this context. The main difficulty involves correcting for mismeasurement of counterfactual tax prices, τ_{ijt}. Mismeasurement of τ_{ijt} arises because I only observe households in their chosen state, so I must compute taxes for each household in each unchosen state based on unobservable counterfactual wages and deductions, which produces a noisy measure of a household's true, theoretically appropriate counterfactual taxes.

The largest itemized deductions for most households are the mortgage interest deduction, the charitable giving deduction, and the SALT deduction. I assume households' counterfactual mortgage interest deduction is constant across states, which is theoretically and empirically justified (Jones, 1993; Drukker, Gayer, and Rosen, 2021). Charitable giving is not dependent on location, so I assume households' counterfactual charitable giving is also constant across states. To calculate counterfactual property taxes, I apply state-specific property tax multipliers as described above, following the same procedure used by Bakija and Gentry (2014) and Moretti and Wilson (2017).

Crucially, counterfactual tax rates are a function of households' counterfactual wages in each state. Following Agarwal and Foremny (2019) and Kleven, Landais, and Saez (2013), I begin by assuming a household's counterfactual wages in each state are equal to their observed wages in their chosen state. This assumption introduces measurement error in the tax rates because, all else equal, a household is more likely to move to a state where they expect to earn higher wages, so the assumed counterfactual wages likely overstate true counterfactual wages. Given that taxes are progressive, overestimating counterfactual wages will overestimate counterfactual tax rates, resulting in attenuation bias, since a higher marginal tax rate implies a lower tax price. In other words, a lower tax price (resulting from mismeasurement) will seem to result in a small migration response.

To remedy inconsistencies arising from potential measurement error, I employ an instrumental variables estimation strategy. However, because the probability that a household moves to a particular state is a non-linear function of the parameters, I cannot estimate the model using two-stage least squares. Instead, I estimate the model using *two-stage residual inclusion*, as described by Terza, Basu, and Rathouz (2008). For estimation purposes, I specify the indirect flow utility function as

$$\ln V'_{ijt} + \varepsilon_{ijt} = \beta \ln \tau_{ijt} + \alpha\zeta_j \ln N_{jt} + \xi_j \mathbf{Z}_{it} + \boldsymbol{\psi}\mathbf{Z}_{ijt} + \boldsymbol{\phi}\mathbf{X}_{jt} + \lambda\kappa_{ijt} + \varepsilon_{ijt}$$

The key to this specification is the inclusion of κ_{ijt} as a regressor, a residual that comes from an auxiliary regression of $\ln \tau_{ijt}$ on an instrument $\ln \tau^*_{ijt}$ and all exogenous regressors.

The instrument is motivated by the key insight that a household's marginal tax rate proxies for the exogenous component of its average tax rate because it is independent of earnings conditional on being in the same tax bracket. I construct a first-dollar tax price instrument originally developed by Feldstein and Taylor (1976) and most recently implemented by Coyne (2017). The instrument is constructed in three steps. First, I assign households a probability of itemizing, $\hat{d}_{ijt}$, and a probability of paying the AMT, $\hat{a}_{ijt}$, based on state-level empirical probabilities by AGI from Statistics of Income. Second, I calculate first-dollar federal marginal tax rates, $\hat{\tau}^F_{ijt}$, by assuming

SALT is not deductible. Third, I construct the first-dollar tax price instrument as $\tau^*_{ijt} = 1 - \hat{d}_{ijt}(1 - \hat{a}_{ijt})\hat{\tau}^F_{ijt}$. This instrument is exogenous because it depends on the marginal tax rate of the first dollar of SALT deductions for each household as opposed to the rate they effectively choose endogenously.

In addition to correcting for measurement error, identification of β requires that the tax variation induced by the TCJA's SALT provision is orthogonal to all other factors affecting households' location choices. Identification is aided by the inclusion of various controls, made possible by the richness of the ACS data. For the first set of controls, I include interactions of state fixed effects ξ_j and household-specific covariates $\mathbf{Z}_{it}$ that likely influence a household's choice of one state over another, but which do not vary by state. Specifically, I include age and age squared, as well as dummies for whether the household head has a child, is married, is a homeowner, and has a bachelor's degree or more. Interacting these household-specific characteristics with state-specific fixed effects helps control for unobservable counterfactual wages by allowing observable characteristics that are correlated with wages (such as age and education) to vary by state. This parameterization also has the benefit of capturing any sorting of specific types of households (based on observables) into particular states.

Second, I include household-specific covariates $\mathbf{Z}_{ijt}$ that vary by state and can be interpreted as influences on moving costs. These include the natural log of the distance between the origin and destination states and a dummy for whether the destination state is the household head's birth state. Third, I include state-specific covariates that do not vary by household $\mathbf{X}_{jt}$, which control for time-varying, state-specific shocks that might be correlated with state tax policies and might make a state more or less attractive for all households. In particular, I include state unemployment rates, log value added in outdoor recreation, the share of the population age 25 and younger, and the share of the population with a bachelor’s degree or more.

Table 5 shows the results of the maximum likelihood estimation of the conditional logit model using two-stage residual inclusion. Standard errors are clustered at the household level to account for the fact that each household appears 51 times in the data set, so there is necessarily correlation of error terms within each household. I compute clustered standard errors via bootstrapping with 500 replications. The main result is shown in column 1, which uses the first-dollar tax price instrument to predict tax price in the first stage and is estimated using frequency weights, as suggested by Bakija and Slemrod (2004). The results suggest that, conditional on moving, households in the 99th percentile of the AGI distribution are highly responsive to differences in the tax price when deciding which state to move to: a 1 percent increase in the tax price is associated with a 4.2 percent decline in the probability of moving to a particular state.

Column 2 shows the results estimated without frequency weights, which, reassuringly, are similar in magnitude to the results shown in column 1. Column 3 shows the results without correcting for endogeneity in the tax price. The estimated coefficient on the log tax price is the correct sign but is smaller in magnitude than the estimates from using the instrument and is not statistically significant, which suggests the instrumental variable strategy reduces attenuation bias as expected. Columns 4 through 6 are analogous to columns 1 through 3, except that in columns 1 thorough 3 the alternative-specific constant is interacted with household demographics, while in columns 4 through 6 there are no demographic interactions. The first-stage residual is a strong predictor in all specifications involving instrumentation.

TABLE 5—CONDITIONAL LOGIT RESULTS, 2012–20

Log odds ratio	(1)	(2)	(3)	(4)	(5)	(6)
Log tax price	–4.298***	–3.772***	–0.171	–3.183**	–3.408***	–0.374
	(1.570)	(1.215)	(0.387)	(1.561)	(1.183)	(0.332)
First-stage residual	3.948***	3.047***		2.737*	2.685**	
	(1.471)	(1.155)		(1.503)	(1.148)	
Housing elasticity × log population	0.012	0.031	0.017	–1.521	1.510	–3.123
	(0.088)	(0.074)	(0.087)	(3.523)	(2.832)	(3.286)
State of birth	1.771***	1.788***	1.768***	1.703***	1.719***	1.702***
	(0.105)	(0.088)	(0.099)	(0.113)	(0.085)	(0.109)
Log distance between states	–0.025*	–0.013	–0.027**	–0.023*	–0.015	–0.024*
	(0.013)	(0.011)	(0.014)	(0.013)	(0.011)	(0.014)
Tax price instrument	Yes	Yes	No	Yes	Yes	No
Economic and demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Household demographics	Yes	Yes	Yes	No	No	No
Frequency weights	Yes	No	Yes	Yes	No	Yes
No. of observations	85,782	85,782	85,782	85,782	85,782	85,782
No. of households	1,682	1,682	1,682	1,682	1,682	1,682
Sum of weights	8,255,574	85,782	8,255,574	8,255,574	85,782	8,255,574

Sources: Author's calculations using TAXSIM and the American Community Survey.

