Using Differences in Knowledge Across Neighborhoods to Uncover the Impacts of the EITC on Earnings

Raj Chetty, Harvard and NBER
John N. Friedman, Harvard and NBER
Emmanuel Saez, UC Berkeley and NBER

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Identifying Policy Impacts

- Two central challenges in identifying the impacts of tax 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
  [Brown 1968, Bises 1990, Chetty and Saez 2009]

- Workers face switching costs for labor supply
Overview

- We develop a new method that addresses these challenges by exploiting differences across neighborhoods in knowledge about tax policies.
  
  - Idea: use cities with low levels of information about tax policies as “control groups” for behavior in the absence of tax policy.

- Apply this approach to characterize the impacts of the Earned Income Tax Credit (EITC) on the earnings distribution in the U.S.
  
  - EITC provides refunds of up to $5,000 to approximately 25 million households in the U.S.
Earned Income Tax Credit Schedule for Single Earners with One Child
Relationship to Prior Work

Large literature has studied the impacts of EITC on labor supply

- Clear evidence of impacts on participation (extensive margin)

- But no clear, non-parametric evidence on impacts of EITC on earnings distribution (intensive margin)

- Same pattern in studies of labor supply elasticities more generally

- Observed extensive responses may be larger because more people know about existence of EITC refund than shape of schedule

- Gains from re-optimization are 2nd-order on intensive but 1st order on extensive margin \(\rightarrow\) frictions attenuate intensive responses [Chetty 2011]
Income Distribution For Single Wage Earners with One Child

W-2 Wage Earnings

Percent of Wage-Earners

EITC Amount ($)

Income Distribution For Single Wage Earners with One Child

W-2 Wage Earnings
Income Distribution For Single Wage Earners with One Child

Is the EITC having an effect on this distribution?
1. Conceptual Framework

2. Data and Institutional Background

3. A Proxy for Knowledge: Sharp Bunching via Income Manipulation

4. Using Neighborhood Effects to Uncover Wage Earnings Responses

5. Implications for Tax Policy
Workers face a two-bracket income tax system $\tau = (\tau_1, \tau_2)$ and choose earnings $z=wl$ to maximize quasi-linear utility $u(c,l)$.

- Tax rate of $\tau_1 < 0$ when reported income is below $K$.
- Marginal tax rate of $\tau_2 > 0$ for reported income above $K$.
- Tax refund maximized when income is $K \Rightarrow$ bunching around $K$.
Cities indexed by \( c = 1, \ldots, N \)

Cities differ only in one attribute: knowledge of tax code

In city \( c \), fraction \( \lambda_c \) of workers know about tax subsidy for work

- Others optimize as if tax rates are 0 (i.e. subsidy is lump-sum)

Firms pay workers fixed wage rate in all cities
Identifying Tax Policy Impacts

- Goal: identify how taxes affect earnings distribution $F(z \mid \tau)$ with average level of knowledge in economy:

$$\Delta F(z \mid \tau) = F(z \mid \tau > 0, \tilde{\lambda}_c) - F(z \mid \tau = 0, \tilde{\lambda}_c)$$

- Challenge: potential outcome without taxes $F(z \mid \tau = 0, \tilde{\lambda}_c)$ unobserved

- Our solution: earnings behavior with no *knowledge* about taxes is equivalent to earnings behavior with no taxes

$$F(z \mid \tau = 0, \tilde{\lambda}_c) = F(z \mid \tau > 0, \lambda_c = 0)$$

$$\Rightarrow \Delta F(z \mid \tau) = F(z \mid \tau > 0, \tilde{\lambda}_c) - F(z \mid \tau > 0, \lambda_c = 0)$$

- Id. assumption: variation in knowledge uncorrelated with unobservables

$\rightarrow$ Quasi-experimental research design to account for omitted variables
Data and Sample Definition

- Selected data from population of U.S. income tax returns, 1996-2009
  - Includes 1040’s and all information forms (e.g. W-2’s)

- Sample restriction: individuals who at least once between 1996-2009:
  (1) file a tax return, (2) have income < $50,000, (3) claim a dependent

- Sample size after restrictions:
  - 77.6 million unique taxpayers
  - 1.09 billion taxpayer-year observations on income
## Summary Statistics: EITC Eligible Sample

