Lecture II: Estimating Labor Supply

Alice Kügler and Attila Lindner

November 1 2019

Overview

- Labor supply elasticity is a key parameter for income tax policy
  - Determines the deadweight loss of the earnings elasticity
    - Is a fundamental parameter for optimal tax formulae
  - Labor supply responses have many dimensions:
    - Intensive margin: choose hours of work on the job, intensity of work, occupational choice
    - Extensive margin: choose whether to work or not; e.g. also retirement, migration etc.
  - Reported earnings for tax purposes also vary because of:
    - (legal) tax avoidance
    - (illegal) tax evasion
  - Different responses in short-run and long-run: long-run response most important for policy but hardest to estimate

Static labor supply model (recap)

- Compensated labor supply $h^c = h^c(w, u)$ is derived by minimizing the expenditure function:

$$\min_{c,h} \quad c - wh \quad s.t. \quad u(c, T - h) \geq u$$

  for consumption c, wage w, hours worked h, and total time T
- Slutsky equation:

$$\underbrace{\frac{\partial h}{\partial w}}_{\text{Uncompensated}} = \underbrace{\frac{\partial h^c}{\partial w}}_{\text{Compensated}} - \underbrace{\frac{\partial h}{\partial y} h}_{\text{Income effect}}$$

- Uncompensated response: income and substitution effect, holding non-wage income y constant, used to estimate the Marshallian elasticity
- Compensated response: substitution effect, e.g. used to evaluate the welfare effects of tax reforms

Basic cross-section estimation

- Based on this model, early studies specified regressions such as

$$h_i = \beta_0 + \beta_1 w_i + \beta_2 y_i + \beta_3 \mathbf{x}_i + \nu_i$$

  - w_i is the net-of-tax wage
  - y_i denotes non-labor income, including spousal income for couples
  - $\mathbf{x}_i$ includes demographic controls such as age, education, etc.
  - β_1 measures the uncompensated wage response: can be converted to the uncompensated wage elasticity
  - β_2 captures income effects: can be converted to measure the income effect
- OLS is only consistent if there is no correlation between the explanatory variables and ν_i

What's wrong with this basic regression?

- Measurement error of w_i measured as earnings/hours in survey data
- Non-participation: Heckman's selection correction
- Identification: omitted variables
- Non-linear taxes
- Non-convex budget sets: discrete participation responses, e.g., if there are fixed costs of work due to child care, commuting etc.

Identification if w_i and ν_i are correlated

For example, tastes for work might differ across skill groups:

- Identification uses cross-section variation in w_i across workers with high skills (and high w_i) and low skills (low w_i)
- The OLS estimator will be upward biased if high-skilled workers have more taste for work, e.g. hard workers acquire better education and have higher wages
- Omitted variable bias if not all factors can be controlled for by including x_i
- As one solution, use tax changes for identification

Non-linear taxes

- Tax schedules are piecewise linear, with different marginal tax rates for each bracket
  - Optimal labor supply in each bracket is a function of the respective marginal tax rate and the virtual income in that bracket
  - Difficulties arise because:
    - Net-of-tax wage and virtual income are endogenous: use only reform-based variation in the marginal tax rates
    - The first order condition may not hold if the worker bunches at a kink

More recent research

Since the late 1980s:

- The literature distinguishes between hours worked and participation: accounts for discrete participation responses and non-convexities
- The **identification revolution**:
  - Randomized control trials
  - Quasi-experiments
- More recently:
  - Use of **large administrative datasets** instead of survey data
  - Effects **visible in graphs** (the graphical revolution)
  - **Sufficient statistics approach** connects reduced-form and structural estimation approaches (see Lecture I)

The identification revolution

Experimental evidence used to estimate labor supply:

- Randomized experiments
  - Solves the selection bias that creates systematic differences between treatment and control groups
  - Early applications were the Negative Income Tax (NIT) experiments in the U.S. in the 1960s and 1970s: for example, Ashenfelter and Plant (1990)
- Quasi-experiments
  - Variation often due to tax reforms
  - Difference-in-differences estimation, when parallel trends assumption holds

The difference-in-differences (diff-in-diff) estimation

Natural experiments, for example, through tax reforms:

- Create a treated group T affected by the reform, and a control group C; B and A denote before and after the reform
- The effect on labor supply L is the difference-in-differences:

$$\Delta L^T - \Delta L^C = (L_A^T - L_B^T) - (L_A^C - L_B^C)$$

- This removes the common (group-invariant) time effects, and the (time-invariant) group effects

The difference-in-differences regression

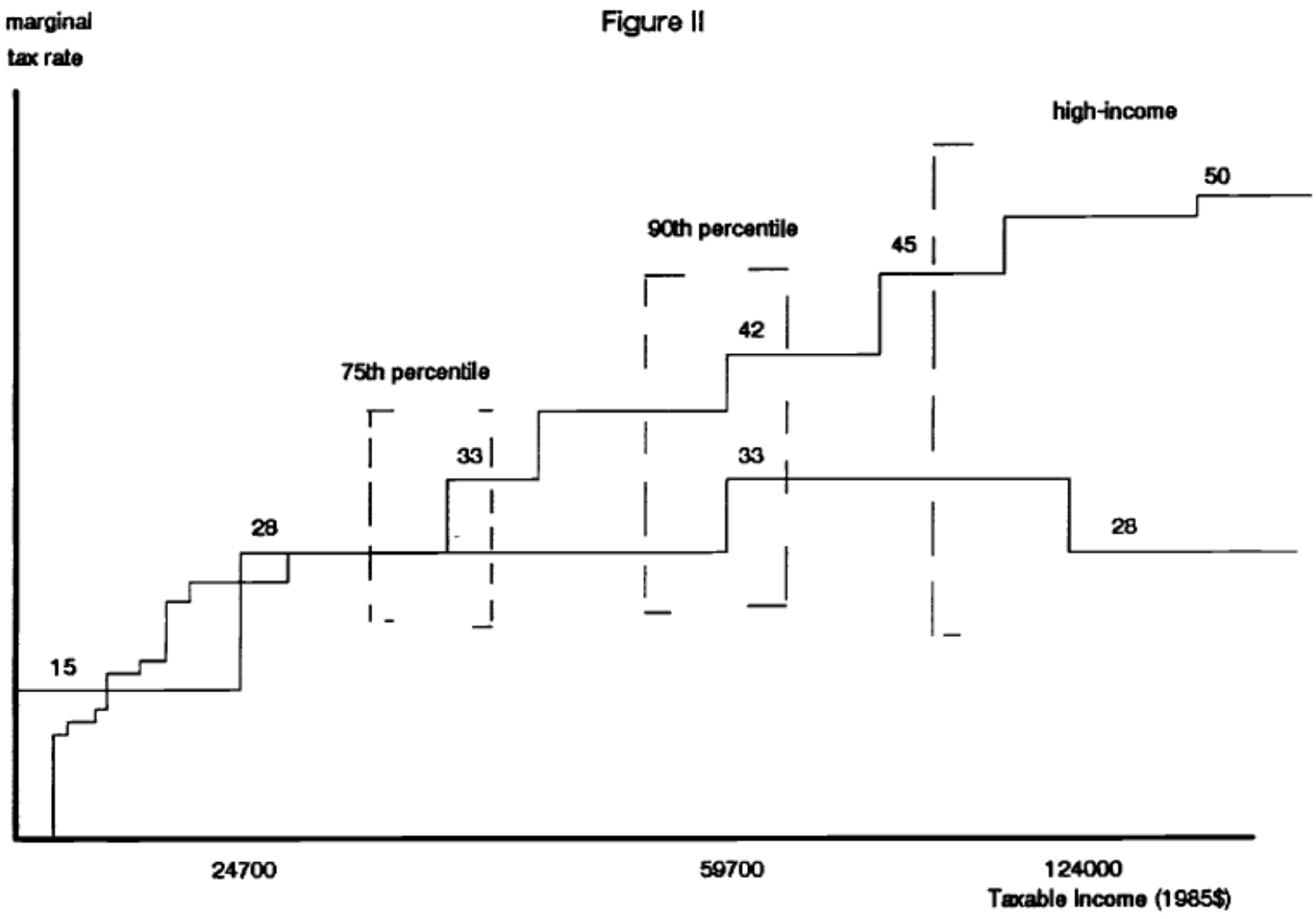
$$L_{it} = \beta_0 + \beta_1 \text{AFTER}_t + \beta_2 \text{TREAT}_i + \beta_3 \text{AFTER}_t \cdot \text{TREAT}_i + \beta_4 \mathbf{x}_i + \nu_{it}$$

- Treatment dummy $\text{TREAT}_i = 1$ if the workers is treated, and time dummy $\text{AFTER}_t = 1$ if t is after the reform
- Assumption 1: Treatment and control have the same time effects: "parallel trends"
- Assumption 2: The composition of treated and control groups does not change over the reform period

Eissa (1995): the labor supply of married women

- Uses the U.S. Tax Reform Act of 1986 (TRA86) as a natural experiment
- Repeated cross-sections data (CPS) before and after TRA86
- **Difference-in-differences strategy:** compare wives affected by the tax change before the reform (1985) to wives not affected after the reform (1989)
- Due to jointness of the U.S. income tax, assignment into treated and control based on husband's earnings
  - treated are wives at the 99th percentile
- This paper was never published but well-cited and is a good example for teaching

Income tax schedule 1985 (top) vs. 1989 (bottom rate)



Eissa (1995): marginal tax rates for treated and controls

Group	Before TRA86	After TRA86	Change	Relative Change
High	.521 (.002)	.382 (.001)	-.139 (.002)	
75th Percentile	.365 (.001)	.324 (.001)	-.041 (.001)	**-.098** **(.002)**
90th Percentile	.430 (.001)	.360 (.001)	-.07 (.001)	**-.069** **(.002)**

Eissa (1995): diff-in-diff labor force participation

Group	Before TRA86	After TRA86	Change	Difference-in-Difference
High	0.464 (.018) [756]	0.554 (.018) [718]	0.090 (.025) {19.5%}	
75th Percentile	0.687 (.010) [3799]	0.740 (.010) [3613]	0.053 (.010) {7.2%}	**0.037 (.028)** **{12.3%}**
90th Percentile	0.611 (.010) [3765]	0.656 (.010) [3584]	0.045 (.010) {6.5%}	**0.045 (.028)** **{13%}**

Eissa (1995): diff-in-diff hours conditional on participation

Group	Before TRA86	After TRA86	Change	Difference-in-Difference
High	1283.0 (46.3) [351]	1446.3 (41.1) [398]	163.3 (61.5) {12.7%}	
75th Percentile	1504.1 (14.3) [2610]	1558.9 (13.9) [2676]	54.8 (20.0) {3.6%}	**108.6 (65.1)** **{9.4%}**
90th Percentile	1434.1 (16.4) [2303]	1530.1 (15.9) [2348]	96.0 (22.8) {6.8%}	**67.3 (64.8)** **{6.2%}**

Eissa (1995): labor supply elasticities

- Relate the diff-in-diff estimate for labor supply to the diff-in-diff for (1 - marginal tax rate t):

$$\frac{(\Delta L^T/L^T) - (\Delta L^C/L^C)}{\Delta(1-t^T)/(1-t^T) - \Delta(1-t^C)/(1-t^C)}$$

- Includes socio-demographic controls to increase the precision of the estimates
- The total elasticity (accounting for participation and hours worked) at the top of the distribution is around 0.8

Why do we not believe the results in Eissa (1995)?

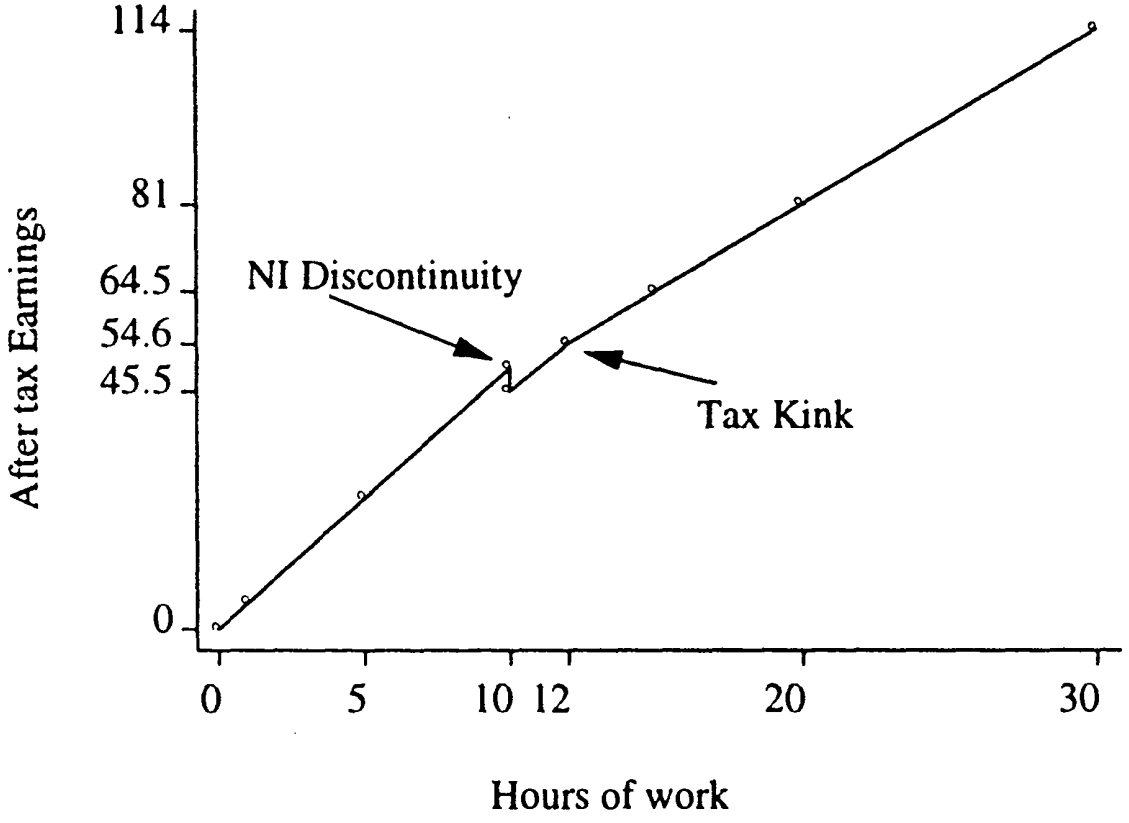
1. The parallel trends assumption is unlikely to hold:
   - Labor supply and demand between the different groups may evolve differently: T starting from a lower level
   - Another alternative story: trend towards "power couples" in the late 1980s
2. The reform affected both treated and controls: require homogeneous responsiveness for T and C
3. Identification requires no cross-substitutability in spousal leisure
   - The estimated elasticity is a mixture of substitution and income effects, not interpretable as in a structural model