Notes: Economic and demographic controls include the unemployment rate, log value added in outdoor recreation, share of the population age 25 and younger, and share of the population with a bachelor's degree or more. Household demographics include age and age squared of the household head, and dummies for whether the household head has a child, is married, has a bachelor's degree or more, and is a homeowner, which are all interacted with the alternative-specific constants. Columns 1, 3, 4, and 6 are estimated using ACS household weights as frequency weights. Standard errors clustered at the household level are shown in parentheses. Columns 1, 2, 4, and 5 are estimated using two-stage residual inclusion, and standard errors are computed using 500 bootstrap replications.

Agarwal and Foremny (2019) note that, due to data limitations, most previous papers have not been able to study heterogeneous migration effects by workers' industry or occupation and, as such, it is not clear whether policymakers can take estimates derived for specialized workers, such as scientists (Moretti and Wilson, 2017) or athletes (Kleven, Landais, and Saez, 2013), and translate them to high-income individuals or households more generally. A benefit of the ACS data is that they contain rich individual and household characteristics, including occupation and industry, which allows for analyses of heterogeneous effects along these dimensions.

To determine if some industries or occupations are more responsive to tax changes than others, I estimate the following equation:

$$\ln V'_{ijt} + \varepsilon_{ijt} = \sum_{g} \beta_g \left(\mathbf{1}_g \times \ln \tau_{ijt}\right) + \lambda_g \kappa_{igjt} + \alpha \zeta_j \ln N_{jt} + \xi_j \mathbf{Z}_{it} + \boldsymbol{\psi} \mathbf{Z}_{ijt} + \boldsymbol{\phi} \mathbf{X}_{jt} + \varepsilon_{ijt}$$

where g indexes either occupation or industry (depending on the specification), $\mathbf{1}_g$ are indicators for whether household head i is in occupation or industry g, and κ_{igjt} is the residual from the first-stage regression of $\left(\mathbf{1}_g \times \ln \tau_{ijt}\right)$ on all the exogenous regressors and instruments.

The top panel of figure 3 shows the estimates for the regression involving occupation and the bottom panel shows the estimates for the regression involving industry. Due to the sparseness and similarity of certain occupations, I collapse 2-digit Standard Occupation Codes into 11 groups. Likewise, I collapse 2-digit North American Industry Classification System codes into 17 groups. The results are broadly similar to those found by Agarwal and Foremny (2019) for high-income taxpayers in Spain; they find that the most mobile individuals are those in the health care, real estate, information, finance, and professional industries. The coefficient estimates for most industries and occupations are negative, but they vary in magnitude and statistical precision.

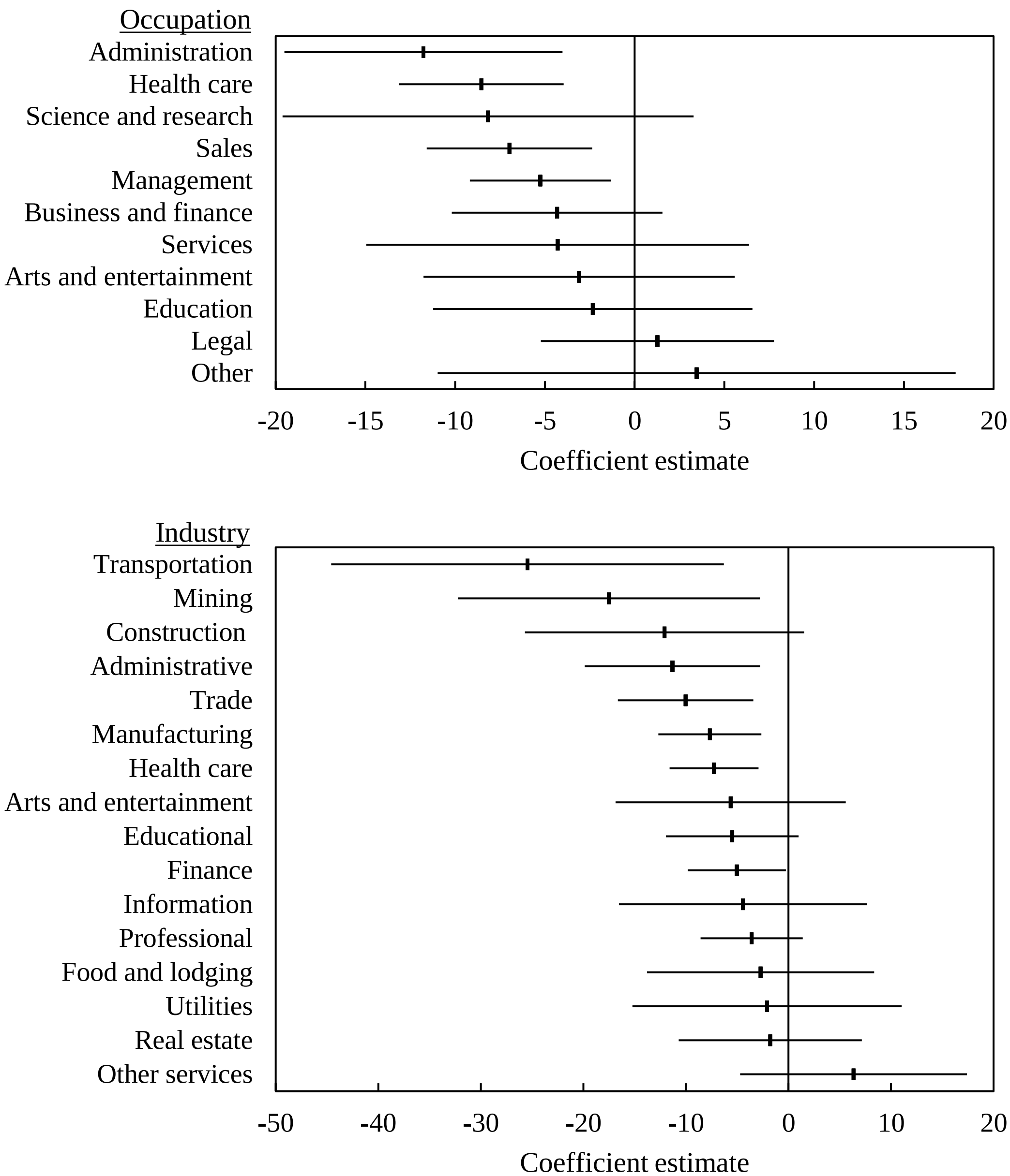


FIGURE 3. CONDITIONAL LOGIT RESULTS BY OCCUPATION AND INDUSTRY

Sources: Author's calculations using TAXSIM and the American Community Survey.
Notes: Coefficient estimates are shown along with 95 percent confidence intervals estimated using 500 bootstrap replications.

This estimated occupational and industrial heterogeneity may result from lower moving costs due to relative ease in relocating jobs. For example, workers in the transportation industry have the largest mobility response. High-skill occupations such as finance and professional services, which include scientific and technical services, have negative and (nearly) statistically significant mobility responses, as do industries and occupations with easily transferable skills, such as health care, administration, education, and sales. The coefficient estimates for legal services, which may be difficult to transfer due to differing licensure standards across states, are statistically indistinguishable from 0, as is the coefficient estimate for the real estate industry, whose workers require specialized knowledge of local real estate markets. Although negative, the coefficient estimates for arts and entertainment, which includes athletes, is not statistically significant, likely due to the small sample size. The general conclusion of these results is that high-income taxpayers' mobility response to taxes varies substantially depending on occupation and industry, and the results of the prior literature studying star athletes and star scientists may not generalize to high-income taxpayers in other occupations and industries.

VI. State-Level Revenue Implications

An important policy question is how tax flight caused by the TCJA's SALT cap will affect state tax revenues and which states will be most affected. Democrats in Congress have objected to the TCJA's SALT provision on the grounds that it would disproportionately harm high-tax states—which tend to vote Democratic—because high-income taxpayers in those states would potentially move to lower-tax states, taking with them crucial sources of tax revenue. To study the differential effects of the SALT cap on migration and state revenues, I modify my structural model to incorporate dynamics. The model derivation closely follows that of Monras (2020a), who studies migration responses to an economic shock.

