Heterogeneous Effects of Personal Income Tax Shocks: a Regional Approach

Edoardo Briganti[1] Carlos Góes[1] Victor Sellemi[1]

[1]Department of Economics, UC San Diego

Outline

Motivation

- Different tax reforms have very different incidence profiles and occur during different states of the economy.
- Could these different events have different macroeconomic implications?

Motivation: four different personal income tax reforms

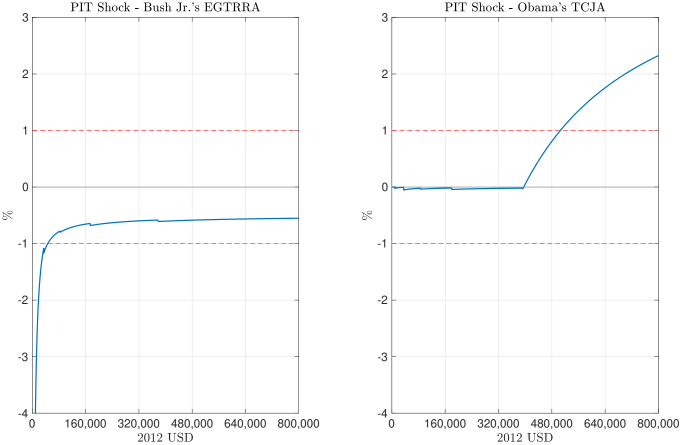


Figure 1: Changes in effective personal income tax rates as a function of real adjusted gross income, calculated from the underlying tax schedules.

Goal

- Our goal: better understand the transmission mechanism of fiscal policy through an **event-study approach**.
- How: estimate the **event-specific causal effect** of different federal personal income tax (PIT) reforms on local economic activity, exploiting **event-county-level** (cross-sectional) variation in tax incidence.
- Events: PIT reforms under Presidents Bush (2002-03), Obama (2013), and Trump (2017).

Related Work: Tax Multipliers

- Literature shows divergence in tax multipliers estimates.
- Blanchard and Perotti (QJE 2002) find multipliers < 1; most macro models tend to fall in the $[0, 1]$ range.
- Narrative methods (Romer & Romer, AER 2010; Mertens & Ravn, JME 2014) find larger multipliers in the $[2, 3]$ interval.
- Little work on cross-sectional tax multipliers. Zidar (JPE 2019) finds average multipliers of 3.5, with heterogeneity in tax cuts for poor and rich.

Related Work: Local Multipliers

- Most of the literature focuses on expenditures (reviews in Ramey, 2019; Chodorow-Reich, AEJ: Policy 2019).
- Federal defense expenditures (Nakamura & Steinsson, AER 2014; Dupor & Guerrero, JME 2017; Auerbach, Gorodnichenko & Daniel Murphy, IMF ER 2019).
- State-level negative or positive windfalls (Clemens & Miran, AEJ: Policy 2012; Shoa, AERP&P 2013; 2017).
- ARRA expenditures impact on GDP and employment (Chodorow-Reich et al, AEJ: Policy 2012)
- Experiments: natural (Suárez Serrato & Wingender, 2016) or designed (Egger et al, 2019).

Roadmap

- Today:
  - Present database of county-level income distributions and tax shocks for tax reforms.
  - Explain identification strategy and methodology.
  - Show *very very* preliminary results for 2013 reform: relative impact over local economic activity probably very small.
- In the future:
  - Use results to calibrate a multi-region HANK model.
- Much needed: your feedback.

Where we differ

- Our work is more closely related to Zidar (JPE, 2019), who finds different macro effects of tax incidence over bottom 90% vs. top 10% across states.
- Differences:
  - Approach each reform as a different event study —variation through county-level data.
  - Use more precise data —tabulations of county-level tax *population*, as in the top-incomes literature.
  - TAXSIM removes state codes for all returns with AGI $> \$200k$, making it impossible to analyze reforms with incidence profiles similar to Obama's tax changes.