Blundell et al. (1998)

Grouping estimator generalizes the diff-in-diff to obtain compensated elasticities

- Use U.K. tax reforms in the 1980s as natural experiments
- Estimate the labor supply response of married or co-habiting women to changes in net-of-tax wages
- Data: repeated cross-sectional data from the U.K. Family Expenditure Survey 1987-1992

Blundell et al. (1998): example budget constraint



The budget constraint (illustrated for NI rate 9%, tax rate 25%, pre-tax wage £5)

Blundell et al. (1998): marginal tax rates after the reforms

TABLE II

MARGINAL TAX RATES BY FINANCIAL YEAR, EDUCATION, AND COHORT

	Compulsory Education				Post-compulsory Education				
	< 1940	1940–49	1950–59	1960 +	< 1940	1940–49	1950–59	1960 +	Total
Financial Year									
1978/79	0.29	0.25	0.31	·	0.37	0.31	0.35	·	0.29
1979/80	0.28	0.24	0.26	·	0.32	0.29	0.32	·	0.27
1980/81	0.29	0.24	0.27	·	0.30	0.26	0.34	·	0.28
1981/82	0.29	0.24	0.28	0.31	0.33	0.28	0.33	·	0.28
1982/83	0.27	0.23	0.25	0.36	·	0.30	0.33	·	0.27
1983/84	0.26	0.23	0.24	0.32	·	0.29	0.29	·	0.26
1984/85	0.28	0.21	0.22	0.31	0.30	0.29	0.31	·	0.26
1985/86	0.29	0.24	0.21	0.32	·	0.26	0.30	0.37	0.27
1986/87	0.27	0.23	0.23	0.31	·	0.27	0.30	0.35	0.27
1987/88	0.24	0.23	0.22	0.28	·	0.30	0.30	0.31	0.26
1988/89	0.23	0.22	0.20	0.24	·	0.25	0.26	0.31	0.24
1989/90	0.23	0.25	0.21	0.23	·	0.29	0.26	0.29	0.25
1990/91	0.24	0.25	0.22	0.24	·	0.27	0.26	0.30	0.25
1991/92	0.24	0.26	0.22	0.24	·	0.29	0.27	0.29	0.25
1992/93	0.25	0.27	0.23	0.25		0.27	0.26	0.28	0.26
Total	0.27	0.24	0.24	0.27	0.33	0.28	0.30	0.30	0.26

Blundell et al. (1998): simple estimation

- With two groups (exposed to a different tax) and two time periods, can do a simple diff-in-diff
  - Difference within group removes the group effect, such as heterogeneity in the preferences for work
  - Difference across group removes the time effect, such as macro shocks
- In this context, there are multiple time periods and multiple groups, so that the generalized Wald estimator (the grouping estimator) is used

Implementing the grouping estimator

- Grouping estimator can be thought as estimating the group-level relationship between net-of-tax changes and hours
- **Blundell et al. (1998)** proposes a more complicated procedure to deal with group level changes in the participation rate
  - STEP 1: Control function implementation (identical to 2SLS)
    - regression of log after-tax wage on time dummies interacted with group dummies (compute residual)
    - Regress hours of work on wage, time and group dummies, controlling for the residual
  - STEP 2: Control for selection into work by estimating the inverse Mills ratio for a given group at a given time (Heckman selection)
- Account for the discontinuities in the budget constraint due to the national insurance (NI) and tax kinks

Blundell et al. (1998): identification

- Groups are defined by the year of birth and the age left education interacted with year, in ten-year intervals
- Identification comes from variation across after-tax wages of cohort-education groups over time
- Identification assumptions (think groups as IVs):
  - Average differences in labor supply across groups the same over time (controlling for demographics, other income and wage)
  - Groups are fixed (not affected by the changes in hourly wages) - individuals do not change their education after age 20

Uncovering the compensated wage elasticities

Effect of increasing the wage on hours worked:

ELASTICITIES: GROUPING INSTRUMENTS: COHORT AND EDUCATION

	Wage	Compensated Wage	Other Income	Group Means: Hours	Group Means: Wage	Group Means: Income
No Children	0.140	0.140	0.000	32	2.97	88.63
	(0.075)	(0.088)	(0.041)			
Youngest Child 0–2	0.205	0.301	−0.185	20	3.36	129.69
	(0.128)	(0.144)	(0.104)			
Youngest Child 3–4	0.371	0.439	−0.173	18	3.10	143.64
	(0.150)	(0.159)	(0.139)			
Youngest Child 5–10	0.132	0.173	−0.102	21	2.86	151.13
	(0.117)	(0.127)	(0.109)			
Youngest Child 11 +	0.130	0.160	−0.063	25	2.83	147.31
	(0.107)	(0.117)	(0.084)			

Note: Asymptotic standard errors in parentheses. The first column refers to the uncompensated wage elasticity.

Blundell et al. (1998): results

- Income elasticities are small, zero for women without children, negative but small for women with children
- Uncompensated elasticities are positive and moderately sized
- This implies positive but moderately sized compensated wage elasticities: welfare effects are not negligible
- Finding: taking (endogenous) taxpayer status as the basis to define C and T groups would yield biased (too high) estimates,
  - The bias is interpreted as coming from composition changes of the groups of women paying taxes over time:

Recent quasi-experimental approaches

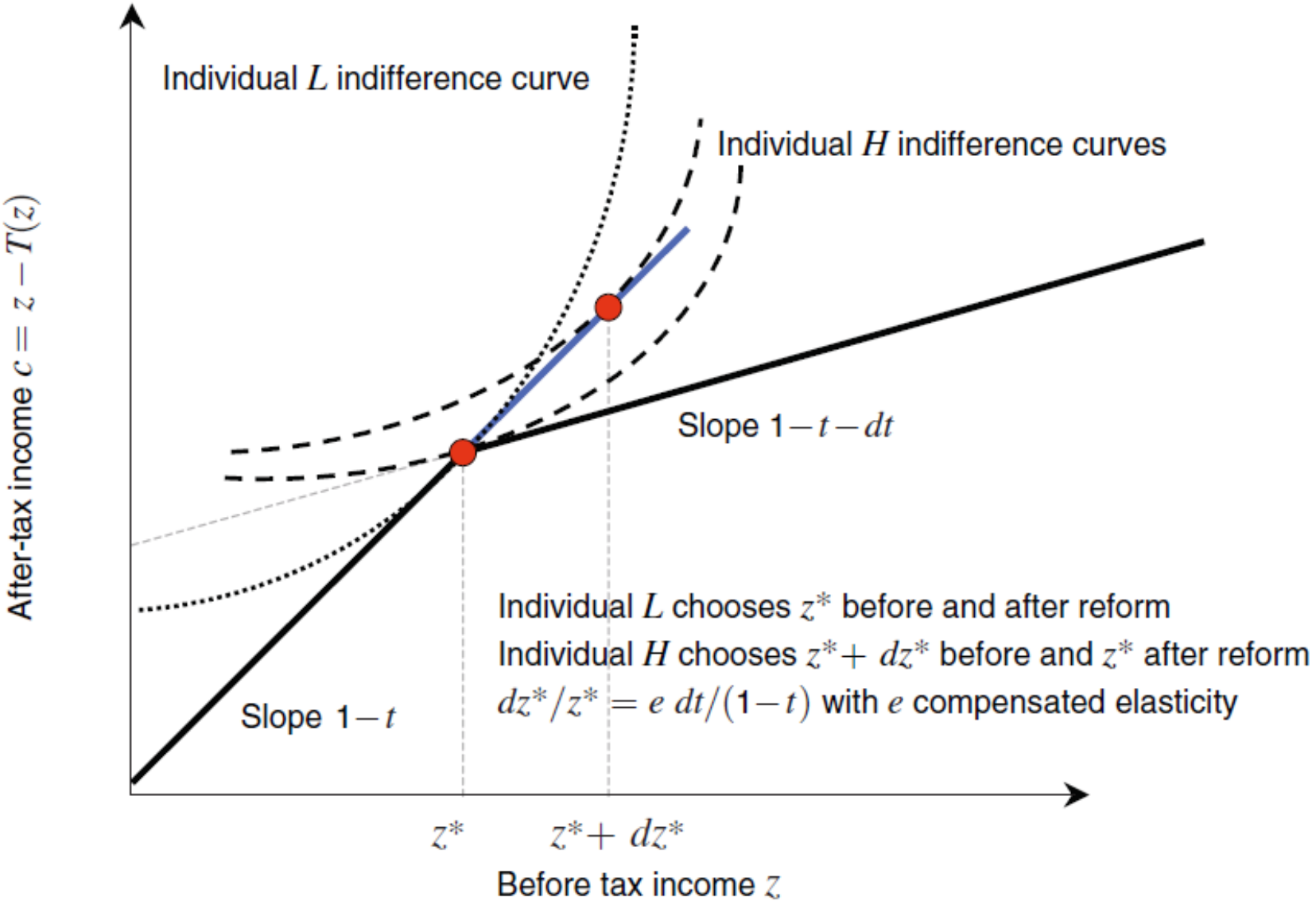
- **Diff-in-diff** using administrative data over long time periods, allowing for graphical identification
- **Bunching** approaches that exploit discontinuous jumps in marginal tax rates (kinks) or discontinuous jumps in tax liability (notches)
- **Regression discontinuity design** and **regression kink design**

Bunching at kink points

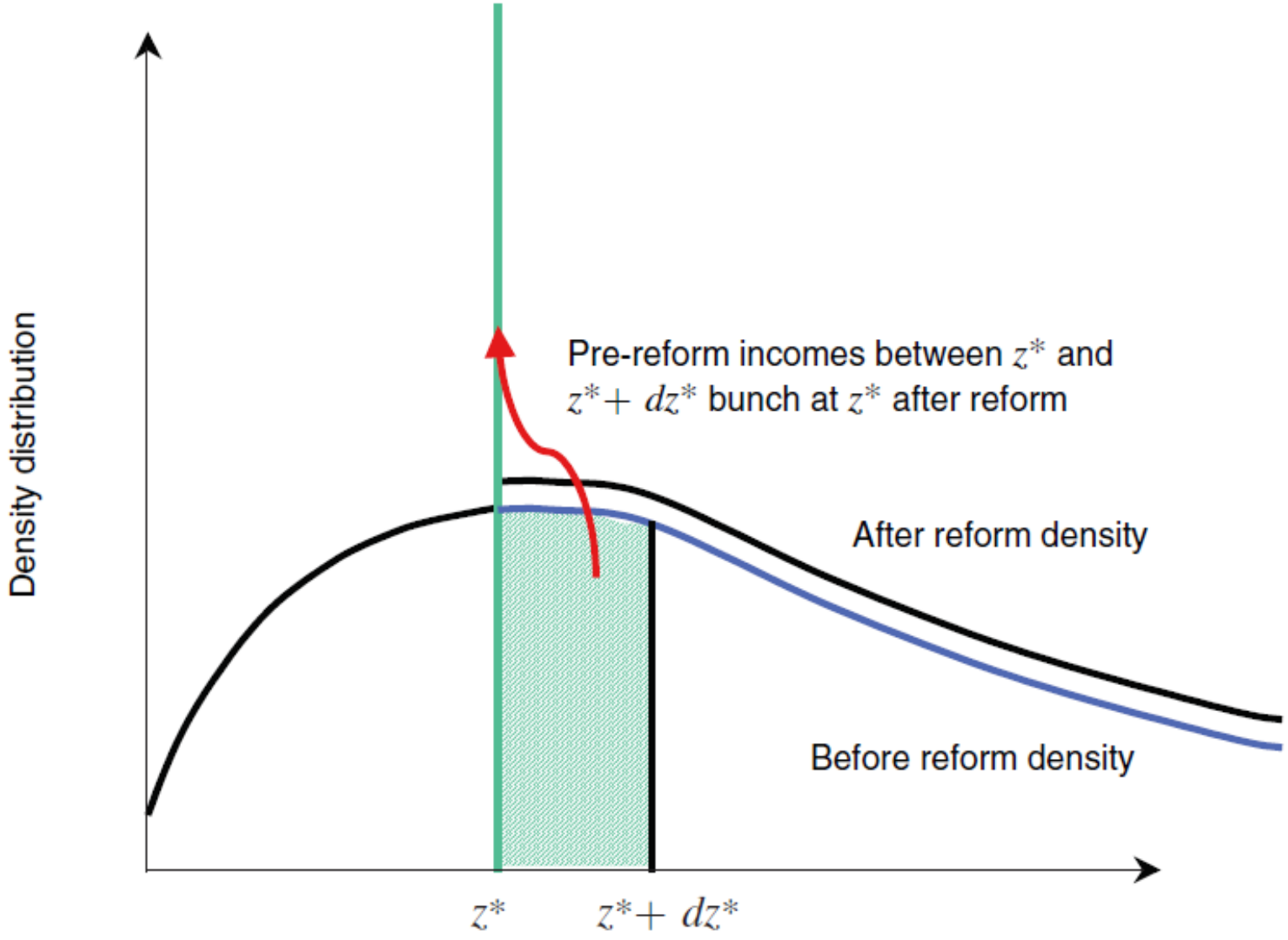
- Instead of a pure technical issue, bunching provides direct evidence of the labor supply response to the marginal tax rate
- To detect bunching precisely, (often) administrative data is needed
- Saez (2010) shows that excess bunching around kinks can be used to identify the compensated elasticity of labor supply
- No income effect if the change in the marginal tax rate at the kink is small
- Formula for elasticity, i.e. the excess mass at the kink over the change in the tax rate t:

$$\varepsilon^c = \frac{dz/z^*}{dt/(1-t)}$$

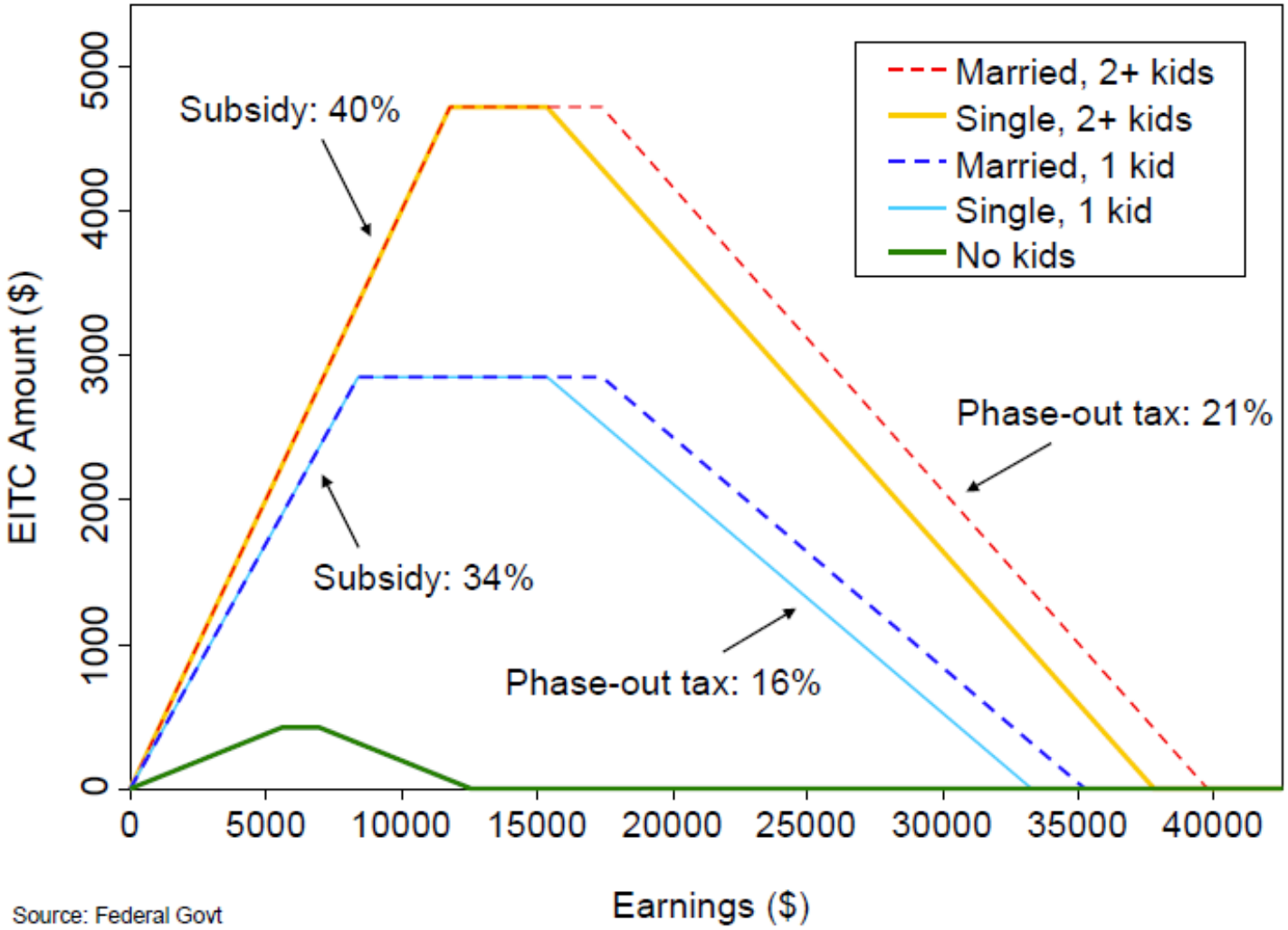
Panel A. Indifference curves and bunching



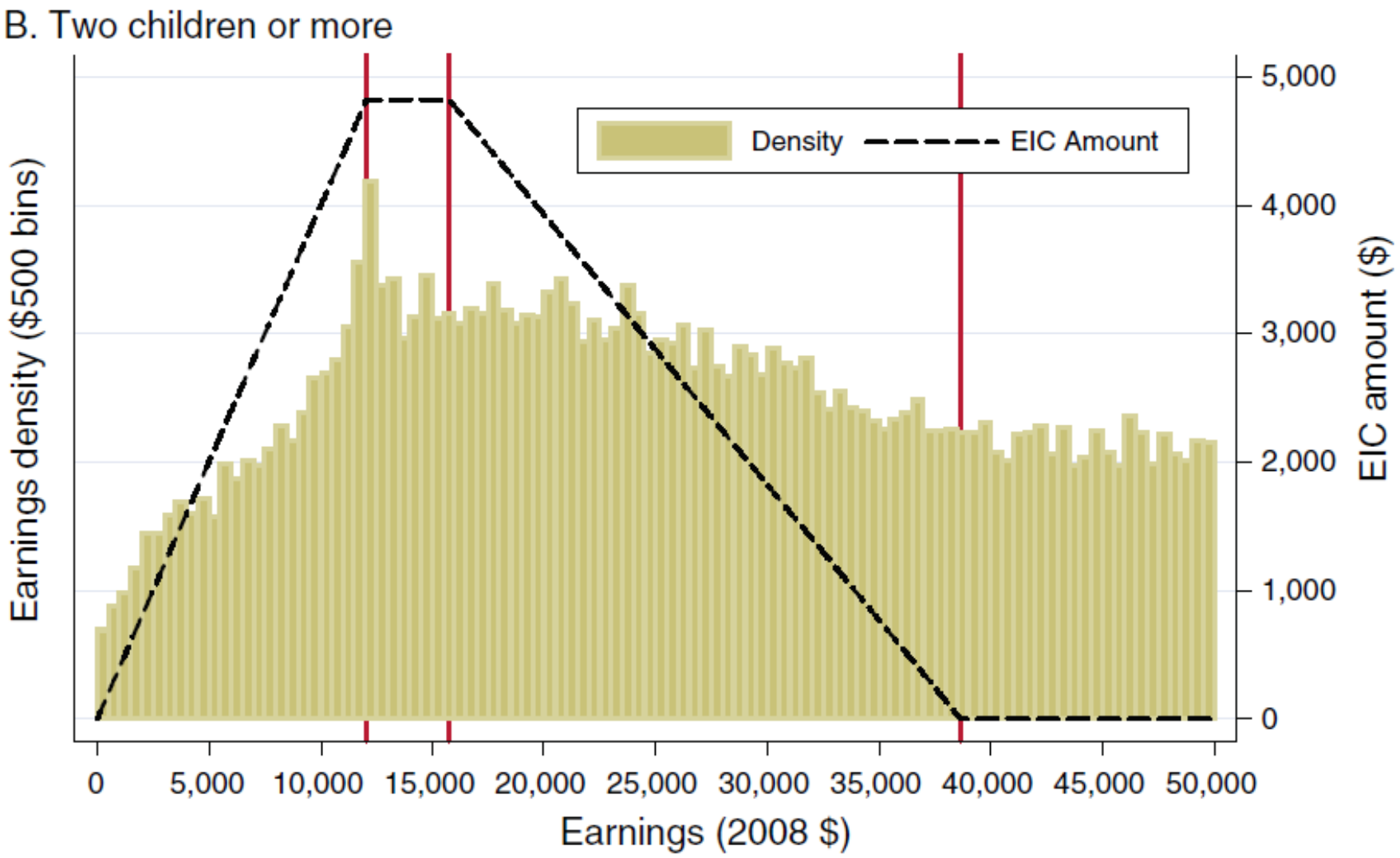
Panel B. Density distributions and bunching



Application: U.S. Earned Income Tax Credit (EITC)



Source: Federal Govt


B. Two children or more
Density
EIC Amount
Earnings density ($500 bins)
EIC amount ($)
5,000
4,000
3,000
2,000
1,000
0
0
5,000
10,000
15,000
20,000
25,000
30,000
35,000
40,000
45,000
50,000
Earnings (2008 $)

Panel B. Two or more children

Saez (2010)

- Uses individual tax return micro data from 1960 to 2004: hardly any measurement error
- Finds bunching at the first kink point of the EITC:
- In particular for the self-employed: might largely be a reporting effect rather than a real labor supply effect
- Elasticities for wage earners are close to zero
- But no bunching observed at the other kink points: why?

  True structural elasticity is small; or the true structural elasticity is not small, but the *observed* elasticity is attenuated by optimization frictions:

  - Imperfect information, inattention, inertia
  - Adjustment costs and hours constraints

Chetty et al. (2011): basic idea

Micro elasticity estimates are small, macro elasticity estimates are large

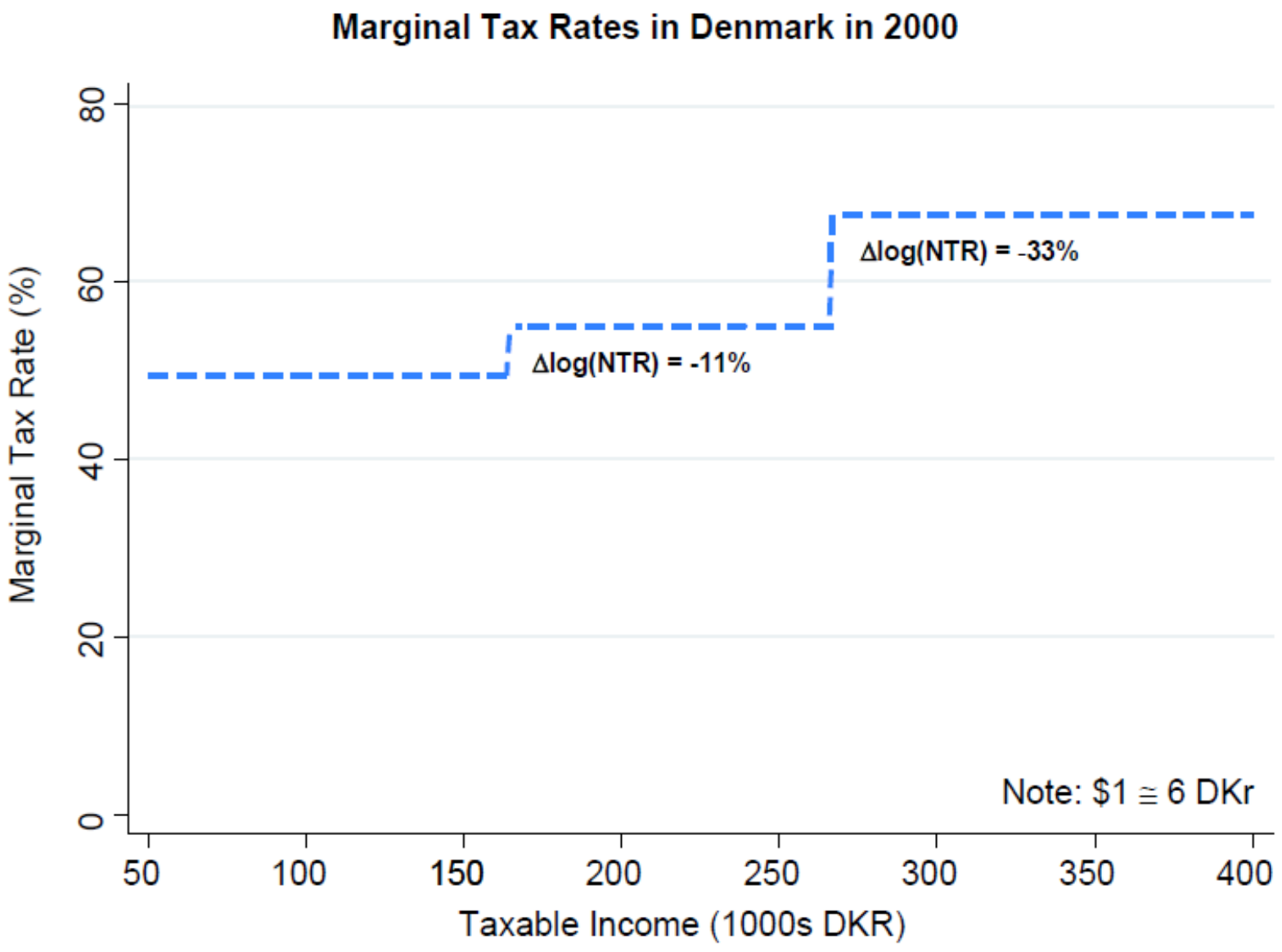
- Micro estimates are attenuated by frictions that prevent workers from re-optimizing in response to small tax changes in the short run
  - Macro estimates are not attenuated by frictions, but they suffer from identification problems

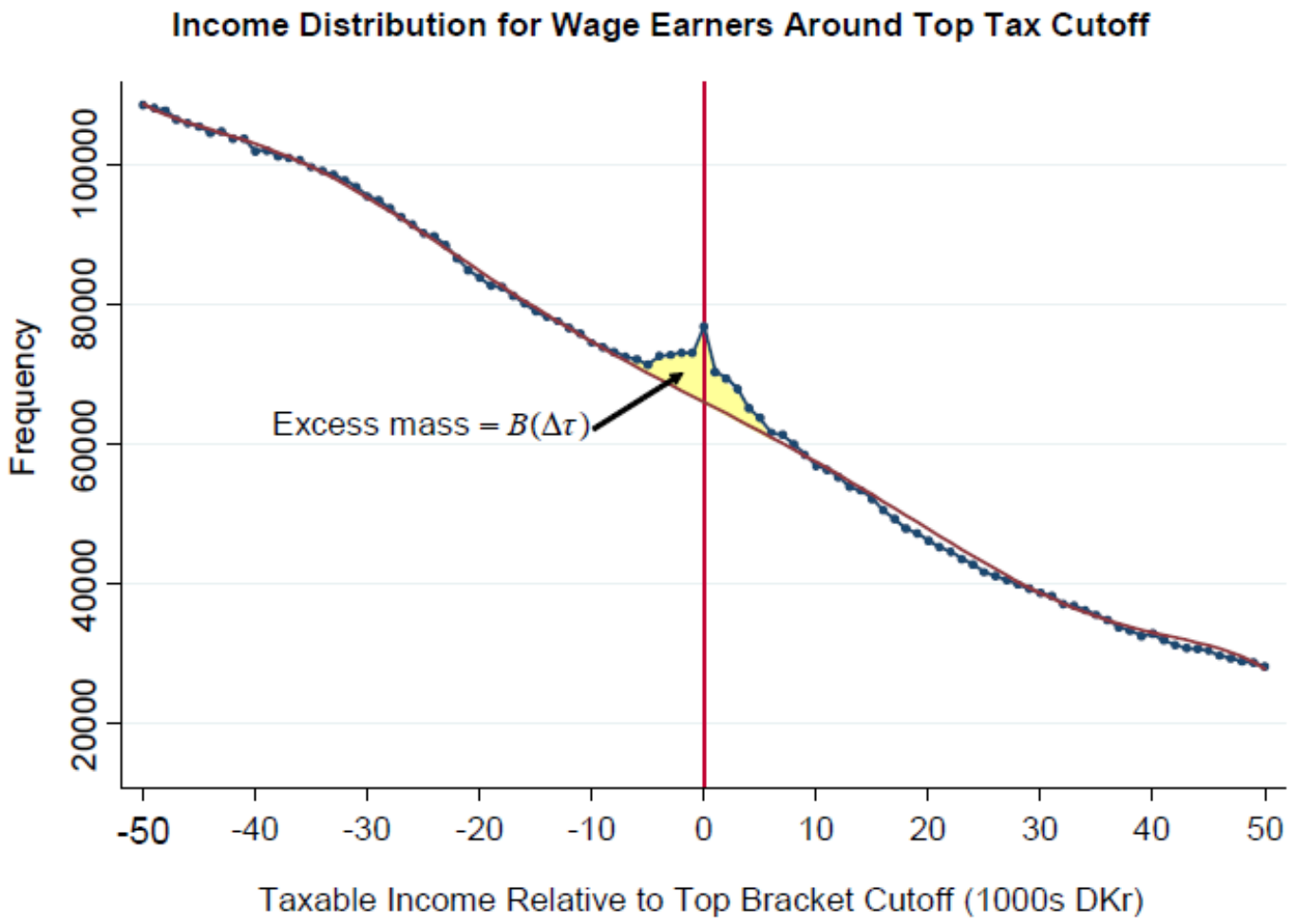
For welfare analysis and optimal policy, we are interested in the long-run structural elasticity that is not attenuated by frictions