Consider the static indirect flow utility function derived previously:

$$\ln V'_{ijt} = \ln\left(A_j B_j\right) - \alpha^* \zeta_j \ln N_{jt} - \beta^* \ln \tau_{ijt} + C_2$$

In each period $t - 1$, workers living in state $k = 1, \ldots, J$ receive a vector of J idiosyncratic taste shocks, $\boldsymbol{\varepsilon}_{ikt} = (\varepsilon_{i1kt}, \ldots, \varepsilon_{iJkt})$, each corresponding to a state $j = 1, \ldots, J$, and decide where to live in period t by considering current and future conditions in each state. Indirect utility, which is composed of flow utility, discounted future utility, and the idiosyncratic taste shock, for worker i living in state k in year t who is considering moving to state j in year $t + 1$ is given by

$$\ln V_{ijt} + \varepsilon_{ijkt} = \ln V'_{ijt} + \delta E_t[\ln V_{ij,t+1}] + \varepsilon_{ijkt}$$

where $\delta \in [0,1)$ is the discount rate for expected future utility.

In each period, a worker selects the state j that maximizes indirect utility. The general solution to this maximization problem gives the probability Pr_{jkt} that an individual residing in state k moves to state j, conditional on current and future amenities, total factor productivity, population, and tax prices in all locations. I assume that the vector of idiosyncratic taste shocks $\boldsymbol{\varepsilon}_{ikt}$ is drawn from a generalized extreme value distribution that gives rise to a nested logit model with two nests (Cardell, 1997), with the upper nest capturing the decision of whether to move or not and the lower nest capturing the decision of where to move conditional on moving. Appendix figure 4 diagrams the implied nesting structure, which is partially degenerate. A key feature of this modeling choice is that the nesting structure makes the home location special relative to all other locations, whereby preferences for staying in the home state are stronger than preferences for moving. This assumption on preferences is consistent with the fact that the vast majority of individuals do not relocate in a given year and eschews the need to consider the fixed cost of moving.

As shown by Anderson, de Palma, and Thisse (1992), this decision structure results in the following closed-form solution for the probability that an individual moves from state k to state j, where the i subscripts have been dropped for ease of notation: $\mathrm{Pr}_{jkt} = \eta_{kt} \cdot V_{jt}^{1/\lambda} / \sum_{\ell} V_{\ell t}^{1/\lambda}$. The parameter λ is the inverse of the elasticity of substitution between different nodes in the lower nest and can be viewed as a measure of heterogeneity between states. Specifically, $1/\lambda$ measures movers' sensitivity to relative tax prices in deciding where to move.

The parameter η_{kt} is the fraction of people in state k who endogenously consider relocating, which is given by $\eta_{kt} = V_t^{1/\gamma}/\left(V_{kt}^{1/\gamma} + V_t^{1/\gamma}\right)$. The parameter γ is the inverse of the elasticity of substitution in the upper nest and can be viewed as a measure of heterogeneity between moving versus staying. Following Monras (2020a), the asymptotic properties of η_{kt} are made more realistic by assuming a positive draw in the home state is $(1-\eta)/\eta$ times more likely than in any other state, with $\eta \in (0,1)$. This additional assumption gives rise to a generalized nested logit model where the two nests take different weights, captured by η. Specifically, we can write

$$\eta_{kt} = \frac{\eta V_t^{1/\gamma}}{(1-\eta)V_{kt}^{1/\gamma} + \eta V_t^{1/\gamma}}$$

In addition, this assumption captures all the reasons why it may be costly to leave the current location, be they monetary or psychic costs. In terms of the decision tree, the upper nest takes place with probability η and the lower nest takes place with probability $(1-\eta)$. Note that $\eta_{kt} = \eta$ when $1/\gamma = 0$, in which case only fraction η considers moving while fraction $1-\eta$ always stays in the home state regardless of economic conditions in the other states.

By the law of large numbers, the flow of people moving from state k to state j is $F_{jkt} = N_{kt} \cdot \mathrm{Pr}_{jkt}$. Computing the flow of people moving from each state $k \in 1, \dots, J$ to each state $j \in 1, \dots, J$ defines a $J \times J$ transition matrix of the flows of people between any two states in the economy, which are determined by the idiosyncratic taste shocks $\boldsymbol{\varepsilon}_{kt}$. An expression for the evolution of the population of state j can be obtained by summing over the flows of workers into state j:

$$N_{j,t+1} = \sum_k F_{jkt} = \tilde{\eta}_t \frac{V_{jt}^{1/\lambda}}{V_t^{1/\lambda}} N_t + \left(1-\eta_{jt}\right)N_{jt}$$

where $\tilde{\eta}_t = \sum_k \eta_{kt}(N_{kt}/N_t)$. This expression shows that the population evolves according to a weighted average between the share of value in state j and the population already in state j. Note that $\tilde{\eta}_t = \eta_{jt} = \eta$ if $1/\gamma = 0$.

With the structural assumption on the distribution of $\boldsymbol{\varepsilon}_{kt}$, substituting in the expressions for w_{jt} and P_{jt}, and setting $\theta = 0$ and $1/\nu = 0$, we can rewrite the indirect utility function as

$$V_{jt} = \left[A_j B_j N_{jt}^{-\alpha^* \zeta_j} \tau_{jt}^{-\beta^*} \left(1 - \bar{\tau}_{jt}^F\right) V_t^{\delta\eta}\right]^{\frac{1}{1-\delta(1-\eta)}}$$

where the expected value of relocating is $\ln V_t = \lambda \ln \sum_j V_{jt}^{1/\lambda}$.

The model can be solved forward by setting initial conditions, which is done by selecting a year for which the US economy was in long-run spatial equilibrium and applying the long-run equilibrium conditions $V_{jt} = V_{j,t+1}$ and $N_{jt} = N_{j,t+1}$.

An expression for the initial value in each state is

$$V_{j0} = \left[A_j B_j N_{j0}^{-\alpha^* \zeta_j} \tau_{j0}^{-\beta^*} \left(1 - \bar{\tau}_{j0}^F\right) V_0^{\delta\eta}\right]^{\frac{1}{1-\delta(1-\eta)}}$$

We can eliminate V_0 on the right-hand side by substituting the equation for V_{j0} into the equation for V_0 and rearranging:

$$V_0 = \left[\sum_k \left(A_k B_k N_{k0}^{-\alpha^* \zeta_k} \tau_{k0}^{-\beta^*} (1 - \bar{\tau}_{k0}^F)\right)^{\frac{1}{\lambda(1-\delta(1-\eta))}}\right]^{\frac{\lambda(1-\delta(1-\eta))}{1-\delta}}$$

The conditions of long-run equilibrium allow for the unobserved amenity-productivity levels $A_j B_j$ to be computed relative to some base location, $A_0 B_0 = 1$. Setting $N_{jt} = N_{j,t+1}$ and letting $j = 0$ denote some base location on which to normalize, we can write

$$A_j B_j = \frac{\left(1 - \bar{\tau}_{j0}^F\right)^{-1} \tau_{j0}^{\beta^*} N_{j0}^{\lambda(1-\delta(1-\eta))+\alpha^* \zeta_j}}{(1 - \bar{\tau}_{00}^F)^{-1} \tau_{00}^{\beta^*} N_{00}^{\lambda(1-\delta(1-\eta))+\alpha^* \zeta_0}}$$

Finally, making all the above substitutions, the evolution of value in state j can be written as

$$V_{j,t+1} = \left[A_j B_j N_{jt}^{-\alpha^* \zeta_j} \tau_{jt}^{-\beta^*} \left(1 - \bar{\tau}_{jt}^{F}\right)\right]^{\frac{-1}{\delta(1-\eta)}} V_{jt}^{\frac{1}{\delta(1-\eta)}} \left[\sum_k \left(\frac{V_{kt}}{A_k B_k N_{kt}^{-\alpha^* \zeta_k} \tau_{kt}^{-\beta^*} (1 - \bar{\tau}_{kt}^{F})}\right)^{\frac{1}{\delta\lambda(1-\eta)}}\right]^{-\eta\lambda}$$

The equations above describe a dynamic system that can be characterized by a set of initial conditions and two equations that govern the evolution of local populations and welfare. The model is relatively simple to solve forward. First, determine initial conditions. Next, apply a shock and recalculate initial conditions. Finally, determine the evolution of each state's population and value using the equations for $N_{j,t+1}$ and $V_{j,t+1}$. Since the iterative process that occurs after a shock is a contraction mapping, the process converges and is globally stable (Monras, 2020a).

