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 federal policies:

   1. Difficult to find counterfactuals to estimate causal impacts of policy changes [Meyer 1995, Gruber 2008]

   2. Difficult to identify steady-state impacts from short-run responses

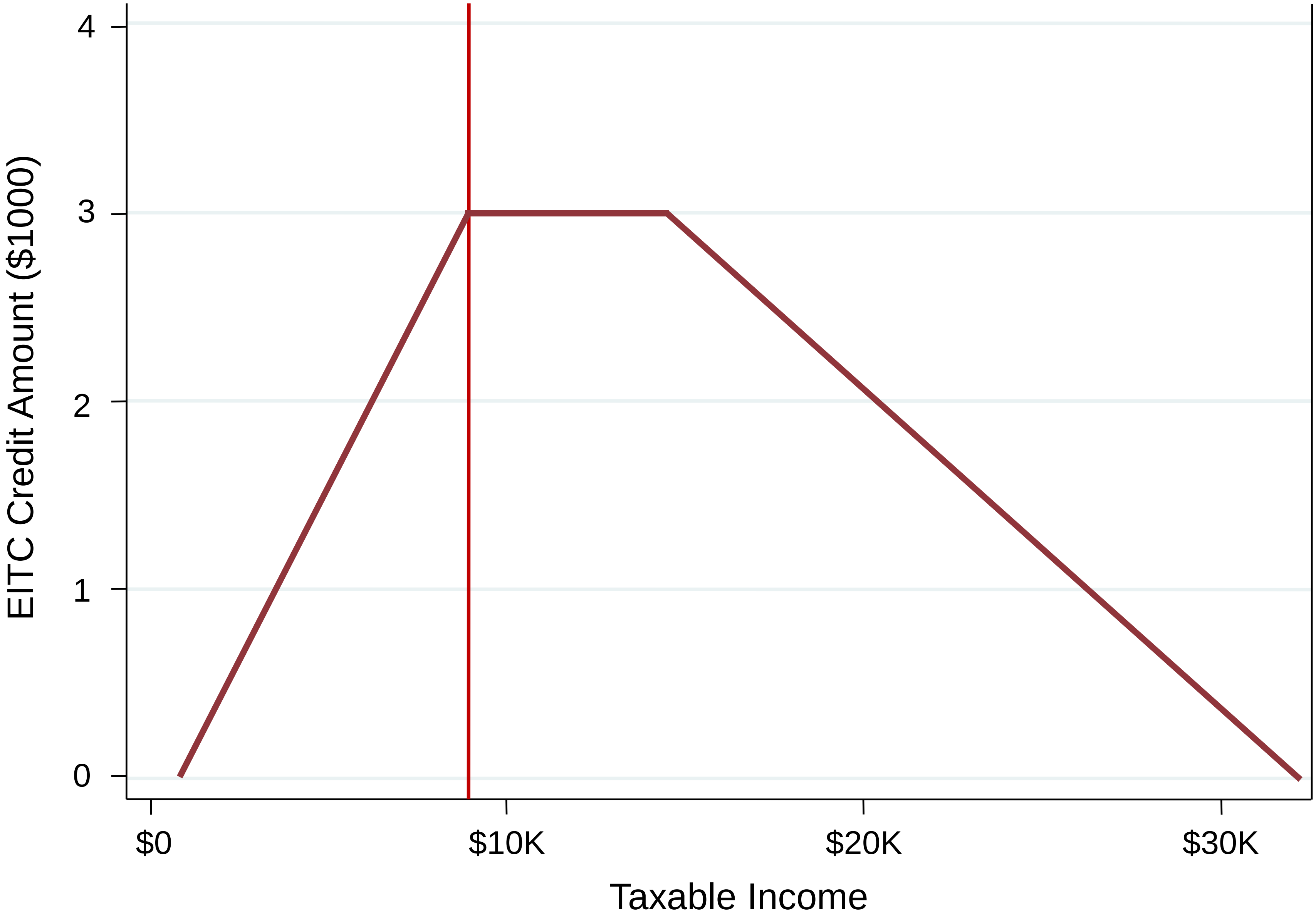
      - Many people are uninformed about tax and transfer policies [Brown 1968, Bises 1990, Chetty and Saez 2009]

      - 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
  - Key idea: use cities with low levels of information about tax policies as counterfactuals 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.

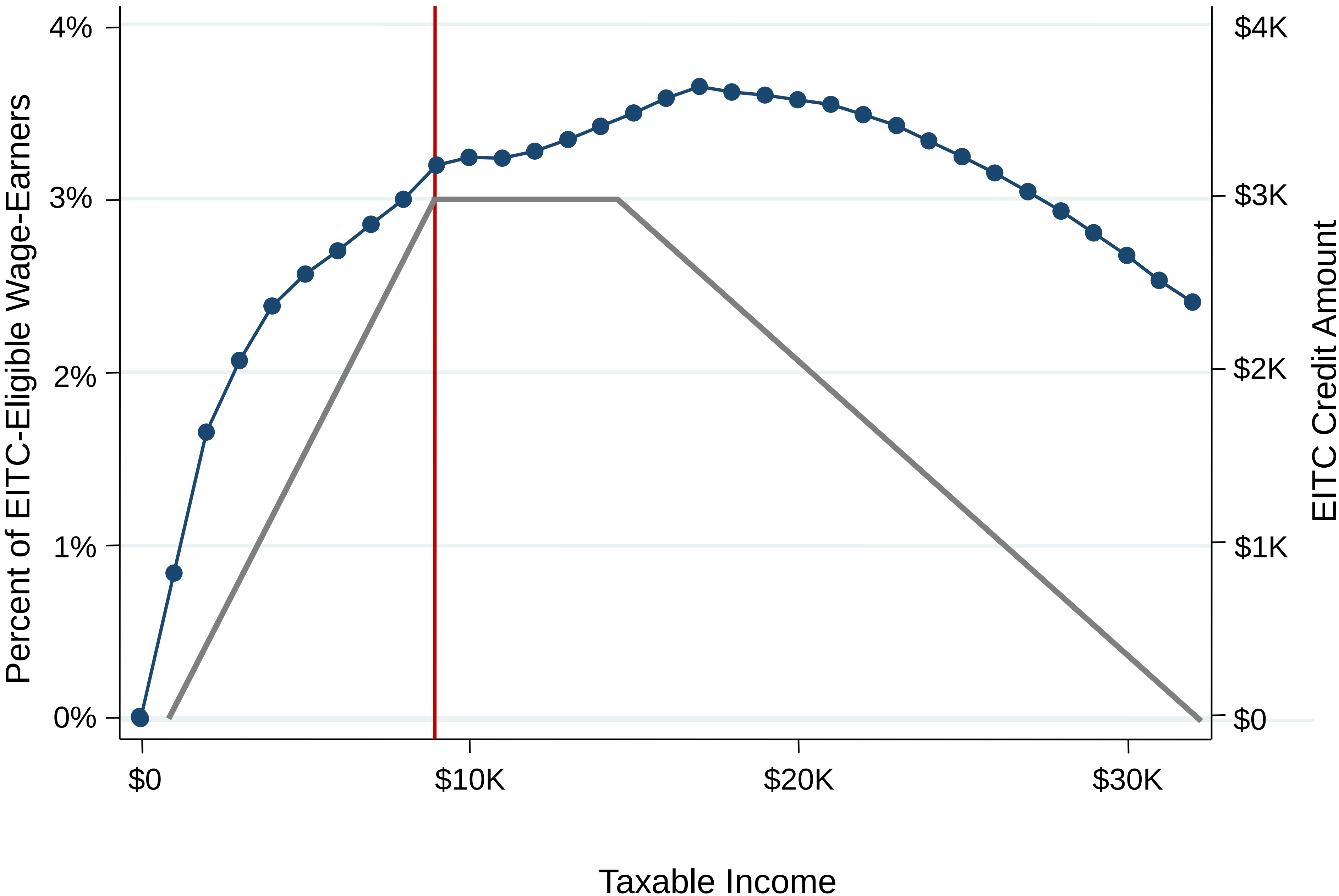
Earned Income Tax Credit Schedule for Single Earners with One Child



Overview

- Large literature has studied the impacts of EITC on labor supply
  [Eissa and Liebman 1996, Meyer and Rosenbaum 2001, Meyer 2002, Grogger 2003, Hoynes 2004, Gelber and Mitchell 2011]
  - Clear evidence of impacts on participation (extensive margin)
  - But mixed evidence on impacts of EITC on earnings distribution (intensive margin)
  - Lack of information and adjustment costs have greater impact on intensive margin since gains from optimization are 2^{nd}-order [Chetty 2011]

Income Distribution for Single Wage Earners with One Child



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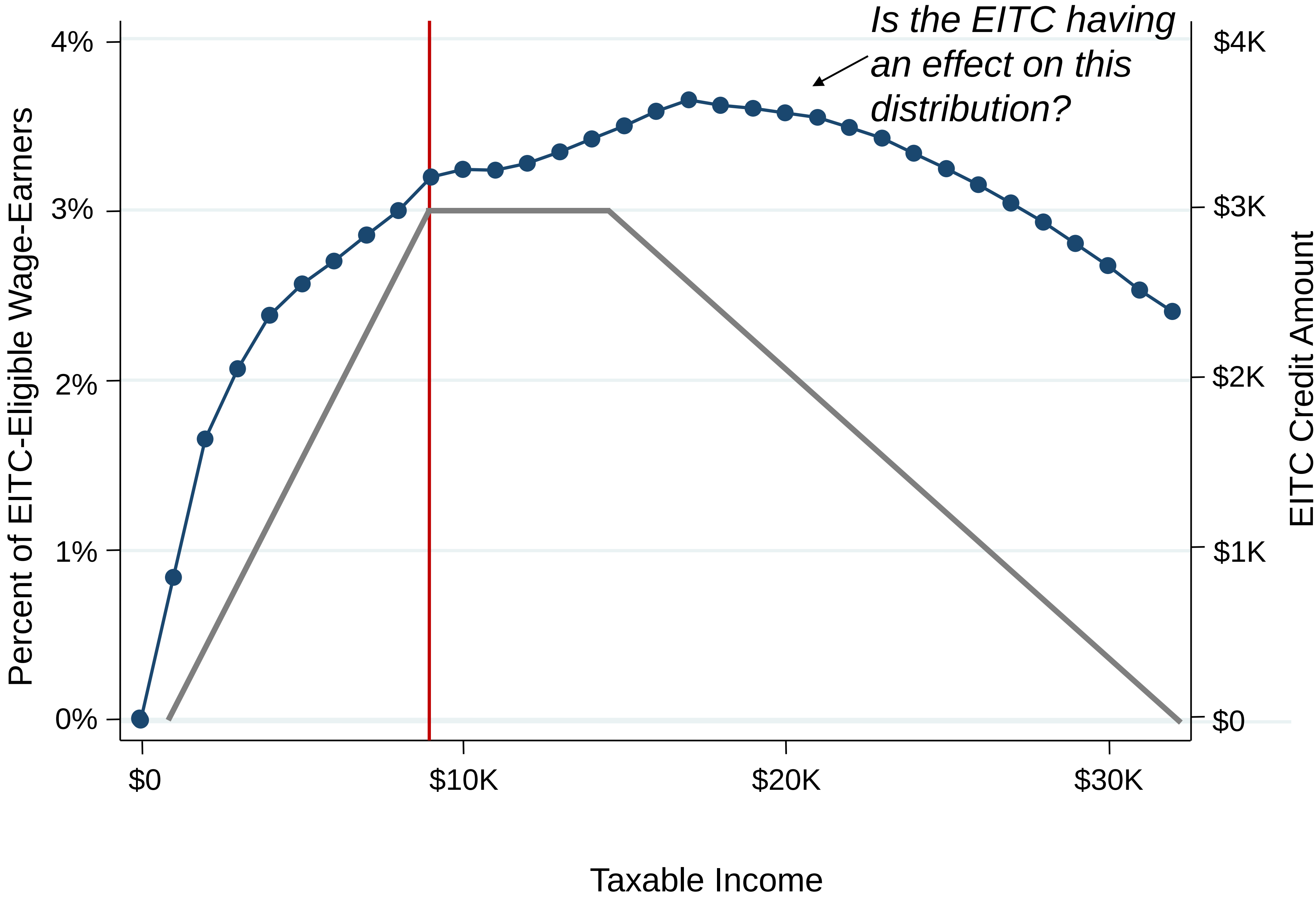
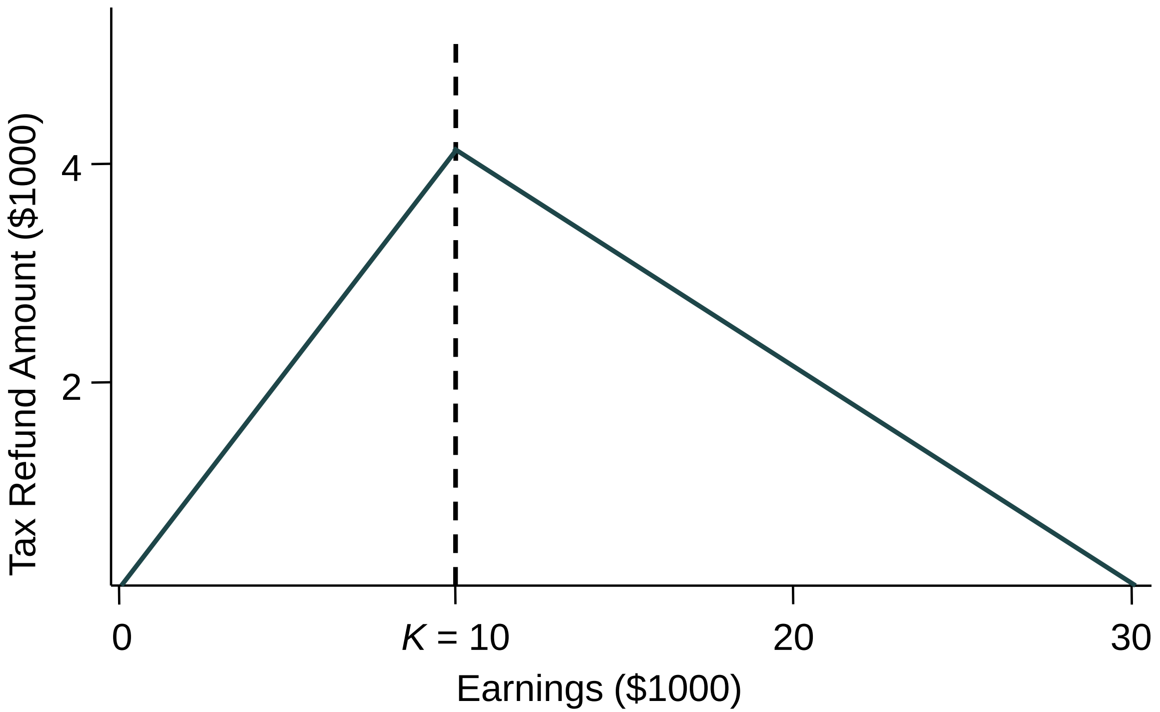


Outline

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

Stylized Model: Tax System

- Workers face a two-bracket income tax system $\tau = (\tau_1, \tau_2)$
  - 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 reported income is K



Stylized Model: Worker Behavior

- Workers choose earnings $z = wl$ to maximize quasilinear utility $u(c,l)$
  - Because of frictions, workers cannot control labor supply perfectly
- Utility maximization therefore produces diffuse "broad bunching" around kink point K rather than a point mass
  - Diffuse response makes it difficult to estimate elasticities using neoclassical non-linear budget set methods (e.g. Hausman 1981)

Neighborhoods

- Cities indexed by $c = 1,...,N$
- Cities differ only in one attribute: knowledge of tax code
- In city c, fraction λ_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:

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

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

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

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

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

Identifying Tax Policy Impacts

- Let μ_c represent a measure of "broad bunching" in earnings around kink K
  - Ex: size of EITC refund, fraction of individuals in plateau

- We identify $\mathbb{E}(\mu \mid \lambda = 0)$ using an estimating equation of the form

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

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

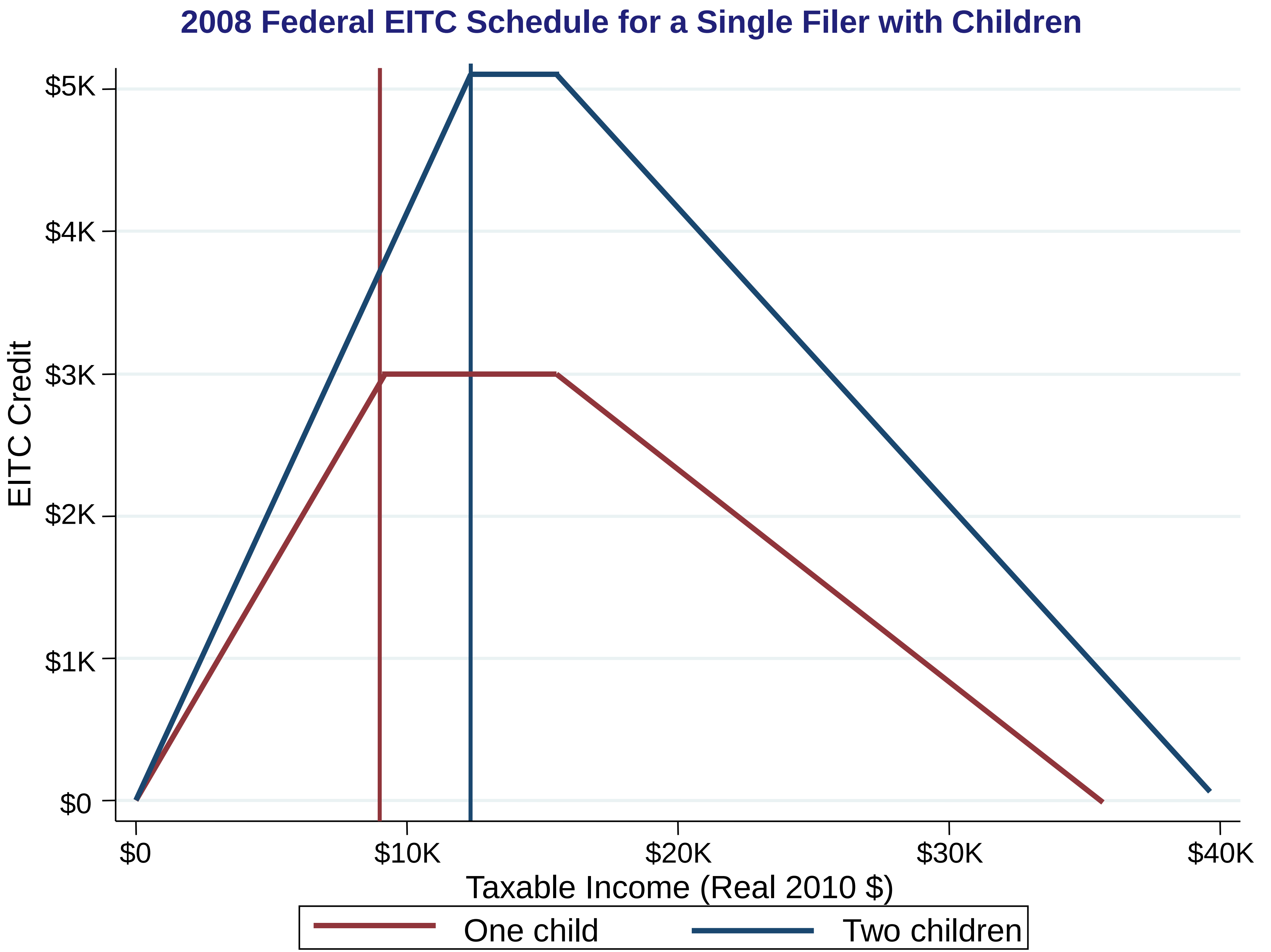
- Selected data from population of U.S. income tax returns, 1996-2009
  - Includes 1040's and all information forms (e.g. W-2's)
  - For non-filers, we impute income and ZIP from W-2's
- Sample restriction: individuals who at least once between 1996-2009: (1) file a tax return, (2) have income < $40,000, (3) claim a dependent
- Sample size after restrictions:
  - 77.6 million individuals
  - 1.09 billion person-year observations on income