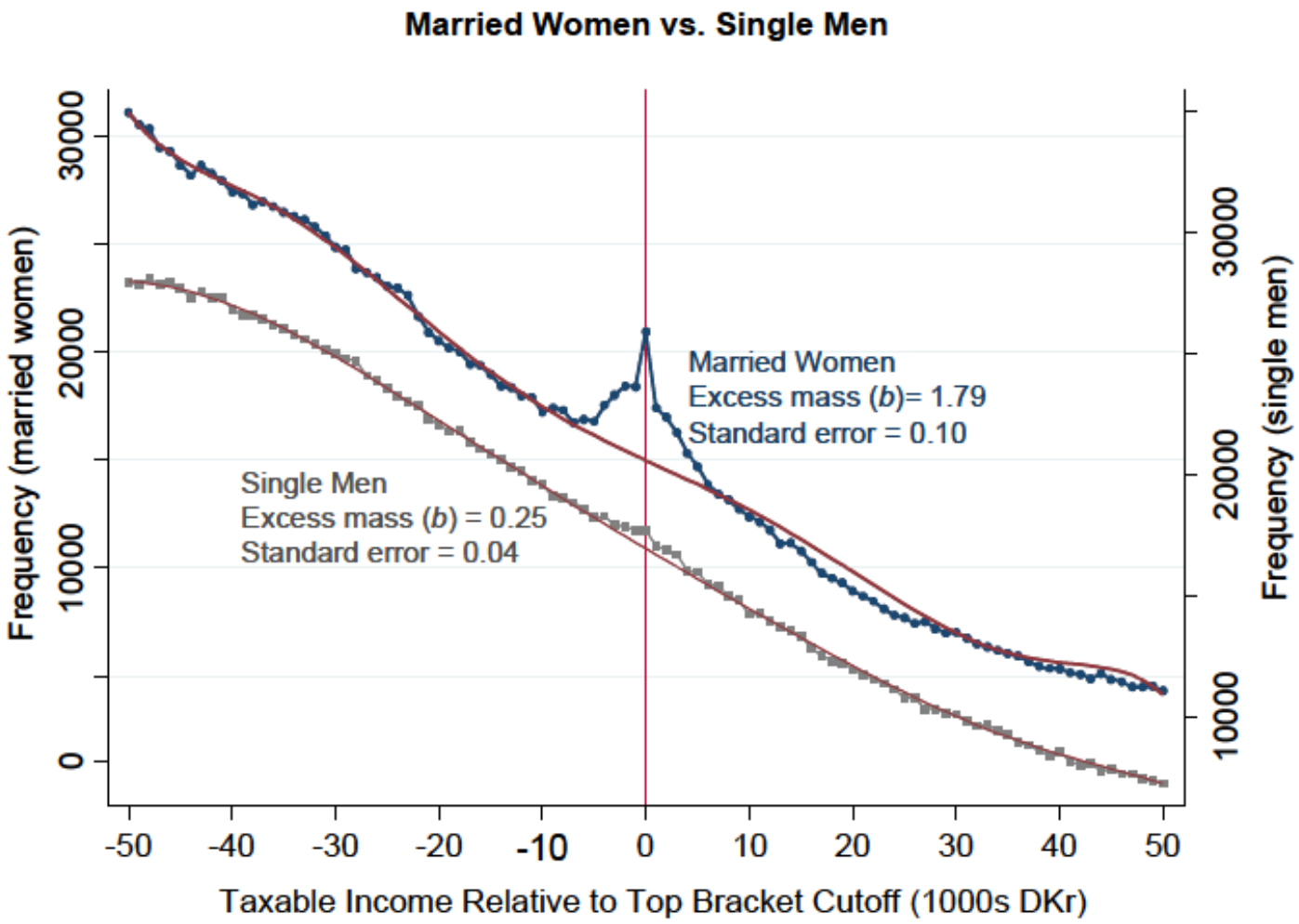
- Micro approach (ensuring identification) to analyze the role of frictions for elasticity estimates

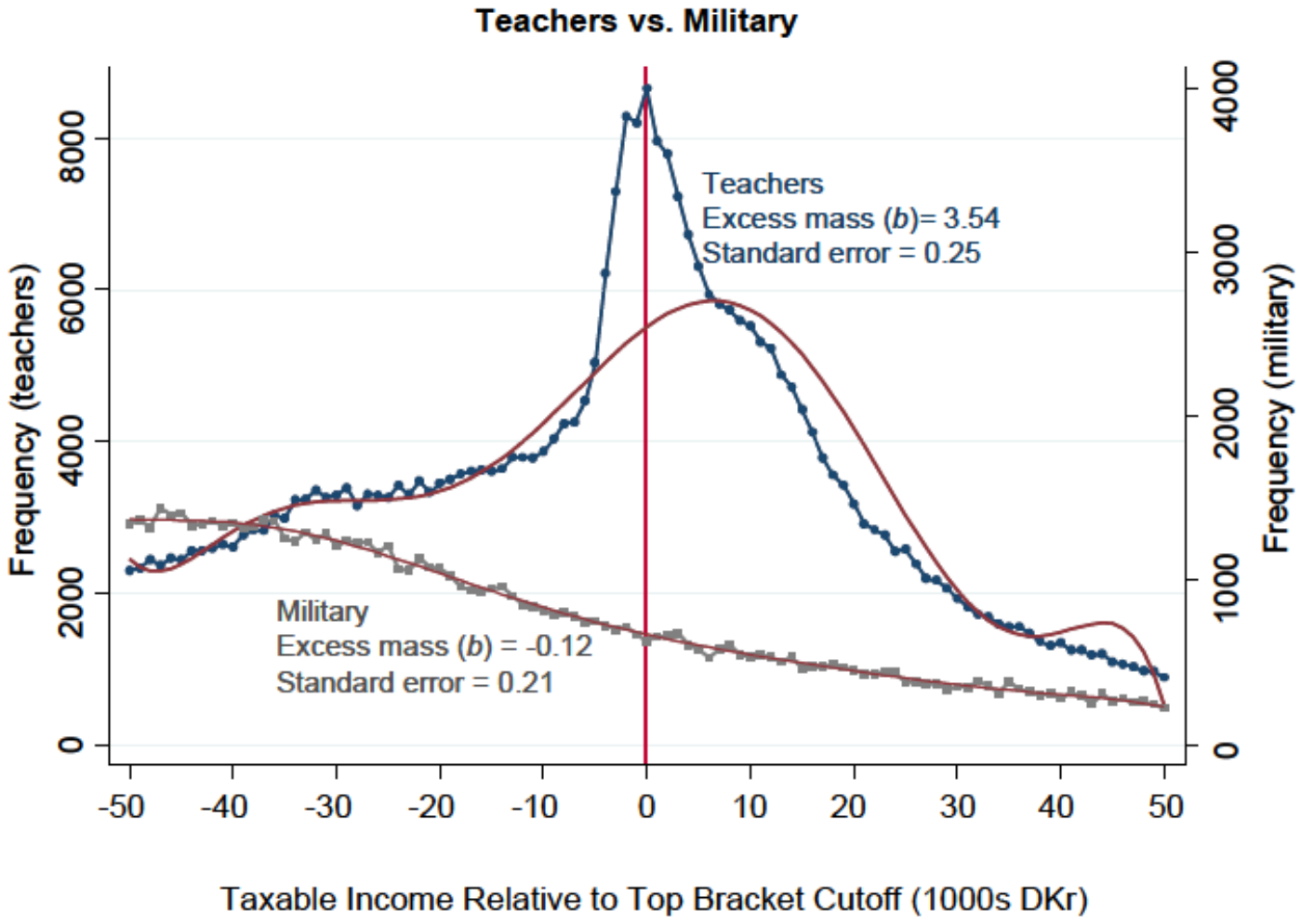
Chetty et al. (2011): context

- Use matched employer-employee administrative panel data for the full population of Denmark, aged 15 to 70, and for years 1994-2001: about 18 million observations
- Quasi-experimental variation from large vs. small kinks in the Danish income tax within a year, and from tax reforms that move bracket cutoffs over time


Marginal Tax Rates in Denmark in 2000
Marginal Tax Rate (%)
0
20
40
60
80
Δlog(NTR) = -33%
Δlog(NTR) = -11%
Note: $1 ≅ 6 DKr
50
100
150
200
250
300
350
400
Taxable Income (1000s DKR)


Income Distribution for Wage Earners Around Top Tax Cutoff
Frequency
20000
40000
60000
80000
100000
Excess mass = $B(\Delta\tau)$
-50
-40
-30
-20
-10
0
10
20
30
40
50
Taxable Income Relative to Top Bracket Cutoff (1000s DKr)


Married Women vs. Single Men
Frequency (married women)
0
10000
20000
30000
Frequency (single men)
10000
20000
30000
Married Women
Excess mass (b)= 1.79
Standard error = 0.10
Single Men
Excess mass (b) = 0.25
Standard error = 0.04
-50
-40
-30
-20
-10
0
10
20
30
40
50
Taxable Income Relative to Top Bracket Cutoff (1000s DKr)


Teachers vs. Military
Teachers
Excess mass (b)= 3.54
Standard error = 0.25
Military
Excess mass (b) = -0.12
Standard error = 0.21
Frequency (teachers)
Frequency (military)
0
2000
4000
6000
8000
0
1000
2000
3000
4000
-50
-40
-30
-20
-10
0
10
20
30
40
50
Taxable Income Relative to Top Bracket Cutoff (1000s DKr)

Chetty et al. (2011): findings

- Size: elasticity estimates increase with the size of kinks
  - Driven by differences in the size of tax changes rather than heterogeneity in elasticities by income levels or tax rates
- Scope: observed elasticities increase with the number of workers affected by a tax change
  - Supply-side response as firms or unions tailor jobs to aggregate workers preferences in equilibrium
- Correlation: more aggregate bunching in sectors with more individual bunching

Chetty et al. (2011): findings

Frictions due to search costs and hours constraints attenuate short-run behavioral responses to taxation:

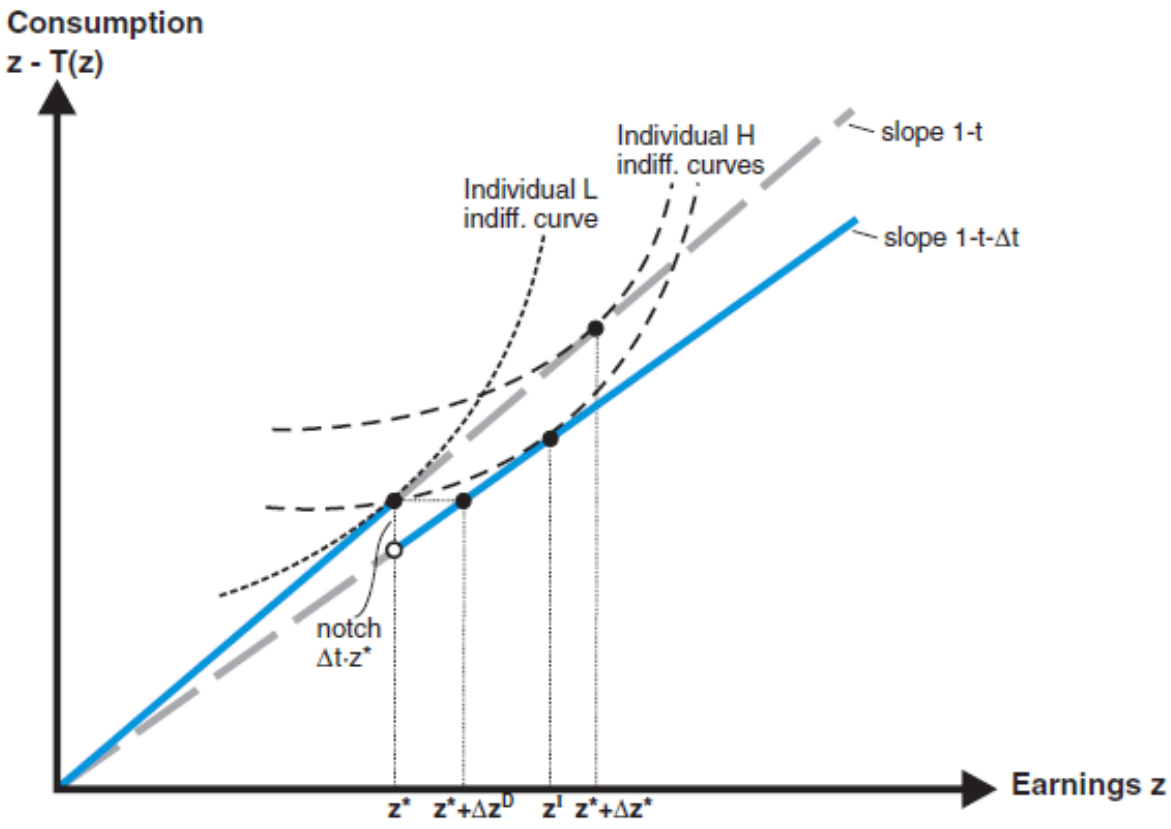
- For wage earners, the observed elasticity is tiny even at the large top kink, i.e. the size effect on elasticity is extremely small
- For the self-employed, the small-kink elasticity is also smaller than the large-kink elasticity, i.e. size effect even when search costs and hours constraints should not matter
- A broader view on frictions is useful: inattention, inertia, etc.

