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

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Identifying Policy Impacts

- 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
       [Brown 1968, Bises 1990, Chetty and Saez 2009]
     
     - Workers face switching costs for labor supply
Overview

- We develop a new method of addressing these challenges by 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.

- 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

- EITC Credit Amount ($1000)
- Family Earnings

Graph showing the EITC credit amount based on family earnings 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 2nd-order on intensive but 1st order on ext. margin \(\rightarrow\) frictions attenuate intensive responses [Chetty 2012]
Income Distribution For Single Wage Earners with One Child

W-2 Wage Earnings

Percent of Wage-Earners

EITC Amount ($)

$0K $1K $2K $3K $4K

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

0% 0.5% 1% 1.5% 2% 2.5% 3% 3.5%
Is the EITC having an effect on this distribution?
Outline

1. Conceptual Framework

2. Data and Institutional Background


4. 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 $z = w l$ to maximize quasi-linear utility $C_i - h(l_i, \alpha_i)$.

- 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 \( c = 1, \ldots, N \)

- In stylized model, assume that cities differ only in one attribute: knowledge of tax code

  - We relax this assumption in our empirical implementation and instead impose an orthogonality condition for identification

- 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: estimate impact of tax system on earnings distribution $F(z | \tau)$ with average level of knowledge in economy

\[
\Delta F(z | \tau) = F(z | \tau \neq 0, \tilde{\lambda}_c) - F(z | \tau = 0, \tilde{\lambda}_c)
\]

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

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

\[
F(z | \tau = 0, \tilde{\lambda}_c) = F(z | \tau > 0, \lambda_c = 0)
\]

$\Rightarrow \Delta F(z | \tau) = F(z | \tau > 0, \tilde{\lambda}_c) - F(z | \tau > 0, \lambda_c = 0)$
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
<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean (1)</th>
<th>Std. Dev. (2)</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>
</tr>
<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><strong>Number of Observations</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>219,742,011</td>
<td></td>
</tr>
</tbody>
</table>
To measure local knowledge, we rely on a critical distinction between wage earnings and 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.
2008 Federal EITC Schedule for a Single Filer with Children

Total Earnings (Real 2010 $)

- One Child
- Two or More Children
Income Distributions for Individuals with Children in 2008

Percent of Tax Filers

Income Distributions for Individuals with Children in 2008

Total Earnings (Real 2010 $)

- One Child
- Two Children
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 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 vs. 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.
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:

$$\phi_c = \theta_c \lambda_c$$
- We use areas with no sharp bunching as counterfactuals for behavior in the absence of the EITC

- Research design rests on two identification assumptions in a model that permits arbitrary differences in distribution of skills $G_c(\alpha_i)$ across cities
Assumption 1 [Tax Knowledge] Individuals in cities with no sharp bunching have no knowledge about EITC schedule and perceive $\tau = 0$

$$\phi_c = 0 \Rightarrow \lambda_c = 0$$

- Requires that individuals in areas with no sharp bunching behave as if tax policy has no impact on marginal incentives
- We present evidence supporting this assumption below
- Violations of this assumption lead us to understate impacts of EITC
Identification Assumption 2: Counterfactuals

- Cross-sectional estimator: compare aggregate earnings distribution with distribution in neighborhoods with 0 sharp bunching

\[ \hat{\Delta F} = F(z|\tau) - F(z|\tau, \phi_c = 0) \]

Assumption 2a [Cross-Sectional Identification] Individuals’ skills \( G_c(\alpha_i) \) do not vary across cities with different levels of knowledge \( \lambda_c \)
Identification Assumption 2: Counterfactuals

- Cross-sectional estimator: compare aggregate earnings distribution with distribution in neighborhoods with 0 sharp bunching

\[
\Delta F = F(z|\tau) - F(z|\tau, \phi_c = 0)
\]

**Assumption 2a [Cross-Sectional Identification]** Individuals’ skills \(G_c(\alpha_i)\) do not vary across cities with different levels of knowledge \(\lambda_c\)

- Panel estimator: compare changes in aggregate earnings distribution around eligibility due to child birth with changes in \(\phi_c = 0\) nbhds.