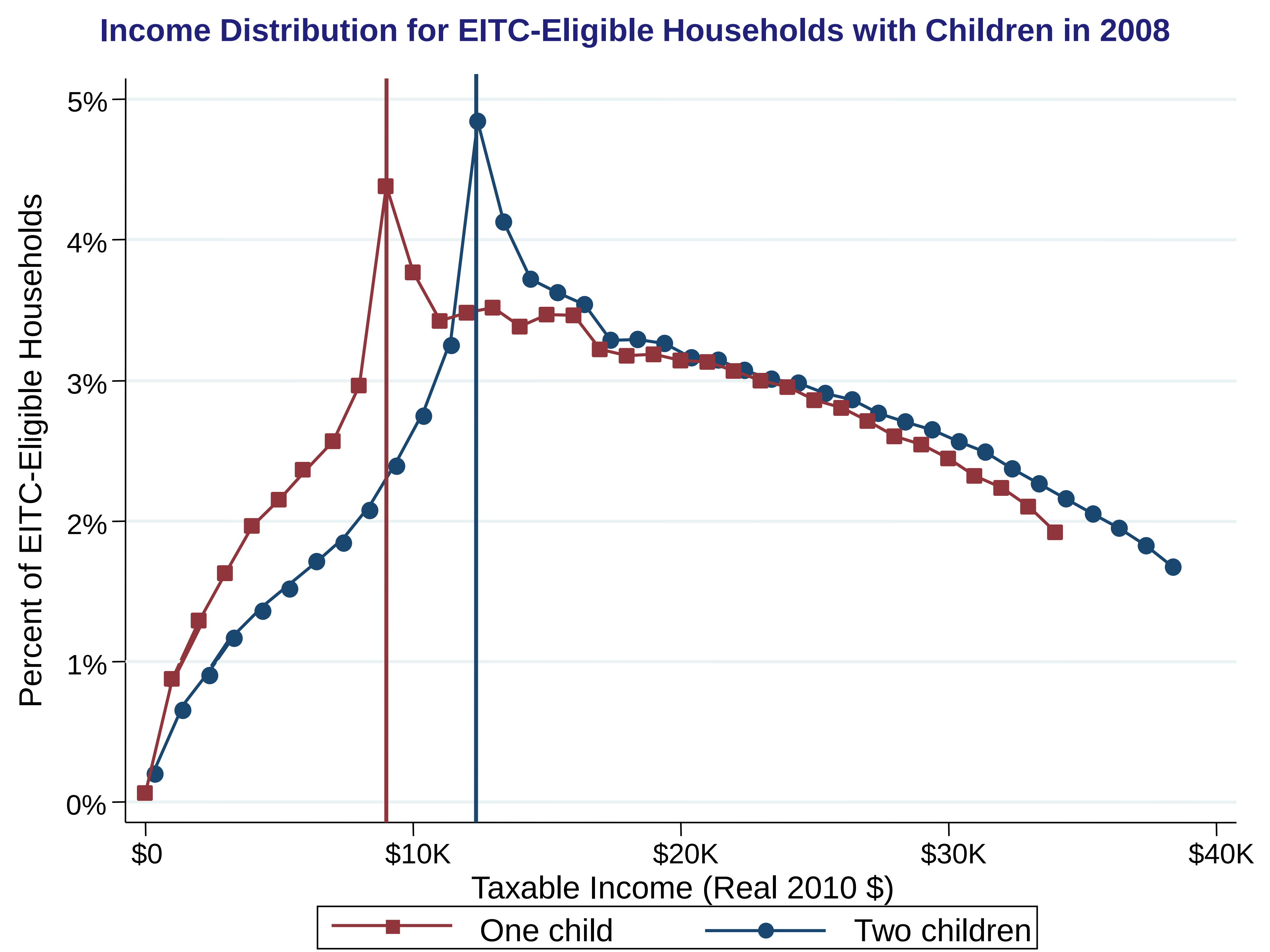
Summary Statistics

Variable	Mean
Income	$21,175
Self Employed	9.1%
Married	24%
Number of Children	0.78
Female (among singles)	58%

Self Employment Income vs. Wage Earnings

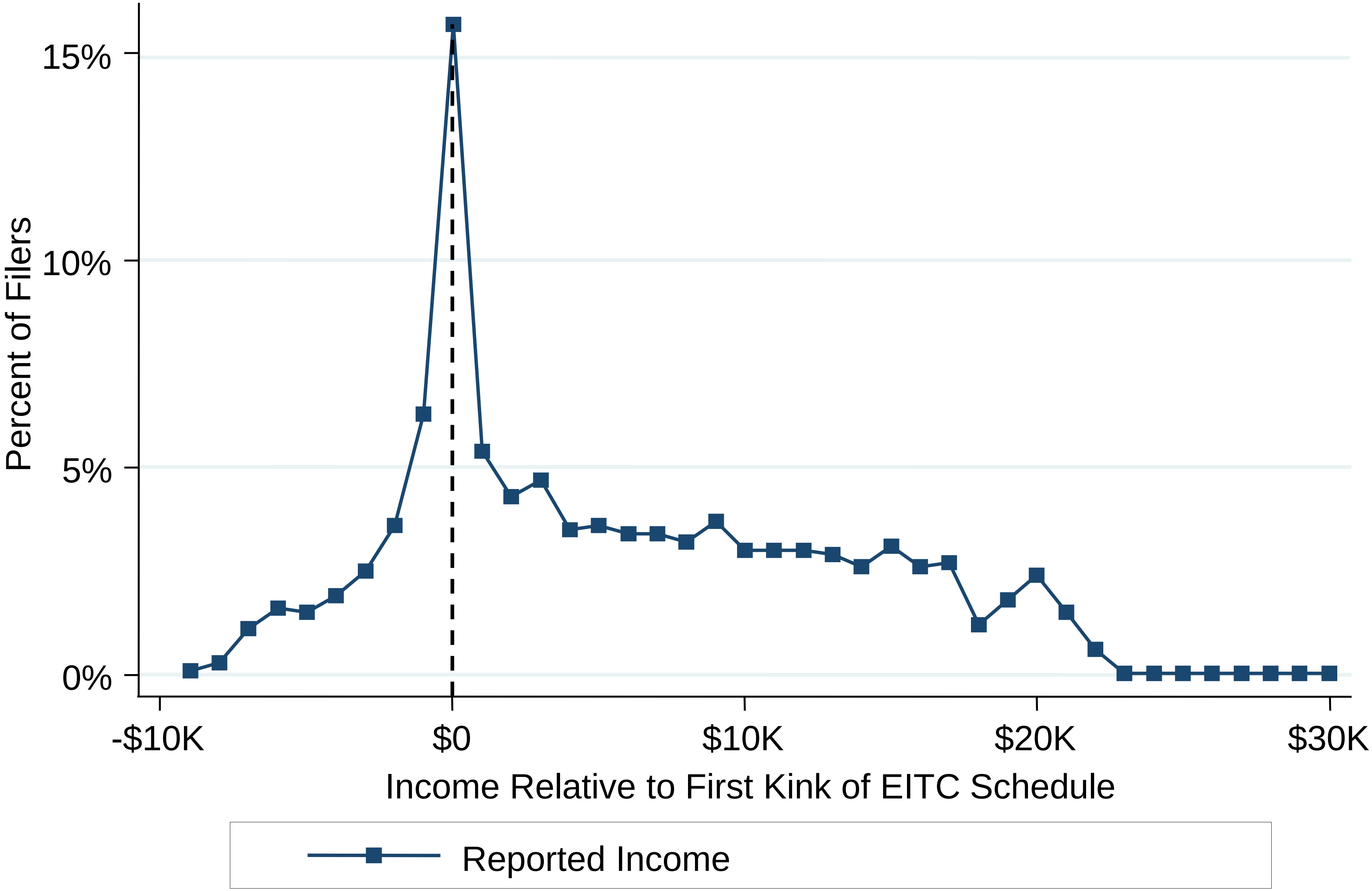
- Critical distinction: wage earnings vs. self-employment income
  - Self employed = filers with any Schedule C income
  - Wage earners = filers with no Schedule C income
- Self-employment income is self-reported → easy to manipulate
- Wage earnings are directly reported to IRS by employers
  - Therefore more likely to reflect "real" earnings behavior
- Analyze misreporting due to EITC using National Research Program Tax Audit data


2008 Federal EITC Schedule for a Single Filer with Children
EITC Credit
$0
$1K
$2K
$3K
$4K
$5K
$0
$10K
$20K
$30K
$40K
Taxable Income (Real 2010 $)
One child
Two children

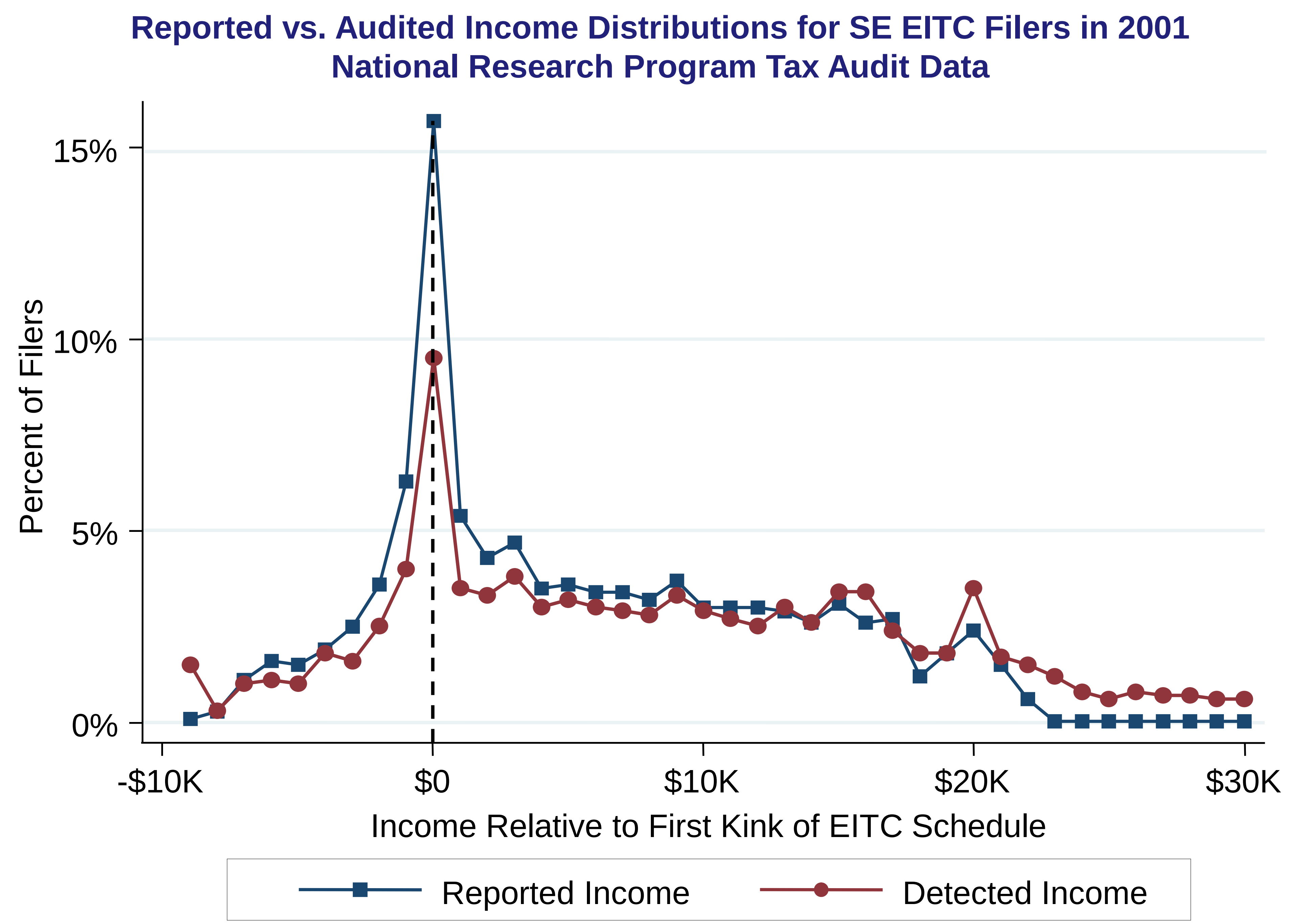


Income Distribution for EITC-Eligible Households with Children in 2008
Percent of EITC-Eligible Households
0%
1%
2%
3%
4%
5%
$0
$10K
$20K
$30K
$40K
Taxable Income (Real 2010 $)
One child
Two children

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.



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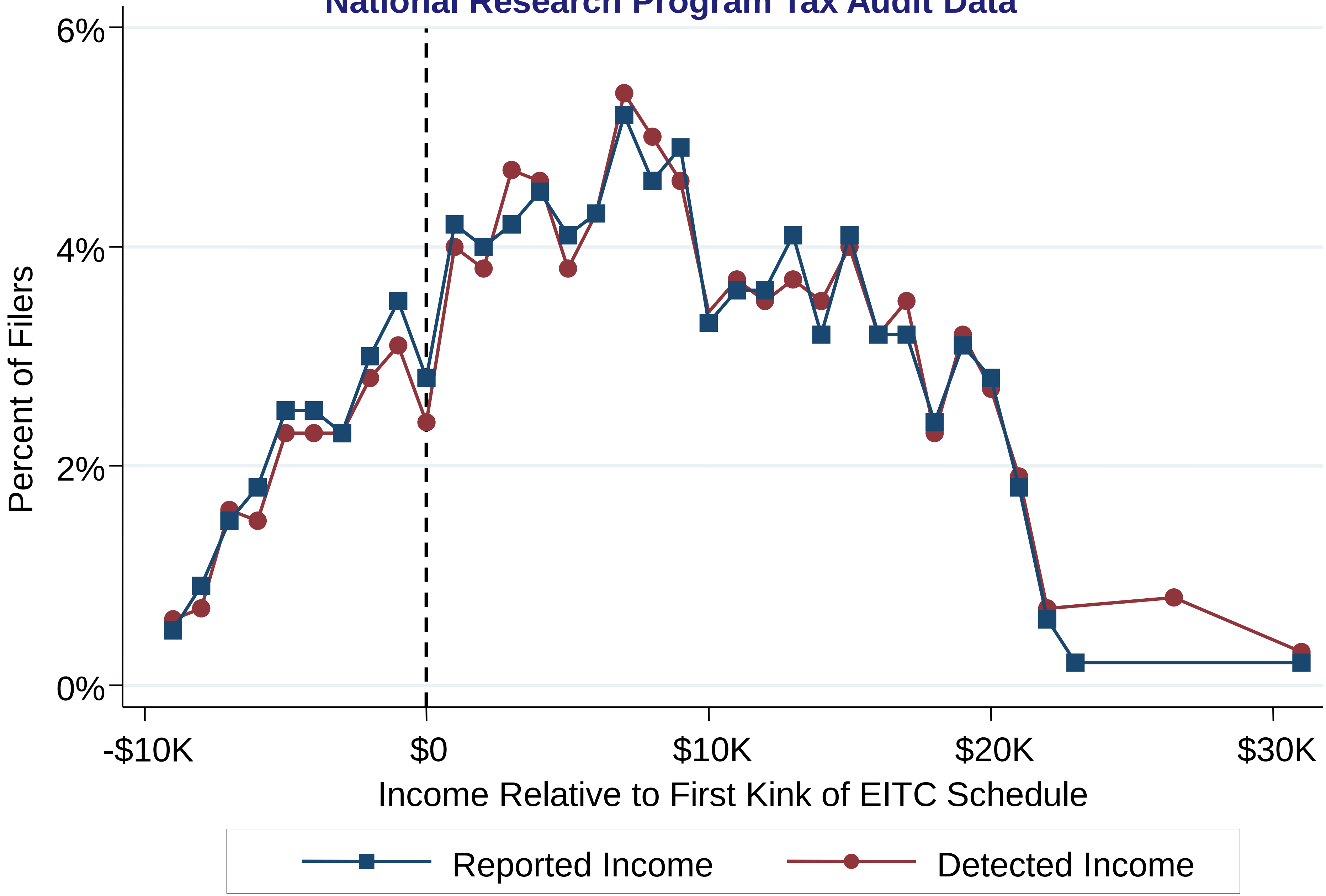
Reported vs. Audited Income Distributions for EITC Wage Earners with Children
National Research Program Tax Audit Data



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Empirical Implementation: Proxy for Knowledge

- We proxy for knowledge λ_c using sharp bunching at refund-maximizing kink among the self-employed
  - Intuition: use amount of misreporting to measure local tax knowledge

Reported vs. Audited Income Distributions for SE EITC Filers in 2001
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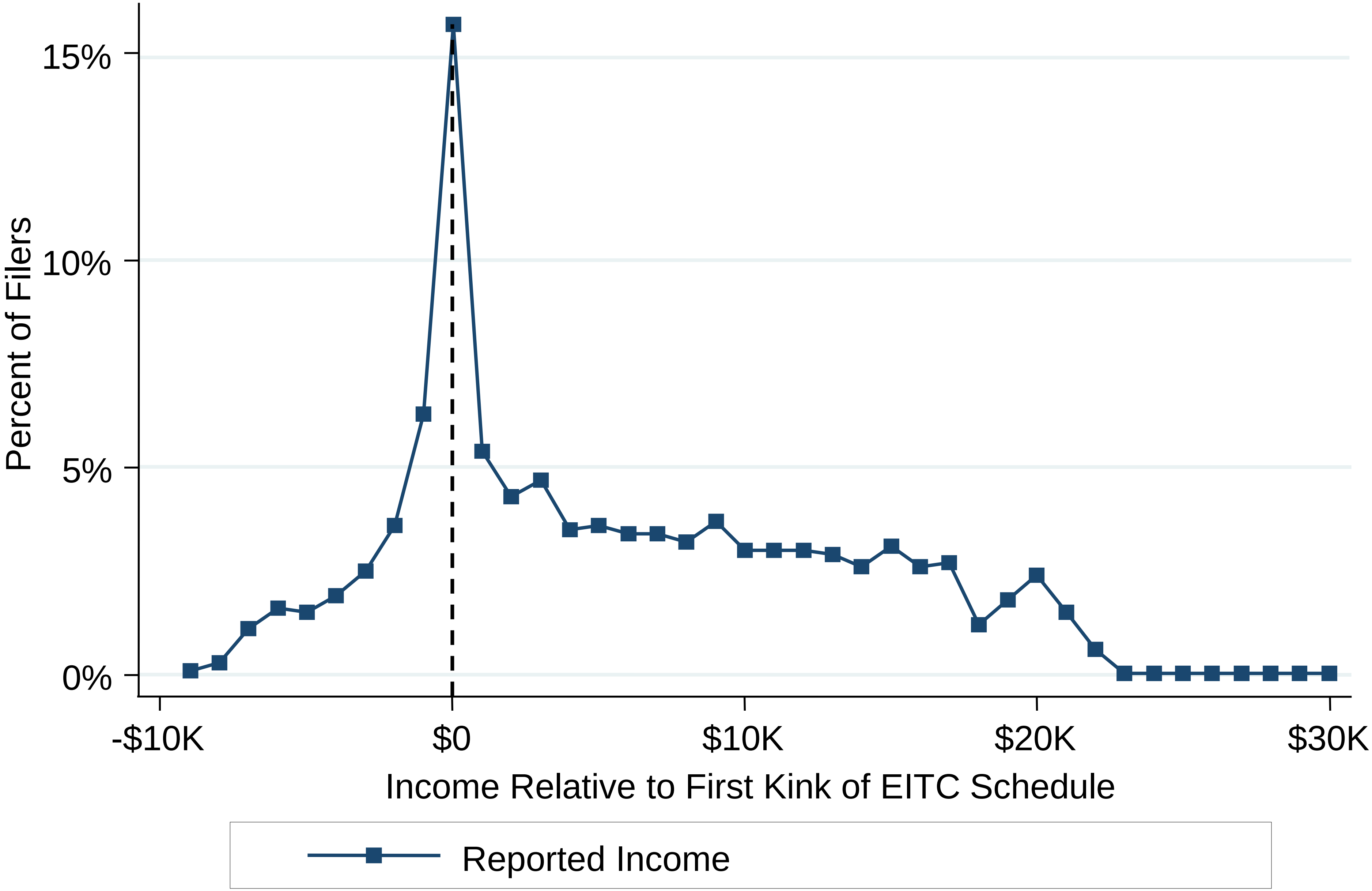

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Empirical Implementation: Proxy for Knowledge

- We proxy for knowledge λ_c using sharp bunching at refund-maximizing kink among the self-employed
  - Intuition: use amount of misreporting to measure local tax knowledge
- Formally, workers make two choices: earnings (z_i) and reported income $(\hat{z}_i)$
  - Fraction θ_c of workers face 0 cost of non-compliance → report $\hat{z}_i = K$
  - Remaining workers face infinite cost of non-compliance → set $\hat{z}_i = z_i$
- Fraction who report $\hat{z}_i = K$ is proportional to local knowledge:

$$f_c = \theta_c \lambda_c$$

Empirical Implementation

- 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 λ_c
  - Differences across cities in f_c may be due to other determinants of tax compliance θ_c rather than knowledge λ_c
  - This measurement error attenuates estimate of β