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Income Measures</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Earnings</td>
<td>$20,091</td>
<td>$10,784</td>
</tr>
<tr>
<td>Wage Earnings</td>
<td>$18,308</td>
<td>$12,537</td>
</tr>
<tr>
<td>Self-Employment Income</td>
<td>$1,770</td>
<td>$6,074</td>
</tr>
<tr>
<td>Non-Zero Self-Emp Income</td>
<td>19.6%</td>
<td>39.7%</td>
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<tr>
<td><strong>Tax Credits</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EITC Refund Amount</td>
<td>$2,543</td>
<td>$1,454</td>
</tr>
<tr>
<td>Claimed EITC</td>
<td>88.9%</td>
<td>31.4%</td>
</tr>
<tr>
<td>Professionally Prepared Return</td>
<td>69.6%</td>
<td>46.0%</td>
</tr>
<tr>
<td><strong>Demographics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>37</td>
<td>13</td>
</tr>
<tr>
<td>Number of Children</td>
<td>1.7</td>
<td>0.8</td>
</tr>
<tr>
<td>Married</td>
<td>30.3%</td>
<td>45.9%</td>
</tr>
<tr>
<td>Female (for single filers)</td>
<td>73.0%</td>
<td>44.4%</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>219,742,011</td>
<td></td>
</tr>
</tbody>
</table>
Critical distinction: wage earnings vs. self-employment income

Self-employment income is self-reported → easy to manipulate

Wage earnings are directly reported to IRS by employers
  Therefore more likely to reflect “real” earnings behavior
Income Distributions for Individuals with Children in 2008

Percent of Tax Filers

0% 1% 2% 3% 4% 5%

Income Distributions for Individuals with Children in 2008

Earnings (Real 2010 $)

$0 $10K $20K $30K $40K

Percent of Tax Filers

$0 $10K $20K $30K $40K

Earnings (Real 2010 $)

One child

Two children
Reported vs. Audited Income Distributions for SE EITC Filers in 2001
National Research Program Tax Audit Data

Reported Income

Source: IRS TY01 NRP reporting compliance study of individual income tax returns for those reporting dependent children; amounts reflect only what was detected by the auditors, weighted to population levels.
Reported vs. Audited Income Distributions for SE EITC Filers in 2001
National Research Program Tax Audit Data

Source: IRS TY01 NRP reporting compliance study of individual income tax returns for those reporting dependent children; amounts reflect only what was detected by the auditors, weighted to population levels.
Reported vs. Audited Income Distributions for EITC Wage Earners with Children
National Research Program Tax Audit Data

Reported Income

Detected Income

Source: IRS TY01 NRP reporting compliance study of individual income tax returns for those reporting dependent children; amounts reflect only what was detected by the auditors, weighted to population levels.
Empirical Implementation: Proxy for Knowledge

- We proxy for knowledge $\lambda_c$ using sharp bunching at refund-maximizing kink among the self-employed

- Intuition: use amount of misreporting to measure local tax knowledge

- Workers make two choices: earnings ($z_i$) and reported income ($\hat{z}_i$)

- Fraction $\theta_c$ of workers face 0 cost of non-compliance $\rightarrow$ report $\hat{z}_i = K$

- Remaining workers face infinite cost of non-compliance $\rightarrow$ set $\hat{z}_i = z_i$

- Fraction who report $\hat{z}_i = K$ is proportional to local knowledge:

$$f_c = \theta_c \lambda_c$$
Assumption 2: No sharp bunching $\Rightarrow$ no knowledge about EITC schedule

$$f_c = 0 \Rightarrow \lambda_c = 0$$

Compare aggregate distribution in economy to distribution of wage earnings in neighborhoods with $f_c = 0$

Under Assumption 2, yields a point estimate of impact of EITC on earnings distribution with average knowledge level in economy

After showing main results, we present evidence suggesting that individuals in low bunching areas completely ignore EITC

Violations of assumption lead us to understate impacts of EITC
Outline of Empirical Analysis

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

Percent of Filers

Income Relative to 1st Kink

- $10K
- $0
- $10K
- $20K
Sharp bunching

- Fraction of EITC-eligible tax filers who report income at first kink and have self-employment income
- Essentially measures fraction of individuals who manipulate reported income to maximize EITC refund in each neighborhood

Begin by examining spatial evolution of sharp bunching across the United States
Sharp Bunching in 1996

- 4.4% – 30.6%
- 3.2% – 4.4%
- 2.5% – 3.2%
- 2.2% – 2.5%
- 1.9% – 2.2%
- 1.6% – 1.9%
- 1.4% – 1.6%
- 1.2% – 1.4%
- 0.9% – 1.2%
- 0% – 0.9%
Sharp Bunching in 2008
Earnings Distributions in Lowest vs. Highest Bunching Decile

