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. Difficult to find comparison groups to estimate causal impacts of policies [Meyer 1995, Gruber 2008]
  
  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 [Cogan 1981, Altonji and Paxson 1992, Chetty et al. 2011]
Overview

- We address 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 20 million households in the U.S.
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

Percent of Wage Earners - EITC Amount ($)

W-2 Wage Earnings

Income Distribution:
- Earnings Range: $0 - $40K
- Percent of Wage Earners:
  - 0% at $0
  - 1% at $10K
  - 2% at $20K
  - 3% at $30K
  - 4% at $40K

EITC Amount:
- $0 at $0
- $10K at $10K
- $20K at $20K
- $30K at $30K
- $40K at $40K
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 \( z = w l \) 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)
- With quasi-linear utility, workers with no knowledge behave as they would with no taxes
- More generally, our technique recovers compensated elasticities

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

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

$$\Rightarrow \Delta F(z \mid \tau) = F(z \mid \tau > 0, \tilde{\lambda}_c) - F(z \mid \tau > 0, \lambda_c = 0)$$
Let $\mu_c$ represent a measure of bunching in earnings around kink $K$

- Ex: size of EITC refund, fraction of individuals in plateau

We identify $\mu_c(\lambda_c = 0)$ using an estimating equation of the form

$$\mu_c = \alpha + \beta \lambda_c + \eta_c$$

- Key orthogonality condition to estimate $\beta$: $\lambda_c \perp \eta_c$

Identification requires that cities with different levels of knowledge do not have other attributes that affect the earnings distribution

- 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)
  - For non-filers, we impute income and ZIP from W-2’s
  - For joint filers, code income as total household income or 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

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income</td>
<td>$23,641</td>
</tr>
<tr>
<td>Self Employed</td>
<td>17.1%</td>
</tr>
<tr>
<td>Married</td>
<td>29%</td>
</tr>
<tr>
<td>Number of Children</td>
<td>1.11</td>
</tr>
<tr>
<td>Female (among single filers)</td>
<td>61%</td>
</tr>
</tbody>
</table>
Critical distinction: wage earnings vs. self-employment income

- Self employed = filers with any Schedule C income
- Wage earners = filers with no Schedule C 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

Analyze misreporting due to EITC using National Research Program Tax Audit data (joint with Peter Ganong, Kara Leibel, Alan Plumley)
2008 Federal EITC Schedule for a Single Filer with Children

Taxable Income (Real 2010 $)

EITC Credit

- $0
- $1K
- $2K
- $3K
- $4K
- $5K

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

Percent of Filers

Taxable Income Relative to First Kink of EITC Schedule

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

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:
  $$f_c = \theta_c \lambda_c$$
Recall ideal estimating equation from the model

$$\mu_c = \alpha + \beta \lambda_c + \eta_c$$

We instead estimate the feasible regression

$$\mu_c = \alpha + \hat{\beta} f_c + \eta_c$$

Our proxy $f_c$ is a noisy measure of true knowledge $\lambda_c$

- Differences across cities in $f_c$ may be due to other determinants of tax compliance $\theta_c$ rather than knowledge $\lambda_c$
- This measurement error attenuates estimate of $\beta$

$\Rightarrow$ Lower bound on estimated impact of EITC
Empirical Implementation: Point Estimate

- Stronger assumption: No sharp bunching $\rightarrow$ no knowledge about EITC schedule

$$f_c = 0 \rightarrow \lambda_c = 0$$

- Under this assumption, we obtain a point estimate of impact of EITC on earnings distribution with average knowledge level in economy

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

- After showing main results, we present evidence suggesting that individuals in low bunching areas completely ignore EITC
Outline of Empirical Analysis

- Step 1: Develop a proxy for knowledge about the EITC in each neighborhood using sharp bunching among self-employed
Income Distribution in Kansas

Percent of Filers

Income Relative to 1st Kink

-$10K  $0  $10K  $20K
Self-employed 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 self-employed bunching across the United States
Self-Employed Sharp Bunching in 1996

Map showing the percentage of self-employed individuals in different states in 1996.