Solving the dynamic system requires estimating or calibrating several parameters, including λ, γ, η, δ, β^*, and α^*. Following Monras (2020a), I calibrate the following parameters based on US data: $\eta = 0.05$ (the share of the population that relocates each year), $\alpha^* = 0.3$ (the share of income spent on housing), $\beta^* = 0.1$ (the share of income paid in SALT), and $\delta = 0.95$ (consistent with an annual interest rate of around 5 percent). I estimate λ and γ using the procedure described by Monras (2020a, 2020b), which relates in-migration with λ and out-migration with γ. The intuition is that potential out-migrants face the decision of whether to move, which is governed by γ in the upper nest, and potential in-migrants face the decision of where to move conditional on moving, which is governed by λ in the lower nest.

Let N_{jt} denote the number of individuals living in state j in year t. Let I_{jt} denote the number of individuals living in state j in year $t+1$ who lived in state $k \neq j$ in year t. Let O_{jt} denote the number of individuals who lived in state j in year t and are living in state $k \neq j$ in year $t+1$. Then I_{jt} is the number of in-migrants and I_{jt}/N_{jt} defines the in-migration rate to state j. Likewise, O_{jt}

is the number of out-migrants and O_{jt}/N_{jt} defines the out-migration rate from state j. The number of individuals in state j at time $t+1$ is then the number of individuals who were living in that state in year t, plus in-migrants, minus out-migrants: $N_{j,t+1} = N_{jt} + I_{jt} - O_{jt}$.

As shown by Monras (2020a, 2020b), we can approximate λ and γ as

$$\lambda \approx \frac{I}{N} \times \frac{-\beta^*}{1-\delta(1-\eta)} \times \frac{1}{\psi_I} \quad , \quad \gamma \approx \frac{O}{N} \times \frac{\beta^*(1-\eta)}{1-\delta(1-\eta)} \times \frac{1}{\psi_O}$$

where ψ_I comes from a regression of the in-migration rate on the log tax price and state and year fixed effects and ψ_O comes from a regression of the out-migration rate on the lag tax price and state and year fixed effects. I estimate ψ_I and ψ_O by difference-in-differences, where the treated and control groups are as before: representative households in the 99th and 85th percentiles of the AGI distribution, respectively.

Table 6 shows the results of the estimations. The number of observations is 918 = 51 × 9 × 2, one for each state, year, and group. The results are consistent with the evidence documented by Monras (2020a) and others that decreases in net-migration from a negative shock are driven primarily by declines in the in-migration rate, with little response of the out-migration rate: The coefficient on the tax price in column 2 suggests $1/\gamma \approx 0$. The coefficient on the tax price in column 1 suggests that a 1 percent increase in the tax price decreases a state's in-migration rate for households in the 99th percentile of the AGI distribution by 0.096 percentage point; from a base in-migration rate of about 5 percent per year, this translates to a 1.92 percent decline in in-migration. The estimate of $\psi_I = -0.096$ in column 1 implies $\lambda \approx 0.536$.[5]

[5] Although mobility elasticities are not transportable to other segments of the labor market or to other countries (Kleven et al., 2020), it is useful to compare my estimate of λ to those estimated by other authors in other contexts. Caliendo et al. (2021) estimate $\lambda = 2.3$ in the context of migration between EU countries in response to real wage

TABLE 6. REDUCED-FORM ESTIMATES USED FOR CALCULATING ELASTICITIES OF SUBSTITUTION, 2012–20

	Migration rate	
	In	Out
	(1)	(2)
Log tax price	–0.096	0.007
Unadjusted standard errors	(0.042)**	(0.041)
Heteroskedasticity-robust standard errors	(0.069)	(0.045)
Year–state clustered standard errors	(0.073)	(0.045)
State fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Control group	85th	85th
No. of observations	918	918
R^2	0.137	0.132

Sources: Author's calculations using TAXSIM and the American Community Survey.
Notes: The treatment group is a representative household in the 99th percentile of the AGI distribution. The control group is a representative household in the indicated percentile of the AGI distribution. Statistical significance is indicated at the **5 percent level.

Armed with estimated structural parameters, I now calibrate the model to investigate how shocks from the TCJA's SALT provision propagate through the economy and how the states are differentially affected. I use the model to predict the change in long-run population levels resulting from a change in the tax price, which, together with administrative data on SALT, is used to predict the long-run change in states' SALT revenues resulting from tax flight. An important caveat of the analysis is that it assumes that after a shock *nothing else is changing in the economy*. Specifically,

changes; Monras (2020a) estimates $\lambda = 2.56$ in the context of migration between US metropolitan areas in response to real wage changes; and Monras (2020b) estimates $\lambda = 1.47$ in the context of Mexican migration to the US in response to real wage changes. My estimate of $\lambda = 0.536$ is smaller in magnitude than the estimates from these papers, implying a higher degree of substitution between potential destinations in response to tax changes. This is to be expected, as I analyze a sample of households that are a priori assumed to have a high mobility response, while the papers previously cited study more general populations.

I hold state-level tax prices constant over time, implying states do not adjust their tax schemes following the 2017 tax law.[6] As such, the analysis corresponds to a potential worst-case scenario.

To quantify the economic shock caused by the TCJA's SALT provision, I assume that increasing the effective price of SALT distorts productive activity, implying a social cost of public funds. We can conceptualize this social cost as a loss in productivity across states of various magnitudes, as captured by B_j. I assume that a 1 percent increase in the SALT burden decreases productivity by 0.5 percent (Reed, 2008; Brewer, Conway, and Rork, 2021). I compute the change in the average SALT burden by state directly from the data, and these two numbers can be used to approximate the change in productivity resulting from the TCJA's SALT provision, which when fed through the model produces new long-run equilibrium valuations and populations for each state. To set the initial conditions, I assume the US economy was in long-run spatial equilibrium in 2017, the year before the TCJA went into effect.

The model predicts the change in the number of households in the 99th percentile of the AGI distribution, which is used to infer the change in (deductible) SALT revenue. Total revenues, which include deductible and non-deductible taxes, as well as non-deductible fees and charges, come from the Annual Survey of State and Local Government Finances. Appendix figure 5 shows the model-predicted change in state revenues resulting from tax-induced migration following the TCJA for all states. Table 7 shows the same results for the top 10 and bottom 10 states ranked by

[6] As shown by Feldstein and Metcalf (1987) and Coyne (2017), state and local governments shift their revenue-raising strategies and expenditures in response to changes in the tax price of SALT. An increase in the tax price for once-deductible taxes may encourage policymakers to shift taxes away from those bases and toward other revenue sources, such as charges and fees.

the predicted change in state revenues, along with other fiscal characteristics, such as the share of total state revenues derived from SALT.