- Generic framework for cross-sectional multipliers for a fiscal impulse that happens at period t: (Chodorow-Reich, 2019) estimates local projection regressions for each horizon $h \in \{-3, -2, \cdots, 5\}$:

$$\frac{Y_{c,t+h} - Y_{c,t-1}}{Y_{c,t-1}} = \alpha_h + \gamma_h \frac{F_{c,t}}{Y_{c,t-1}} + \mathbf{X}'_{c,t-1}\boldsymbol{\beta}_h + \varepsilon_{c,h} \quad (1)$$

where $Y_{c,t}$ is a measure of economic activity in county c and $F_{c,t}$ is a component of fiscal policy such as taxes or expenditure.

General Empirical Framework

- For us, $F_{c,t} := \Delta\tau_{c,t}$ is the change in aggregate tax bill in county c:

$$\Delta\tau_{c,t} = \underbrace{n_{c,t}}_{\text{returns in } c} \underbrace{\int_0^{\infty} \Delta\tau_t(y) \cdot y \cdot f_{c,t}(y) dy}_{\text{avg tax bill change per return}} \qquad (2)$$

where:

- $\Delta\tau_t(y) = \tau_t(y) - \tau_{t-1}(y)$ is the change in personal income *effective tax rate* induced by federal policy variation.
- $f_{c,t}(y)$ is *distribution* of adjusted gross income in county c.
- In the shift-share terminology, we have shifters $\tau_t(y) \cdot y$ and shares $f_{c,t}(y)$.

Outline

Shares: constructing adjusted gross income distributions

- We begin with county-level administrative tax return data from the IRS.
  - Population Adjusted Gross Income tabulations at the county-level
  - 4 income brackets 1998-2002, 6 brackets 2003-2011, and 7 brackets 2012-Present
- We estimate income distributions using Generalized Pareto Interpolation (GPI) as in Blanchet, Fournier, Piketty (2017). Goal:

$$\hat{f}_{c,t}(y) : [0, \infty) \to (0, 1) \quad c = 1, ..., C \quad t = 1998, ..., 2019$$

Generalized Pareto Interpolation

The main idea. non-parametric approach with quintic spline interpolation and Generalized Pareto tails.

Advantages:

- precise and **smooth** estimates of the entire distribution, even when the number of brackets is **small**.
- **precise** estimates of the **top shares** of income: BFP (2017) show that estimates based on population subsamples (e.g., TAXSIM data) can lead to **tail** estimation error.

Example

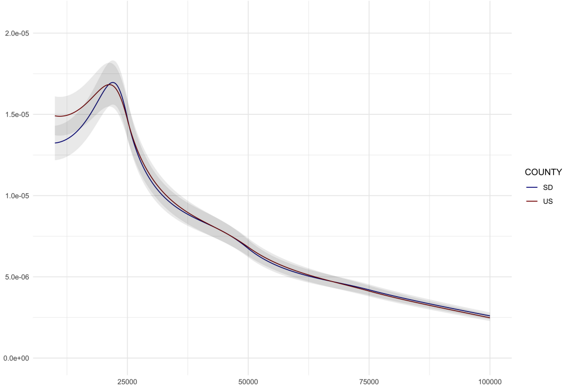


Figure 2: Estimated income density for San Diego County vs. the U.S. national level distribution, GPI estimated using 2012 IRS data

Implementation

- We exclude counties with
  - Number of returns under 5,000.
  - Missing administrative data.

  Sample size:
  - **2911** counties for the Obama tax reform.
  - **3135** counties for the Bush tax reforms (aggregating over zipcodes).