Percent of Tax Filers

Total Income Relative to First EITC Kink

Lowest Decile ZIP-3’ s

Highest Decile ZIP-3’ s
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
Movers: Neighborhood Changes

- 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 (0.13)
Effect of Moving to 1st Decile = -0.41 (0.11)
Effect of Moving to 10th Decile = $150.1 (22.5)

Effect of Moving to 1st Decile = $5.1 (19.0)
Total Earnings Distribution in Years Before Move

Percent of Movers

- $10K
- $0K
- $10K
- $20K
- $30K

Total Income Relative to First Kink

Movers to Lowest Bunching Decile
Movers to Middle Bunching Decile
Movers to Highest Bunching Decile
Total Earnings Distribution in Years After Move

Percent of Movers

Total Income Relative to First Kink

Movers to Lowest Bunching Decile
Movers to Middle Bunching Decile
Movers to Highest Bunching Decile
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 ($)
- Change in EITC Refunds vs. Change in Sharp Bunching for Movers

\[ \beta = 59.7 \quad (5.7) \]

\[ \beta = 6.0 \quad (6.2) \]

p-value for diff. in slopes: \( p < 0.0001 \)
Agglomeration: Sharp Bunching vs. EITC Filer Density by ZIP Code
Evolution of Sharp Bunching in Low vs. High EITC-Density Areas

Year | Below-Median EITC Density | Above-Median EITC Density
--- | --- | ---
1995 | 0% | 1%
2000 | 1% | 2%
2005 | 2% | 3%
2010 | 3% | 4%
Sharp Bunching vs. Fraction of Professionally Prepared Returns in ZIP-3

\[ \beta = 7.55 \quad (0.24) \]
\[ \beta = 6.04 \quad (0.18) \]
Correlation Between EITC Bunching and Google Search Patterns

Google Search Intensity for “Tax” in ZIP Code (%)
## Cross-Sectional Correlates of Sharp Bunching

**Dep. Var.: Sharp Bunching Rate in ZIP-3 (%)**

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<tbody>
<tr>
<td><strong>EITC Filer Density in ZIP-3</strong></td>
<td>1.93</td>
<td>1.82</td>
<td>0.44</td>
<td>0.69</td>
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<td></td>
<td>(0.05)</td>
<td>(0.05)</td>
<td>(0.06)</td>
<td>(0.06)</td>
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<td><strong>Fraction of Tax Prepared Returns in ZIP-3</strong></td>
<td>1.98</td>
<td>3.02</td>
<td>3.46</td>
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<td></td>
<td>(0.57)</td>
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<td>(0.56)</td>
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<td><strong>Google Search Intensity</strong></td>
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<td></td>
<td>(0.05)</td>
<td>(0.03)</td>
<td>(0.03)</td>
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<td><strong>State EITC</strong></td>
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<td></td>
<td>(0.05)</td>
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<td><strong>State Non-Compliance Rate</strong></td>
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<td></td>
<td>-1.51</td>
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<td></td>
<td></td>
<td>(9.94)</td>
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<tr>
<td><strong>Demographic Controls</strong></td>
<td>x</td>
<td></td>
<td></td>
<td>x</td>
<td></td>
<td>x</td>
<td></td>
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<tr>
<td><strong>State Fixed Effects</strong></td>
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<td></td>
<td></td>
<td>x</td>
<td></td>
<td></td>
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<tr>
<td><strong>R-squared</strong></td>
<td>0.603</td>
<td>0.798</td>
<td>0.012</td>
<td>0.032</td>
<td>0.728</td>
<td>0.848</td>
<td>0.105</td>
<td>0.001</td>
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<tr>
<td><strong>Number of ZIP-3's</strong></td>
<td>873</td>
<td>873</td>
<td>881</td>
<td>875</td>
<td>870</td>
<td>849</td>
<td>886</td>
<td>886</td>
</tr>
</tbody>
</table>
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 high-knowledge neighborhoods to uncover impacts of EITC on earnings
W-2 Earnings Distribution For Single Wage Earners with One Child

Percent of Wage-Earners

W-2 Wage Earnings

EITC Amount ($)
W-2 Earnings Distributions in High vs. Low Bunching Decile Areas
Wage Earners with One Child

Percent of Wage-Earners

W-2 Wage Earnings

EITC Amount ($)

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

W-2 Wage Earnings

EITC Amount ($)

$0k  $5k  $10k  $15k  $20k  $25k  $30k  $35k

W-2 Wage Earnings

All Firms
Difference in Wage Earnings Distributions Between Top and Bunching Decile Wage Earners with One Child