Bunching at notches: Kleven and Waseem (2013)

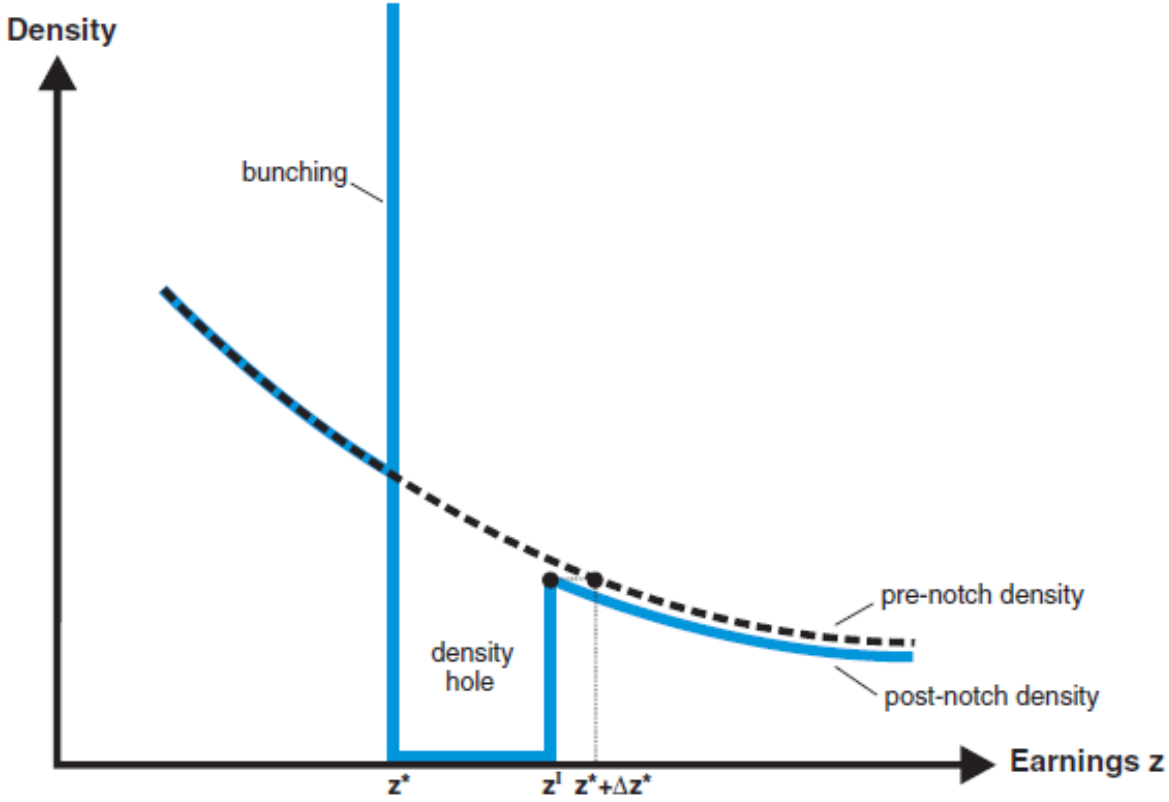
- Taxes and transfers sometimes also generate notches (i.e. discontinuities) in the budget set
- Example: Pakistani income tax creates notches because the *average* tax rate jumps: bunching below the notch and a gap in density just above the notch
- Kleven and Waseem use the empirical density in the theoretical gap area to measure the fraction of unresponsive individuals
- This allows them to identify the amount of friction and the structural elasticity (i.e. the elasticity among responsive individuals)

Personal income (average) tax schedule in Pakistan

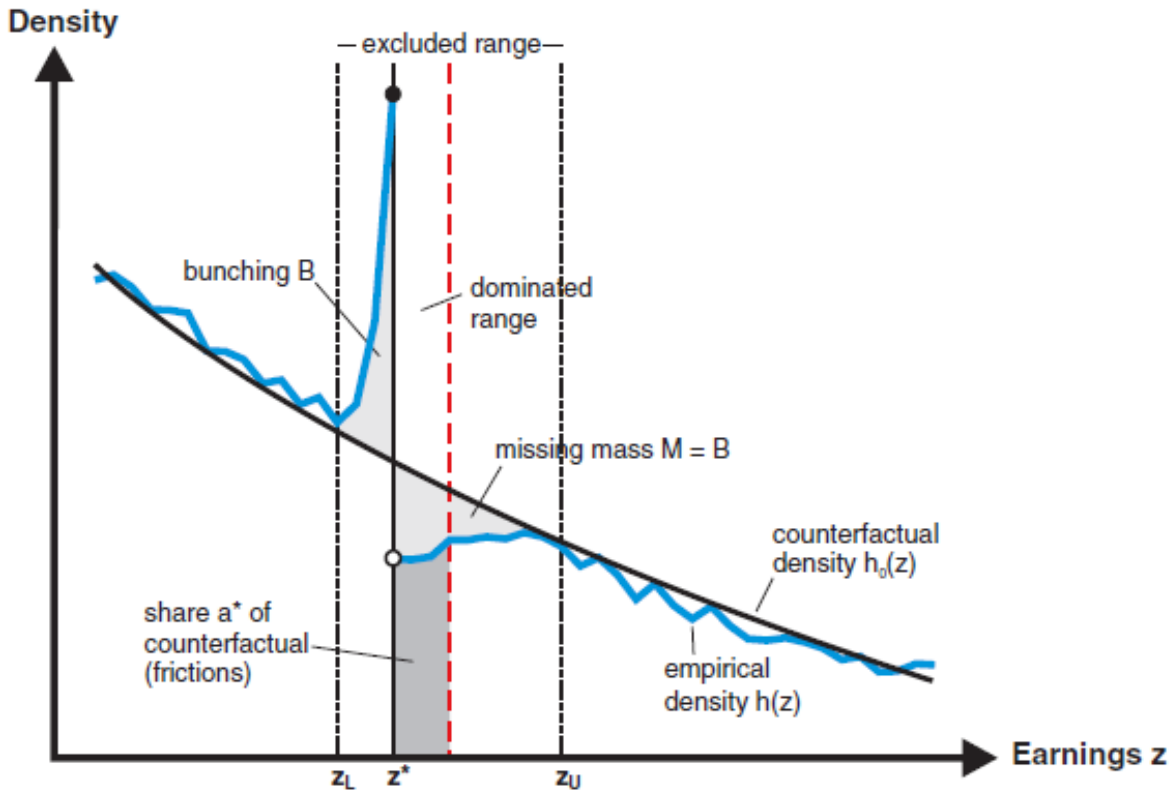
Behavioral responses to a tax notch: budget sets



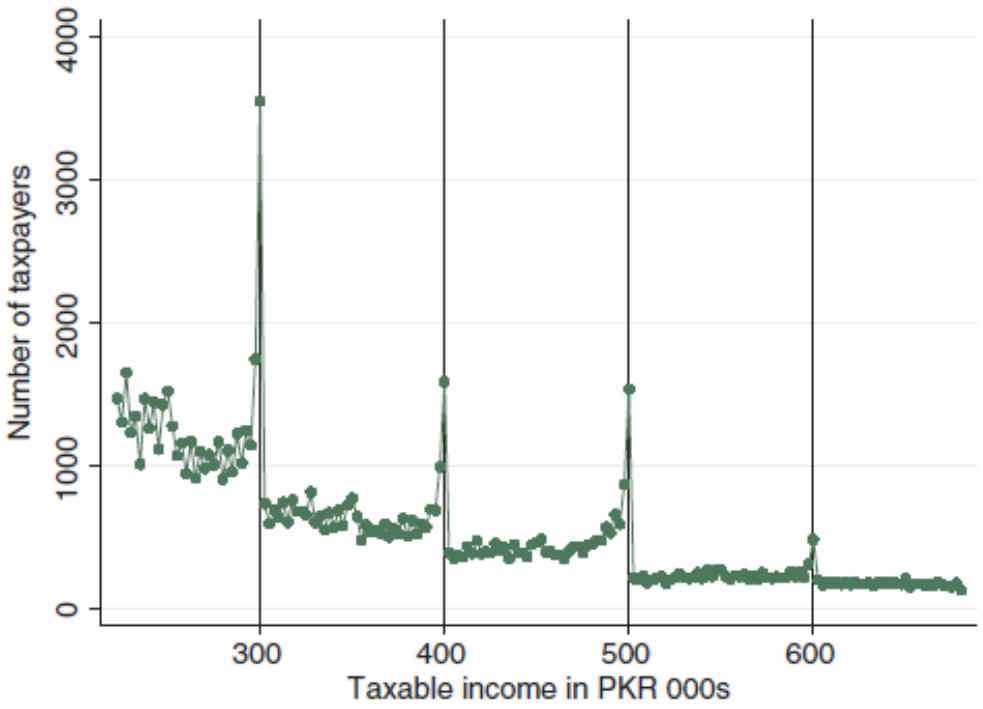
Behavioral responses to a tax notch: density distributions



Empirical vs. counterfactual density



Empirical distribution around notches: Self-employed individuals (non-rounder sample)



Kleven and Waseem (2013): findings

- Large and sharp observed bunching at notches
- Optimization frictions are also large: most taxpayers in the dominated ranges are unresponsive
- Using bunching and the density mass in dominated regions allows identifying the structural elasticity, which is modest
  - Notches allow using two moments (bunching and hole) for identification
  - Kinks provide only one moment (bunching): cannot distinguish between the relative size of structural elasticities and frictions
- Inefficiency of notches: strong price distortions give rise to large behavioral responses even when structural elasticities are small

Chetty et al. (2013): Exploit Differences in Knowledge Across Neighborhoods

Two central challenges in identifying the impacts of govt. policies:

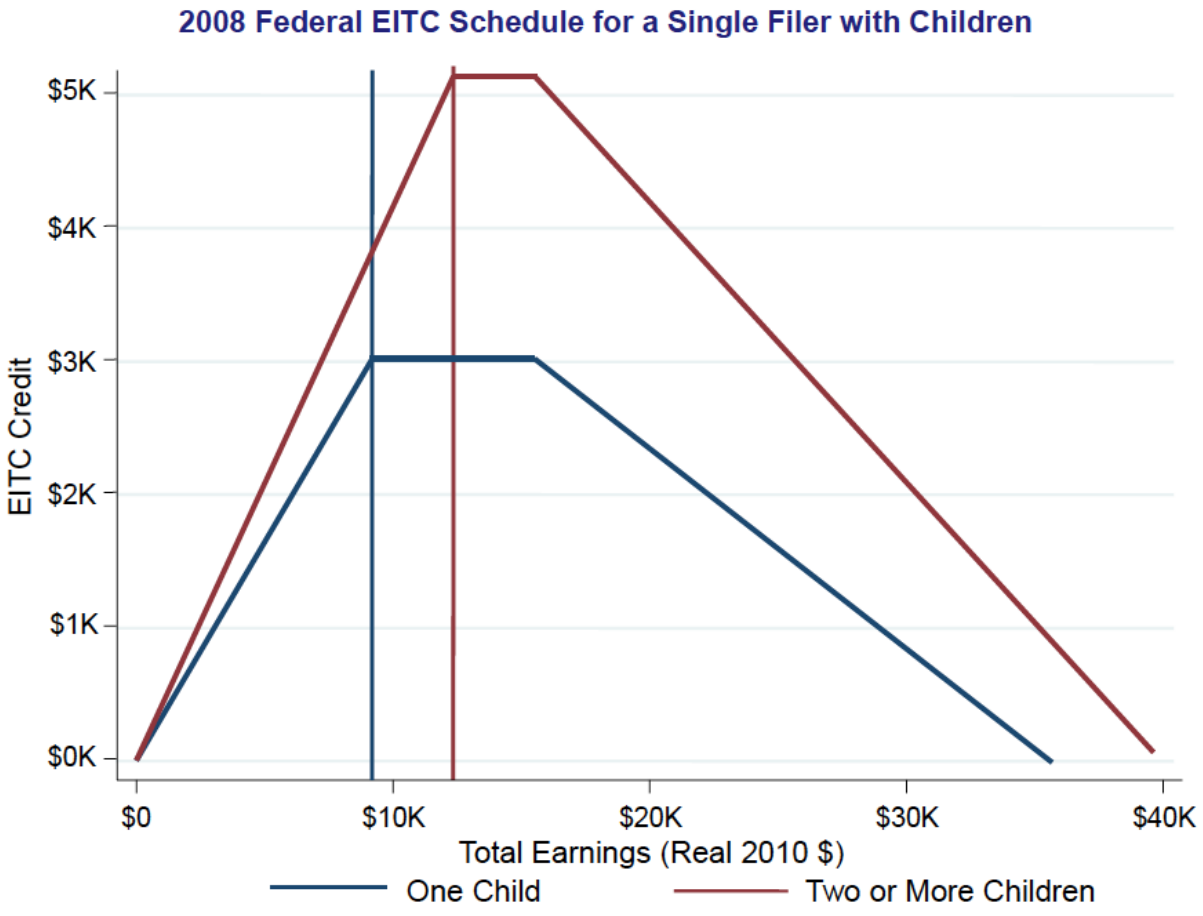
1. Lack of counterfactuals to estimate causal impacts of policies
2. Difficult to identify long run impacts from short-run responses to tax changes
   - Many people are uninformed about tax and transfer policies
   - Workers face switching costs for labor supply

Key idea: exploiting **differences across neighborhoods in knowledge** about tax policies

- Individuals with no knowledge of a policy's marginal incentives behave as they would in the absence of a policy
- Cities with low levels of information about policies yield counterfactuals for behavior in absence of policy

Chetty et al. (2013): Exploit Differences in Knowledge Across Neighborhoods

Apply this approach to characterize the impacts of the Earned Income Tax Credit (EITC) on the earnings distribution in the U.S.