Evidence of county-level heterogeneity - AGI inequality

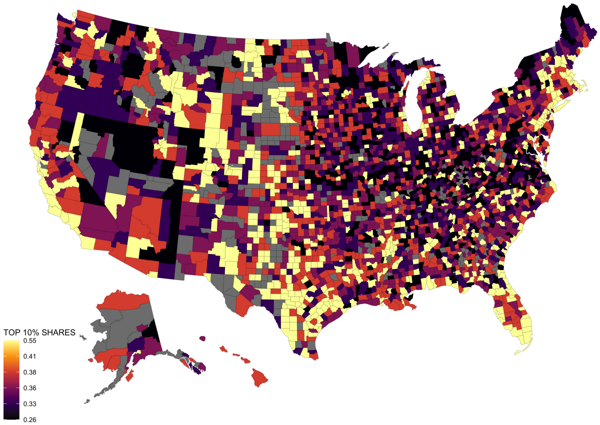
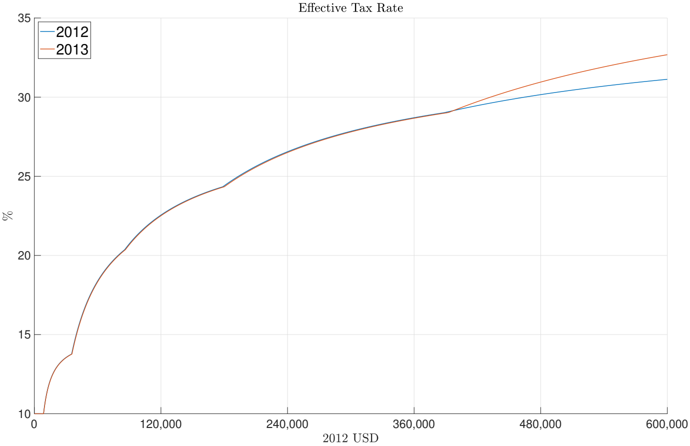


Figure 3: Spatial distribution of top 10% adjusted gross income (AGI) top shares in tax year 2012, based on Generalized Pareto Interpolation estimates using IRS data

Shifters: Obama's Reform



Obama Tax Shock 2013

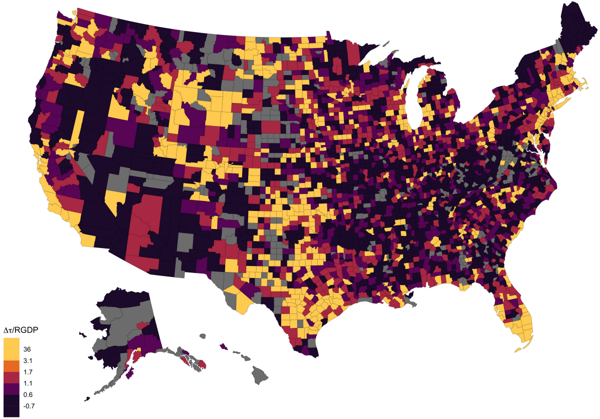
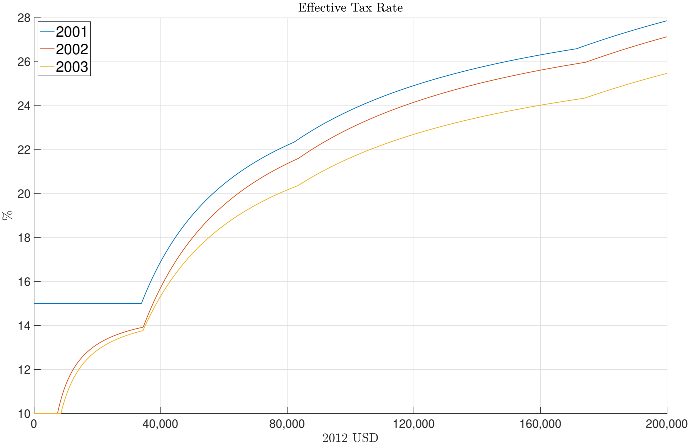
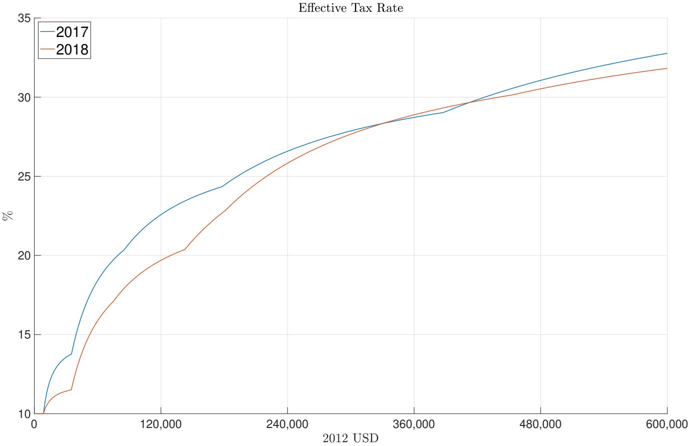