Difference in Wage Earnings Densities

W-2 Wage Earnings

EITC Amount ($)

0.005

0

4k

3k

2k

1k

0

1k

2k

3k

4k

0k

$0k

$5k

$10k

$15k

$20k

$25k

$30k

$35k

W-2 Wage Earnings

Difference in W-2 Earnings Densities

All Firms

>100 Employees
Difference in Wage Earnings Distribution Between Top and Bunching Decile Wage Earners with Two Children

W-2 Wage Earnings

EITC Amount ($)

Difference in W-2 Earnings Densities

Wage Earners with Two Children
EITC Credit Amount for Wage Earners vs. Sharp Bunching

β = 17.6

(2.5)
Effects of Changes in Neighborhood Bunching for Wage-Earner Movers

\[ \beta \text{ for } \Delta B < 0 = -19.4 (6.3) \]
\[ \beta \text{ for } \Delta B > 0 = 43.9 (5.7) \]

p-value for Difference: \( p < 0.0001 \)
Outline of Empirical Analysis

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

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- **Step 3:** Compare wage earnings distributions across low- and high-knowledge 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
Cross-sectional differences in income distributions could be biased by omitted variables

- City effects: differences in industry structure or labor demand
- Individual sorting: preferences may vary across cities

We account for these omitted variables by analyzing impacts of changes in EITC subsidy

- Do EITC changes affect earnings more in high knowledge cities?
Cross-sectional differences in income distributions could be biased by omitted variables.

To identify causal impacts of EITC, need variation in tax incentives.

- Birth of first child $\Rightarrow$ substantial change in EITC incentives
- Although birth affects labor supply directly, cross-neighborhood comparisons provide good counterfactuals

12 million EITC-eligible individuals give birth within our sample.
Earnings Distribution in the Year Before First Child Birth for Wage Earners

- Percent of Individuals
  - 2%
  - 4%
  - 0%
  - 6%

- Wage Earnings
  - $0
  - $10K
  - $20K
  - $30K
  - $40K

- Lowest Bunching
- Middle Bunching
- Highest Bunching
Earnings Distribution in the Year of First Child Birth for Wage Earners

Percent of Individuals

- 2%
- 4%
- 6%

Wage Earnings

- $0
- $10K
- $20K
- $30K
- $40K

Lowest Bunching Decile
Middle Bunching Decile
Highest Bunching Decile
Simulated One-Child EITC Amount ($)

All Wage Earners

DD High vs. Low = $126 (3.9)

Age of Child

Lowest Bunching Decile

Middle Bunching Decile

Highest Bunching Decile
All Individuals Working at Firms with More than 100 Employees

Simulated One-Child EITC Amount ($)

Lowest Bunching Decile

Middle Bunching Decile

Highest Bunching Decile

DD High vs. Low = $111 (4.8)
Composition of Wage Earnings Responses

- Where is the increase in EITC refunds coming from?
  - Phase-in, phase-out, or extensive margin?
  - Important for understanding welfare consequences of EITC

- Calculate change in EITC amounts from year -1 to 0
  - Compare across low and high information areas to recover causal impact of EITC
Changes in Simulated EITC around Births for Wage Earners

Change in Simulated One-Child EITC Amount ($)

ZIP-3 Sharp Bunching

$\beta = 28.1$

(0.61)

0 to 1 Child
Changes in Simulated EITC around Births for Wage Earners

![Graph showing changes in simulated EITC amount ($) for different ZIP-3 Sharp Bunching percentages.]

- **0 to 1 Child**
  - Change in Simulated One-Child EITC Amount ($)
  - Line equation: $\beta = 28.1$ (0.61)

- **2 to 3 Children**
  - Change in Simulated One-Child EITC Amount ($)
  - Line equation: $\beta = 1.37$ (0.74)
Simulated Phase-In Credit

Phase-in Simulated Credit Amount

Total Income

$0K $5K $10K $15K $20K $25K $30K $35K

$0K $1K $2K $3K $4K
Changes in Simulated EITC around Births for Wage Earners

$\beta = 28.0 \\
(0.62)$
Simulated Phase-Out Credit

- Income vs. Simulated Credit Amount

- Income: $0K to $35K
- Simulated Credit Amount: $0K to $3K

- Line graph showing a decrease in simulated credit amount as income increases.