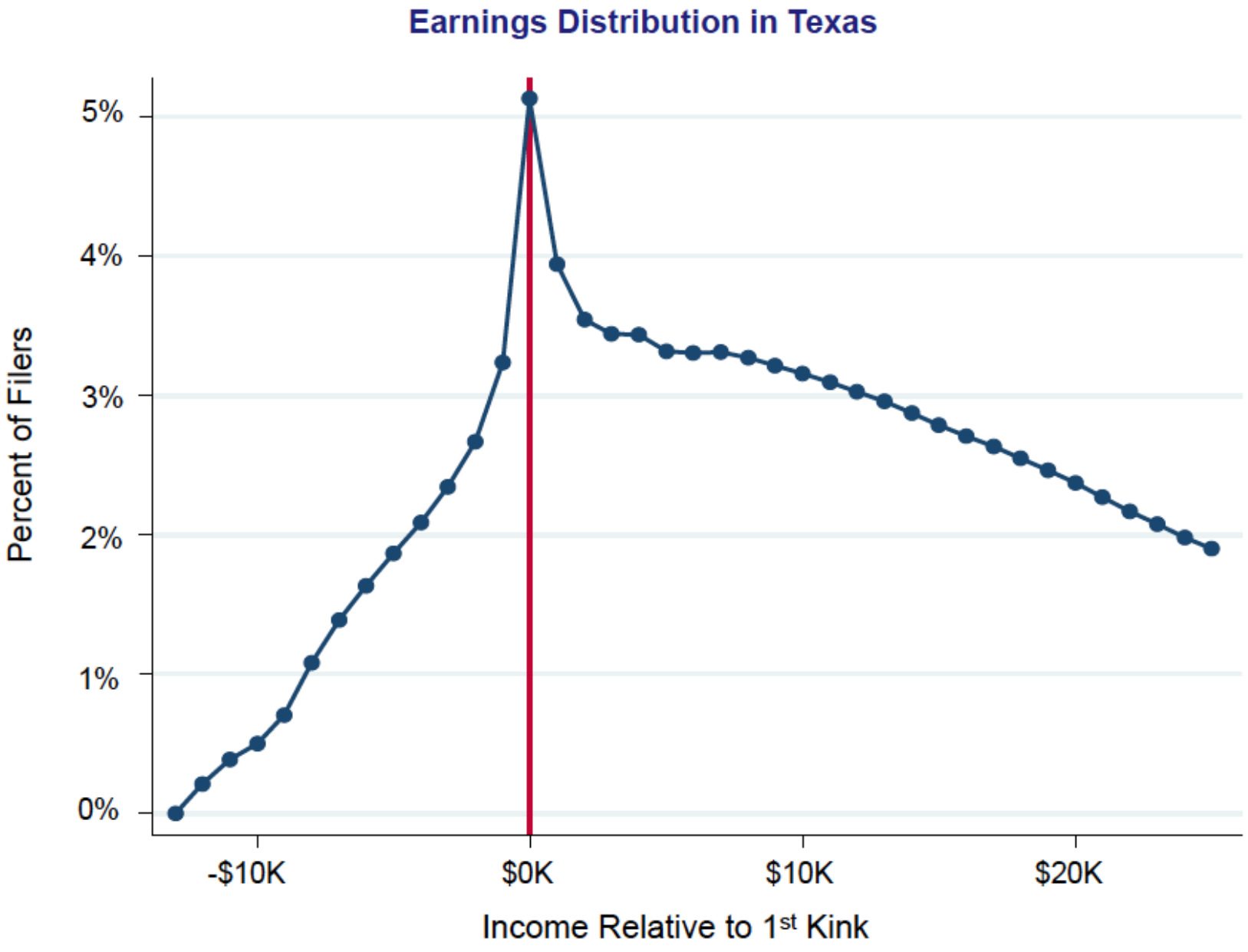


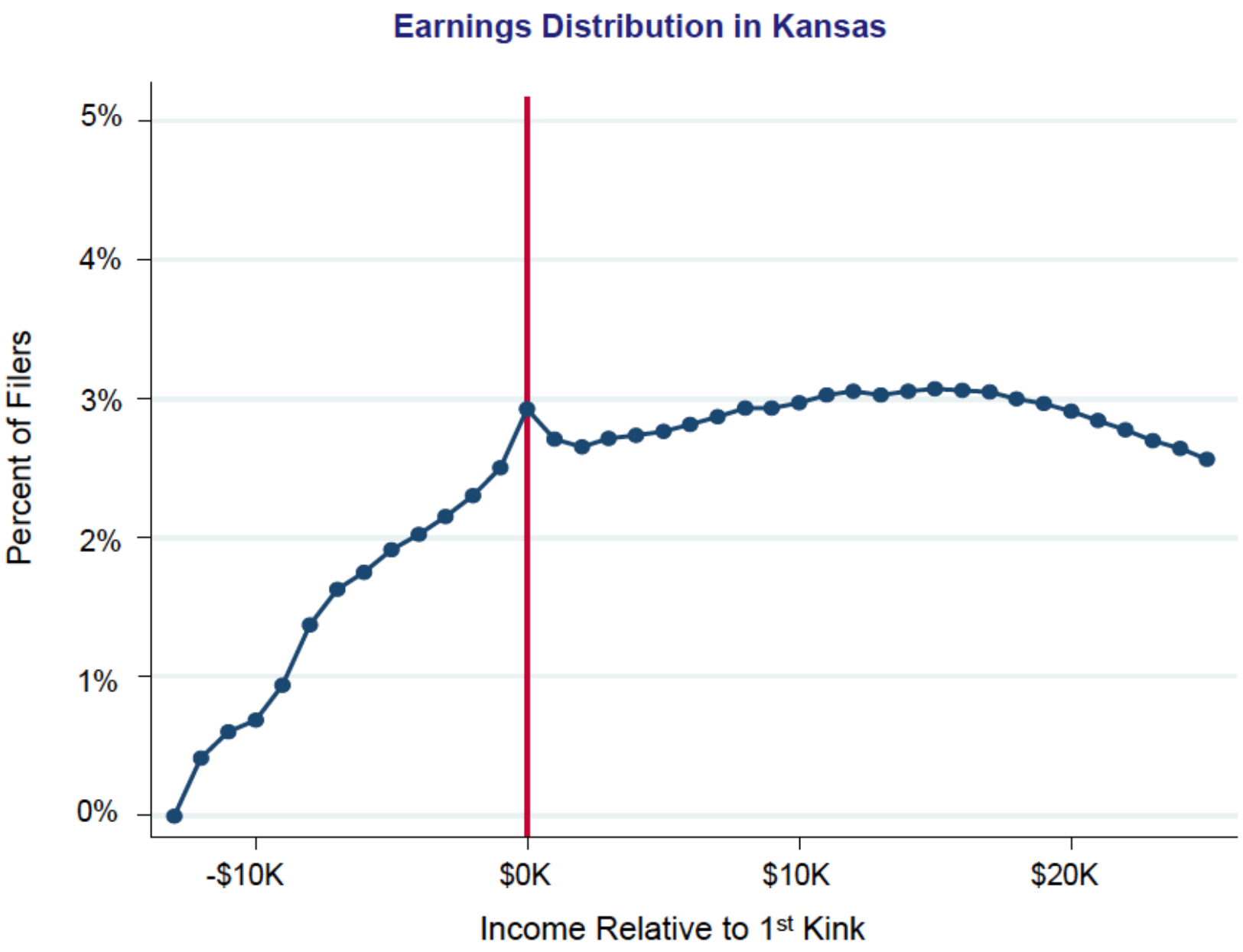
Self Employment Income vs. Wage Earnings

- To measure local knowledge, we rely on a critical distinction between wage earnings and self-employment income
- Self-employment income is self-reported $\Rightarrow$ easy to manipulate
- Wage earnings are directly reported to IRS by employers
  - Therefore more likely to reflect "real" earnings behavior

Outline of Empirical Analysis

- Step 1: Document variation across neighborhoods in sharp bunching among self-employed

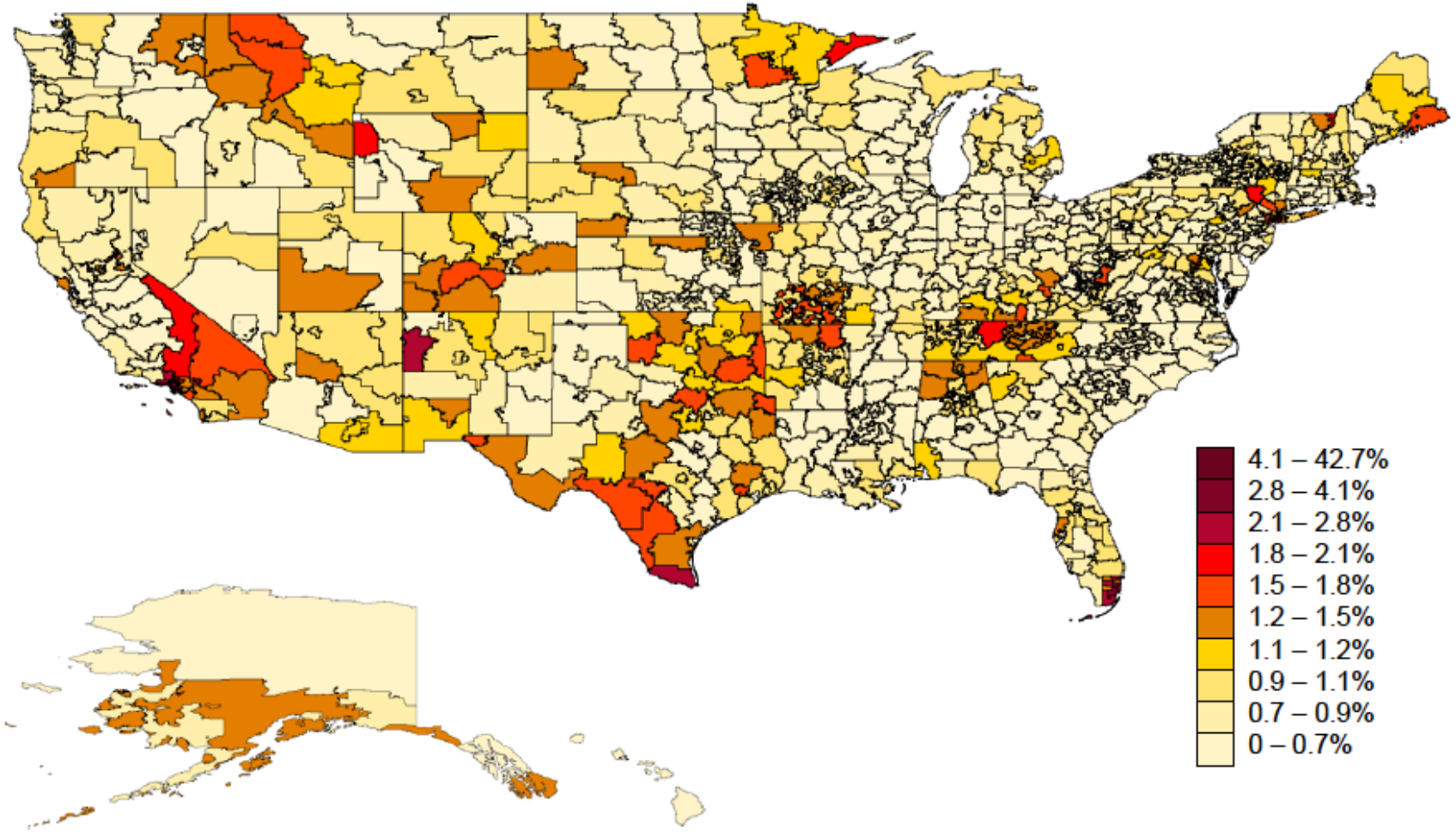

Earnings Distribution in Texas
5%
4%
3%
2%
1%
0%
Percent of Filers
-$10K
$0K
$10K
$20K
Income Relative to 1st Kink


Earnings Distribution in Kansas
5%
4%
3%
2%
1%
0%
Percent of Filers
-$10K
$0K
$10K
$20K
Income Relative to 1st Kink