Figure 4: Distribution of county-level tax-shocks

Other events: Bush's Reforms



Other events: Trump's Reform



Outline

$Y_{c,t}$: Local Effects of Total PIT shocks

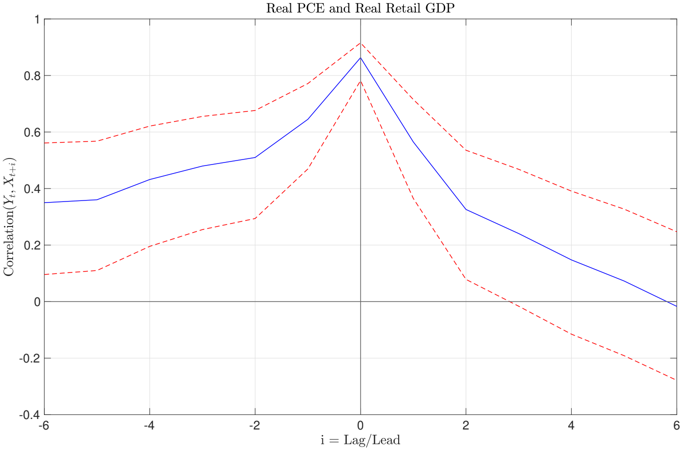
where our outcome variables are:

- Real GDP growth.
  1. Advantage: we can estimate **Local Multipliers**.
  2. Disadvantage: at the county level:

$$GDP_{c,t} \neq (Personal\ Income)_{c,t}$$

- Proxy for real PCE growth:
  1. Retail Employment (see **guren˙housing˙2018** and Mian and Sufi (2014)).
  2. **Retail GDP** (Innovation thanks to newly available data).

PCE and Retail GDP



Correlation at different lags and leads between Aggregate Real Quarterly Retail GDP and Aggregate Real Quarterly PCE detrended using linear time and splines filter. Sample: 2005Q1 to 2020Q2. Source: BEA.

Threats to identification - reverse causality

- Fiscal policy might be implemented as a response to changes in income.
- We address this through a **shift-share design**.
- Assumption: U.S. does not enact tax reform at the federal level *because* some counties are faring better economically than others.

Threats to identification - share endogeneity

- For a valid Bartik instrument, we need exogenous shares $f_{c,t}(y)$ (Goldsmith-Pinkerman, Sorkin & Swift, AER 2020).
- Shocks to income (including news about the tax reform) can induce individuals to change their reported AGI: $\text{cov}(f_{c,t}(y), \varepsilon_{c,h}) \neq 0$.
- We instrument following a well-established strategy in public-finance (Grueber & Saez, JPE 2002) using predicted tax liability as an instrument:

$$\Delta\tau_{c,t}^{pred} = n_{c,t-1} \int_0^\infty \Delta\tau_t(y) \cdot y \cdot f_{c,t-1}(y) dy$$

Threats to identification - omitted variables

- Cross-sectional variation in the tax shock $\Delta\tau_{c,t}$ must be conditionally uncorrelated with economic growth
- Controls:
  - economic growth from previous years: growth rate of county GDP, changes in unemployment in previous years.
  - cross-sectional features correlated with growth: state-fixed effects, rural-urban codes, inequality, population
- Other potential controls that we have not accounted for yet: (differential) oil prices, interest rates, exposure to automatic stabilizers, housing prices.

Threats to identification - measurement error

- There is evidence of measurement error in regional GDP data: Bickenback (2015), Aruoba et al. (2016), Corbi et al. (2018)
- In our analysis we assume that measurement error is small and **random** across counties.
- We also include dependent variables which are more precisely measured, such as unemployment.