TABLE 7—MODEL-PREDICTED CHANGE IN STATE REVENUES

State	Percentage change in revenues	Income tax as a percentage of revenues	Property tax as a percentage of revenues	Tax price increase
Top 10				
NV*	0.48	0	15	0.05
FL	0.42	0	21	0.07
TN	0.31	1	13	0.05
WY	0.31	0	20	0.10
TX	0.24	0	28	0.15
SD	0.24	0	25	0.08
WA*	0.15	0	16	0.06
NH*	0.15	1	44	0.20
ND	0.05	4	17	0.23
AK	0.04	0	18	0.11
Bottom 10				
CT*	–0.55	23	32	0.23
MO	–0.38	17	17	0.30
GA*	–0.38	18	20	0.30
MA*	–0.35	23	26	0.30
NJ*	–0.34	17	35	0.24
KS	–0.33	10	19	0.31
MD*	–0.31	29	19	0.31
NC	–0.30	17	14	0.30
DC*	–0.28	19	25	0.21
NY*	–0.25	23	23	0.23

Sources: Author’s calculations using TAXSIM and the American Community Survey, Statistics of Income, and the Annual Survey of State and Local Government Finances.

Notes: States marked with * voted for the Democratic presidential candidate in 2020. Revenues refer to all sources of revenue at all levels of government.

The states most positively affected by the TCJA’s SALT provision largely coincide with the low-tax states shown in table 2, including all 9 states that (effectively) do not levy an income tax. Table 7 shows that a representative taxpayer in those 9 states experienced a relatively small increase in tax price, about 11 percentage points on average. The states most negatively affected by the TCJA's SALT provision somewhat coincide with the high-tax states shown in table 2, but with a few key differences. Although states like Maine, Minnesota, Oregon, Rhode Island, and Vermont rank high in the share of returns claiming SALT and average SALT claims, they experienced relatively small decreases in revenue due to tax flight, likely because these states do not rank high in terms of average income and have relatively few households in the top 99th percentile of the AGI distribution.[7] The states most negatively affected are generally those with a high reliance on SALT for total state revenue (43 percent of total revenues on average) and those that experienced a large tax price increase following the tax law (about 30 percentage points on average). The total predicted revenue loss among the bottom 10 states is about $2.2 billion, and the total predicted revenue gain among the top 10 states is about $1.4 billion.

VII. Conclusion

Taken together, the estimates presented in this paper provide evidence of a behavioral response to changes in SALT deductibility by households in the 99th percentile of the AGI distribution. These findings are consistent with those of Agarwal and Foremny (2019), Akcigit, Baslandze, and Stantcheva (2016), and Moretti and Wilson (2017), who find evidence of tax-induced migration among similar samples of relatively well-off individuals; but in contrast to those of Young (2018), Young and Varner (2011), and Young et al. (2016), who reject the "mobile millionaire hypothesis" based on analyses of administrative tax data.

High-tax states, which tend to vote Democratic, are likely to be the most adversely affected by the TCJA's limitation of the SALT deduction, while low-tax states stand to gain from the in-migration of high-income households. Whether SALT *should* be federally deductible is a normative debate to be had. But as a practical matter, given the current tax environment in which

[7] California, which is omitted from table 7, ranks 13 in terms of largest predicted revenue loss.

federal deductibility of SALT is limited, the mobility of high-income households in response to changes in SALT deductibility implies the optimal degree of state tax progressivity is less than it would be without such responses. State policymakers should therefore take seriously the idea that imposing high taxes could cause high-income taxpayers to flee their states, thereby attenuating the intended revenue and distributional outcomes of such policies.

REFERENCES

Agrawal, David R., and Dirk Foremny. 2019. "Relocation of the Rich: Migration in Response to Top Tax Rate Changes from Spanish Reforms." *Review of Economics and Statistics* 101 (2): 214–32.

Akcigit, Ufuk, Salomé Baslandze, and Stefanie Stantcheva. 2016. "Taxation and the International Mobility of Inventors." *American Economic Review* 106 (10): 2930–81.

Anderson, Simon P., André de Palma, and Jacques-François Thisse. 1992. *Discrete Choice Theory of Product Differentiation*. MIT Press.

Bakija, Jon, and William M. Gentry. 2014. "Capital Gains Taxes and Realizations: Evidence from a Long Panel of State-Level Data." Unpublished.

Bakija, Jon, and Joel Slemrod. 2004. "Do the Rich Flee from High State Taxes? Evidence from Federal Estate Tax Returns." National Bureau of Economic Research Working Paper 10645.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan. 2004. "How Much Should We Trust Differences-in-Differences Estimates?" *Quarterly Journal of Economics* 119 (1): 249–75.

Brewer, Ben, Karen Smith Conway, and Jonathan C. Rork. 2021. "A Replication of 'The Robust Relationship between Taxes and US State Income Growth' (*National Tax Journal* 2008)." *Public Finance Review* 49 (3): 464–87.

Caliendo, Lorenzo, Luca David Opromolla, Fernando Parro, and Alessandro Sforza. 2021. "Goods and Factor Market Integration: A Quantitative Assessment of the EU Enlargement." *Journal of Political Economy* 129 (12): 3491–545.

Callaway, Brantly, Andrew Goodman-Bacon, and Pedro H. C. Sant'Anna. 2021. "Difference-in-Differences with a Continuous Treatment." Unpublished. https://arxiv.org/abs/2107.02637

Cardell, N. Scott. 1997. "Variance Components Structures for the Extreme-Value and Logistic Distributions with Application to Models of Heterogeneity." *Econometric Theory* 13 (2): 185–213.

Coyne, David. 2017. "Unmasking Local Fiscal Responses to Federal Tax Deductibility." *National Tax Journal* 70 (2): 223–56.

Drukker, Austin J., Ted Gayer, and Harvey S. Rosen. 2021. "The Mortgage Interest Deduction: Revenue and Distributional Effects." *Journal of Housing Research* 30 (1): 1–33.

Feenberg, Daniel, and Elisabeth Coutts. 1993. "An Introduction to the TAXSIM Model." *Journal of Policy Analysis and Management* 12 (1): 189–94.

Feldstein, Martin S., and Gilbert E. Metcalf. 1987. "The Effect of Federal Tax Deductibility on State and Local Taxes and Spending." *Journal of Political Economy* 95 (4): 710–36.

Feldstein, Martin, and Amy Taylor. 1976. "The Income Tax and Charitable Contributions." *Econometrica* 44 (6): 1201–22.

Goodman-Bacon, Andrew. 2021. "Difference-in-Differences with Variation in Treatment Timing." *Journal of Econometrics* 225 (2): 254–77.

Internal Revenue Service. 2006. "State and Local General Sales Taxes." Internal Revenue Service Publication 600.

Jones, Lawrence D. 1993. "The Demand for Home Mortgage Debt." *Journal of Urban Economics* 33 (1): 10–28.

Kleven, Henrik, Camille Landais, Mathilde Muñoz, and Stefanie Stantcheva. 2020. "Taxation and Migration: Evidence and Policy Implications." *Journal of Economic Perspectives* 34 (2): 119–42.

Kleven, Henrik Jacobsen, Camille Landais, and Emmanuel Saez. 2013. "Taxation and International Migration of Superstars: Evidence from the European Football Market." *American Economic Review* 103 (5): 1892–924.

Monras, Joan. 2020a. "Economic Shocks and Internal Migration." Unpublished.

Monras, Joan. 2020b. "Immigration and Wage Dynamics: Evidence from the Mexican Peso Crisis." *Journal of Political Economy* 128 (8): 3017–89.

Moretti, Enrico, and Daniel Wilson. 2017. "The Effect of State Taxes on the Geographical Location of Top Earners: Evidence from Star Scientists." *American Economic Review* 107 (7): 1858–903.

Moretti, Enrico, and Daniel Wilson. Forthcoming. "Taxing Billionaires: Estate Taxes and the Geographical Location of the Ultra-Wealthy." *American Economic Journal: Economic Policy*.

Moulton, Brent R. 1990. "An Illustration of a Pitfall in Estimating the Effects of Aggregate Variables on Micro Units." *Review of Economics and Statistics* 72 (2): 334–38.

Reed, W. Robert. 2008. "The Robust Relationship between Taxes and U.S. State Income Growth." *National Tax Journal* 61 (1): 57–80.