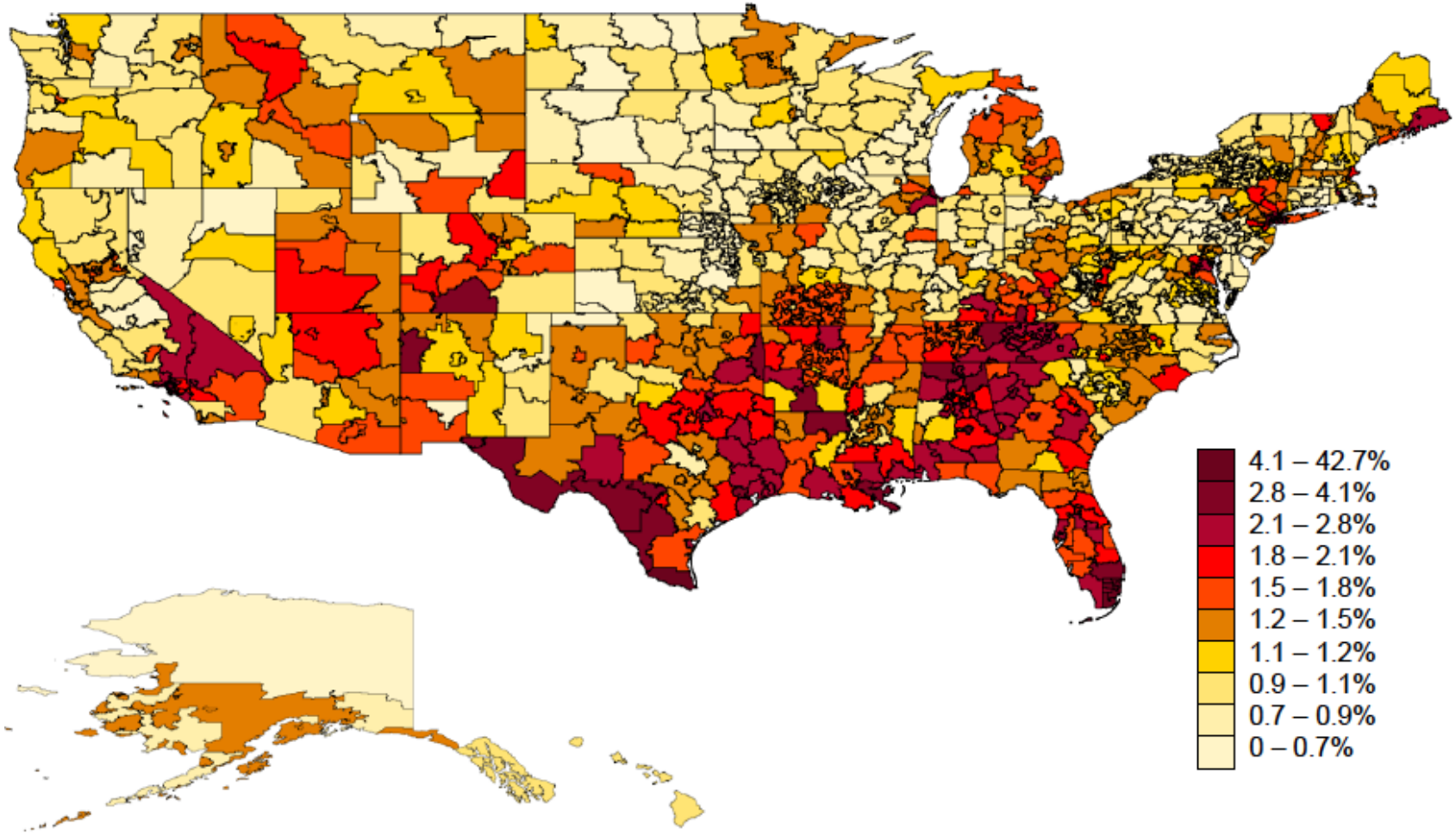
Neighborhood-Level Measure of Bunching

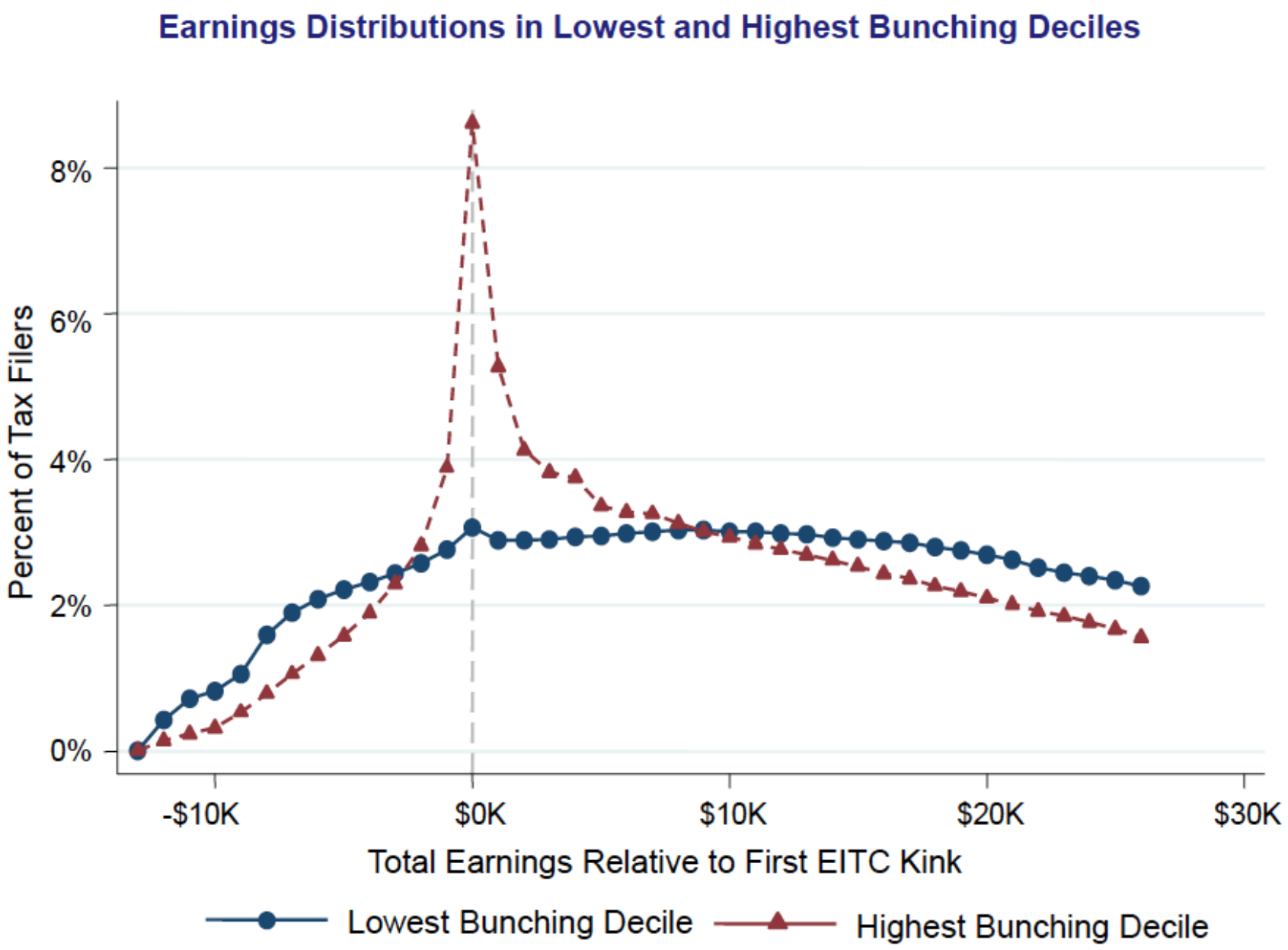
- Define a measure of "sharp bunching" in each neighborhood
  - Fraction of EITC-eligible tax filers who report income at first kink and have self-employment income
  - Measures fraction of individuals who manipulate reported income to maximize EITC refund in each neighborhood

Fraction of Tax Filers Who Report SE Income that Maximizes EITC Refund in 1996



Fraction of Tax Filers Who Report SE Income that Maximizes EITC Refund in 2002



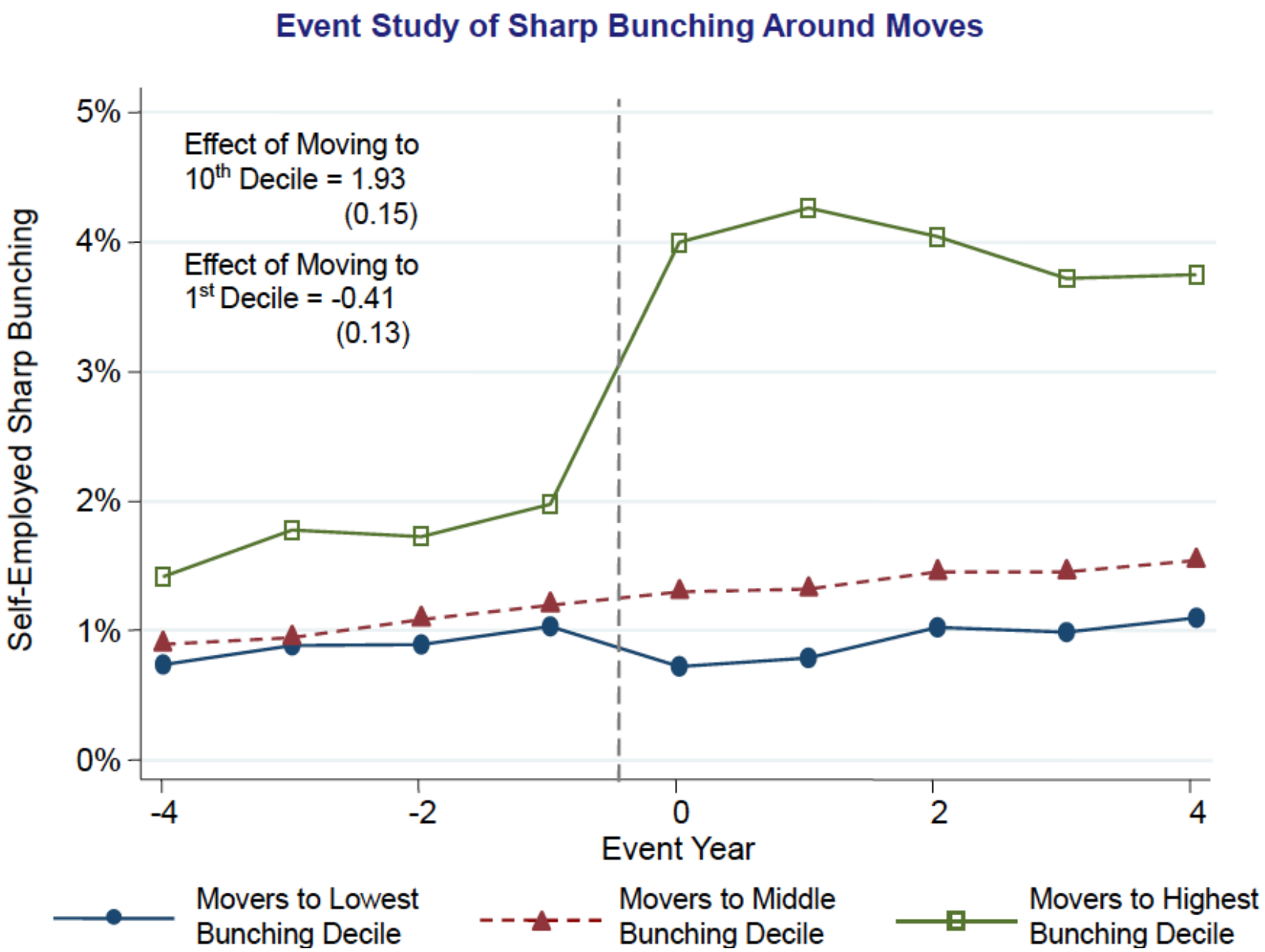

Earnings Distributions in Lowest and Highest Bunching Deciles
Percent of Tax Filers
8%
6%
4%
2%
0%
-$10K
$0K
$10K
$20K
$30K
Total Earnings Relative to First EITC Kink
Lowest Bunching Decile
Highest Bunching Decile

Outline of Empirical Analysis

- Step 1: Document variation across neighborhoods in sharp bunching among self-employed
- Step 2: Establish that variation in sharp bunching across neighborhoods is driven by differences in knowledge about EITC schedule

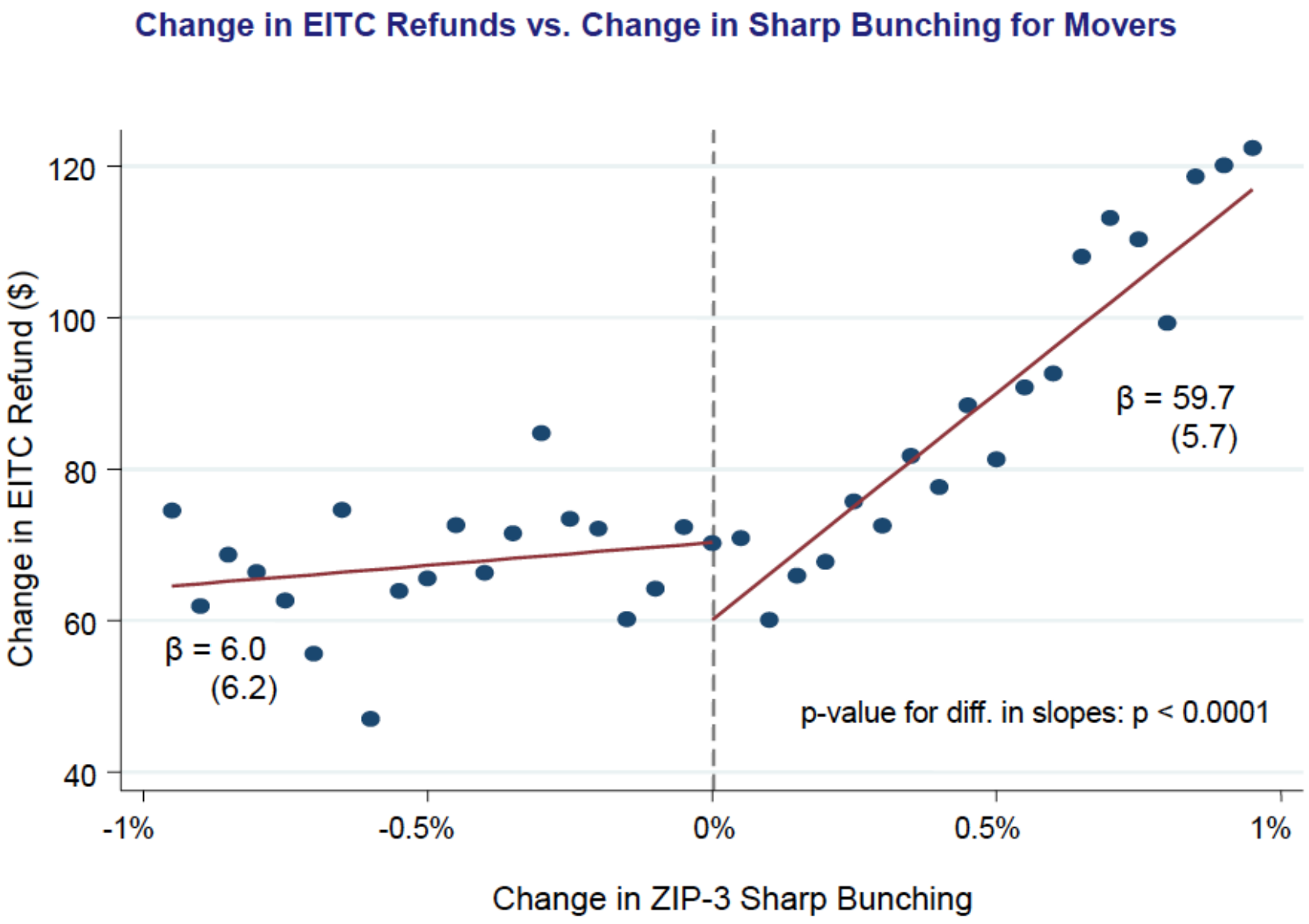
Outline of Empirical Analysis

- Consider individuals who move across neighborhoods to isolate causal impacts of neighborhoods on elasticities
  - 54 million observations in panel data on cross-zip movers
- Define "neighborhood sharp bunching" as degree of bunching for stayers
- Analyze how changes in neighborhood sharp bunching affect movers' behavior


Event Study of Sharp Bunching Around Moves
Effect of Moving to
10th Decile = 1.93
(0.15)
Effect of Moving to
1st Decile = -0.41
(0.13)
Self-Employed Sharp Bunching
5%
4%
3%
2%
1%
0%
-4
-2
0
2
4
Event Year
Movers to Lowest Bunching Decile
Movers to Middle Bunching Decile
Movers to Highest Bunching Decile