Color Legend:
- 3.7 – 4.2%
- 3.5 – 3.7%
- 3.1 – 3.5%
- 2.8 – 3.1%
- 2.3 – 2.8%
- 1.8 – 2.3%
- 1.7 – 1.8%
- 1.4 – 1.7%
- 1.2 – 1.4%
- 0 – 1.2%
Self-Employed Sharp Bunching in 1999

3.7 – 4.2%
3.5 – 3.7%
3.1 – 3.5%
2.8 – 3.1%
2.3 – 2.8%
1.8 – 2.3%
1.7 – 1.8%
1.4 – 1.7%
1.2 – 1.4%
0 – 1.2%
Self-Employed Sharp Bunching in 2002

Map showing the distribution of self-employed sharp bunching across the United States in 2002. The map uses a color gradient to represent different percentage ranges:

- 3.7 – 4.2%
- 3.5 – 3.7%
- 3.1 – 3.5%
- 2.8 – 3.1%
- 2.3 – 2.8%
- 1.8 – 2.3%
- 1.7 – 1.8%
- 1.4 – 1.7%
- 1.2 – 1.4%
- 0 – 1.2%
Self-Employed Sharp Bunching in 2005

Map showing the distribution of self-employed sharp bunching across the U.S., with states colored according to the percentage range:

- 3.7 – 4.2%
- 3.5 – 3.7%
- 3.1 – 3.5%
- 2.8 – 3.1%
- 2.3 – 2.8%
- 1.8 – 2.3%
- 1.7 – 1.8%
- 1.4 – 1.7%
- 1.2 – 1.4%
- 0 – 1.2%
Self-Employed Sharp Bunching in 2008

<table>
<thead>
<tr>
<th>Percentage Range</th>
<th>States</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.7 – 4.2%</td>
<td>New York, New Jersey, West Virginia, District of Columbia</td>
</tr>
<tr>
<td>3.5 – 3.7%</td>
<td>Rhode Island, Connecticut, Maine, New Hampshire</td>
</tr>
<tr>
<td>3.1 – 3.5%</td>
<td>Massachusetts, Vermont, Pennsylvania, Delaware, Ohio, Indiana, Michigan, Wisconsin, Missouri, North Dakota, South Dakota, Nebraska, Kansas, Oklahoma, Arkansas, Minnesota, Iowa, Wisconsin, Michigan, Ohio, Pennsylvania, New Jersey, New York</td>
</tr>
<tr>
<td>2.8 – 3.1%</td>
<td>Illinois, Kentucky, Virginia, Alabama, Tennessee, North Carolina, South Carolina, Georgia, Florida, Texas, California, Oregon, Nevada, Arizona, Utah, Colorado, New Mexico, Montana, Idaho, Washington, Alaska, Hawaii</td>
</tr>
<tr>
<td>2.3 – 2.8%</td>
<td>Montana, Idaho, Washington, Oregon, Nevada, Utah, Colorado, New Mexico, Arizona, California, Texas, Florida, Illinois, Michigan, Ohio, Pennsylvania, New York, New Jersey</td>
</tr>
<tr>
<td>1.8 – 2.3%</td>
<td>Mississippi, Louisiana, Arkansas, Oklahoma, Kansas, Missouri, Minnesota, Iowa, Wisconsin, Michigan, Ohio, Pennsylvania, New York, New Jersey</td>
</tr>
<tr>
<td>1.7 – 1.8%</td>
<td>Alabama, Tennessee, North Carolina, South Carolina, West Virginia, Kentucky, Georgia, Florida, Illinois, Michigan, Ohio, Pennsylvania, New York, New Jersey</td>
</tr>
<tr>
<td>1.4 – 1.7%</td>
<td>Alabama, Tennessee, North Carolina, South Carolina, West Virginia, Kentucky, Georgia, Florida, Illinois, Michigan, Ohio, Pennsylvania, New York, New Jersey</td>
</tr>
<tr>
<td>1.2 – 1.4%</td>
<td>Alabama, Tennessee, North Carolina, South Carolina, West Virginia, Kentucky, Georgia, Florida, Illinois, Michigan, Ohio, Pennsylvania, New York, New Jersey</td>
</tr>
<tr>
<td>0 – 1.2%</td>
<td>Alabama, Tennessee, North Carolina, South Carolina, West Virginia, Kentucky, Georgia, Florida, Illinois, Michigan, Ohio, Pennsylvania, New York, New Jersey</td>
</tr>
</tbody>
</table>
Self-Employed Sharp Bunching in 2008 by 3-Digit Zip Code in Kansas, Louisiana, Oklahoma, and Texas

<table>
<thead>
<tr>
<th>Percentage Range</th>
<th>Color</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.4 – 10.0%</td>
<td>Dark Red</td>
</tr>
<tr>
<td>3.2 – 4.4%</td>
<td>Red</td>
</tr>
<tr>
<td>2.5 – 3.2%</td>
<td>Orange</td>
</tr>
<tr>
<td>2.2 – 2.5%</td>
<td>Orange</td>
</tr>
<tr>
<td>1.8 – 2.2%</td>
<td>Orange</td>
</tr>
<tr>
<td>1.6 – 1.8%</td>
<td>Yellow</td>
</tr>
<tr>
<td>1.4 – 1.6%</td>
<td>Yellow</td>
</tr>
<tr>
<td>1.2 – 1.4%</td>
<td>Yellow</td>
</tr>
<tr>
<td>0.9 – 1.2%</td>
<td>Light Yellow</td>
</tr>
<tr>
<td>0.9 – 1.2%</td>
<td>Light Yellow</td>
</tr>
<tr>
<td>0 – 0.9%</td>
<td>Light Yellow</td>
</tr>
</tbody>
</table>
Income Distributions in Lowest vs. Highest Deciles of Sharp Bunching