Econometric specification

We estimate the following cross-sectional 2SLS model for each horizon $h \in \{-3, -2, \cdots, 5\}$:

First stage:

$$\frac{\Delta\tau_{c,t}}{Y_{c,t-1}} = \vartheta_0 + \vartheta_1 \frac{\Delta\tau_{c,t}^{pred}}{Y_{c,t-2}} + \vartheta_2^{\top}\mathbf{X}_c + \nu_c$$

Second stage:

$$\frac{Y_{c,t+h} - Y_{c,t-1}}{Y_{c,t-1}} = \alpha_h + \beta^{\top}\mathbf{X}_c + \gamma_h \frac{\Delta\hat{\tau}_{c,t}}{Y_{c,t-1}} + \varepsilon_{c,h},$$

where Y is the outcome variable of interest (i.e., retail GDP), α_h is a time fixed effect, $\mathbf{X}_c$ is the vectors of controls, $\Delta\tau_{c,t}$ is the county tax shock, and $\varepsilon_{c,h}$ is the cross-sectional residual.

Obama Tax Shock 2013 impact over Retail Real GDP (unweighted, full sample)

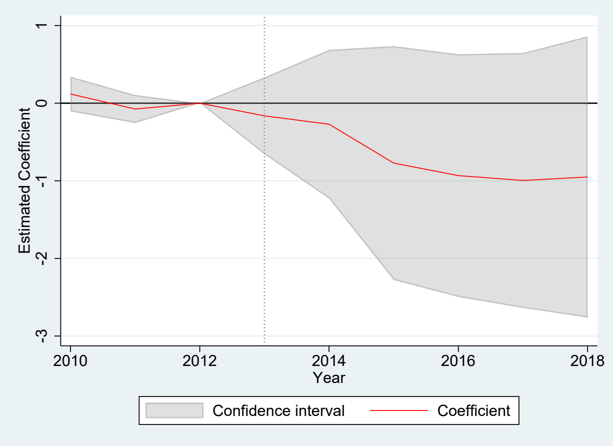


Figure 5: Local Projection Impulse Response Function of County-Level Retail Real GDP to tax-shock, unweighted. First-stage F-statistic ≈ 190

Obama Tax Shock 2013 impact over Retail Real GDP (weighted by population, full sample)

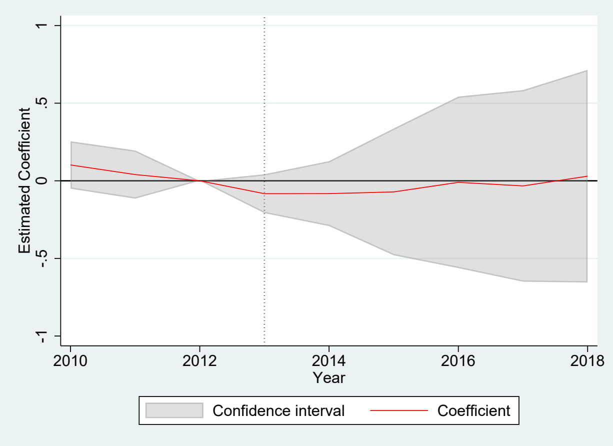


Figure 6: Local Projection Impulse Response Function of County-Level Retail Real GDP to tax-shock, weighted by population. First-stage F-statistic ≈ 190

Obama Tax Shock 2013 impact over Retail Real GDP (unweighted, dropping outliers)

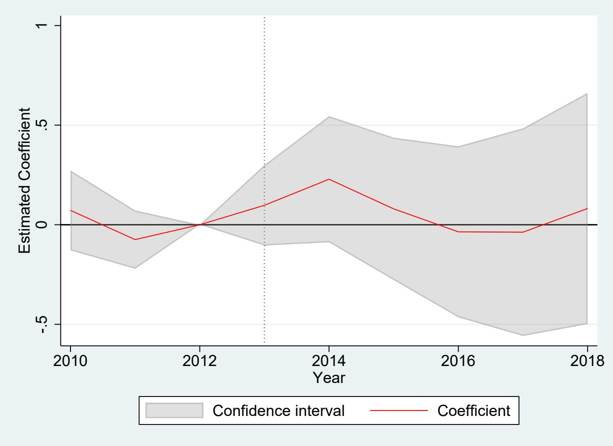


Figure 7: Local Projection Impulse Response Function of County-Level Retail Real GDP to tax-shock, dropping counties that had annual growth in Retail GDP $> 100\%$ or $< -50\%$ at any year in the sample.