→ Lower bound on estimated impact of EITC

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
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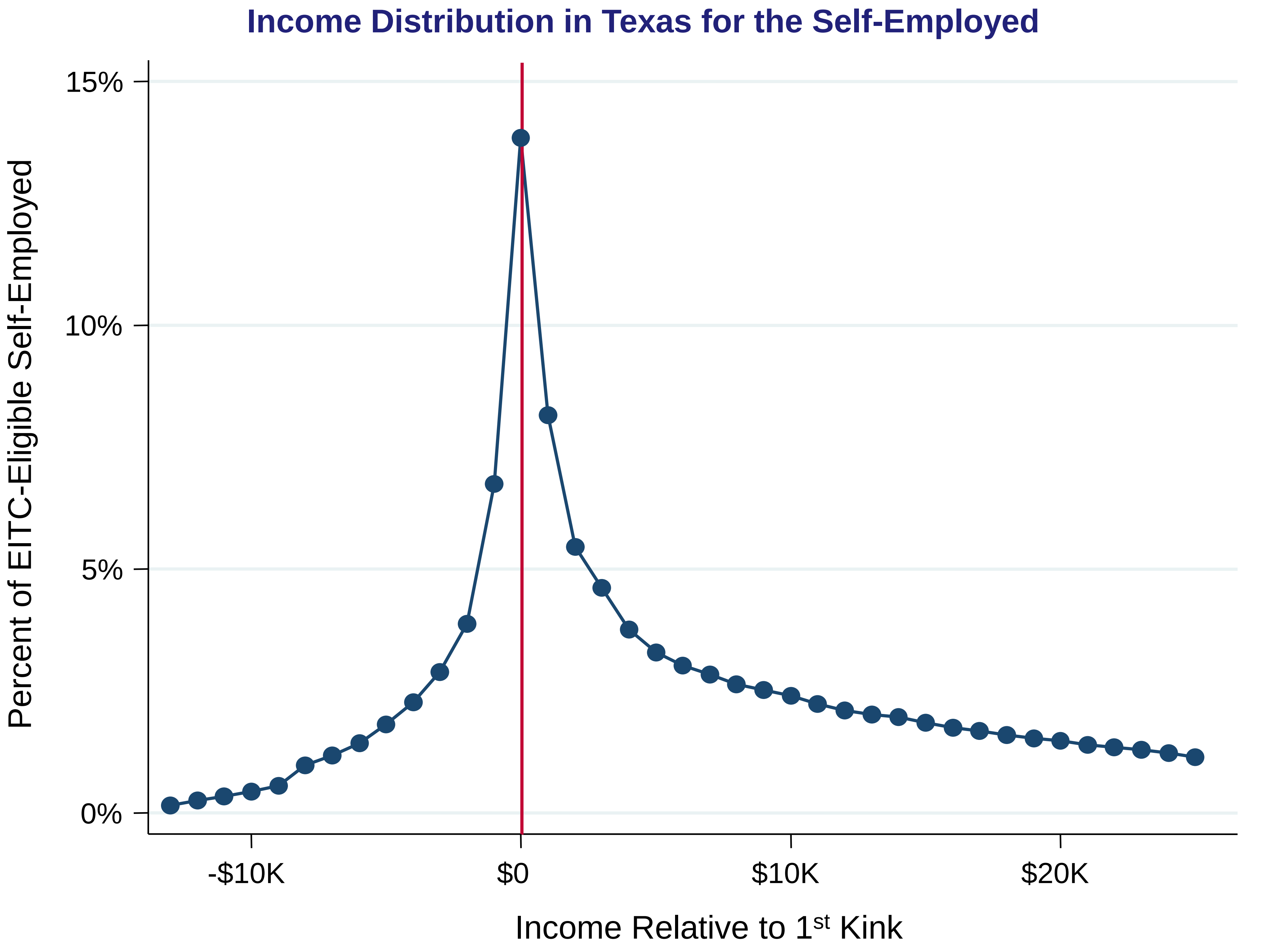
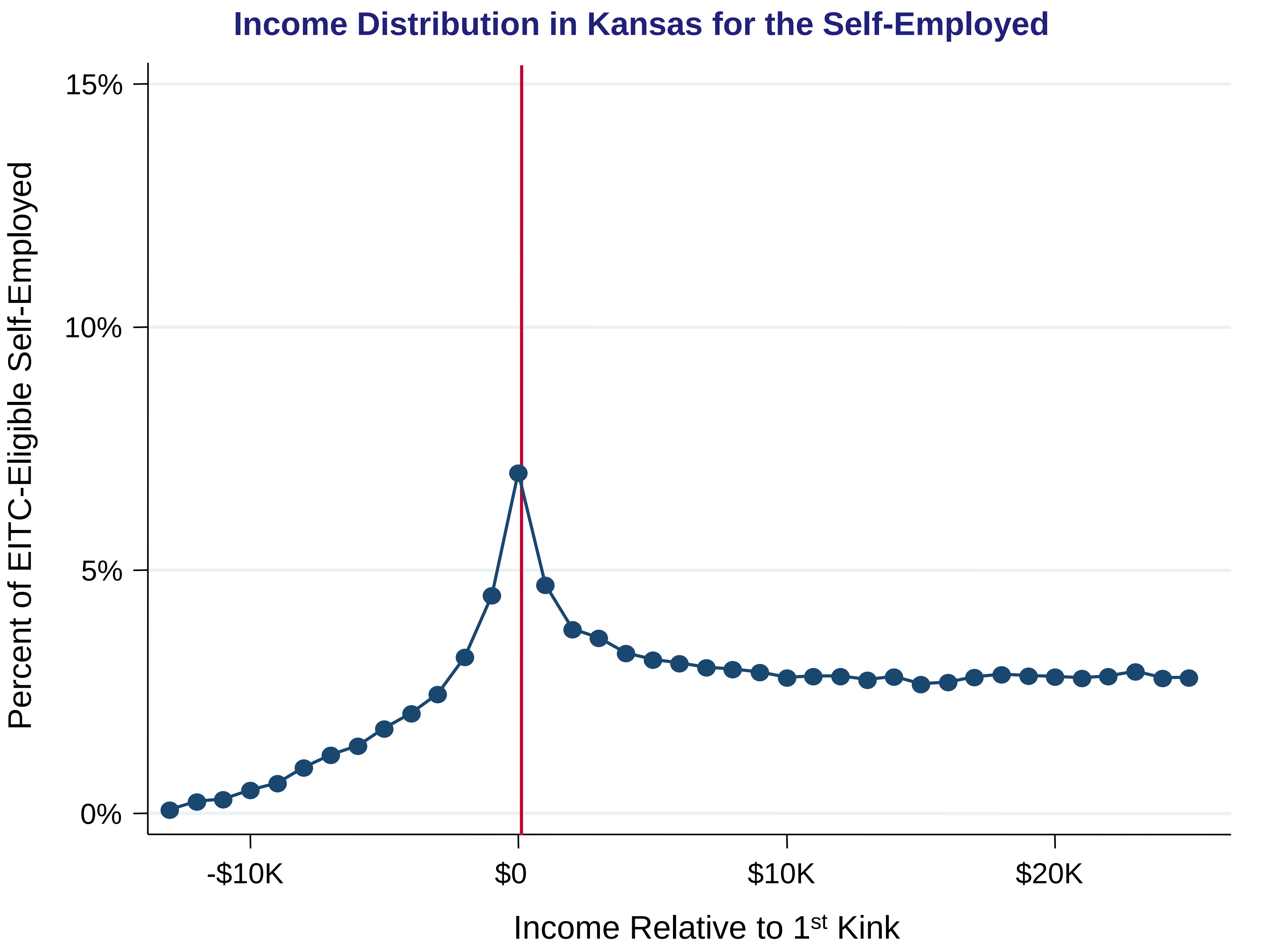
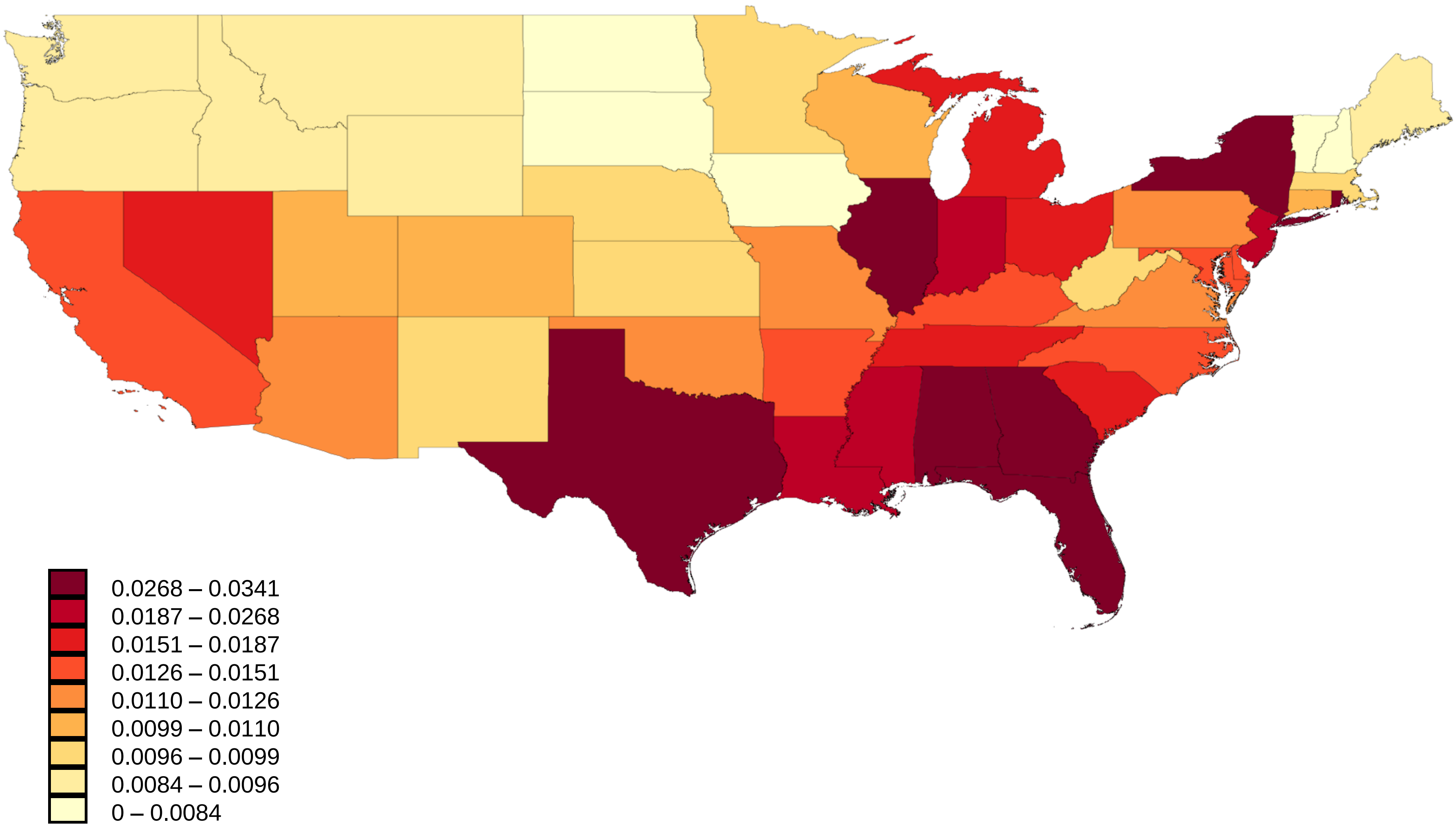

Income Distribution in Texas for the Self-Employed
15%
10%
5%
0%
Percent of EITC-Eligible Self-Employed
-$10K
$0
$10K
$20K
Income Relative to 1st Kink


Income Distribution in Kansas for the Self-Employed
15%
10%
5%
0%
Percent of EITC-Eligible Self-Employed
-$10K
$0
$10K
$20K
Income Relative to 1st Kink

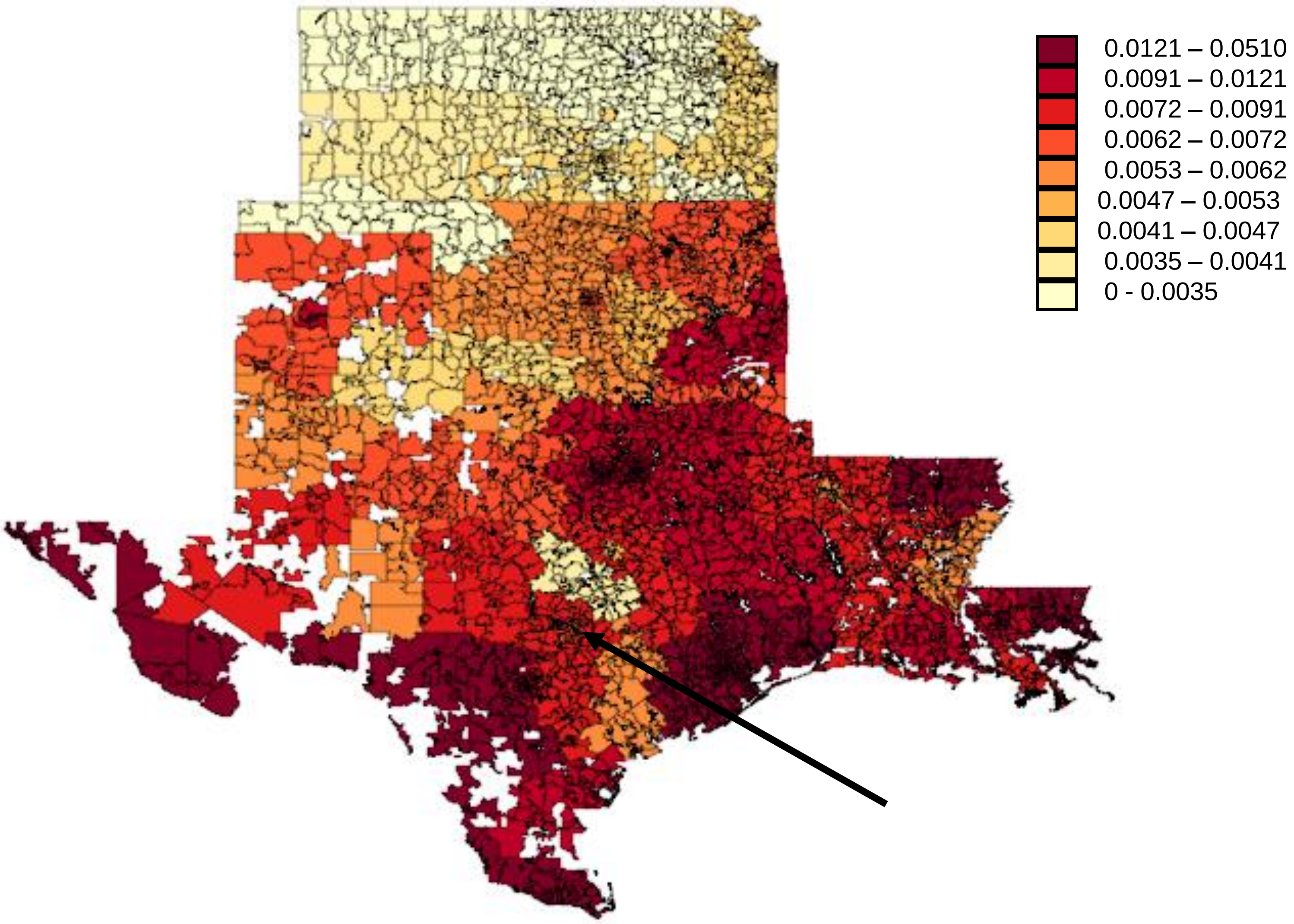
Neighborhood-Level Measure of Bunching

- 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

Self-Employed Sharp Bunching by State in 2008



Self-Employed Sharp Bunching in 2008
by 3-Digit Zip Code in Kansas, Louisiana, Oklahoma, and Texas



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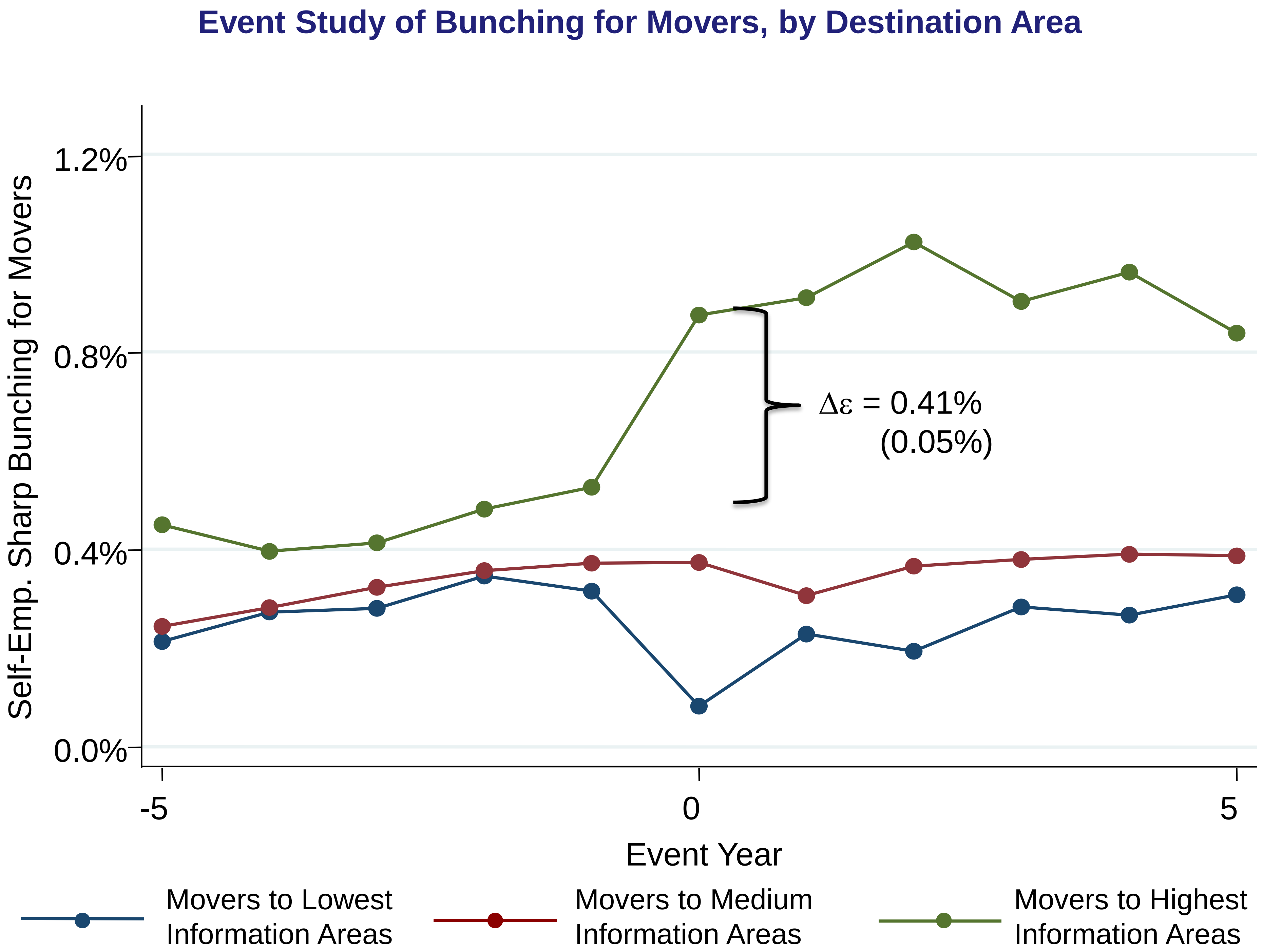
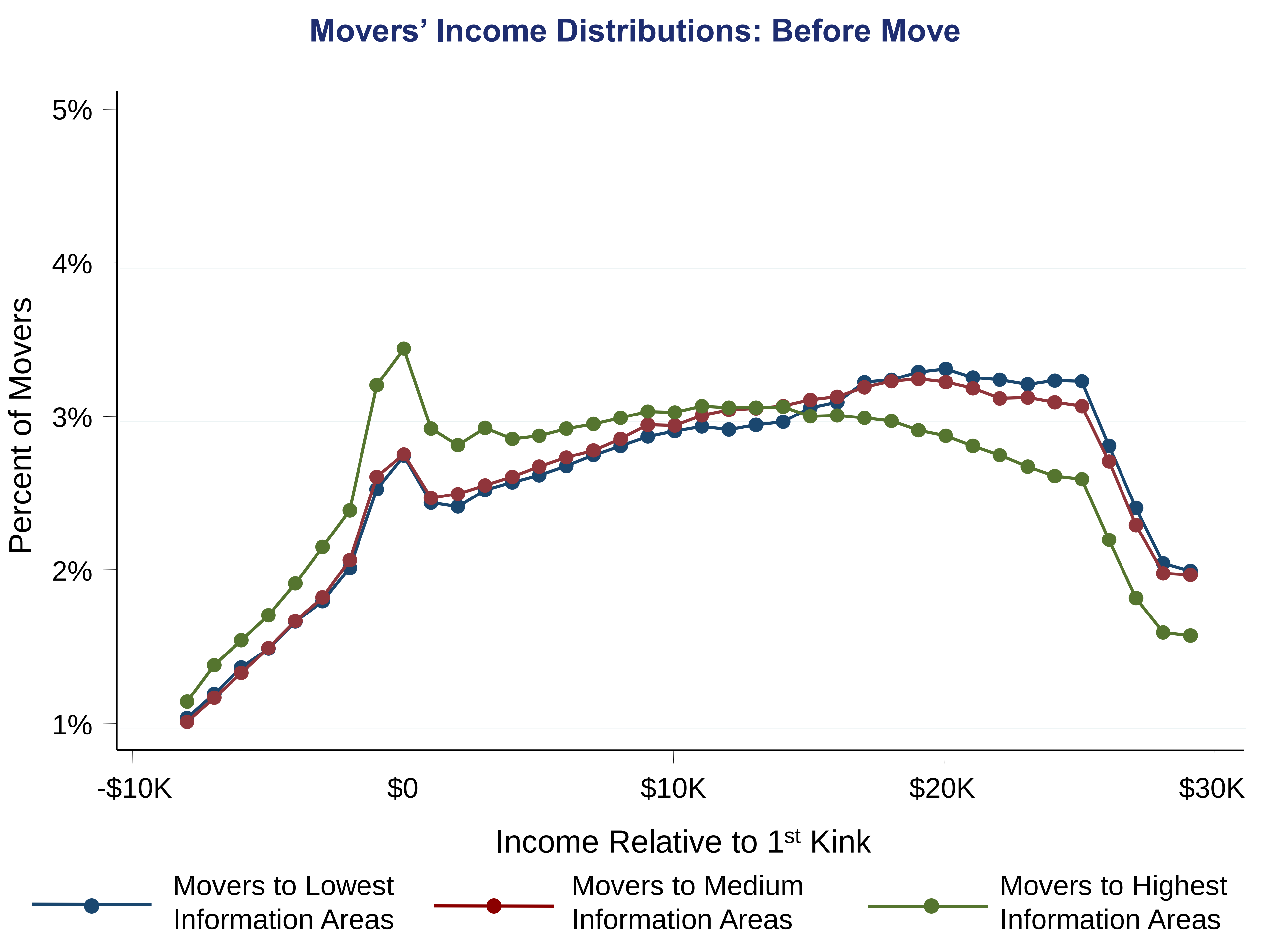
Are Neighborhood Effects Driven by Knowledge?