- Key points:
  - $10K: Simulated Credit Amount = $3K
  - $20K: Simulated Credit Amount = decrease from $3K

- The graph indicates a phase-out credit structure.
Changes in Simulated EITC around Births for Wage Earners

ZIP-3 Sharp Bunching

Phase In

Phase Out

β = 28.0
(0.62)

β = 0.10
(0.48)
Extensive Margin: Changes in Fraction Working around First Birth

Percent of Individuals with Positive W-2 Earnings

ZIP-3 Sharp Bunching

β = 0.53% (0.11)

Implied Effect on Credit: $6.0 (1.3)

Change in Simulated EITC Credit ($)
## Impact of EITC on Wage Earnings

<table>
<thead>
<tr>
<th>Dep. Var.: Change in Sim. EITC Amount</th>
<th>Baseline Specs. Sim. EITC Amount</th>
<th>With State Effects Sim. EITC Amount</th>
<th>Placebo Test: 3rd Child Sim. EITC Amount</th>
<th>Phase-in vs. Phase-out responses: (4)+(5)=(1) Sim. Phase-in Credit</th>
<th>Extensive Margin Sim. Phase-out Credit</th>
<th>Positive W-2 Earnings Mean EITC x (Pos. W-2 Earnings)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ZIP-3 Sharp Bunching</td>
<td>28.1 (0.61)</td>
<td>19.6 (0.59)</td>
<td>1.4 (0.74)</td>
<td>28.0 (0.62)</td>
<td>0.1 (0.48)</td>
<td>0.53% (0.11)</td>
</tr>
</tbody>
</table>
Our estimates can be used to characterize impact of EITC on income distribution taking into account behavioral responses.

- Use neighborhoods in bottom decile of sharp bunching as counterfactual for earnings distribution without EITC.

- Recall key assumption: neighborhoods with no sharp bunching are places where people perceive marginal tax rates as zero.

- First present two pieces of evidence supporting this assumption.
Fraction of Individuals Reporting Self-Employment Income Around Child Birth

- Lowest Bunching Decile
- Middle Bunching Decile
- Highest Bunching Decile

\[ \beta = 5.38 \quad (0.10) \]
### Impact of EITC on Income Distribution

<table>
<thead>
<tr>
<th>Percent of EITC Recipients with 2+ Kids Below:</th>
<th>1/2 Poverty Line</th>
<th>1 x Poverty Line</th>
<th>1.5 x Poverty Line</th>
<th>2 x Poverty Line</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>No EITC Counterfactual</strong></td>
<td>17.0%</td>
<td>41.4%</td>
<td>69.3%</td>
<td>93.0</td>
</tr>
<tr>
<td><strong>EITC, No Behavioral Response</strong></td>
<td>11.4%</td>
<td>29.6%</td>
<td>60.1%</td>
<td>91.0%</td>
</tr>
<tr>
<td><strong>EITC, with Avg. Behavioral Response</strong></td>
<td>10.1%</td>
<td>29.0%</td>
<td>60.2%</td>
<td>91.1%</td>
</tr>
<tr>
<td><strong>EITC with Top Decile Behavioral Response</strong></td>
<td>7.9%</td>
<td>28.2%</td>
<td>60.7%</td>
<td>91.4%</td>
</tr>
</tbody>
</table>
### Elasticity Estimates Based on Change in EITC Refunds Around Birth of First Child

<table>
<thead>
<tr>
<th></th>
<th>Phase-in Elasticity</th>
<th>Phase-out Elasticity</th>
<th>Extensive Margin</th>
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</thead>
<tbody>
<tr>
<td><strong>A. Wage Earnings</strong></td>
<td></td>
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<tr>
<td>Elasticity in U.S. 2000-2005</td>
<td>0.37</td>
<td>0.00</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.003)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Elasticity in top decile ZIP-3's</td>
<td>1.83</td>
<td>0.05</td>
<td>0.66</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.03)</td>
<td>(0.05)</td>
</tr>
<tr>
<td><strong>B. Total Earnings</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elasticity in U.S. 2000-2005</td>
<td>0.52</td>
<td>0.07</td>
<td>0.18</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.001)</td>
<td>(0.038)</td>
</tr>
<tr>
<td>Elasticity in top decile ZIP-3's</td>
<td>2.40</td>
<td>0.40</td>
<td>1.13</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.03)</td>
<td>(0.06)</td>
</tr>
</tbody>
</table>
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.

Differences in knowledge can be used to develop counterfactuals when traditional approaches are unavailable

Characterizing impacts of social security on retirement behavior using social security earnings test

Analyzing responses to corporate taxation

Many policies likely to have diffuse impacts → substantial value in developing novel methods of characterizing long-term impacts