Ruggles, Steven, Sarah Flood, Sophia Foster, Ronald Goeken, Jose Pacas, Megan Schouweiler, and Matthew Sobek. 2021. *IPUMS USA: Version 11.0 [dataset]*. University of Minnesota.

Saiz, Albert. 2010. "The Geographic Determinants of Housing Supply." *Quarterly Journal of Economics* 125 (3): 1253–96.

Schmidheiny, Kurt. 2006. "Income Segregation and Local Progressive Taxation: Empirical Evidence from Switzerland." *Journal of Public Economics* 90 (3): 429–58.

Terza, Joseph V., Anirban Basu, and Paul J. Rathouz. 2008. "Two-Stage Residual Inclusion Estimation: Addressing Endogeneity in Health Econometric Modeling." *Journal of Health Economics* 27 (3): 531–43.

Tiebout, Charles M. 1956. "A Pure Theory of Local Expenditures." *Journal of Political Economy* 64 (5): 416–24.

Young, Cristobal. 2018. *The Myth of Millionaire Tax Flight: How Place Still Matters for the Rich*. Stanford University Press.

Young, Cristobal, and Charles Varner. 2011. "Millionaire Migration and State Taxation of Top Incomes: Evidence from a Natural Experiment." *National Tax Journal* 64 (2): 255–83.

Young, Cristobal, Charles Varner, Ithai Z. Lurie, and Richard Prisinzano. 2016. "Millionaire Migration and Taxation of the Elite: Evidence from Administrative Data." *American Sociological Review* 81 (3): 421–46.

APPENDIX A: TAXSIM DATA CONSTRUCTION

NBER's TAXSIM 35 model was used to calculate marginal tax rates and tax liabilities. A vector of 35 tax-relevant variables for each individual is fed through the calculator to produce marginal tax rates and tax liabilities. The 35 TAXSIM variables are constructed using ACS (IPUMS-USA) variables, as detailed below. After all TAXSIM variables are constructed, I set them equal to 0 for spouses of married household heads and for dependents, and collapse all household members into one observation per household.

1. *taxsimid*: Case ID (arbitrary)
2. *year*: Tax year (given)
3. *state*: State of residence (given)
4. *mstat*: Marital status

   The following marital statuses in the ACS are recoded as married filing jointly: married, spouse present; married, spouse absent; separated. The following marital statuses in the ACS are recoded as single or head of household: divorced; never married/single.
5. *page*: Age of primary taxpayer (given)
6. *sage*: Age of spouse

   Households are identified in the ACS by the *serial* variable, and the *relate* variable gives each household member's relationship to the household head. I assume the household head is the primary taxpayer. If the household head is married filing jointly, I identify the age of the spouse.
7. *depx*: Number of dependents

   The *relate* variable is used to determine if the primary taxpayer claims dependents. I assume child, child-in-law, parent, parent-in-law, and grandchild are dependents if they are within the same household.
8. *age1*: Age of first dependent

   I use the *relate* and *age* variables to determine the ages of the primary taxpayer's dependents.
9. *age2*: Age of second dependent

   I use the *relate* and *age* variables to determine the ages of the primary taxpayer's dependents.
10. *age3*: Age of third dependent

    I use the *relate* and *age* variables to determine the ages of the primary taxpayer's dependents.

11. *pwages*: Wage and salary income of primary taxpayer

    The *classwkr* variable is used to determine if a worker is self-employed or earns wage income. This item is set equal to the ACS variable *incearn* for the household head if not self-employed.

12. *swages*: Wage and salary income of spouse

    The *classwkr* variable is used to determine if a worker is self-employed or earns wage income. If the household head is married filing jointly, this item is set equal to the ACS variable *incearn* for the spouse (identified using the *relate* variable) if not self-employed.

13. *psemp*: Self-employment income of primary taxpayer

    The *classwkr* variable is used to determine if a worker is self-employed or earns wage income. This item is set equal to the ACS variable *incearn* for the household head if self-employed.

14. *ssemp*: Self-employment income of spouse

    The *classwkr* variable is used to determine if a worker is self-employed or earns wage income. If the household head is married filing jointly, this item is set equal to the ACS variable *incearn* for the spouse (identified using the *relate* variable) if self-employed.

15. *dividends*: Dividend income (qualified dividends after 2003)

    Dividends are set to 0. This choice is made because of the complicated historical tax treatment of dividends and the fact that the ACS does not have a satisfactory question about dividends. Prior to 2003, dividends were taxed at the ordinary income tax rate (top rate 35 percent). Starting in 2003, qualified dividends were taxed at the long-term capital gains rate (top rate 20 percent) while ordinary dividends continued to be taxed at the ordinary income tax rate.

16. *intrec*: Interest received

    Interest received is set equal to the ACS variable *incinvst*, which includes income in the form of income from an estate or trust, interest, dividends, royalties, and rents received. These income sources are all taxed at the ordinary income tax rate.

17. *stcg*: Short-term capital gains

    The ACS does not ask about capital gains. The only variable related to investment income is *incinvst*. I set short-term capital gains to 0. Short-term capital gains are taxed at the ordinary income tax rate.

18. *ltcg*: Long-term capital gains

    The ACS does not ask about capital gains. The only variable related to investment income is *incinvst*. I set long-term capital gains to 0. Long-term capital gains are taxed at a lower rate than ordinary income.

19. *otherprop*: Other property income subject to the Net Investment Income Tax

    This item essentially corresponds to other income not otherwise enumerated. This item is set equal to the ACS variable *incother*, a residual variable reporting how much of each respondent's total personal income came from sources not included in the other income variables.

20. *nonprop*: Other non-property income

    This item includes income such as alimony and fellowships. I set this item to 0.

21. *pensions*: Taxable pensions and individual retirement account distributions

    This item is set equal to the ACS variable *incretir*, which corresponds to retirement income.

22. *gssi*: Gross Social Security benefits

    This item is set equal to the ACS variable *incss*, which corresponds to Social Security income.

23. *pui*: Unemployment compensation for primary taxpayer

    The ACS does not ask about unemployment compensation. I set this item to 0.

24. *sui*: Unemployment compensation for spouse

    The ACS does not ask about unemployment compensation. I set this item to 0.

25. *transfer*: Non-taxable transfer income

    This item is set equal to the sum of welfare receipts (ACS variable *incwelfr*) and Supplemental Security Income (ACS variable *incsupp*).

26. *rentpaid*: Rent paid

    This item is set equal to the ACS variable *rentgrs* × 12, which corresponds to 12 times monthly gross rent.

27. *proptax*: Real estate taxes paid

    The ACS variable *proptx99* is a categorical variable that corresponds property taxes paid. For each of the 70 categories I take the midpoint of the range. The variable is top coded at $10,000. For households with top coded property tax payments, this item is set equal to the average property tax payment within cells of year, state of residence, and AGI bucket from Statistics of Income.

28. *otheritem*: Other itemized deductions

    This item includes taxes paid other than state and local income or sales taxes, real estate taxes, and personal property taxes. I set this item to 0.

29. *childcare*: Childcare expenses

    The ACS contains no information about eligible childcare expenses. I set this item to 0.

30. *mortgage*: Itemized deductions

    This item includes several itemized deductions from Schedule A of Form 1040, most notably mortgage interest paid, charitable contributions, and qualified medical expenses. Charitable contributions, qualified medical expenses, and itemization status are imputed based on year, state of residence, and AGI bucket from Statistics of Income. The ACS variable *mortamt1* corresponds to monthly mortgage payments on a first mortgage. Mortgage interest payments are set equal to $12 \times {}^{3}/_{5}$ of monthly mortgage payments. This assumption is reasonable because it results in a nationwide itemization rate that is close to the true itemization rate, and because roughly ${}^{3}/_{5}$ of the mean monthly mortgage payment for a 30-year mortgage at 7 percent interest corresponds to interest payments. The ACS variable *taxincl* indicates whether the respondent included real estate taxes in their report of monthly mortgage payments. For individuals who report including property taxes, I assume ${}^{1}/_{5}$ of reported mortgage payments are actually property taxes, and the remaining ${}^{4}/_{5}$ are mortgage payments. This breakdown is chosen based on the relative size of mortgage payments with taxes included versus without taxes included.