- Variation in sharp bunching could simply reflect heterogeneity in individual preferences across places
- We evaluate whether variation in sharp bunching across cities is driven by differences in knowledge using four tests
  - Movers: do individuals begin to respond when they move to a high response city?
  - Learning: do individuals continue to respond after leaving a high response city?
  - Spatial diffusion: does response spread spatially and continue to increase over time?
  - Agglomeration: response higher in cities with many EITC claimants

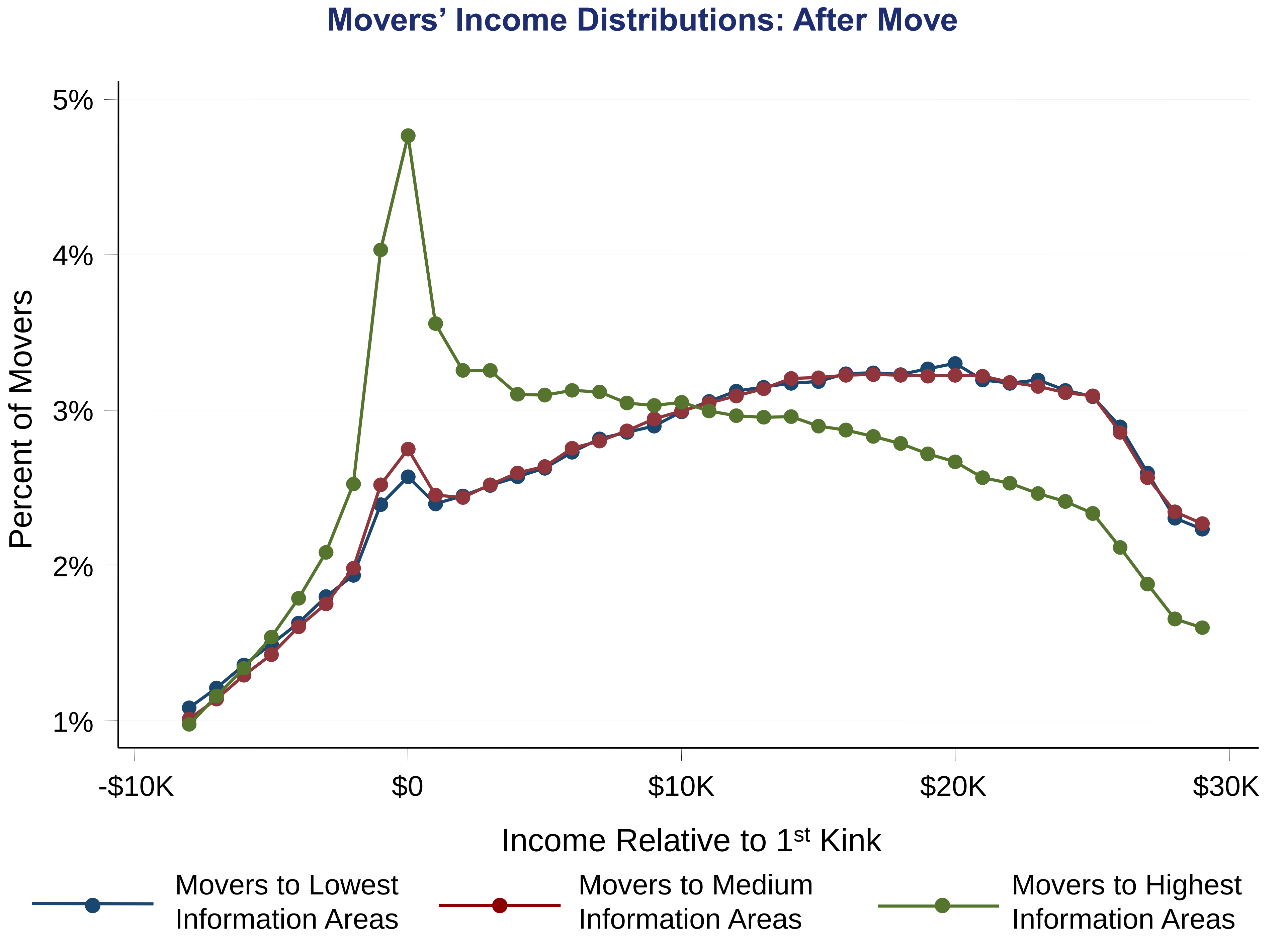
Movers: Neighborhood Changes

- 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
1.2%
0.8%
0.4%
0.0%
-5
0
5
Event Year
Δε = 0.41%
(0.05%)
Movers to Lowest Information Areas
Movers to Medium Information Areas
Movers to Highest Information Areas



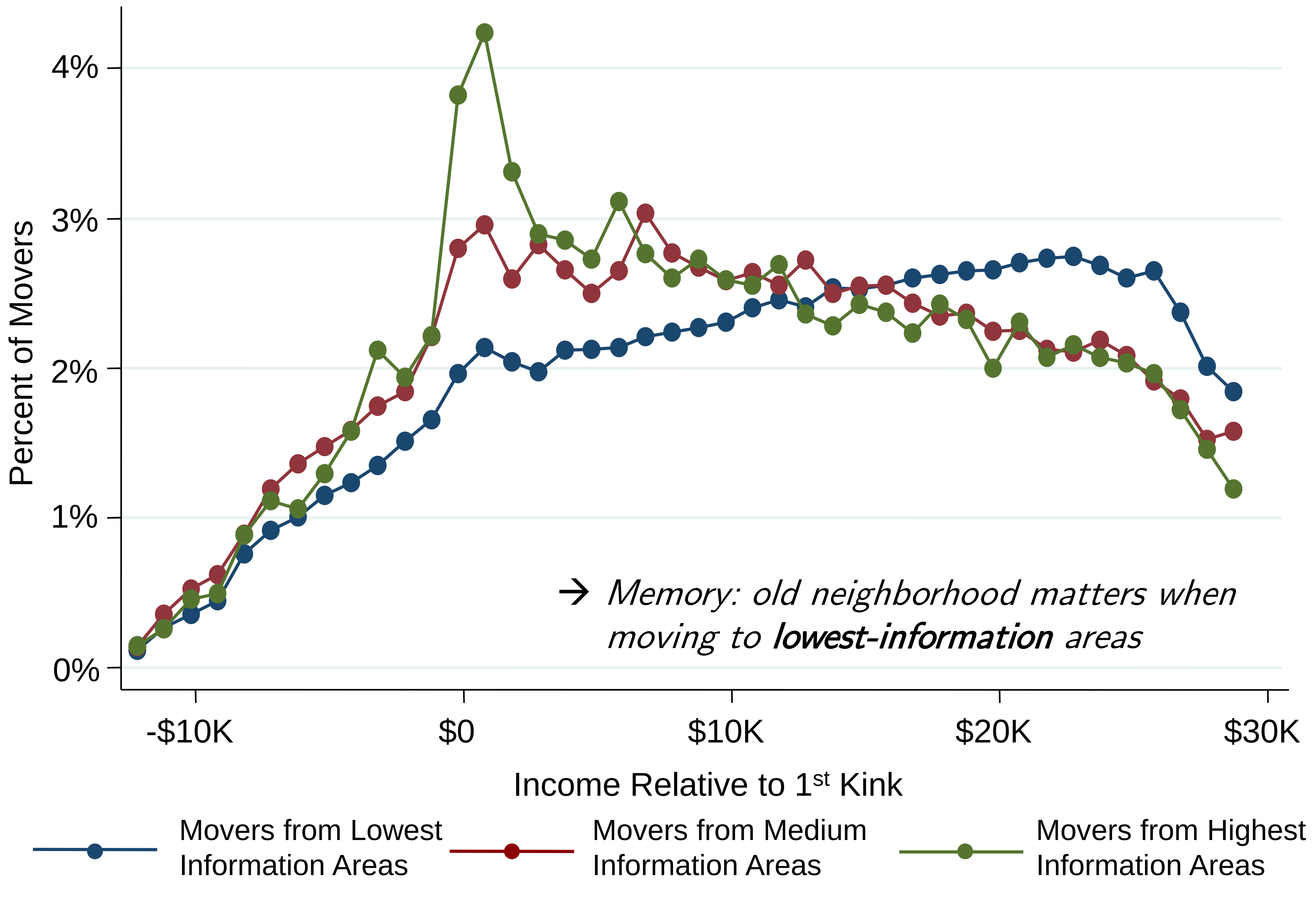
Movers' Income Distributions: Before Move
Percent of Movers
5%
4%
3%
2%
1%
-$10K
$0
$10K
$20K
$30K
Income Relative to 1st Kink
Movers to Lowest Information Areas
Movers to Medium Information Areas
Movers to Highest Information Areas


Movers' Income Distributions: After Move
Percent of Movers
5%
4%
3%
2%
1%
-$10K
$0
$10K
$20K
$30K
Income Relative to 1st Kink
Movers to Lowest Information Areas
Movers to Medium Information Areas
Movers to Highest Information Areas

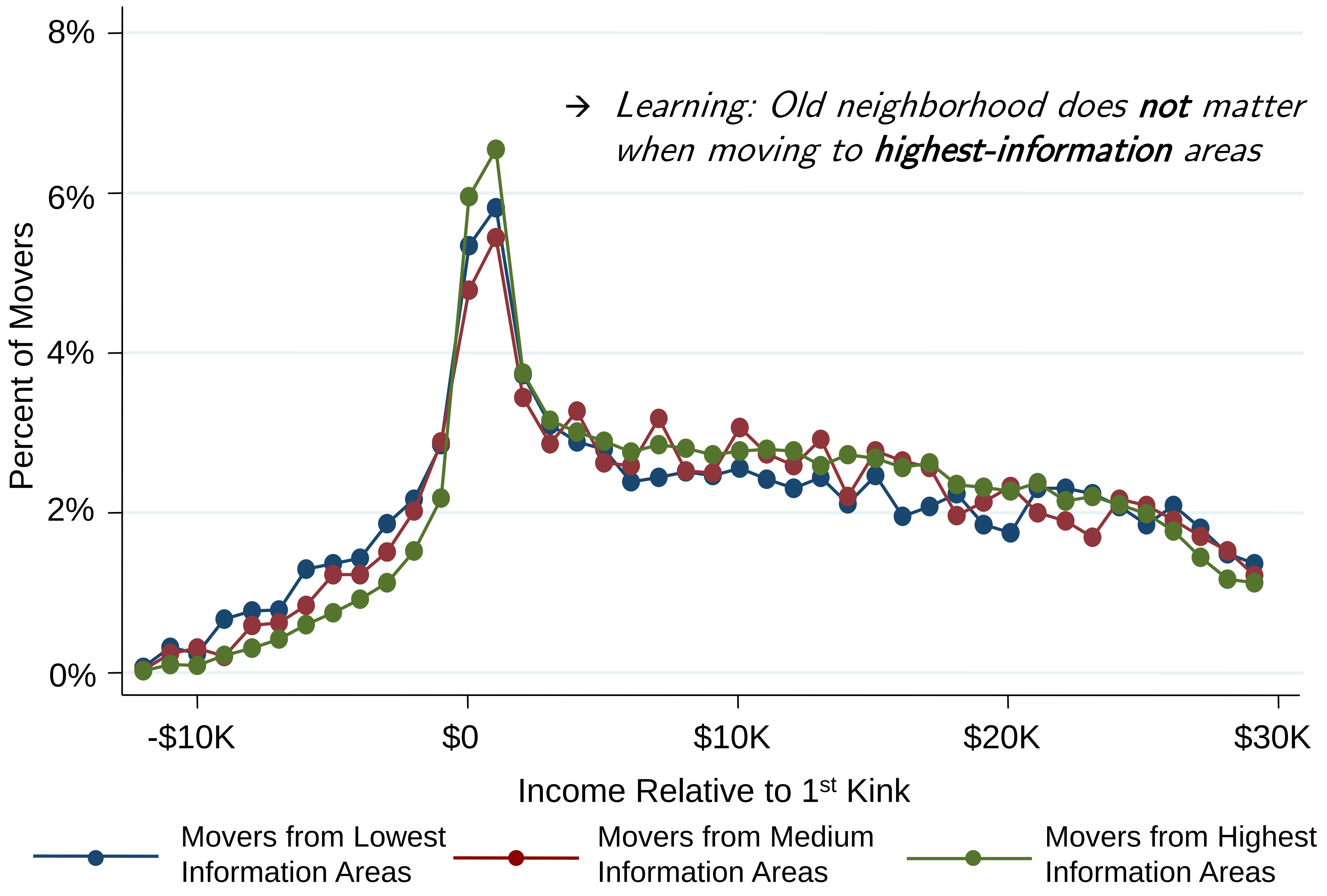
Learning and Asymmetry

- 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-Information Neighborhoods



Post-Move Distributions for Movers to Highest-Information Neighborhoods



Asymmetric Impact of Neighborhoods on Bunching

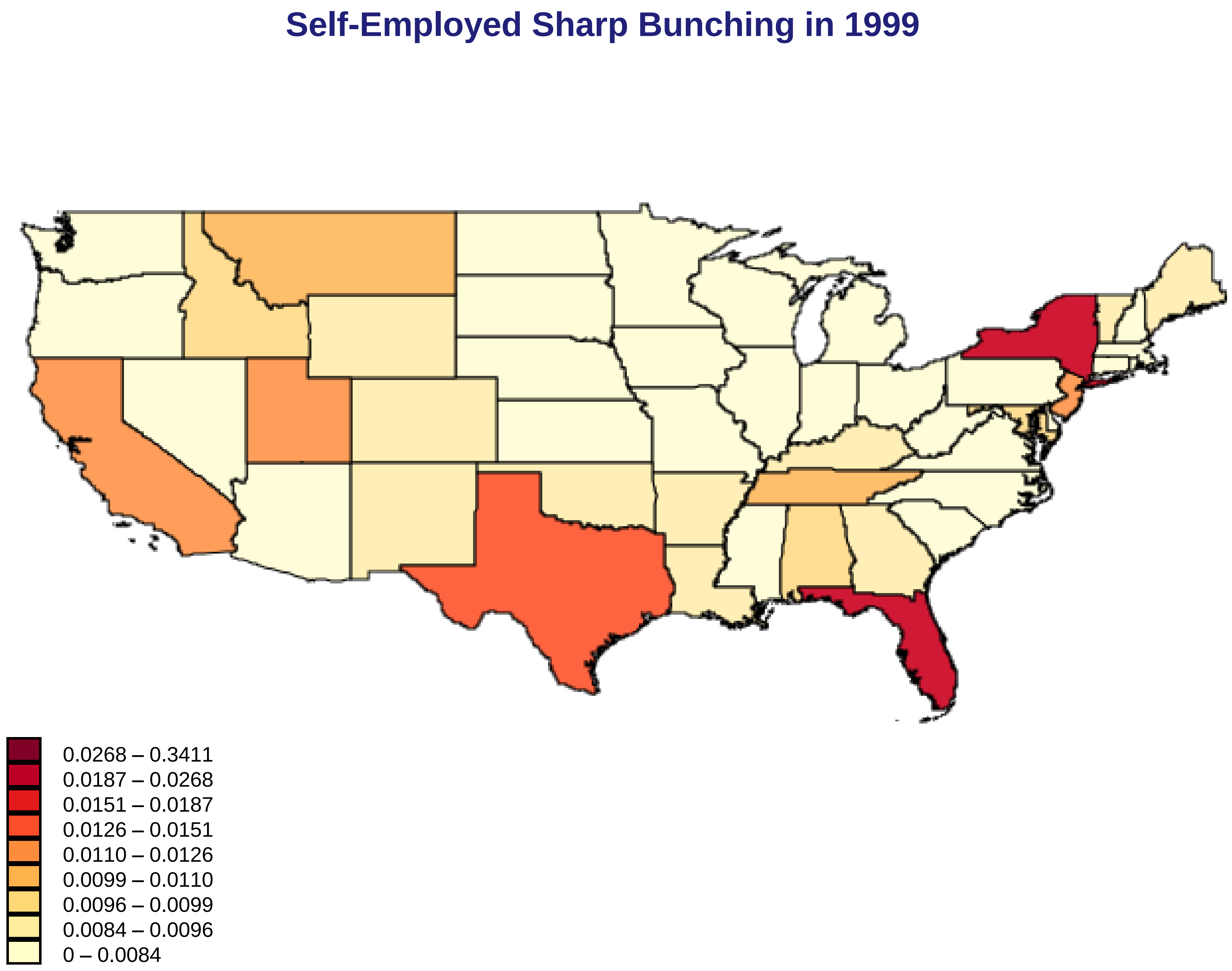
$$b_{\text{mover}} = \alpha + \beta_{\text{old}}\, b_{\text{neighborhood}}^{\text{old}} + \beta_{\text{new}}\, b_{\text{neighborhood}}^{\text{new}}$$

	Dependent variable: b for movers	
	Move Up	Move Down
	(1)	(2)
β_{old}	0.252	**0.496**
	(0.058)	(0.046)
β_{new}	**0.822**	0.354
	(0.058)	(0.046)

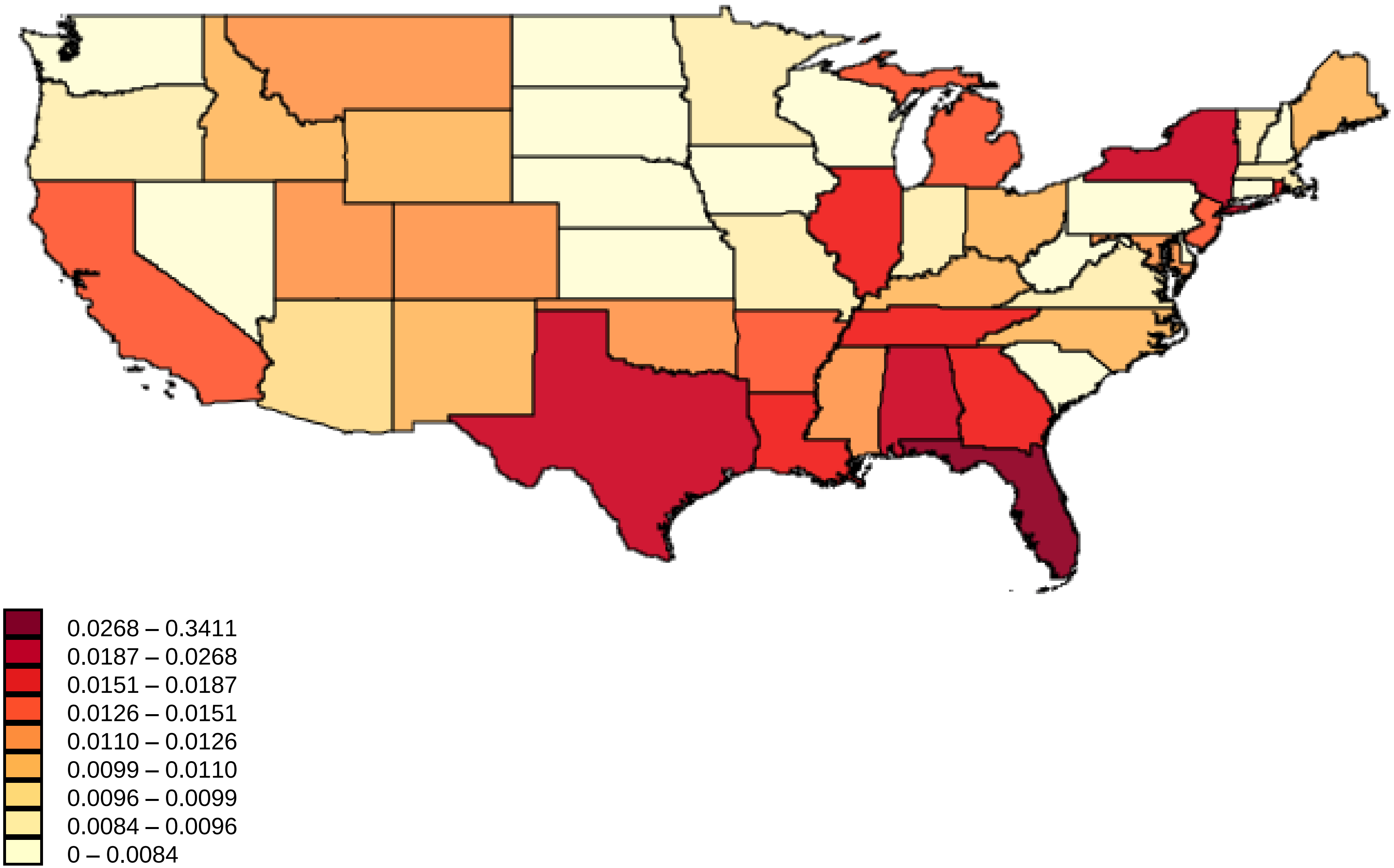
p Value for Relative Change in Coefficients Across Columns: $p < 0.001$