\[
\hat{\Delta F_{DD}} = \left[ F_t(z|\tau) - F_t(z|\tau, \phi_c = 0) \right] - \left[ F_{t-1}(z|\tau) - F_{t-1}(z|\tau, \phi_c = 0) \right]
\]

**Assumption 2b [Panel Identification]** Changes in skills when an individual becomes eligible for credit do not vary across cities with different \(\lambda_c\)
Step 1: Document variation across neighborhoods in sharp bunching among self-employed
Earnings Distribution in Texas

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

Income Relative to 1st Kink

Percent of Filers

- $10K
- $0K
- $10K
- $20K
Earnings Distribution in Kansas

Percent of Filers

Income Relative to 1st Kink
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

Begin by documenting spatial evolution of sharp bunching across U.S.
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
Fraction of Tax Filers Who Report SE Income that Maximizes EITC Refund in 2005
Fraction of Tax Filers Who Report SE Income that Maximizes EITC Refund in 2008
Earnings Distributions in Lowest and Highest Bunching Deciles

Percent of Tax Filers

Lowest Bunching Decile

Highest Bunching Decile

Total Earnings Relative to First EITC Kink

- $10K

$0K

$10K

$20K

$30K

Percent of Tax Filers

Lowest Bunching Decile

Highest Bunching Decile

Total Earnings Relative to First EITC Kink

- $10K

$0K

$10K

$20K

$30K
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
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)
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 ($) vs. Change in ZIP-3 Sharp Bunching for Movers

- $\beta = 59.7$ (5.7)
- $\beta = 6.0$ (6.2)

p-value for diff. in slopes: $p < 0.0001$
Cross-Sectional Correlations

- What drives the variation in sharp bunching across neighborhoods?

- Evaluate predictive power of proxies for information, tax compliance, and other variables
Agglomeration: Sharp Bunching vs. EITC Filer Density by ZIP Code

\[ R^2 = 0.6 \]
Evolution of Sharp Bunching in Low vs. High EITC-Density Areas

- Below-Median EITC Density
- Above-Median EITC Density

<table>
<thead>
<tr>
<th>Year</th>
<th>Self-Employed Sharp Bunching</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995</td>
<td>0%</td>
</tr>
<tr>
<td>2000</td>
<td>1%</td>
</tr>
<tr>
<td>2005</td>
<td>2%</td>
</tr>
<tr>
<td>2010</td>
<td>3%</td>
</tr>
<tr>
<td></td>
<td>4%</td>
</tr>
</tbody>
</table>
Sharp Bunching vs. Fraction of Professionally Prepared Returns in ZIP-3

**Self-Employed Sharp Bunching**

\[ \beta = 13.2 \quad (0.9) \]
Sharp Bunching vs. Fraction of Professionally Prepared Returns in ZIP-3

β = 13.2 (0.9)

β = 9.4 (0.7)
Correlation Between EITC Bunching and Google Search Patterns

Self-Employed Sharp Bunching

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

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

<table>
<thead>
<tr>
<th>EITC Filer Density in ZIP-3</th>
<th>1.93</th>
<th>1.82</th>
<th>0.44</th>
<th>0.69</th>
<th>(0.05)</th>
<th>(0.05)</th>
<th>(0.06)</th>
<th>(0.06)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fraction of Tax Prepared Returns in ZIP-3</td>
<td>9.86</td>
<td>3.02</td>
<td>3.46</td>
<td>(1.48)</td>
<td>(0.51)</td>
<td>(0.56)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Google Search Intensity</td>
<td>0.30</td>
<td>0.14</td>
<td>0.19</td>
<td>(0.05)</td>
<td>(0.03)</td>
<td>(0.03)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>State EITC</td>
<td>0.07</td>
<td>(0.05)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>State Non-Compliance Rate</td>
<td>-1.51</td>
<td>(5.32)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Demographic Controls</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>State Fixed Effects</td>
<td></td>
<td>x</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.603</td>
<td>0.798</td>
<td>0.169</td>
<td>0.032</td>
<td>0.728</td>
<td>0.848</td>
<td>0.105</td>
<td>0.002</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>873</td>
<td>873</td>
<td>883</td>
<td>875</td>
<td>870</td>
<td>870</td>
<td>886</td>
<td>51</td>
</tr>
</tbody>
</table>
Perceptions of EITC in Low-Bunching Areas

- Preceding evidence indicates that self-emp. sharp bunching provides a proxy for local knowledge about first kink of EITC schedule.