31. *scorp*: Active income from S corporation

    The ACS contains no information about income from S corporations. I set this item to 0.

32. *pbusinc*: Primary taxpayer’s qualified business income subject to a preferential rate

    The ACS contains no information about qualified business income. I set this item to 0.

33. *pprofinc*: Primary taxpayer’s specialized service trade or business service with a special rate

    The ACS contains no information about specialized service trade or business. I set this to 0.

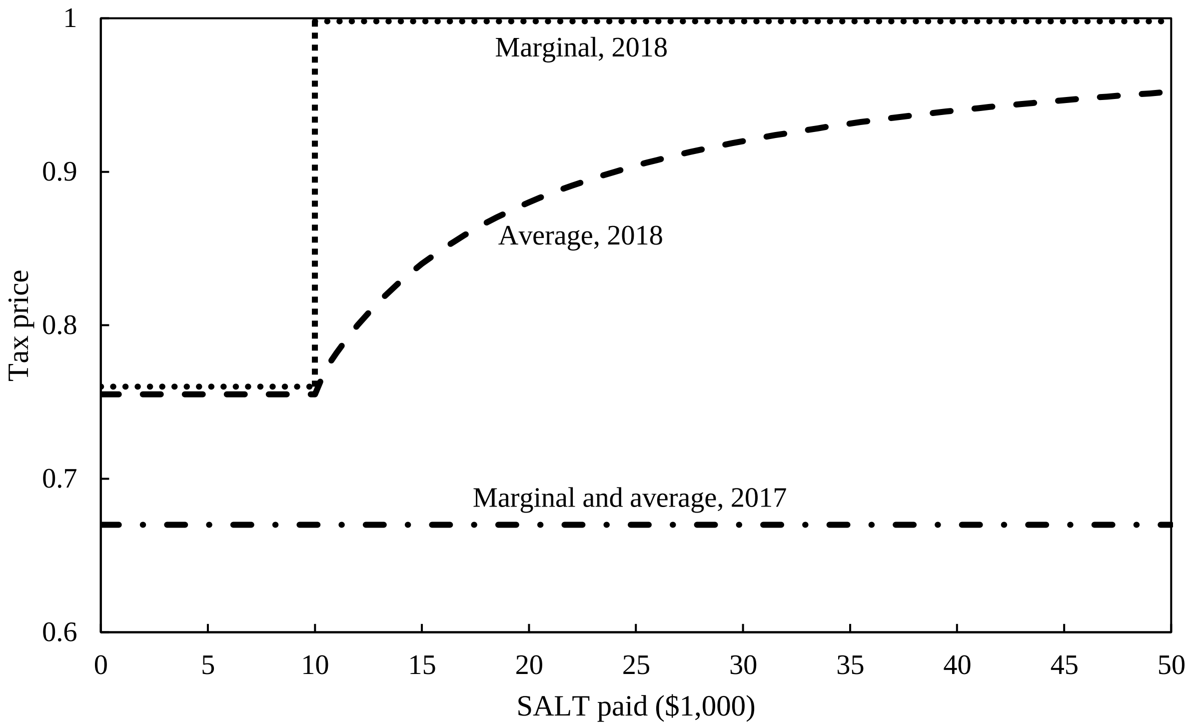
34. *sbusinc*: Spouse’s qualified business income subject to a special rate

    The ACS contains no information about qualified business income. I set this to 0.

35. *sprofinc*: Spouse’s specialized service trade or business service with a preferential rate

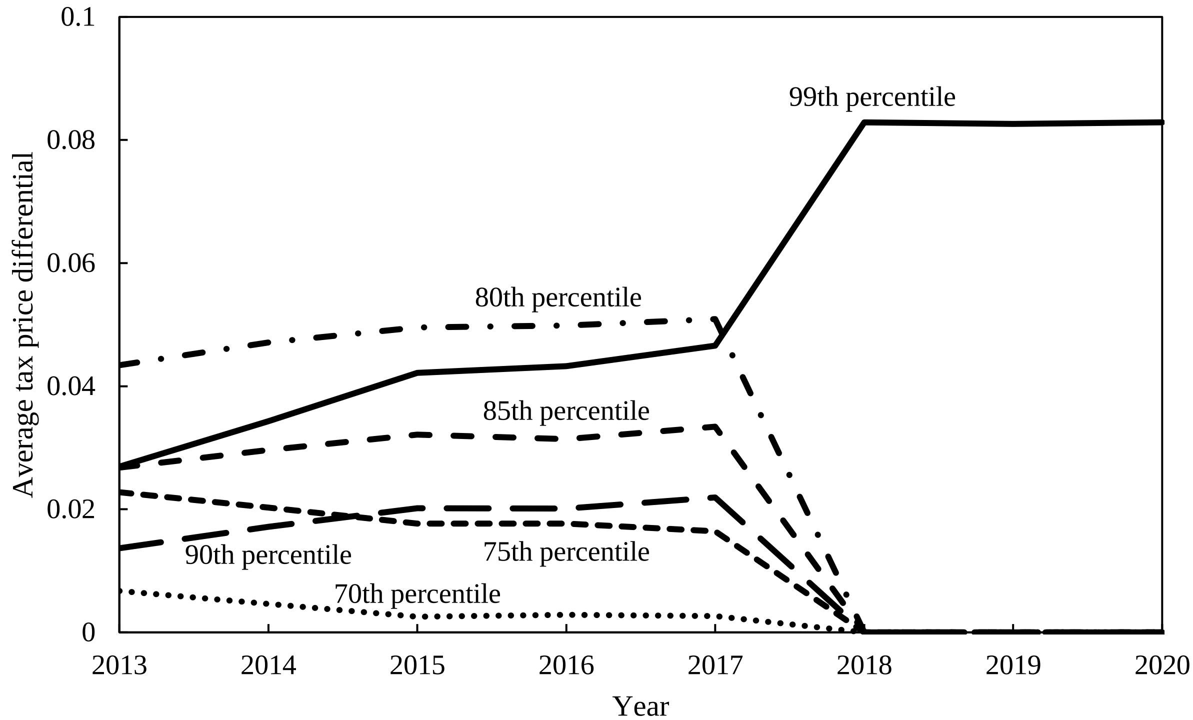
    The ACS contains no information about specialized service trade or business. I set this to 0.