Spatial Diffusion

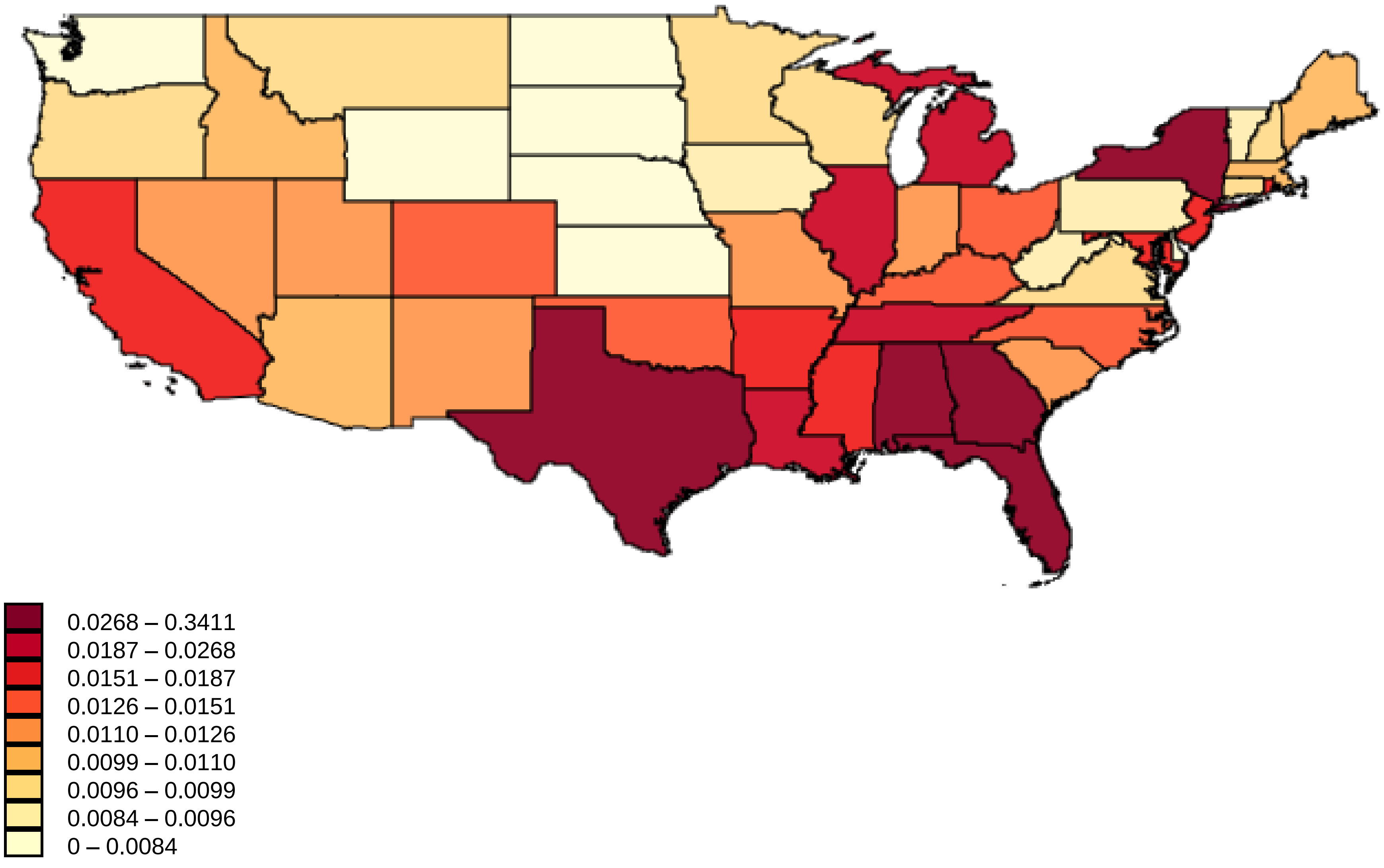
- Macro-level implication of learning is that degree of sharp bunching should increase over time and diffuse spatially
  - Evaluate by examining evolution of bunching by year across states


Self-Employed Sharp Bunching in 1999
0.0268 – 0.3411
0.0187 – 0.0268
0.0151 – 0.0187
0.0126 – 0.0151
0.0110 – 0.0126
0.0099 – 0.0110
0.0096 – 0.0099
0.0084 – 0.0096
0 – 0.0084

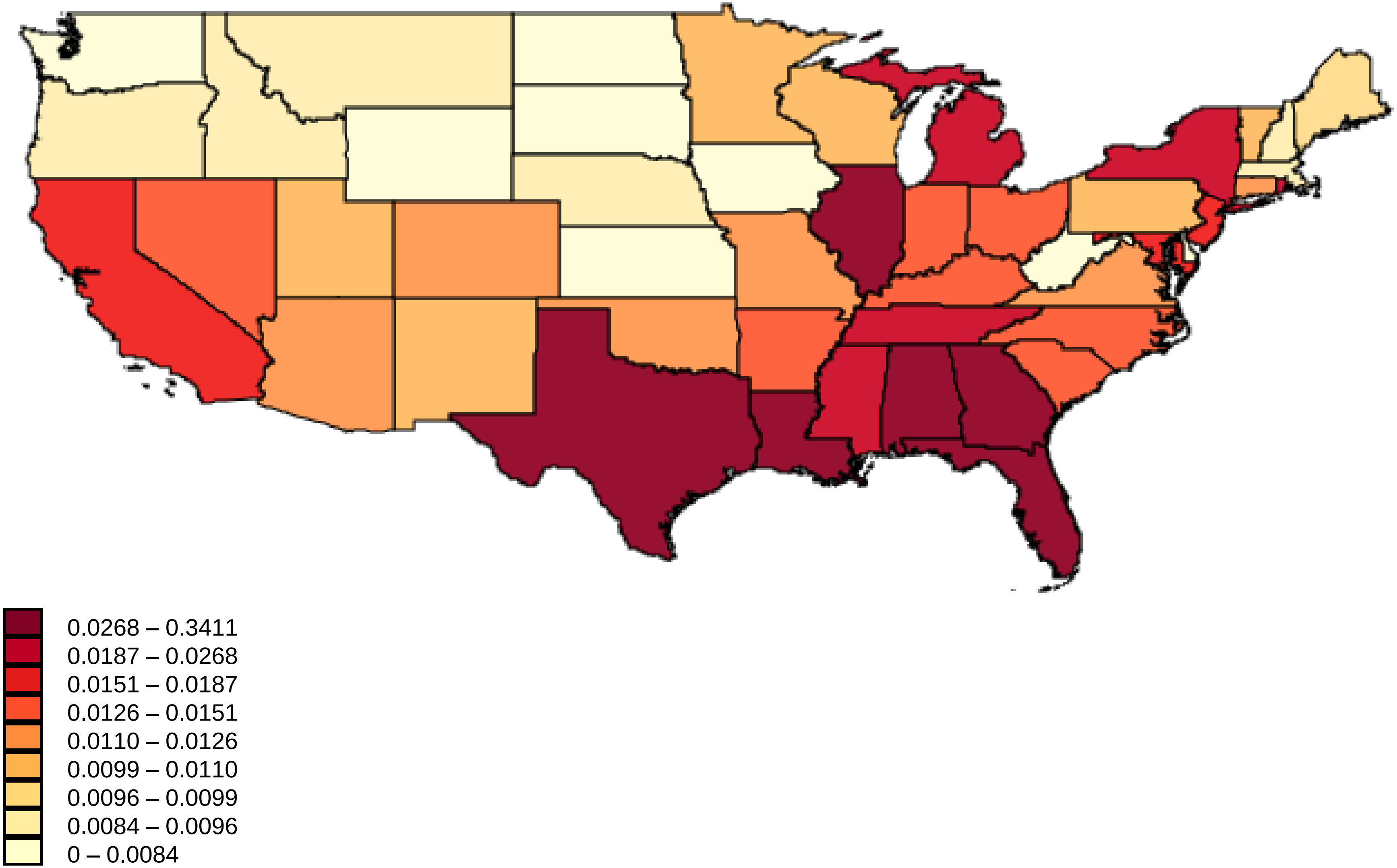
Self-Employed Sharp Bunching in 2002



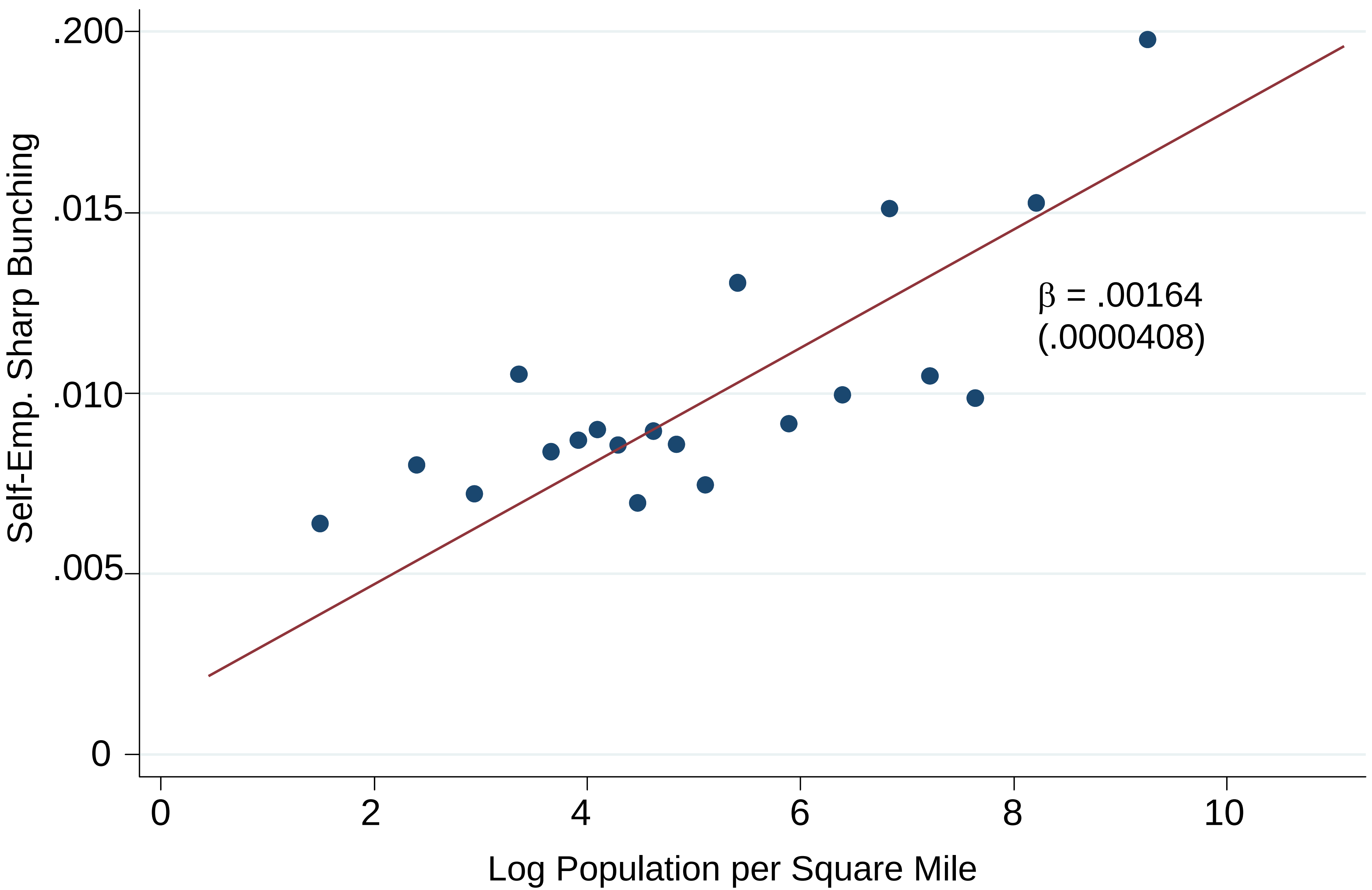
Self-Employed Sharp Bunching in 2005



Self-Employed Sharp Bunching in 2008



Agglomeration: Sharp Bunching vs. Population Density by 3-Digit Zip Code



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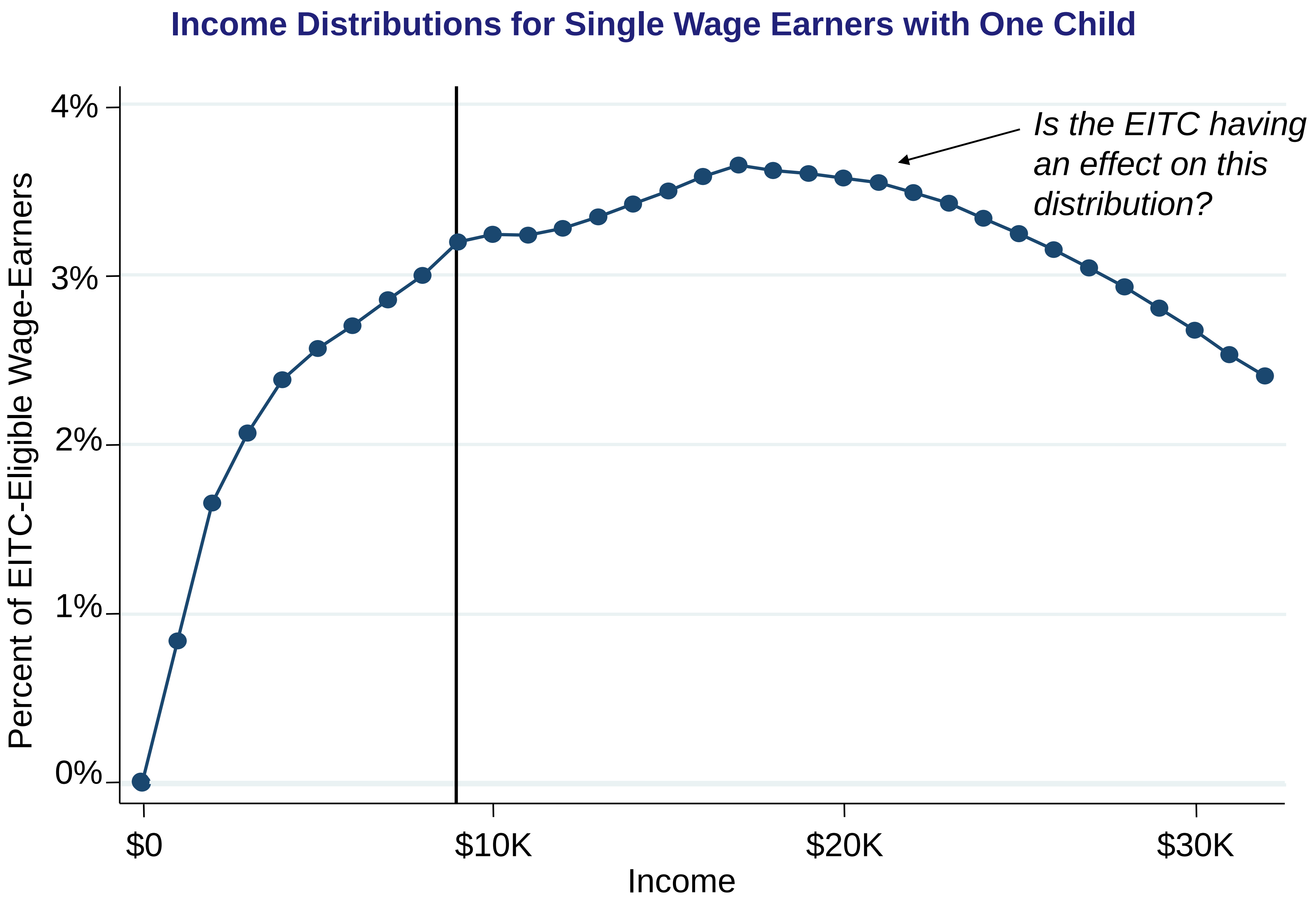
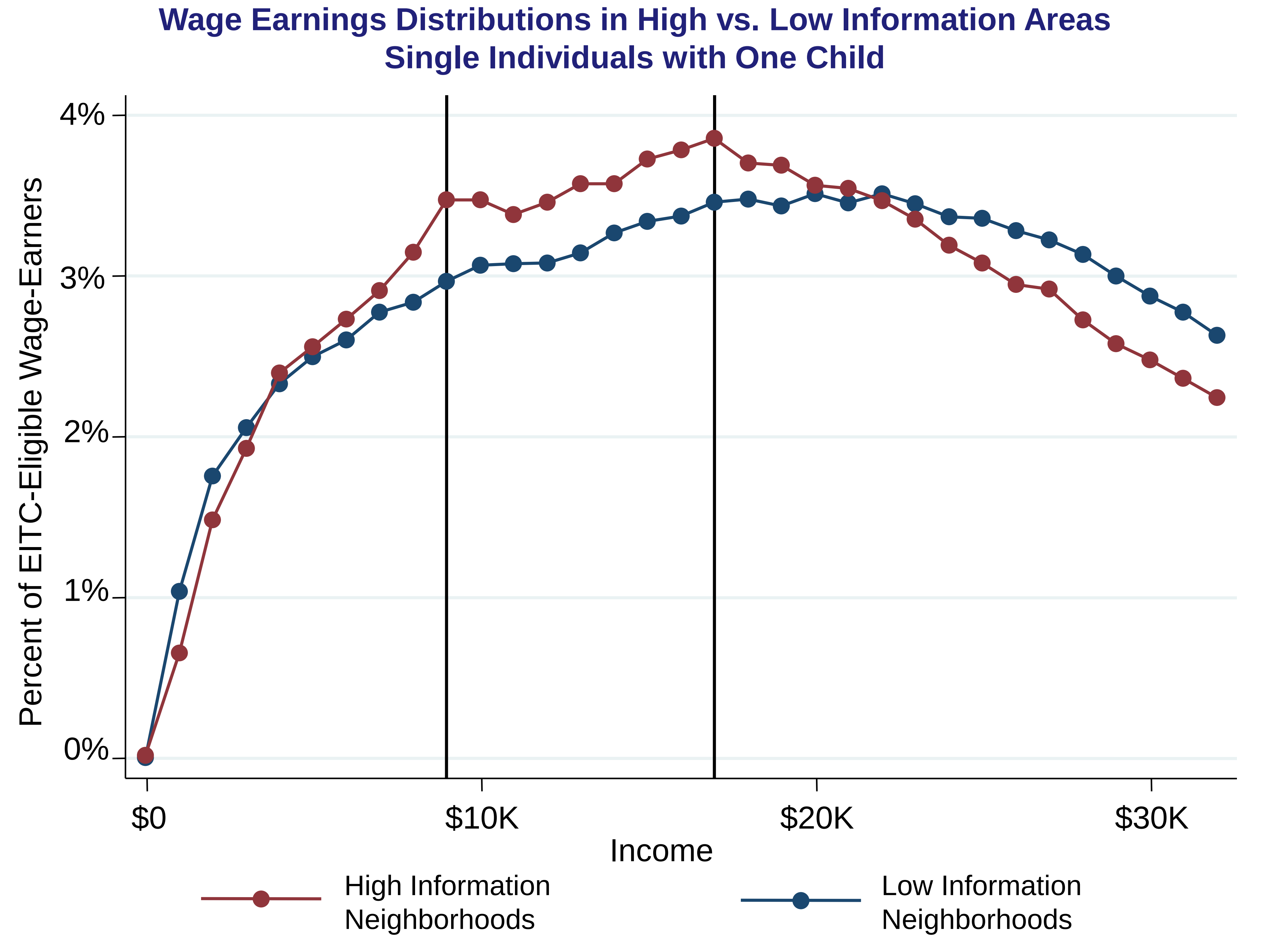
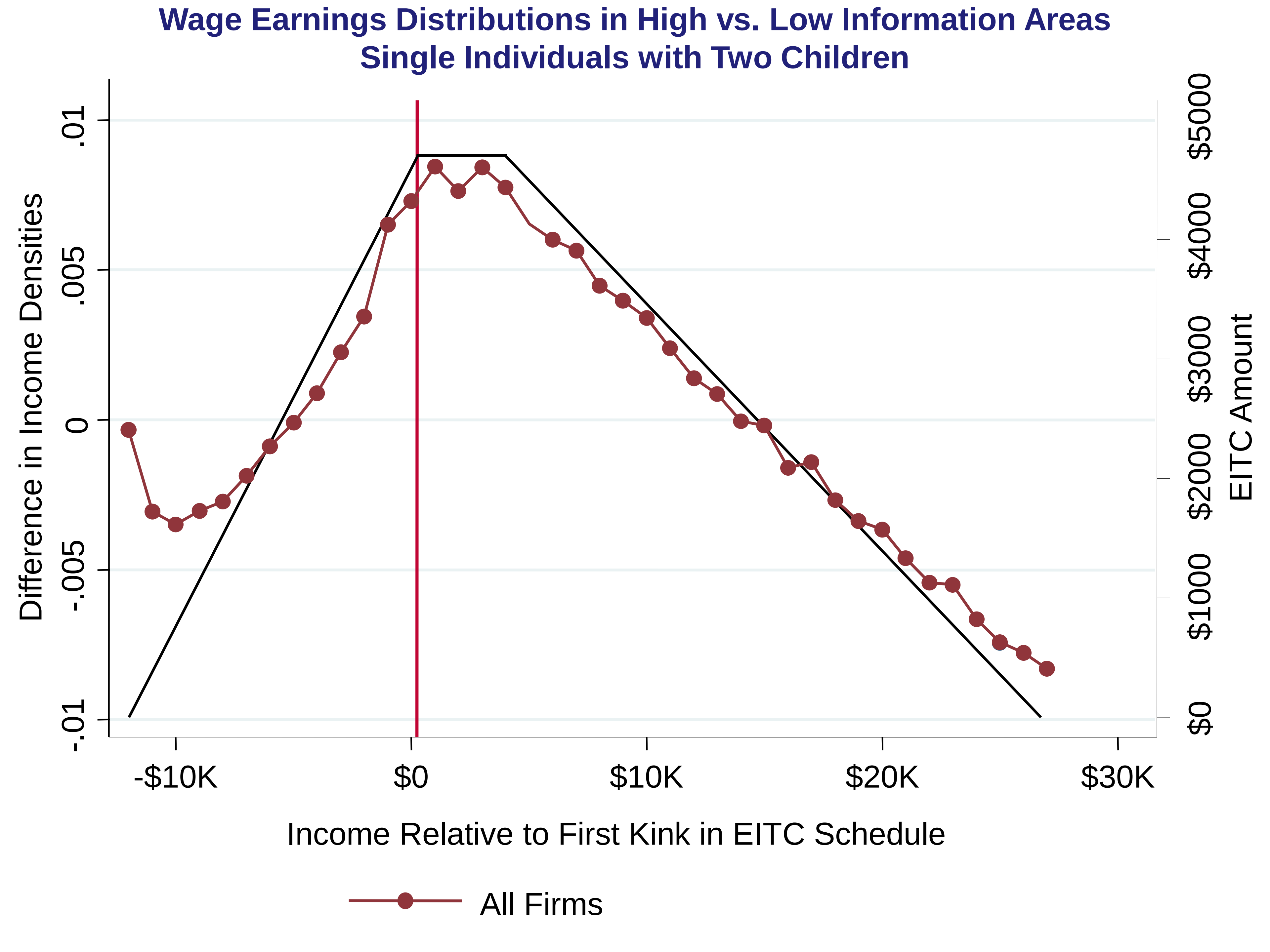
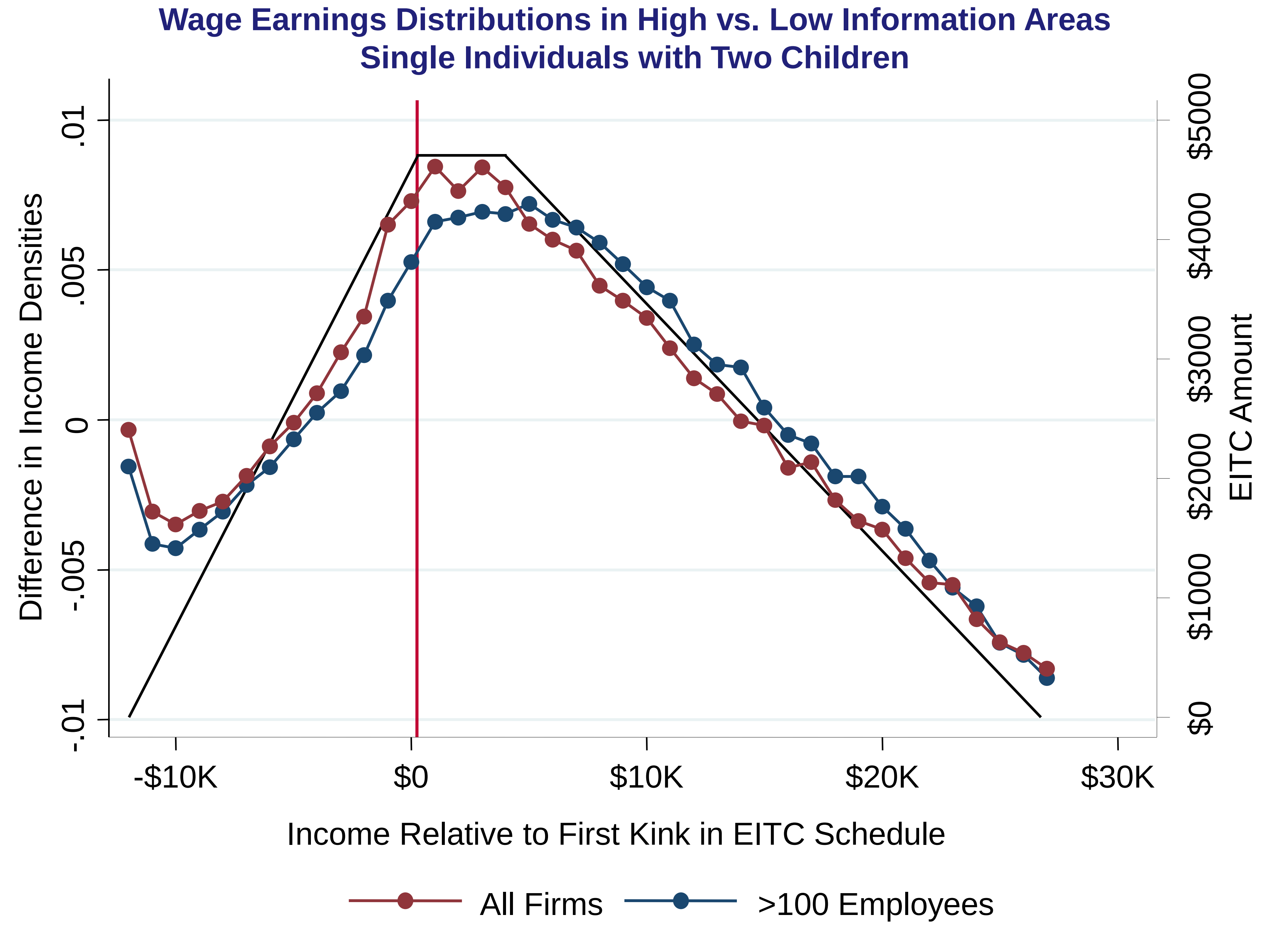