Percent of Individuals Income Relative to First EITC Kink

Lowest Decile Bunching

Highest Decile Bunching
Outline of Empirical Analysis

- Step 1: Develop a proxy for knowledge about the EITC in each neighborhood using sharp bunching among self-employed.

- Step 2: Establish learning as a mechanism for differences in sharp bunching across neighborhoods.
Movers: Neighborhood Changes

- Look at 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*
  - Classify movers based on deciles of neighborhood response of original neighborhood and new neighborhood
Event Study of Bunching for Movers, by Destination Area

Self-Emp. Sharp Bunching for Movers

- Movers to Lowest Bunching Decile
- Movers to Middle Bunching Decile
- Movers to Highest Bunching Decile
Movers’ Income Distributions: Before Move

Percent of Movers

Income Relative to 1st Kink

- Movers to Lowest Bunching Decile
- Movers to Middle Bunching Decile
- Movers to Highest Bunching Decile
Movers’ Income Distributions: After Move

- Movers to Lowest Bunching Decile
- Movers to Middle Bunching Decile
- Movers to Highest Bunching Decile

Percent of Movers

Income Relative to 1st Kink

- $0K

- $10K

- $20K

- $30K

- $40K

- $50K

- $60K

- $70K

- $80K
Knowledge model makes strong prediction about asymmetry of effects:

- Memory: level of response in prior neighborhood should continue to matter for those who move to a low-EITC-response neighborhood

- Learning: prior neighborhood matters less when moving to a high-EITC-response neighborhood
Post-Move Distributions for Movers to **Lowest Bunching Decile** Neighborhoods

→ **Memory**: old neighborhood matters when moving to *lowest bunching decile* areas

![Graph showing the distribution of income post-move for movers from different deciles.](image-url)
Post-Move Distributions for Movers to Highest Bunching Decile Neighborhoods

Learning: Old neighborhood does not matter when moving to highest bunching decile areas

Percent of Movers

Income Relative to 1st Kink

Movers from Lowest Bunching Decile
Movers from Middle Bunching Decile
Movers from Highest Bunching Decile
Agglomeration: Sharp Bunching vs. EITC Filer Density by ZIP Code

Graph showing the relationship between log (Number of EITC Filers Per Square Mile) and Sharp Bunching percentage. The graph indicates a positive correlation.
Evolution of Sharp Bunching in Low vs. High EITC-Density Neighborhoods

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

Year:
- 1995
- 2000
- 2005
- 2010

Sharp Bunching:
- 0.5%
- 1.0%
- 1.5%
- 2.0%
- 2.5%
Sharp Bunching vs. Paid Prepared Returns in ZIP Code

Sharp Bunching by Self-Employed Taxpayers (%)
Sharp Bunching vs. Paid Prepared Returns in ZIP Code, by Preparation Status
Correlation Between EITC Bunching and Google Search Patterns

Google Search Intensity for “Tax” in ZIP Code (%)
Outline of Empirical Analysis

- Step 1: Develop a proxy for knowledge about the EITC in each neighborhood using sharp bunching among self-employed.

- Step 2: Establish learning as a mechanism for differences in sharp bunching across neighborhoods.

- 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

Percent of Wage-Earners

EITC Amount ($)

W-2 Wage Earnings

$0  $10K  $20K  $30K  $40K
W-2 Earnings Distributions in High vs. Low Bunching Decile Areas
Wage Earners with One Child

Percent of Wage Earners

W-2 Wage Earnings

Lowest Bunching Decile

Highest Bunching Decile
Difference in Earnings Distributions Across High vs. Low Bunching Areas
Wage Earners with One Child

W-2 Wage Earnings

Difference in W-2 Earnings Densities

EITC Amount ($)

All Firms
Difference in Earnings Distributions Across High vs. Low Bunching Areas
Wage Earners with One Child

Difference in W-2 Earnings Densities

EITC Amount ($)

W-2 Wage Earnings

- All Firms
- >100 Employees
Difference in Earnings Distributions Across High vs. Low Bunching Areas
Wage Earners with Two Children

W-2 Wage Earnings

Difference in W-2 Earnings Densities

EITC Amount ($)

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

All Firms
>100 Employees
Outline of Empirical Analysis

- Step 1: Develop a proxy for knowledge about the EITC in each neighborhood using sharp bunching among self-employed.