- Assumption 1 requires that individuals in low-bunching areas have no knowledge about entire EITC schedule and behave as if $\tau = 0$.

- Now assess beliefs about broader EITC schedule in low-bunching areas.
  - Analyze reported incomes of self-employed around birth of first child.
  - Birth of first child $\rightarrow$ substantial change in EITC incentives.
Effect of Child Birth on Total Earnings Distribution for the Self-Employed

Percent of Individuals

Total Earnings

Lowest Decile: Before Birth
Lowest Decile: After Birth
Top Decile: After Birth
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
Income Distribution For Single Wage Earners with One Child

Is the EITC having an effect on this distribution?
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 ($)

-0.5%
-0.25%
0%
0.25%
0.5%

$0K
$5K
$10K
$15K
$20K
$25K
$30K
$35K
$4K
$3K
$2K
$1K
$0K

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

EITC Amount ($)

W-2 Wage Earnings Density

All Firms

>100 Employees
EITC Credit Amount for Wage Earners vs. Sharp Bunching

\[ \beta = 15.9 \quad (0.59) \]

<table>
<thead>
<tr>
<th>ZIP-3 Self-Employed Sharp Bunching (%)</th>
<th>EITC Refund Amount for Wage Earners ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0%</td>
<td>$2350</td>
</tr>
<tr>
<td>2%</td>
<td>$2400</td>
</tr>
<tr>
<td>4%</td>
<td>$2450</td>
</tr>
<tr>
<td>6%</td>
<td>$2500</td>
</tr>
</tbody>
</table>

Graph showing the relationship between EITC credit amount and self-employed sharp bunching.
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

- Step 4: Compare impacts of changes in EITC subsidies on earnings across low vs. high knowledge nbhds. to account for omitted variables
Child Birth Research Design

- Cross-sectional differences in income distributions could be biased by omitted variables

- To identify causal impacts of EITC, need variation in tax incentives
  - Use child birth as an instrument for EITC eligibility
  - Birth affects labor supply directly, but 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

<table>
<thead>
<tr>
<th>Wage Earnings</th>
<th>Lowest Sharp Bunching Decile</th>
<th>Middle Sharp Bunching Decile</th>
<th>Highest Sharp Bunching Decile</th>
</tr>
</thead>
<tbody>
<tr>
<td>$0K</td>
<td>2%</td>
<td>6%</td>
<td>0%</td>
</tr>
<tr>
<td>$10K</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$20K</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$30K</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$40K</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Earnings Distribution in the Year of First Child Birth for Wage Earners

Percent of Individuals

- 2%
- 4%
- 6%

Wage Earnings

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

Lowest Sharp Bunching Decile

Middle Sharp Bunching Decile

Highest Sharp Bunching Decile
Simulated EITC Credit Amount for Wage Earners Around First Child Birth

Simulated One-Child EITC Refund ($)

<table>
<thead>
<tr>
<th>Age of Child</th>
<th>Lowest Sharp Bunching Decile</th>
<th>Middle Sharp Bunching Decile</th>
<th>Highest Sharp Bunching Decile</th>
</tr>
</thead>
<tbody>
<tr>
<td>$1800</td>
<td>$1750</td>
<td>$1900</td>
<td></td>
</tr>
</tbody>
</table>

\[ \beta = 85.4 \quad (7.2) \]
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

- Compare change in simulated EITC amount (with 1 child) from year -1 to year 0 across low and high information areas
Changes in W-2 Based Simulated EITC around Child Birth vs. Sharp Bunching

Change in Simulated One-Child EITC Refund ($)

ZIP-3 Self-Employed Sharp Bunching

β = 19.4
(1.61)

0 to 1 Child
Changes in W-2 Based Simulated EITC around Child Birth vs. Sharp Bunching

$\beta = 19.4 \quad (1.61)$

$\beta = -1.89 \quad (0.63)$

Change in Simulated One-Child EITC Refund ($)