Income Distributions for Single Wage Earners with One Child
4%
3%
2%
1%
0%
Percent of EITC-Eligible Wage-Earners
Is the EITC having an effect on this distribution?
$0
$10K
$20K
$30K
Income



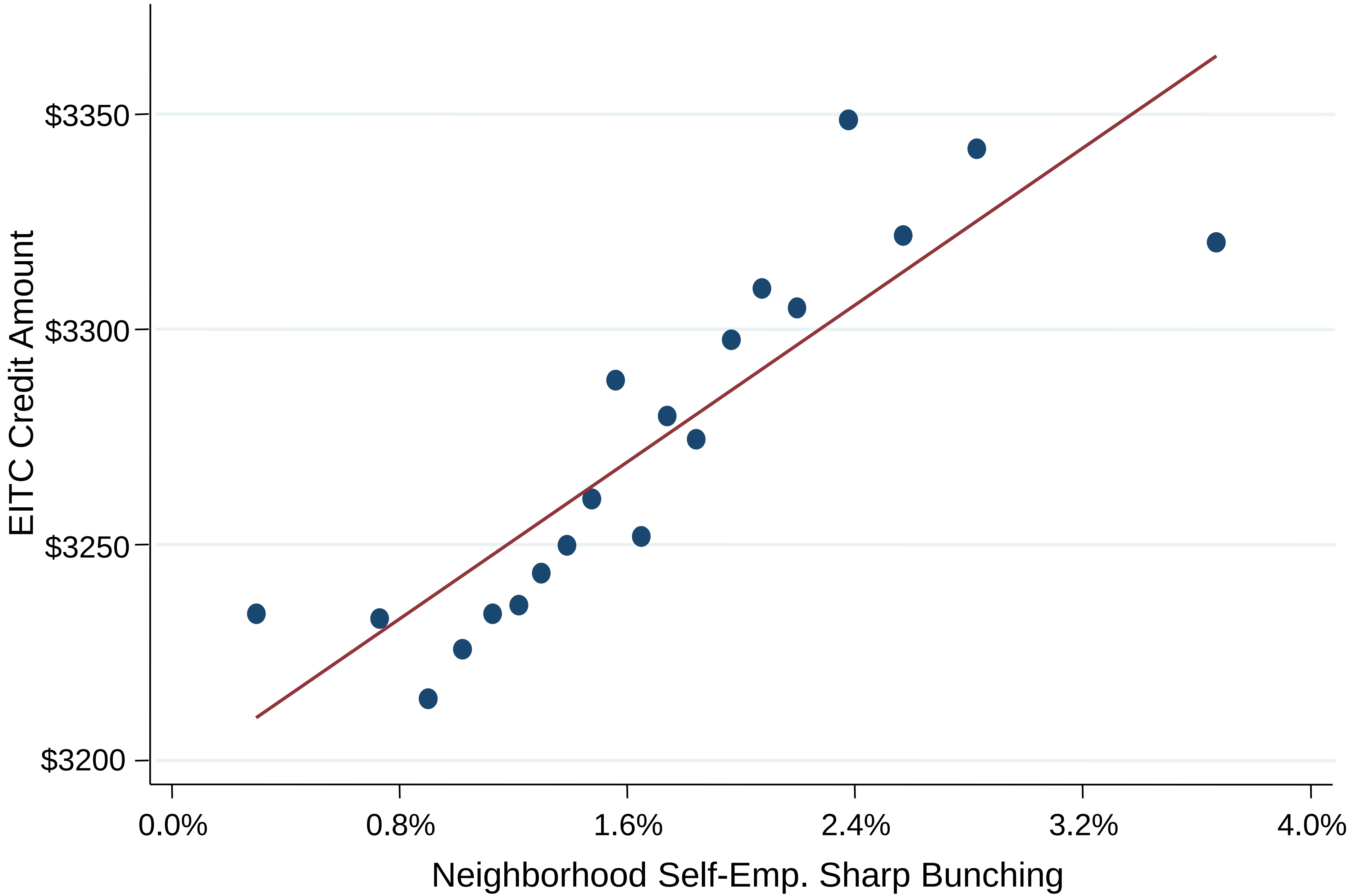
Wage Earnings Distributions in High vs. Low Information Areas
Single Individuals with One Child
Percent of EITC-Eligible Wage-Earners
4%
3%
2%
1%
0%
$0
$10K
$20K
$30K
Income
High Information Neighborhoods
Low Information Neighborhoods


Wage Earnings Distributions in High vs. Low Information Areas
Single Individuals with Two Children
Difference in Income Densities
.01
.005
0
-.005
-.01
EITC Amount
$5000
$4000
$3000
$2000
$1000
$0
-$10K
$0
$10K
$20K
$30K
Income Relative to First Kink in EITC Schedule
All Firms



Wage Earnings Distributions in High vs. Low Information Areas
Single Individuals with Two Children
Difference in Income Densities
.01
.005
0
-.005
-.01
EITC Amount
$5000
$4000
$3000
$2000
$1000
$0
-$10K
$0
$10K
$20K
$30K
Income Relative to First Kink in EITC Schedule
All Firms
>100 Employees

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



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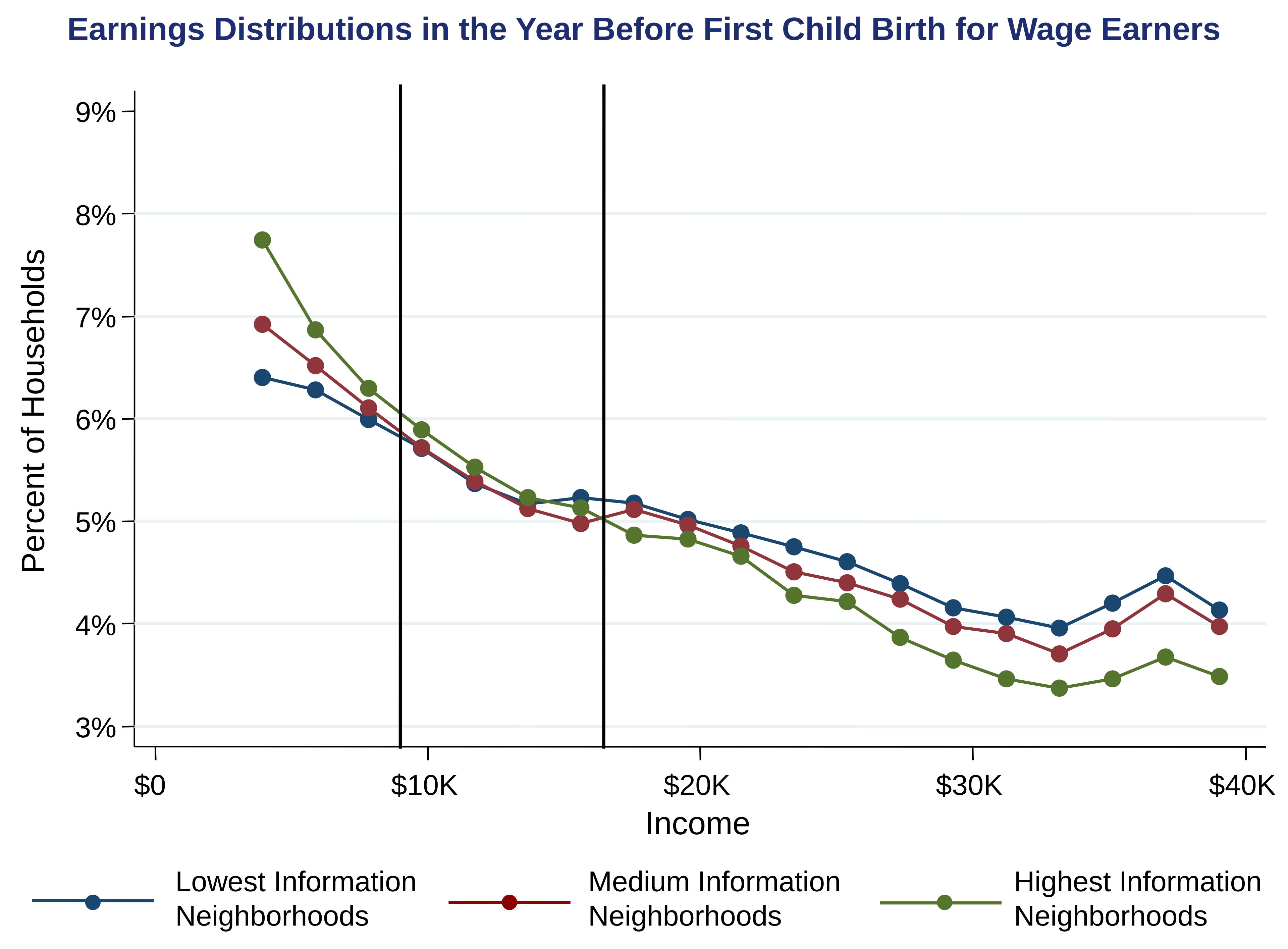
Accounting for Omitted Variables: Tax Changes

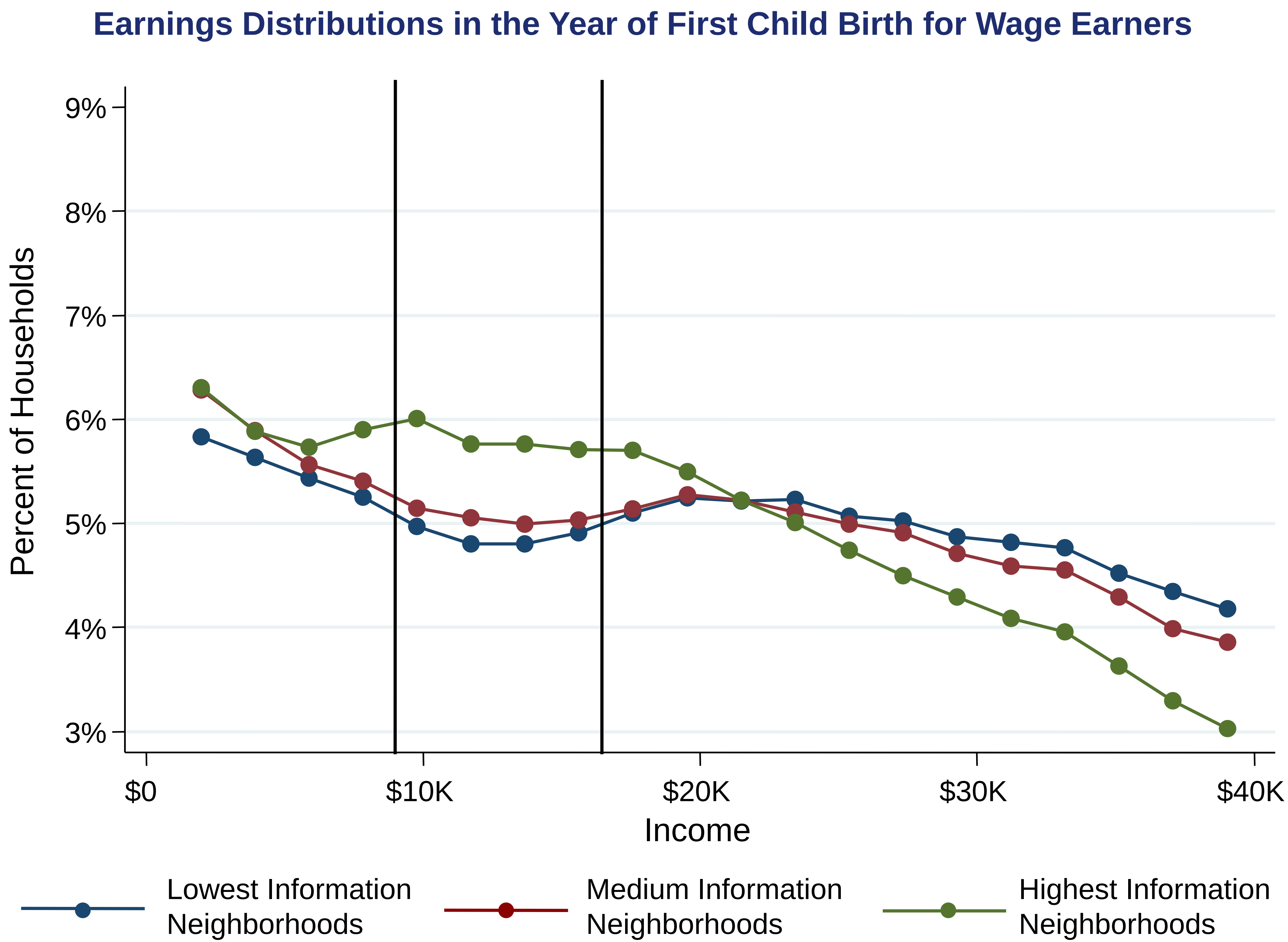
- Cross-sectional differences in income distributions could be biased by omitted variables
  - City effects: differences in industry structure or labor demand
  - Individual sorting: preferences may vary across cities
- We account for these omitted variables by analyzing impacts of changes in EITC subsidy
  - Do EITC changes affect earnings more in high knowledge cities?