Obama Tax Shock 2013 impact over unemployment rate (unweighted, full sample)

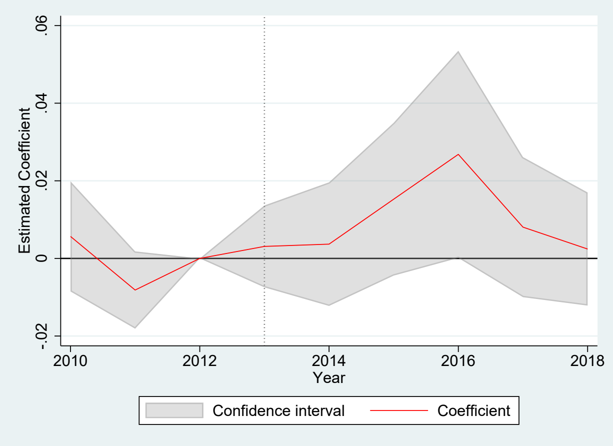


Figure 8: Local Projection Impulse Response Function of county unemployment rate to tax-shock, unweighted. First-stage F-statistic ≈ 190

Obama Tax Shock 2013 impact over unemployment rate (weighted, full sample)

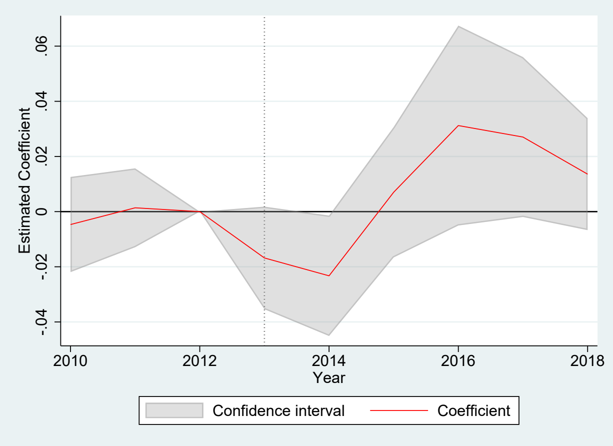


Figure 9: Local Projection Impulse Response Function of county unemployment rate to tax-shock, weighted by population. First-stage F-statistic ≈ 190

Outline

Next Steps

- Newly available local GDP data + novel use of IRS tabulations allow us to reliably estimate cross-sectional causal effect of recent U.S. tax reforms over the local economy.
- Preliminary evidence suggests local effect of Obama's reform, which targeted the rich, was small (aligned with average effects from Zidar, 2019).
- We will refine our empirical exercise and hope to soon have IRFs for tax reforms under Bush and Trump.
- After the empirical work is done, we aim to rationalize these results with a multi-region HANK model.

Outline

Motivation: two different personal income tax reforms

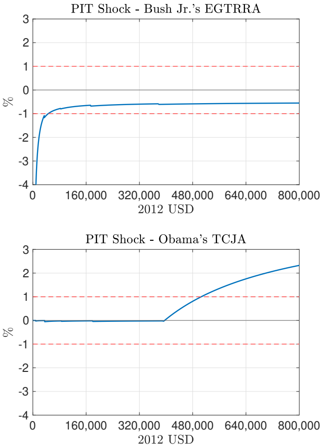


Figure 10: Changes in effective personal income tax rates as a function of real adjusted gross income, calculated from the underlying tax schedules.

The ordinary PIT schedule

The following ordinary PIT schedule applies to ordinary income minus deductions ($w - D$):

Tax Rate	Lower income bracket	Upper income bracket
$\tau_{1,t}$	$b_{1,t}$	$b_{2,t}$
$\tau_{2,t}$	$b_{2,t}$	$b_{3,t}$
$\vdots$	$\vdots$	$\vdots$
$\tau_{N_t,t}$	$b_{N_t,t}$	∞

where:

- $b_{k,t}$ is the k^{th} income threshold in year t.
- N_t is the number of income thresholds in year t.