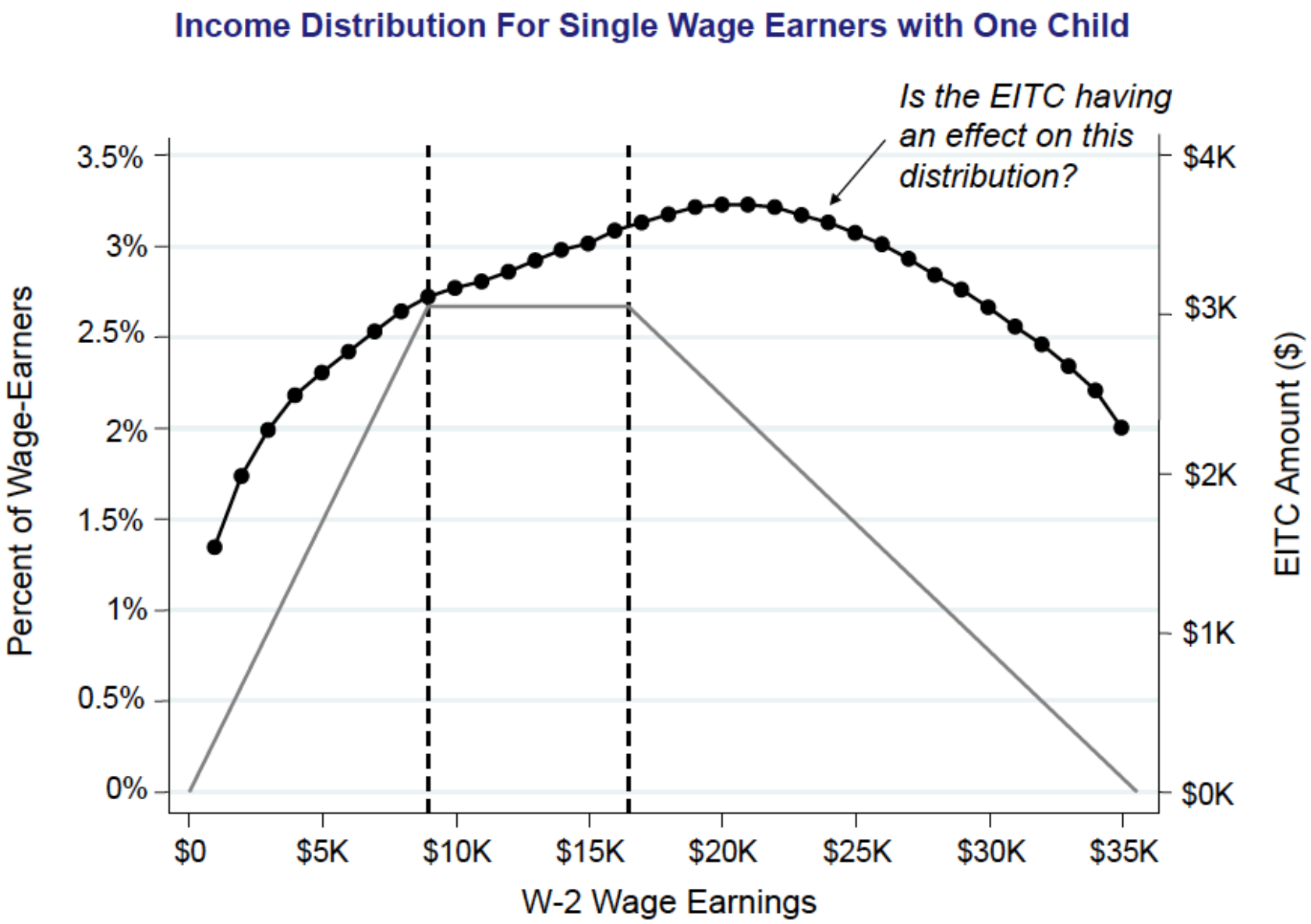
Learning and Memory

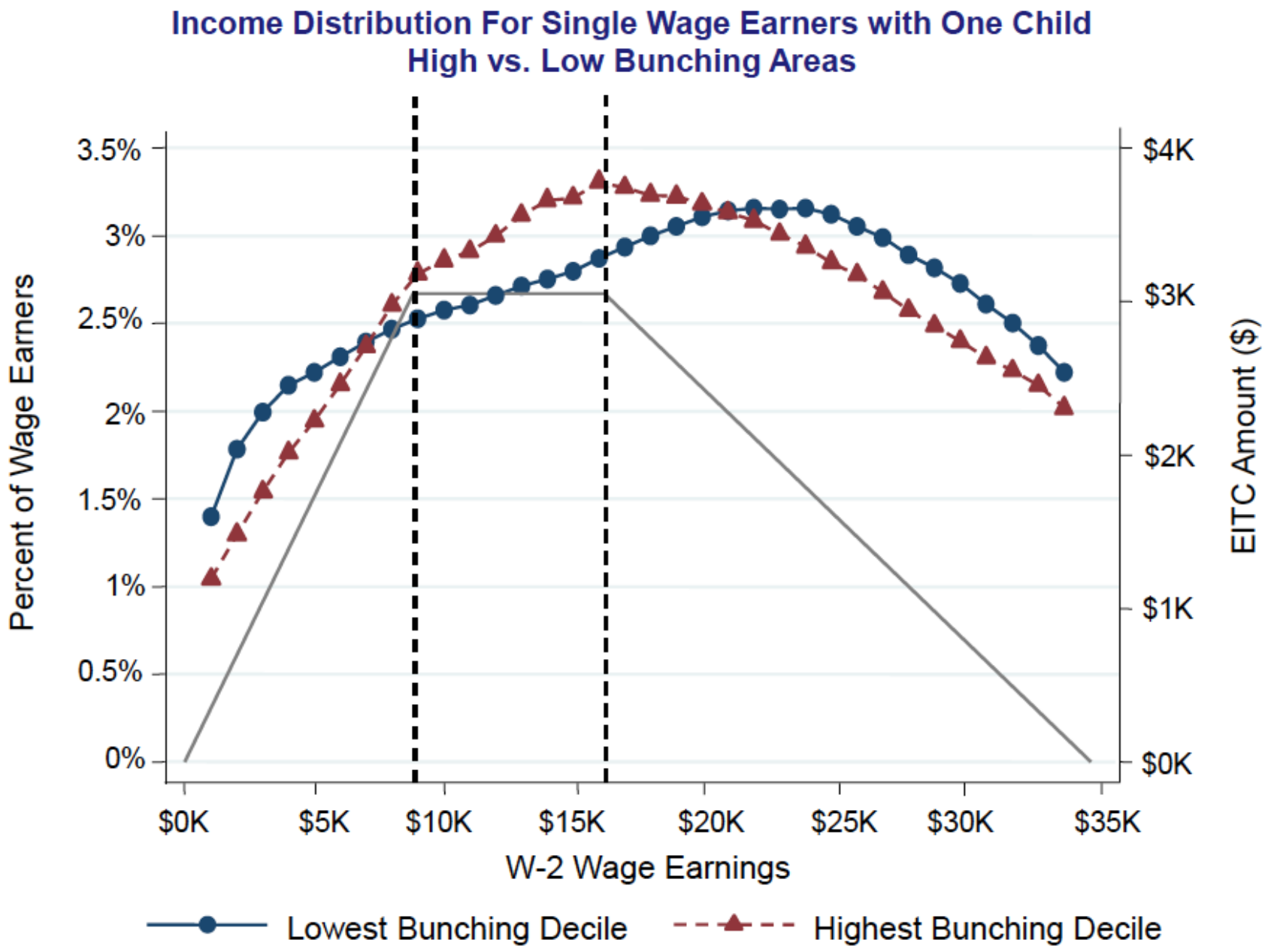
- Knowledge model predicts asymmetric impact of moving:
  - Moving to a higher-bunching neighborhood should raise EITC refund
  - Moving to a lower-bunching should not affect EITC refund

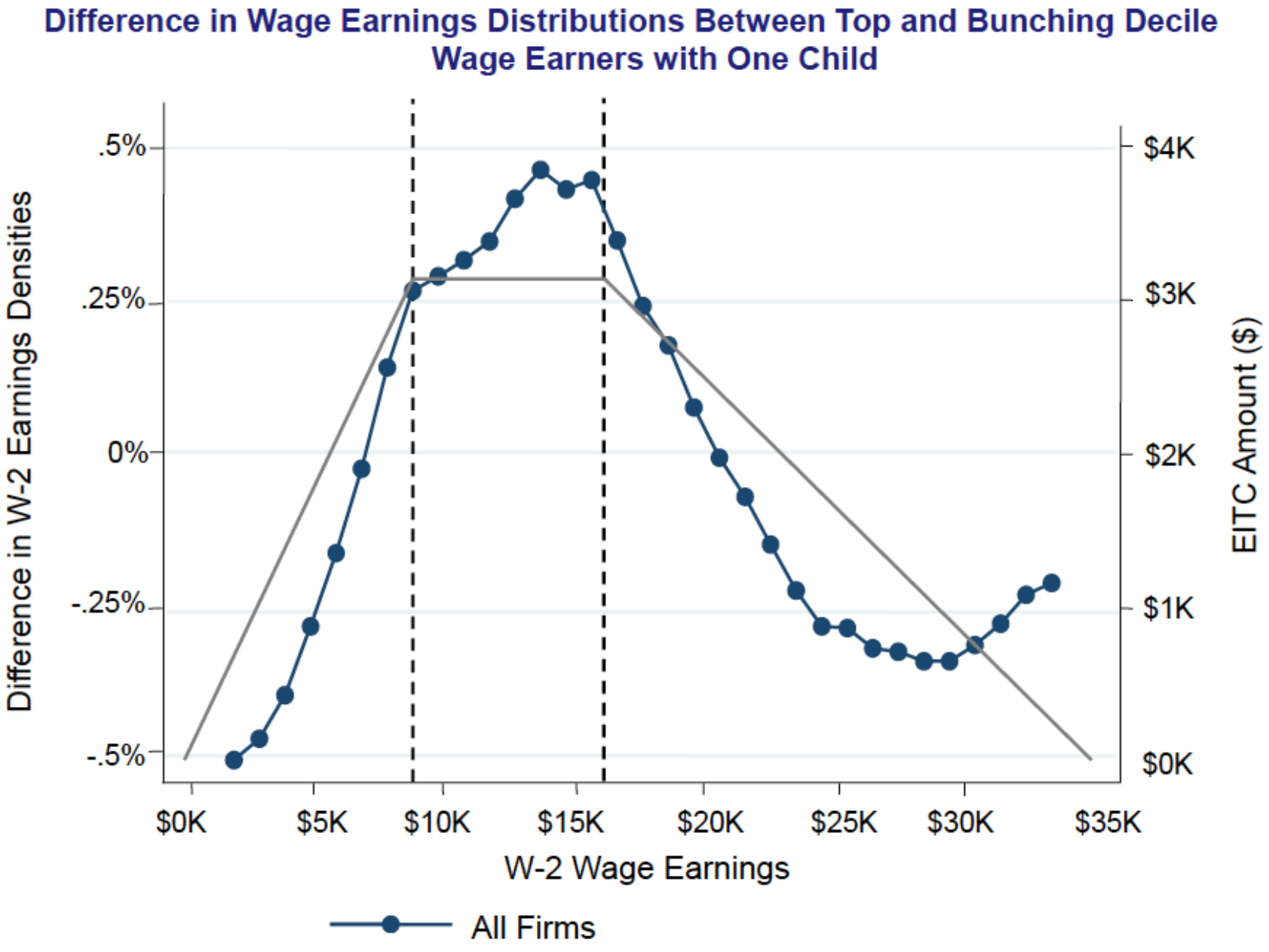

Change in EITC Refunds vs. Change in Sharp Bunching for Movers
Change in EITC Refund ($)
120
100
80
60
40
-1%
-0.5%
0%
0.5%
1%
Change in ZIP-3 Sharp Bunching
β = 6.0
(6.2)
β = 59.7
(5.7)
p-value for diff. in slopes: p < 0.0001

Outline of Empirical Analysis

- Step 1: Document variation across neighborhoods in sharp bunching among self-employed
- Step 2: Establish that variation in sharp bunching across neighborhoods is driven by differences in knowledge about EITC schedule
- Step 3: Compare wage earnings distributions across low- and highknowledge neighborhoods to uncover impacts of EITC on earnings


Income Distribution For Single Wage Earners with One Child
Is the EITC having an effect on this distribution?
3.5%
3%
2.5%
2%
1.5%
1%
0.5%
0%
Percent of Wage-Earners
$4K
$3K
$2K
$1K
$0K
EITC Amount ($)
$0
$5K
$10K
$15K
$20K
$25K
$30K
$35K
W-2 Wage Earnings


Income Distribution For Single Wage Earners with One Child
High vs. Low Bunching Areas
Percent of Wage Earners
3.5%
3%
2.5%
2%
1.5%
1%
0.5%
0%
EITC Amount ($)
$4K
$3K
$2K
$1K
$0K
$0K
$5K
$10K
$15K
$20K
$25K
$30K
$35K
W-2 Wage Earnings
Lowest Bunching Decile
Highest Bunching Decile


Difference in Wage Earnings Distributions Between Top and Bunching Decile Wage Earners with One Child
Difference in W-2 Earnings Densities
.5%
.25%
0%
-.25%
-.5%
EITC Amount ($)
$4K
$3K
$2K
$1K
$0K
$0K
$5K
$10K
$15K
$20K
$25K
$30K
$35K
W-2 Wage Earnings
All Firms

Outline of Empirical Analysis

- Step 1: Document variation across neighborhoods in sharp bunching among self-employed
- Step 2: Establish that variation in sharp bunching across neighborhoods is driven by differences in knowledge about EITC schedule
- Step 3: Compare wage earnings distributions across low- and highknowledge neighborhoods to uncover impacts of EITC on earnings
- Step 4: Compare impacts of changes in EITC subsidies on earnings across low vs. high knowledge nbhds. to account for omitted variables (skip)

Chetty et al. (2013)

- EITC has significantly increased incomes of low-income families with children through mechanical effects + behavioral responses
- Behavioral responses still concentrated in a few areas but continuing to spread across the U.S.
- Contrary to prior findings, intensive margin responses are substantial and may even be larger than extensive margin responses

Bibliography I

Ashenfelter, O. and Plant, M. W. (1990). Nonparametric Estimates of the Labor-Supply Effects of Negative Income Tax Programs. *Journal of Labor Economics*, 8(1): S396–S415.

Blundell, R., Duncan, A., and Meghir, C. (1998). Estimating Labor Supply Responses Using Tax Reforms. *Econometrica*, 66(4): 827–861.

Chetty, R., Friedman, J. N., Olsen, T., and Pistaferri, L. (2011). Adjustment Costs, Firm Responses, and Micro vs. Macro Labor Supply Elasticities: Evidence from Danish Tax Records. *Quarterly Journal of Economics*, 126(2): 749–804.

Eissa, N. (1995). Taxation and Labor Supply of Married Women: The Tax Reform Act of 1986 as a Natural Experiment. Working Paper 5023, National Bureau of Economic Research.

Kleven, H. J. and Waseem, M. (2013). Using Notches to Uncover Optimization Frictions and Structural Elasticities: Theory and Evidence from Pakistan. *Quarterly Journal of Economics*, 128(2): 669–723.

Saez, E. (2010). Do Taxpayers Bunch at Kink Points? *American Economic Journal: Economic Policy*, 2(3): 180–212.