Child Birth as a Source of Tax Variation

- To identify causal impacts of EITC, need variation in tax incentives
  - Birth of first child → 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 Distributions in the Year Before First Child Birth for Wage Earners
9%
8%
7%
6%
5%
4%
3%
Percent of Households
$0
$10K
$20K
$30K
$40K
Income
Lowest Information Neighborhoods
Medium Information Neighborhoods
Highest Information Neighborhoods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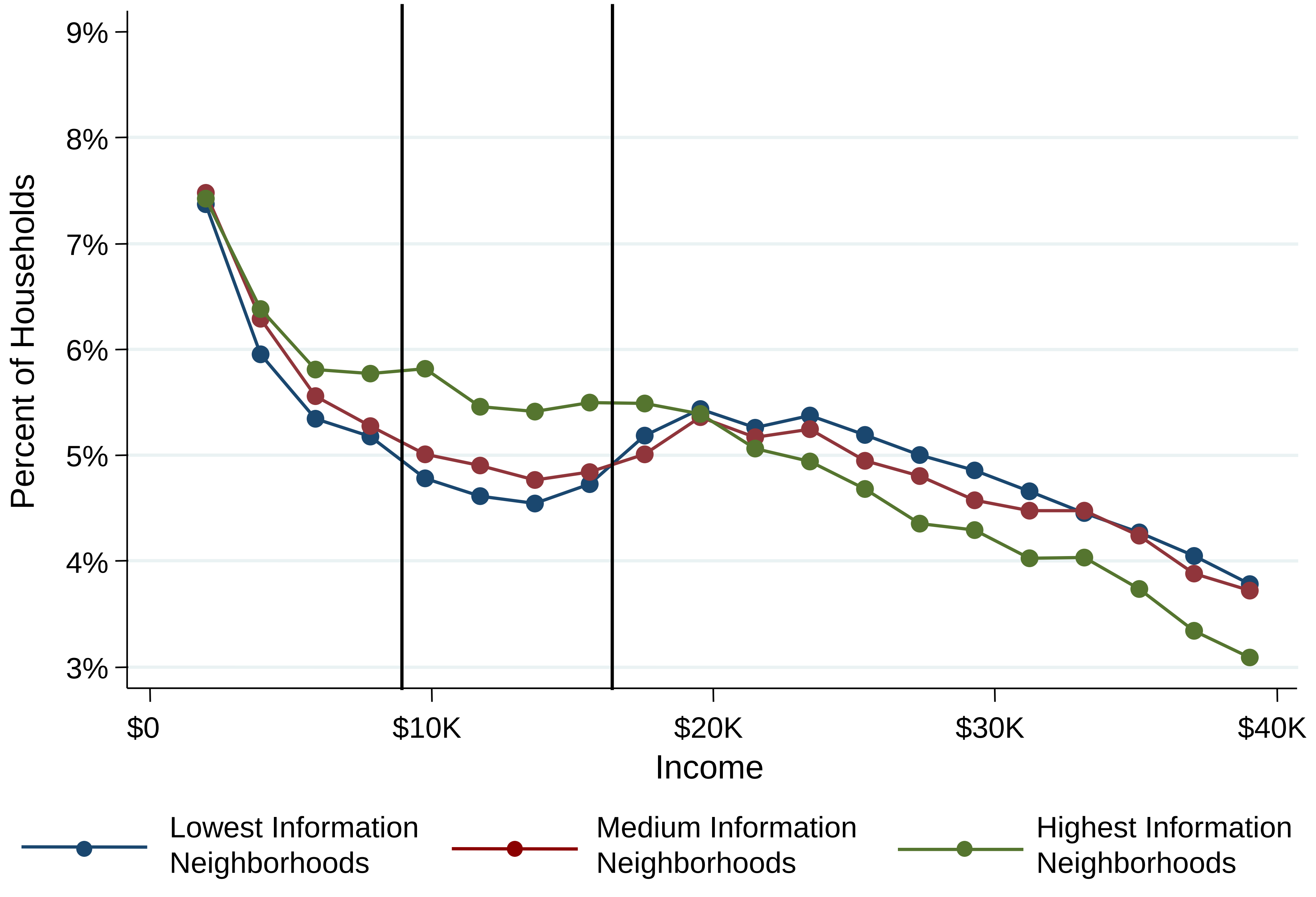
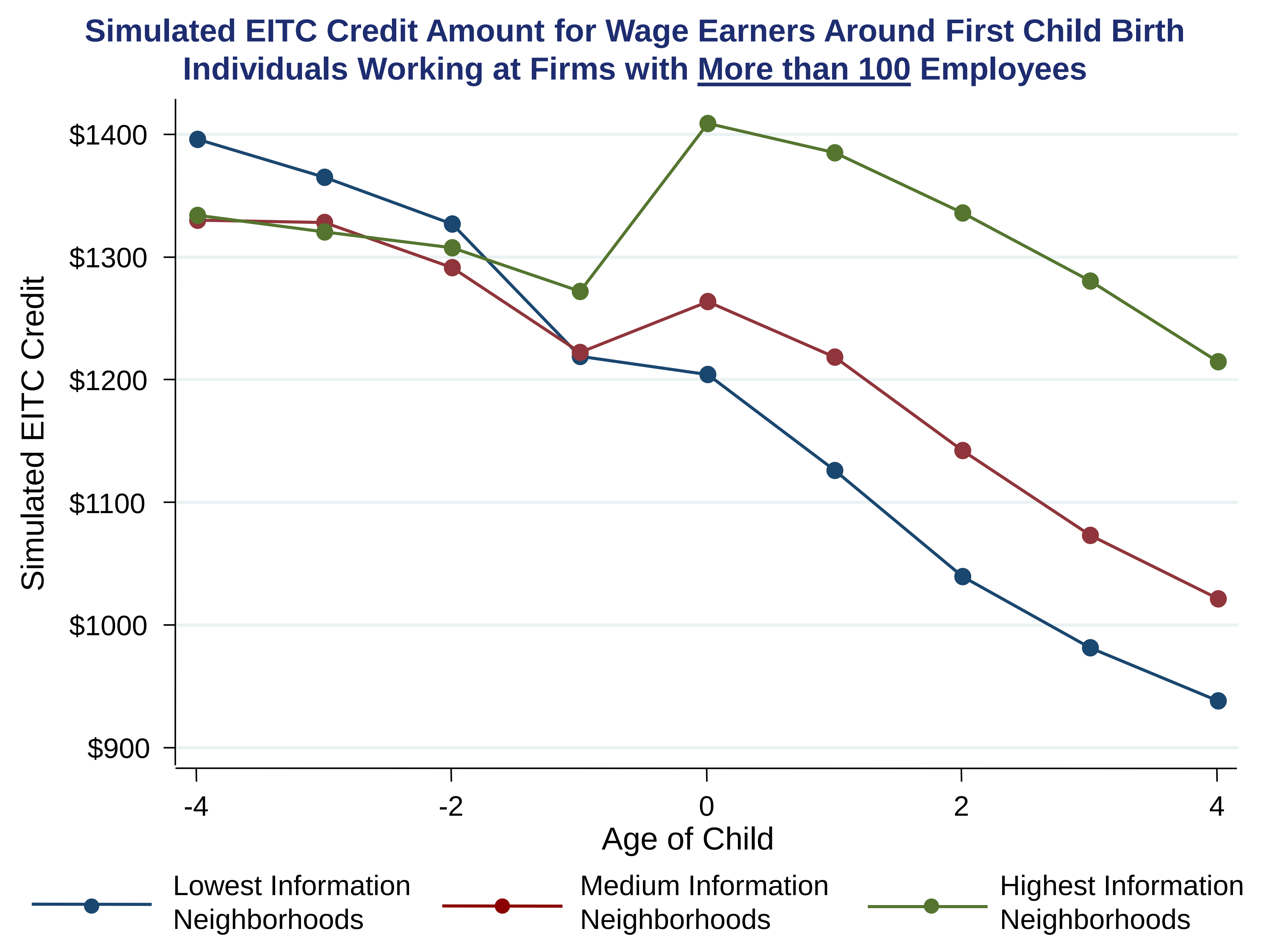
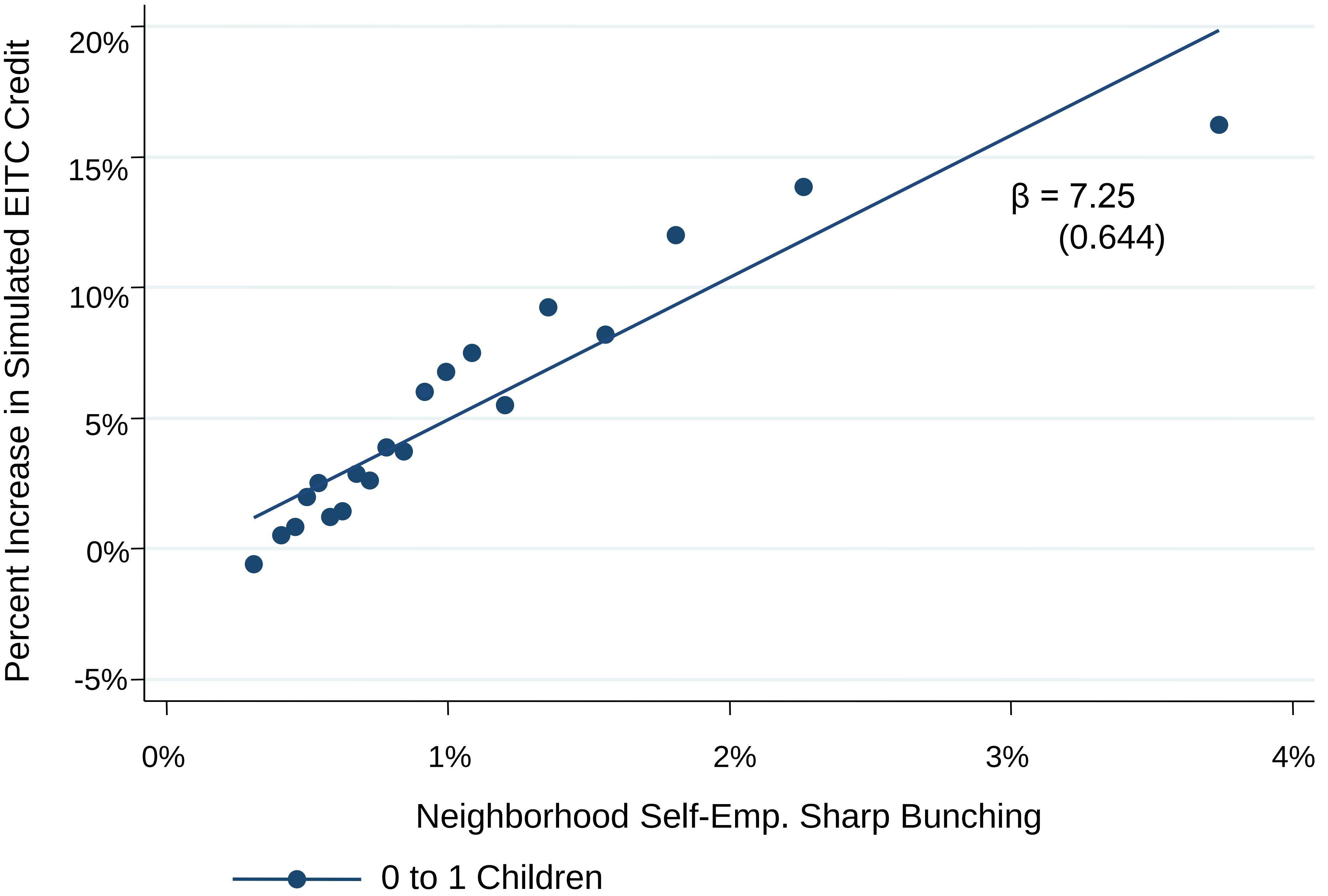
9%
8%
7%
6%
5%
4%
3%
Percent of Households
$0
$10K
$20K
$30K
$40K
Income
Lowest Information Neighborhoods
Medium Information Neighborhoods
Highest Information Neighborhoods

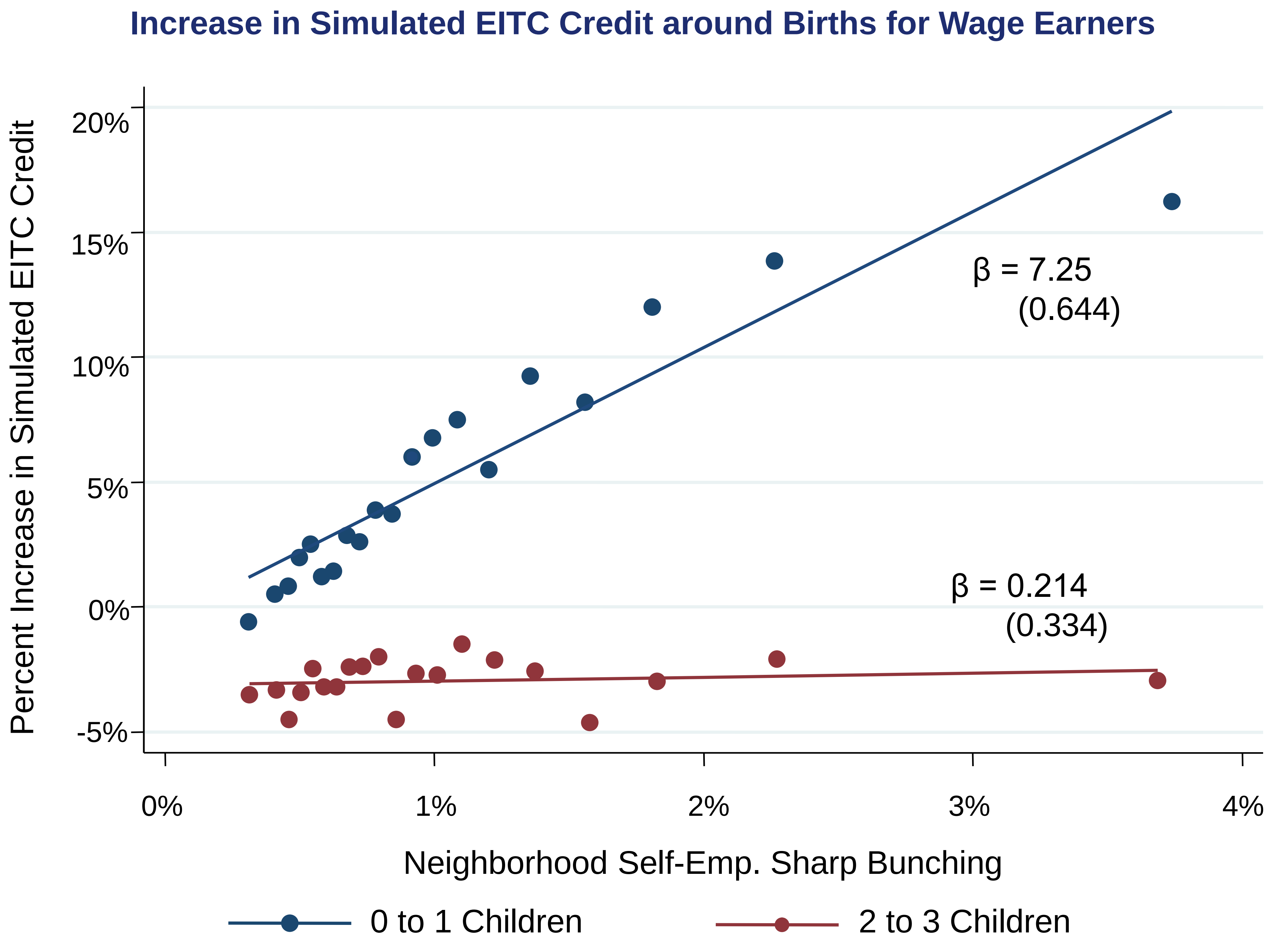
Earnings Distributions in the Year of First Child Birth for Wage Earners
Individuals Working at Firms with More than 100 Employees




Simulated EITC Credit Amount for Wage Earners Around First Child Birth
Individuals Working at Firms with More than 100 Employees
$1400
$1300
$1200
$1100
$1000
$900
Simulated EITC Credit
-4
-2
0
2
4
Age of Child
Lowest Information Neighborhoods
Medium Information Neighborhoods
Highest Information Neighborhoods

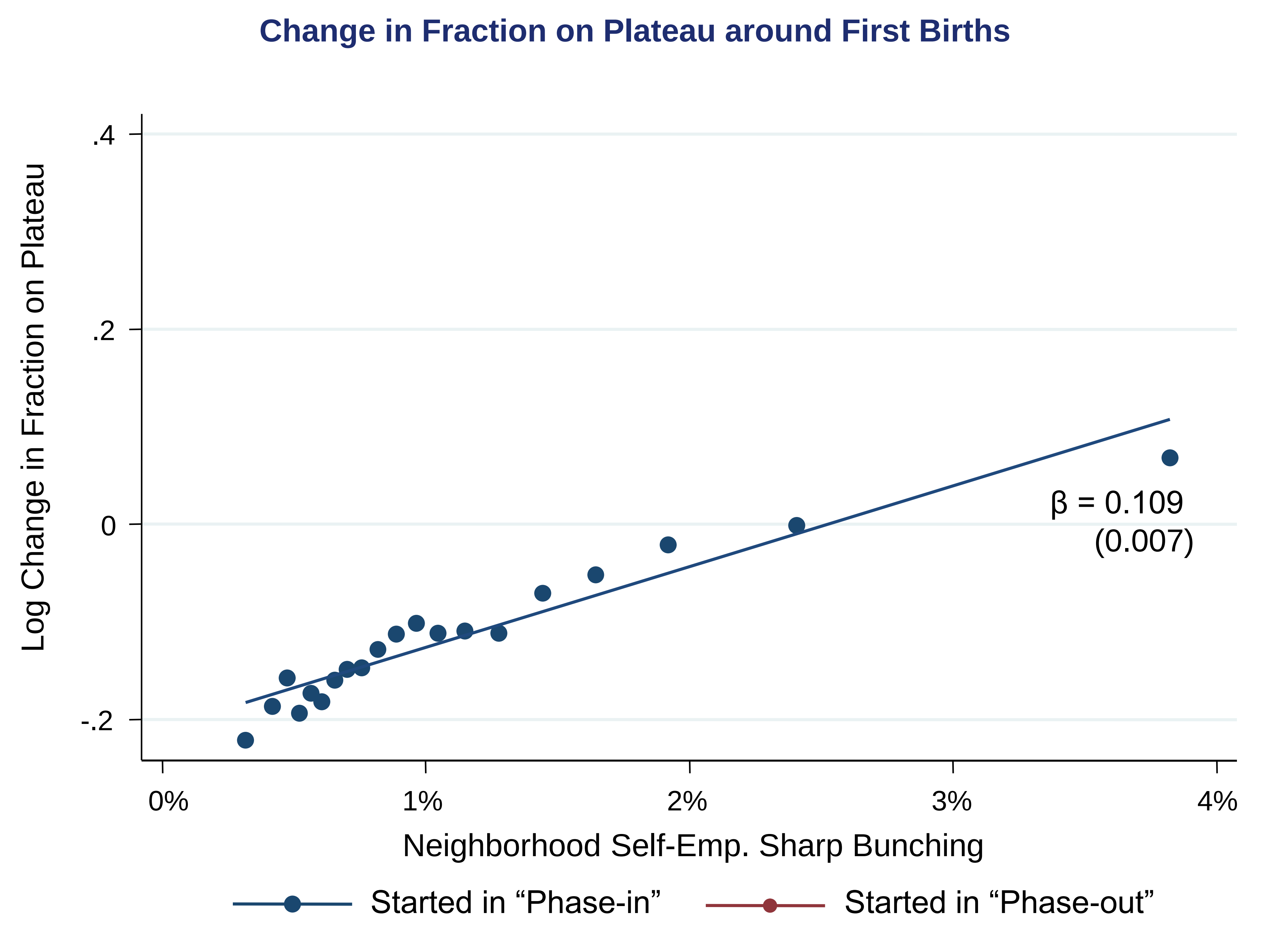
Increase in Simulated EITC Credit around Births for Wage Earners



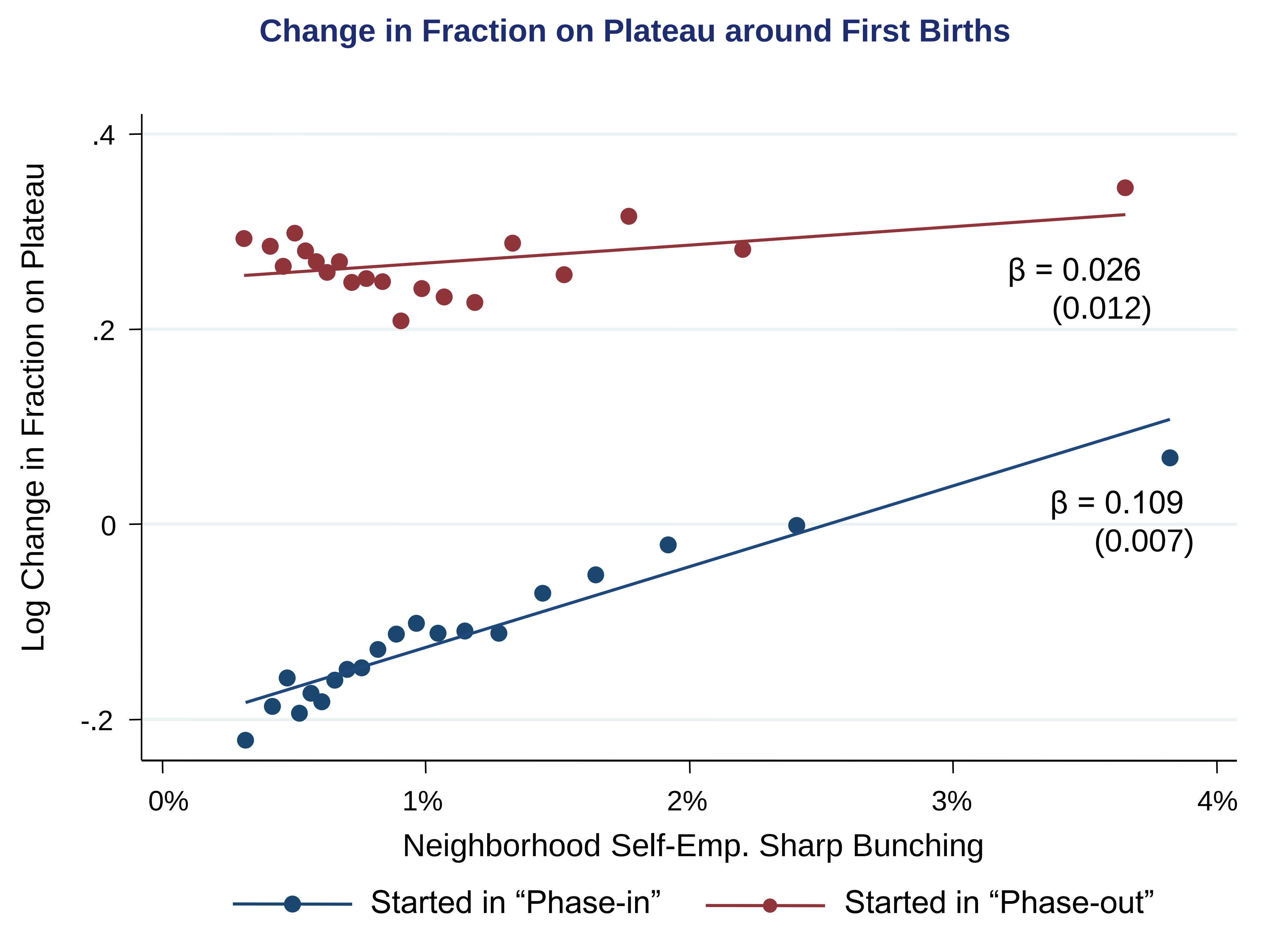

Increase in Simulated EITC Credit around Births for Wage Earners
Percent Increase in Simulated EITC Credit
20%
15%
10%
5%
0%
-5%
0%
1%
2%
3%
4%
Neighborhood Self-Emp. Sharp Bunching
β = 7.25
(0.644)
β = 0.214
(0.334)
0 to 1 Children
2 to 3 Children

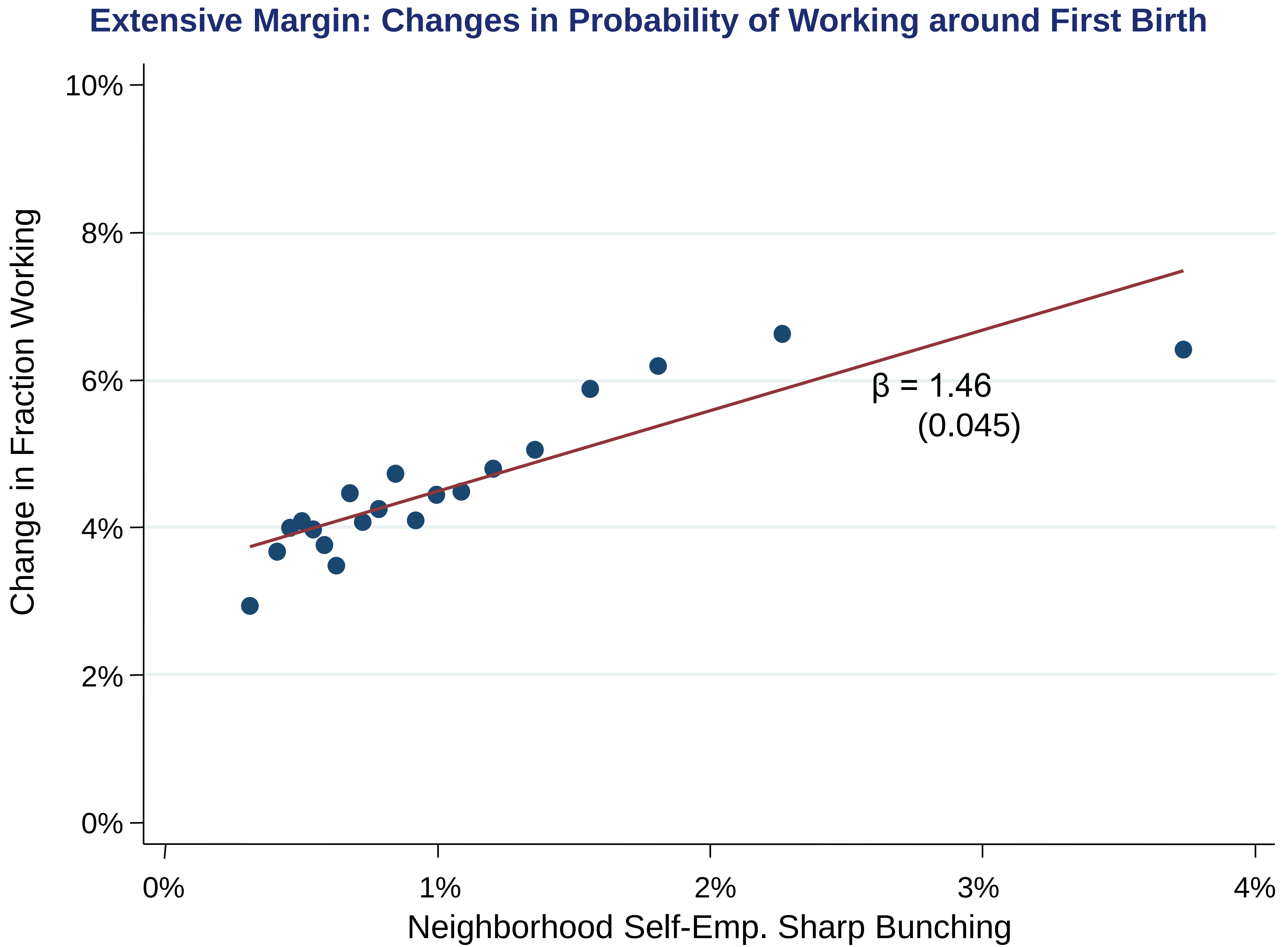
Composition of Wage Earnings Responses

- Where is the excess mass in the plateau coming from?
  - Phase-In
  - Phase-Out
  - Extensive Margin
- Important for understanding welfare implication of EITC