The capital gain PIT schedule

The following ordinary PIT schedule applies to Capital Gains ($K + Q$):

Tax Rate	Lower Cap. Inc. bracket	Upper Cap. Inc. bracket
$\tau_{1,t}^{C}$	$b_{1,t}^{C}$	$b_{2,t}^{C}$
$\tau_{2,t}^{C}$	$b_{2,t}^{C}$	$b_{3,t}^{C}$
$\vdots$	$\vdots$	$\vdots$
$\tau_{N_t^C,t}$	$b_{N_t,t}^{C}$	∞

The income brackets for capital gains are calculated using AGI and not Capital Gains income.

Modeling Personal Income Tax, II

Consider an individual with income y in year t, such that $y - D(y) > b_{N_t,t}$ (top income earner). Then Her effective tax rate is defined as:

$$\tau_t(y) = \frac{\sum_{k=1}^{N_t}(b_{k+1,t} - b_{k,t}) \cdot \tau_{k,t} + (y - b_{N_t,t}) \cdot \tau_{N_t,t}}{y}$$

Then we construct the Effective Tax Rate function:

Effective Tax Rate

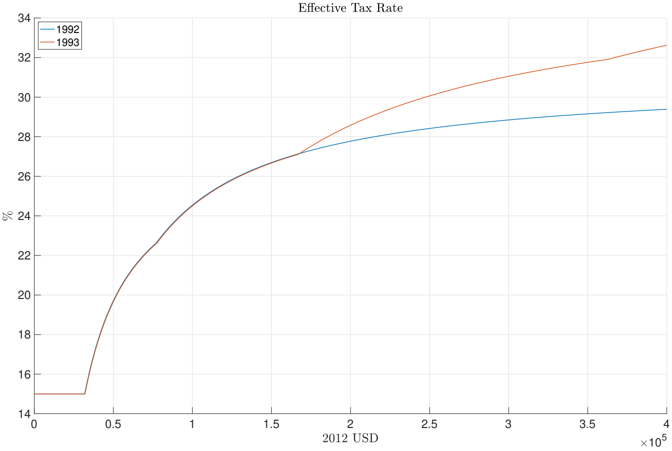
Consider the a generic income tax bracket:

Tax Rate	Lower income bracket	Upper income bracket
$\tau_{1,t}$	$b_{0,t}$	$b_{1,t}$
$\tau_{2,t}$	$b_{1,t}$	$b_{2,t}$
$\vdots$	$\vdots$	$\vdots$
$\tau_{N_t-1,t}$	$b_{N_t-1,t}$	∞

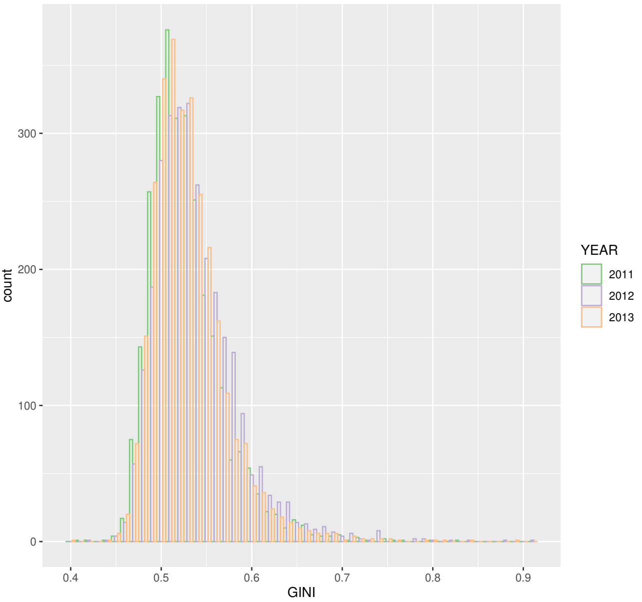
Then we construct the Effective Tax Rate function:

$$\tau_t(y) = \frac{\sum_{i=1}^{n-1}(b_{i,t} - b_{i-1,t}) \cdot \tau_{k,t} + (y - b_{n-1,t}) \cdot \tau_{n,t}}{y}$$