ZIP-3 Self-Employed Sharp Bunching

0 to 1 Child

2 to 3 Children
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 W-2 Based Simulated EITC around Child Birth vs. Sharp Bunching

\[ \beta = 14.2 \quad (1.55) \]
Changes in W-2 Based Simulated EITC around Child Birth vs. Sharp Bunching

![Graph showing changes in EITC refund with respect to ZIP-3 self-employed sharp bunching. The graph includes two lines: one for phase in (β = 14.2, 1.55) and one for phase out (β = 5.2, 0.69).]
Extensive Margin: Changes in Fraction Working around First Birth

The graph illustrates the change in the percent of individuals with positive W-2 earnings around the first birth. The x-axis represents ZIP-3 self-employed sharp bunching, while the y-axis shows the change in percent of individuals with positive W-2 earnings.

A regression line is shown, with the equation $\beta = 0.54\% (0.05)$. The implied effect on credit is $5.8 (0.52)$, indicating a positive relationship between self-employment and the percent of individuals with positive W-2 earnings around the first birth.
## Impact of EITC on Wage Earnings

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Baseline Specification</th>
<th>Large Firms Only</th>
<th>With ZIP-3 Fixed Effects</th>
<th>Placebo Test: 3rd Child</th>
</tr>
</thead>
<tbody>
<tr>
<td>ZIP-3 Sharp Bunching</td>
<td>$19.4</td>
<td>$14.4</td>
<td>$34.7</td>
<td>-$1.89</td>
</tr>
<tr>
<td></td>
<td>(1.61)</td>
<td>(1.14)</td>
<td>(3.20)</td>
<td>(0.63)</td>
</tr>
</tbody>
</table>
## Impact of EITC on Wage Earnings

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Phase-in vs. Phase-out</th>
<th>Extensive Margin</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sim. Phase-in Credit</td>
<td>Sim. Phase-out Credit</td>
</tr>
<tr>
<td>ZIP-3 Sharp Bunching</td>
<td>$14.2</td>
<td>$5.2</td>
</tr>
<tr>
<td></td>
<td>(1.55)</td>
<td>(0.69)</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
## Impact of EITC on Income Distribution

<table>
<thead>
<tr>
<th></th>
<th>Percent of EITC-Eligible Households Below Threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>50% of Poverty Line</td>
</tr>
<tr>
<td>No EITC Counterfactual</td>
<td>13.2%</td>
</tr>
<tr>
<td>EITC, No Behavioral</td>
<td>8.9%</td>
</tr>
<tr>
<td>Response</td>
<td></td>
</tr>
<tr>
<td>EITC, with Avg. Behavioral Response</td>
<td>8.2%</td>
</tr>
<tr>
<td>EITC with Top Decile Behavioral Response</td>
<td>6.7%</td>
</tr>
</tbody>
</table>
### Elasticity Estimates Based on Change in EITC Refunds Around Birth of First Child

<table>
<thead>
<tr>
<th></th>
<th>Mean Elasticity</th>
<th>Phase-in Elasticity</th>
<th>Phase-out Elasticity</th>
<th>Extensive Elasticity</th>
</tr>
</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>0.21 (0.012)</td>
<td>0.31 (0.018)</td>
<td>0.14 (0.015)</td>
<td>0.19 (0.019)</td>
</tr>
<tr>
<td>Elasticity in top decile ZIP-3's</td>
<td>0.55 (0.020)</td>
<td>0.84 (0.031)</td>
<td>0.29 (0.020)</td>
<td>0.60 (0.034)</td>
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<td><strong>B. Total Earnings</strong></td>
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<tr>
<td>Elasticity in U.S. 2000-2005</td>
<td>0.36 (0.017)</td>
<td>0.65 (0.030)</td>
<td>0.11 (0.006)</td>
<td>0.36 (0.019)</td>
</tr>
<tr>
<td>Elasticity in top decile ZIP-3's</td>
<td>1.06 (0.029)</td>
<td>1.70 (0.047)</td>
<td>0.31 (0.010)</td>
<td>1.06 (0.040)</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.

- Contrary to prior findings, intensive margin responses are substantial and may even be larger than extensive margin responses

- Differences in knowledge can provide useful counterfactuals when traditional approaches are unavailable

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

  - Analyzing responses to corporate taxation