APPENDIX B: SUPPLEMENTAL FIGURES AND TABLES



APPENDIX FIGURE 1. MARGINAL AND AVERAGE TAX PRICES FOR A HYPOTHETICAL HOUSEHOLD IN 2017 AND 2018

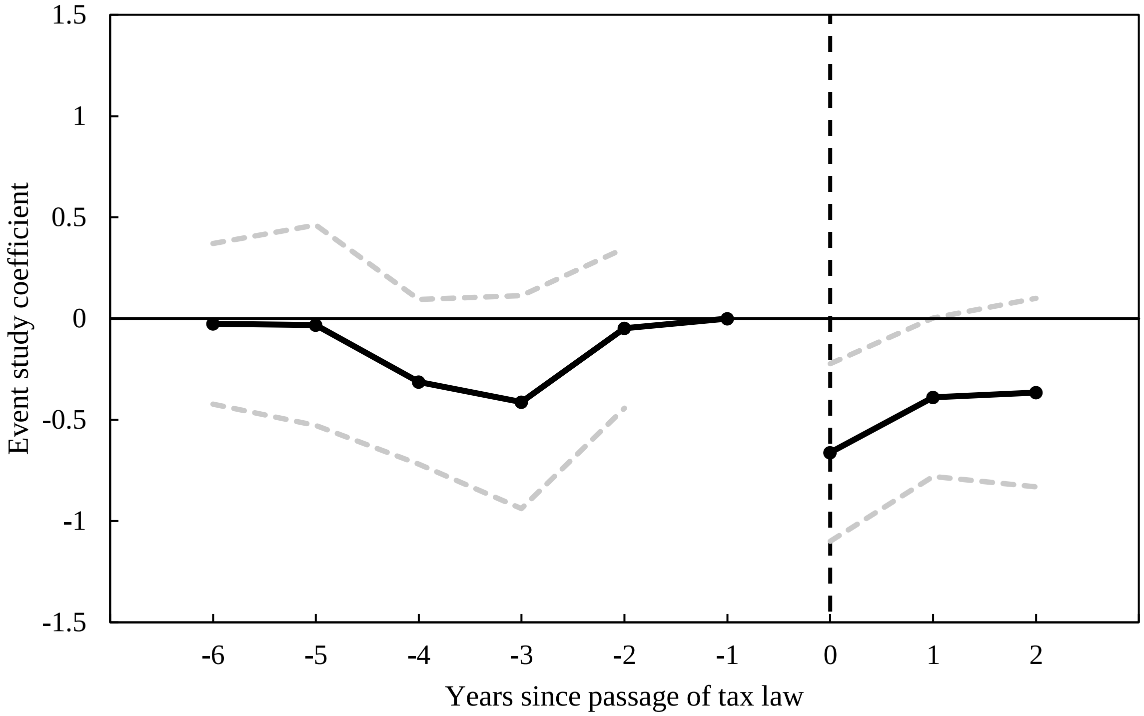
Notes: The hypothetical household is assumed to be married, have taxable income of $250,000, itemize deductions, and not pay the AMT.



APPENDIX FIGURE 2. AVERAGE BETWEEN-STATE TAX PRICE DIFFERENTIAL FOR REPRESENTATIVE HOUSEHOLDS IN VARIOUS PERCENTILES OF THE AGI DISTRIBUTION

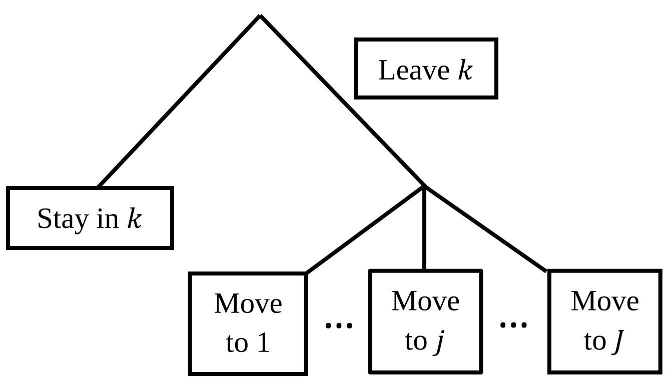
Sources: Author's calculations using TAXSIM and the American Community Survey.

Notes: Tax price differentials are for representative households in the indicated percentiles of the AGI distribution. The average is calculated over all 1,275 combinations of the 51 states.

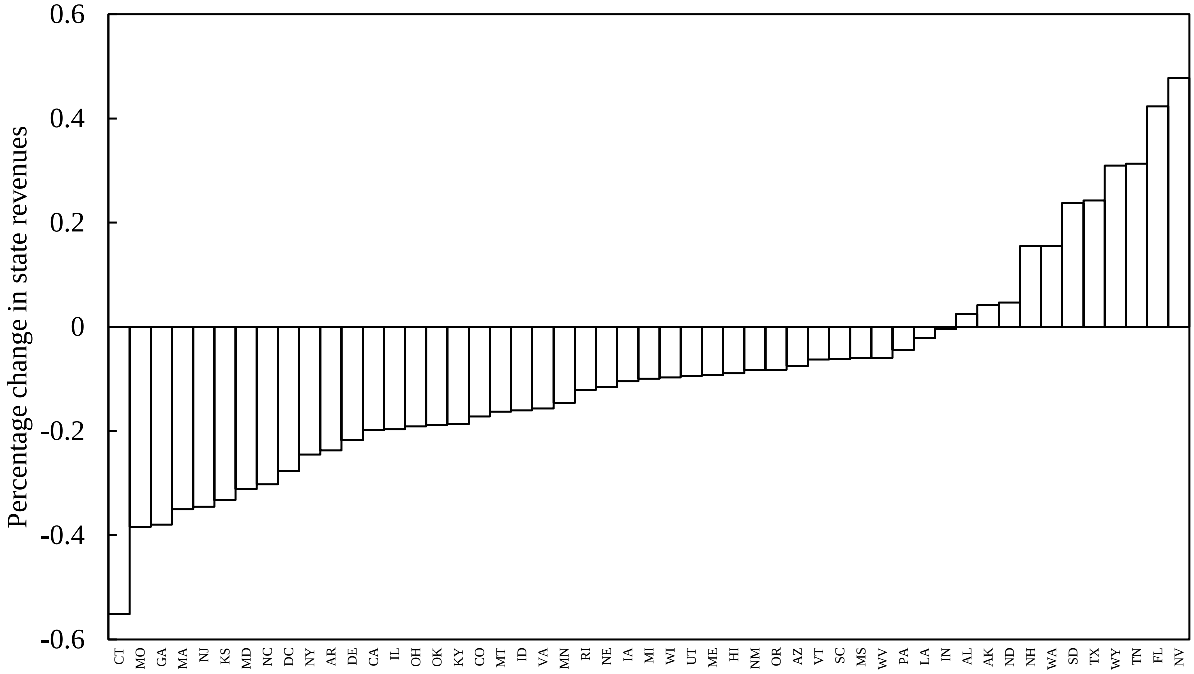


APPENDIX FIGURE 3. EVENT STUDY RESULTS TO TEST FOR THE EXISTENCE OF PRETRENDS

Sources: Author's calculations using TAXSIM and the American Community Survey.
Notes: The solid lines plot the coefficient estimates from the event study regression. The dashed lines plot the 90 percent confidence intervals. Year 0 corresponds to 2018.



APPENDIX FIGURE 4. NESTED LOGIT STRUCTURE FOR THE CHOICE OF STATE IN THE DYNAMIC MODEL



APPENDIX FIGURE 5. STATES RANKED BY MODEL-PREDICTED CHANGE IN REVENUES

Sources: Author's calculations using TAXSIM and the American Community Survey, Statistics of Income, and the Annual Survey of State and Local Government Finances.

Notes: Revenues refer to all sources of revenue at all levels of government.

APPENDIX TABLE 1—DIFFERENCE-IN-DIFFERENCES AGGREGATE REGRESSION RESULTS USING DIFFERENT CONTROL GROUPS, 2012–20

Log population ratio	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log tax price ratio	–0.613***	–0.918**	–0.642**	–1.014**	–0.654***	–1.012***	–0.604**	–0.979***	–0.593**	–0.967**
	(0.230)	(0.365)	(0.257)	(0.403)	(0.249)	(0.393)	(0.254)	(0.379)	(0.248)	(0.391)
Housing elasticity	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Control group	90th	90th	85th	85th	80th	80th	75th	75th	70th	70th
No. of observations	22,950	22,950	22,950	22,950	22,950	22,950	22,950	22,950	22,950	22,950
R^2	0.994	0.905	0.992	0.880	0.991	0.873	0.991	0.869	0.991	0.867

Sources: Author’s calculations using TAXSIM and the American Community Survey.

Notes: Housing elasticity indicates whether the population ratio was adjusted for local housing supply elasticities, as explained in the text. The treatment group is a representative household in the 99th percentile of the AGI distribution. The control group is a representative household in the indicated percentile of the AGI distribution. The regressions include origin fixed effects, destination fixed effects, year fixed, and economic and demographic controls, including: unemployment rate, labor force participation rate, share white, share age 25 and younger, share age 65 and older, and share with a bachelor’s degree or more. Robust standard errors clustered at the origin-year, destination-year, and origin-destination levels are shown in parentheses. Statistical significance is indicated at the ***1 percent and **5 percent levels.