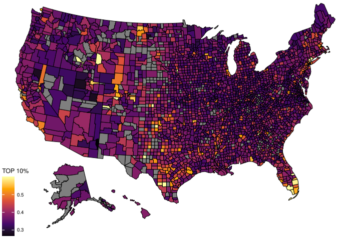
Effective Tax Rate: Clinton & OBRA93



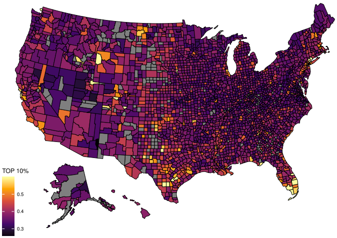
Evidence of county-level heterogeneity - income inequality



Evidence of county-level heterogeneity - top 10% shares



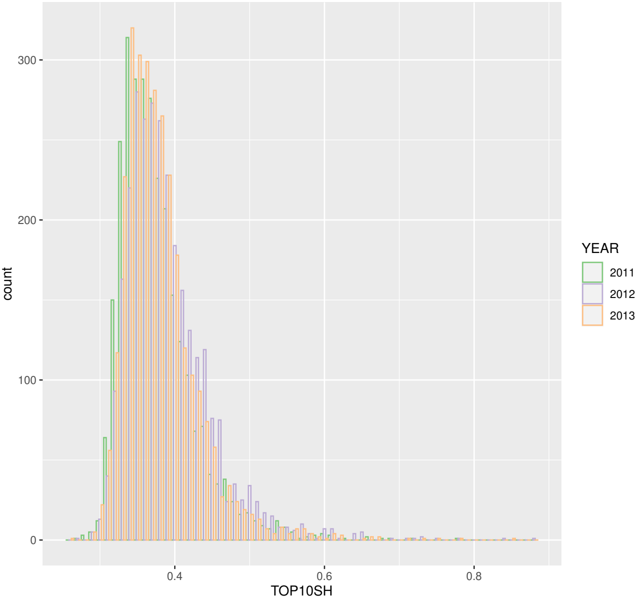
(a) 2011



(b) 2013

Figure 12: Spatial distribution of top 10% income share in tax years 2011 and 2013, based on GPI estimates using IRS administrative data

Evidence of county-level heterogeneity - top 10% shares



Threats to identification - spillovers

With highly disaggregated data, one concern is spillovers from

- tax increases in neighboring counties
- economic growth in neighboring counties

We can construct a spatial component for each county as a weighted sum of neighbors:

$$\xi_{c,t} = \sum_{c' \neq c} w_{c,c'} \cdot x_{c',t}, \quad w_{c,c'} = \frac{1}{DIST_{c,c'}} \cdot \frac{POP_{c'}}{POP_{c'} + POP_c},$$

where $w_{c,c'}$ is the population weighted distance to county c's neighbors and $x_{c',t}$ is the spatial variable we are interested in.

Modeling Personal Income Tax, I

We need to distinguish between:

- *Ordinary Income* (w): labor earnings, profits, short-run capital gains, non-qualified dividends, others.
- *Capital Gains*: long-run capital gains (K) and qualified dividends (Q).
- *Gross Income* (Y): sum of Ordinary Income and Capital Gains.
- *Deductions* (D).
- *Adjusted Gross Income* (y) = Gross Income minus Deductions (AGI henceforth).

Modeling Personal Income Tax, II

- AGI can be broken down as follows:

$$\begin{aligned} y &= Y - D \\ &= w + K + Q - D \\ &= \underbrace{w - D}_{\text{Subject to Ordinary PIT}} + \underbrace{K + Q}_{\text{Subject to Capital Gain PIT}} \end{aligned}$$

- We incorporate tax schedule changes for ordinary income and capital income at the federal level.
- In the future, we will incorporate automatic changes at the state-level that respond to federal reform.

Effective Tax Rate used to be more progressive...