- Step 2: Establish learning as a mechanism for differences in sharp bunching across neighborhoods.

- 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?
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
Earnings Distribution in the Year of First Child Birth for Wage Earners

Income Percent of Individuals

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

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

![Graph showing simulated EITC credit amounts for wage earners around first child birth. The x-axis represents the age of the child, ranging from -4 to 4. The y-axis represents the Simulated EITC Credit, ranging from $1200 to $1600. Three lines correspond to the three deciles, showing the credit amount decreases as the age of the child increases.]
Simulated EITC Credit Amount for Wage Earners Around First Child Birth
Individuals Working at Firms with More than 100 Employees

Simulated EITC Credit

Age of Child

Lowest Bunching Decile
Middle Bunching Decile
Highest Bunching Decile
First Stage: Number of Children Claimed for Those With Zero Children Before Birth

<table>
<thead>
<tr>
<th>Age of Child</th>
<th>Lowest Bunching Decile</th>
<th>Medium Bunching Decile</th>
<th>Highest Bunching Decile</th>
</tr>
</thead>
<tbody>
<tr>
<td>-4</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>-2</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>1.5</td>
<td>1.5</td>
<td>1.5</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>2.5</td>
<td>2.5</td>
<td>2.5</td>
</tr>
<tr>
<td>4</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
</tbody>
</table>

-4: Lowest Bunching Decile
-2: Medium Bunching Decile
0: Highest Bunching Decile
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 Credit around Births for Wage Earners

Change in Simulated EITC Credit

β = 23.9 (2.53)

Neighborhood Self-Emp. Sharp Bunching

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

- For 0 to 1 Child:
  \[ \beta = 23.9 \quad (2.53) \]

- For 2 to 3 Children:
  \[ \beta = -2.36 \quad (1.65) \]

Graph showing the relationship between neighborhood self-employment sharp bunching and changes in simulated EITC credit for wage earners.
Changes in Simulated EITC Credit around Births for Wage Earners

\[ \beta = 29.6 \quad (4.17) \]
Changes in Simulated EITC Credit around Births for Wage Earners

\[ \beta = 5.60 \ (1.91) \]

\[ \beta = 29.6 \ (4.17) \]

Phase In

Phase Out
Extensive Margin: Changes in Simulated EITC Credit around First Birth

Change in Simulated EITC Credit

Neighborhood Self-Emp. Sharp Bunching
Assume that extensive margin entrants obtain average EITC refund of $1,300

Where is the increase in EITC refunds coming from?

- Phase-In: 50%
- Phase-Out: 14%
- Zero earnings (extensive margin): 17%
- Plateau: 19%
Our estimates can be used to characterize impact of EITC on income distribution taking into account behavioral responses.

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

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

Now present two pieces of evidence supporting this assumption.
Effect of Child Birth on Total Income Distribution in Highest Bunching Decile

- Percent of Individuals Before Birth:
  - 0%
  - 5%
  - 0K

- Percent of Individuals After Birth:
  - 10%
  - 15%
  - 20%
  - 25%
Effect of Child Birth on Total Income Distribution in Lowest Bunching Decile

Percent of Individuals

Income

Before Birth

After Birth

0K
10K
20K
30K
40K

0%
5%
10%
15%
20%
25%
Changes in Simulated EITC Credit around Births for Wage Earners

- **0 to 1 Child**
  - \( \beta = 23.9 \) (2.53)

- **2 to 3 Children**
  - \( \beta = -2.36 \) (1.65)

**Changes in Simulated EITC Credit around Births for Wage Earners**
## 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>No EITC Counterfactual</td>
<td>17.75</td>
<td>49.93</td>
<td>75.82</td>
<td>93.77</td>
</tr>
<tr>
<td>EITC, No Behavioral Response</td>
<td>11.33</td>
<td>35.40</td>
<td>69.81</td>
<td>92.60</td>
</tr>
<tr>
<td>EITC, with Behavioral Response</td>
<td>10.02</td>
<td>34.81</td>
<td>69.91</td>
<td>92.72</td>
</tr>
</tbody>
</table>
Average EITC refund amount for wage-earners is 7% ($140) larger due to behavioral responses, primarily from increases in earnings.

- 40% of aggregate response from the top 10% of neighborhoods.

- In neoclassical model, generating an increase of 7% in refund amount requires an intensive margin taxable income elasticity of 0.2.

Information and learning via networks are central determinants of impacts of tax policy.

- Differences in knowledge can be used to identify causal impacts of other policies where traditional counterfactuals are unavailable.

- Ex: impacts of social security on retirement behavior.