Change in Fraction on Plateau around First Births
Log Change in Fraction on Plateau
.4
.2
0
-.2
0%
1%
2%
3%
4%
Neighborhood Self-Emp. Sharp Bunching
β = 0.109
(0.007)
Started in “Phase-in”
Started in “Phase-out”

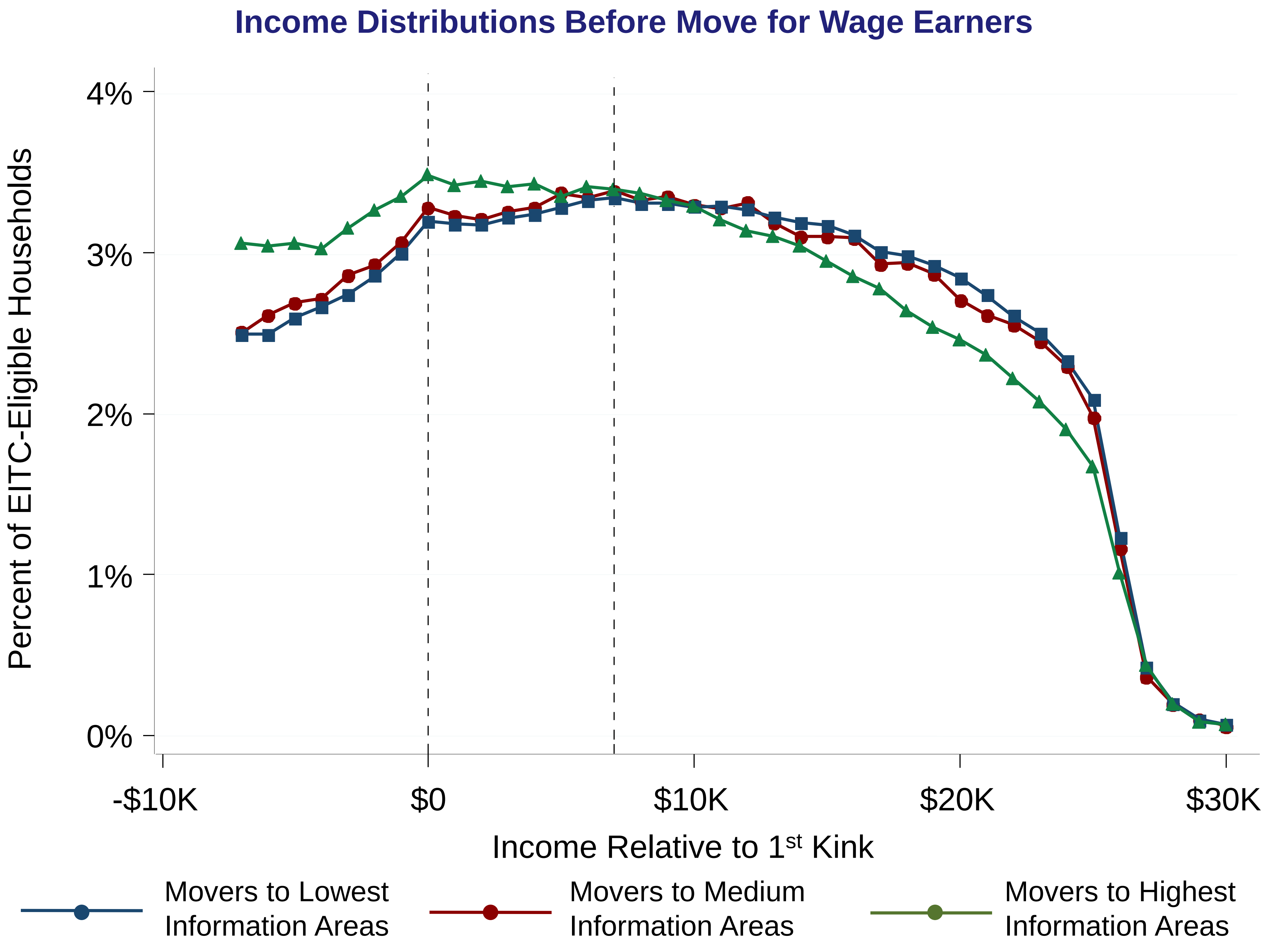

Change in Fraction on Plateau around First Births
Log Change in Fraction on Plateau
.4
.2
0
-.2
β = 0.026
(0.012)
β = 0.109
(0.007)
0%
1%
2%
3%
4%
Neighborhood Self-Emp. Sharp Bunching
Started in “Phase-in”
Started in “Phase-out”

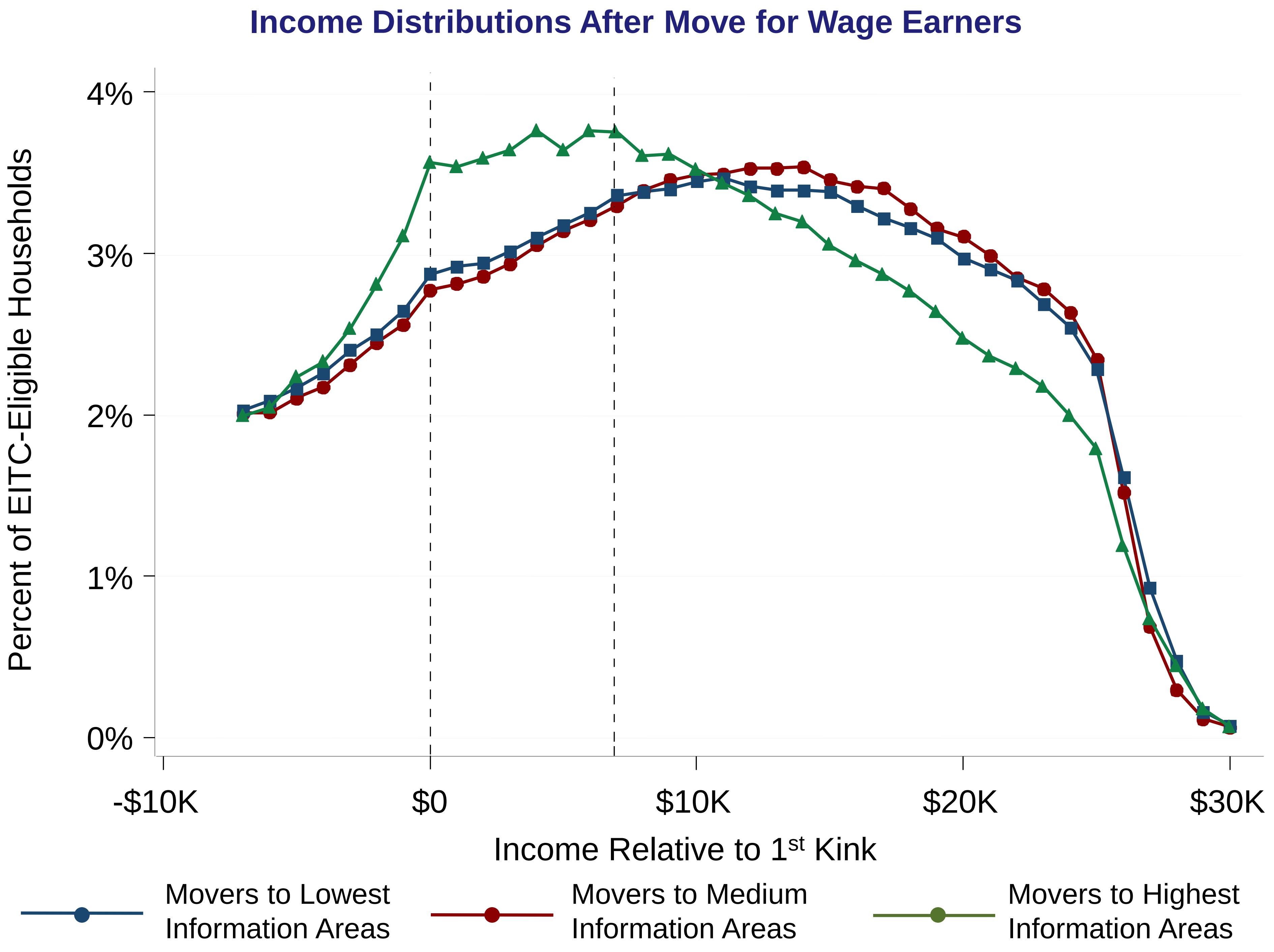


Extensive Margin: Changes in Probability of Working around First Birth
Change in Fraction Working
10%
8%
6%
4%
2%
0%
β = 1.46
(0.045)
0%
1%
2%
3%
4%
Neighborhood Self-Emp. Sharp Bunching

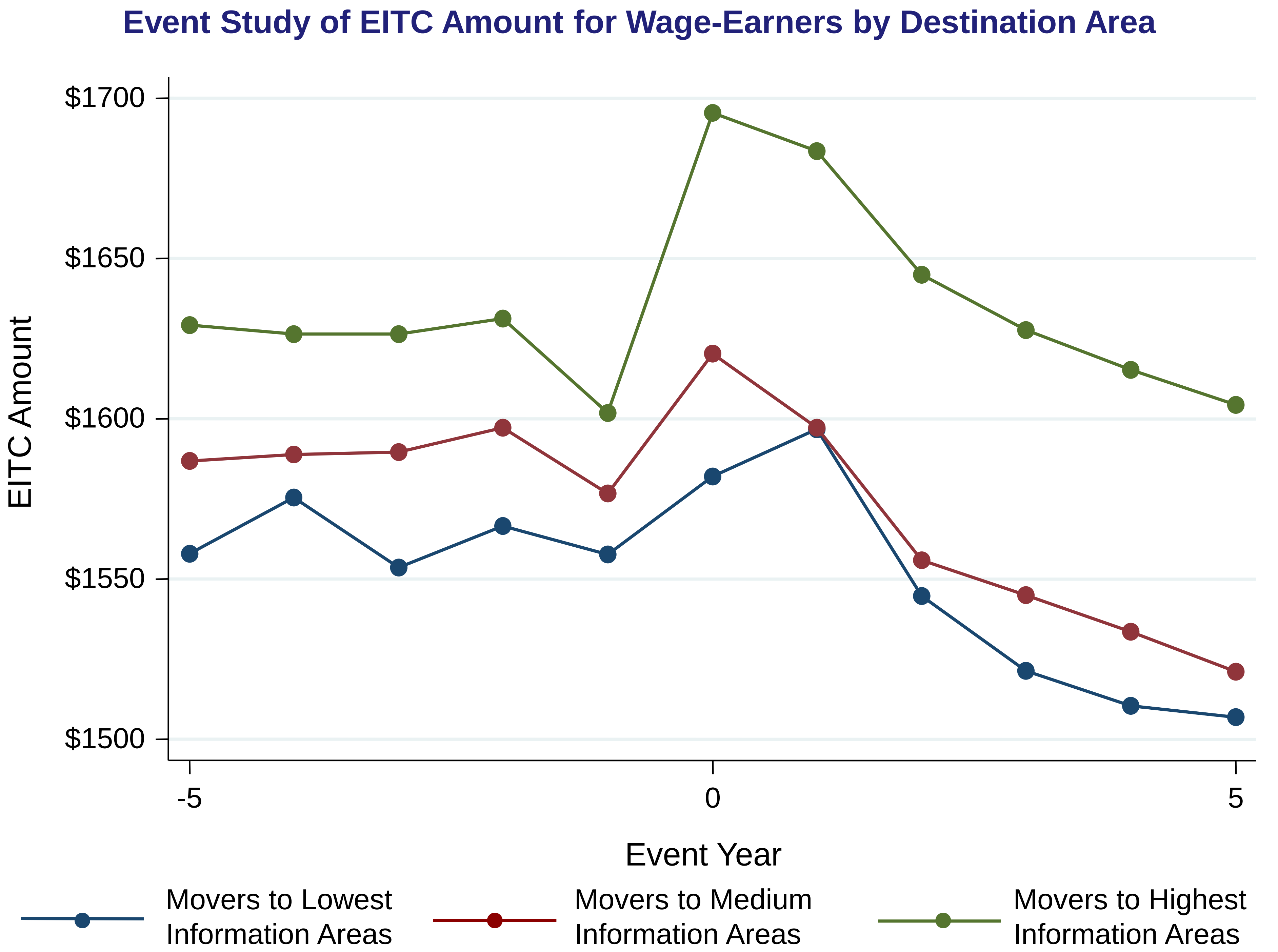
Overidentification Test: Movers

- Response to the EITC varies across cities for wage earners
  - Our hypothesis is that this is because of differences in knowledge
- To verify the causal effect of neighborhoods, we again use movers
  - Do EITC-eligible individuals who move to high response cities have higher concentration of earnings near plateau?


Income Distributions Before Move for Wage Earners
Percent of EITC-Eligible Households
4%
3%
2%
1%
0%
-$10K
$0
$10K
$20K
$30K
Income Relative to 1st Kink
Movers to Lowest Information Areas
Movers to Medium Information Areas
Movers to Highest Information Areas



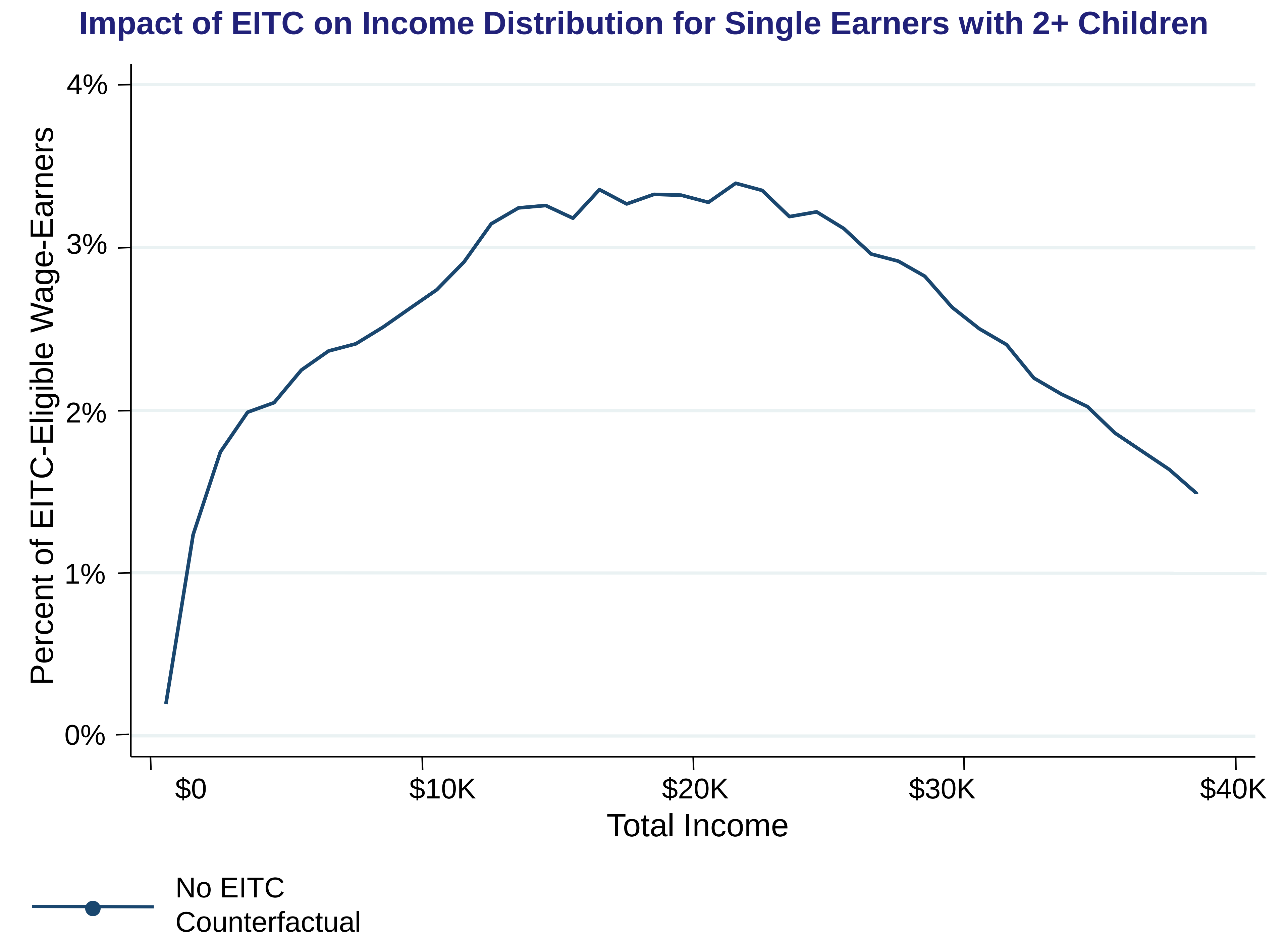
Income Distributions After Move for Wage Earners
4%
3%
2%
1%
0%
Percent of EITC-Eligible Households
-$10K
$0
$10K
$20K
$30K
Income Relative to 1st Kink
Movers to Lowest Information Areas
Movers to Medium Information Areas
Movers to Highest Information Areas


Event Study of EITC Amount for Wage-Earners by Destination Area
EITC Amount
$1700
$1650
$1600
$1550
$1500
-5
0
5
Event Year
Movers to Lowest Information Areas
Movers to Medium Information Areas
Movers to Highest Information Areas

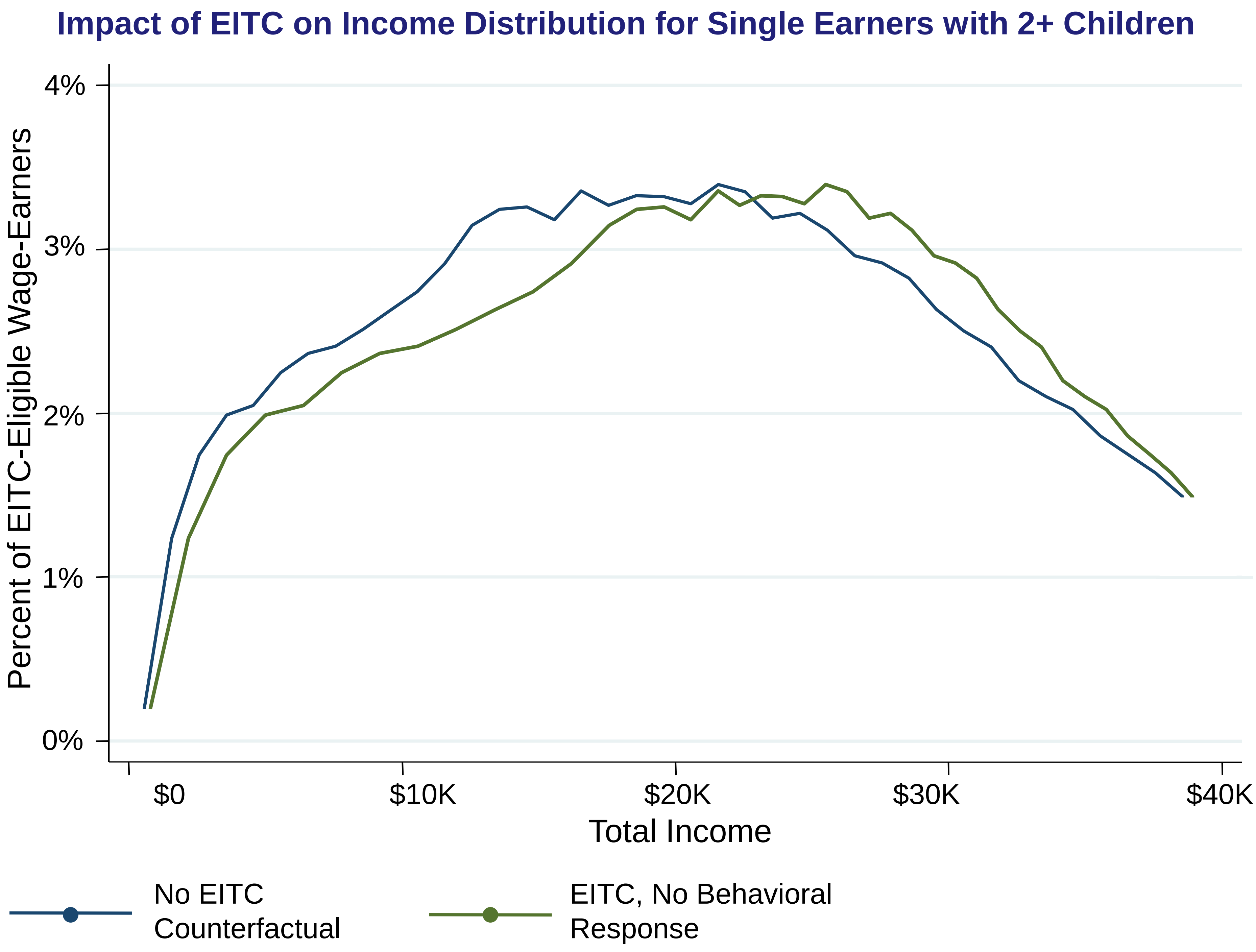
Tax Policy Implications

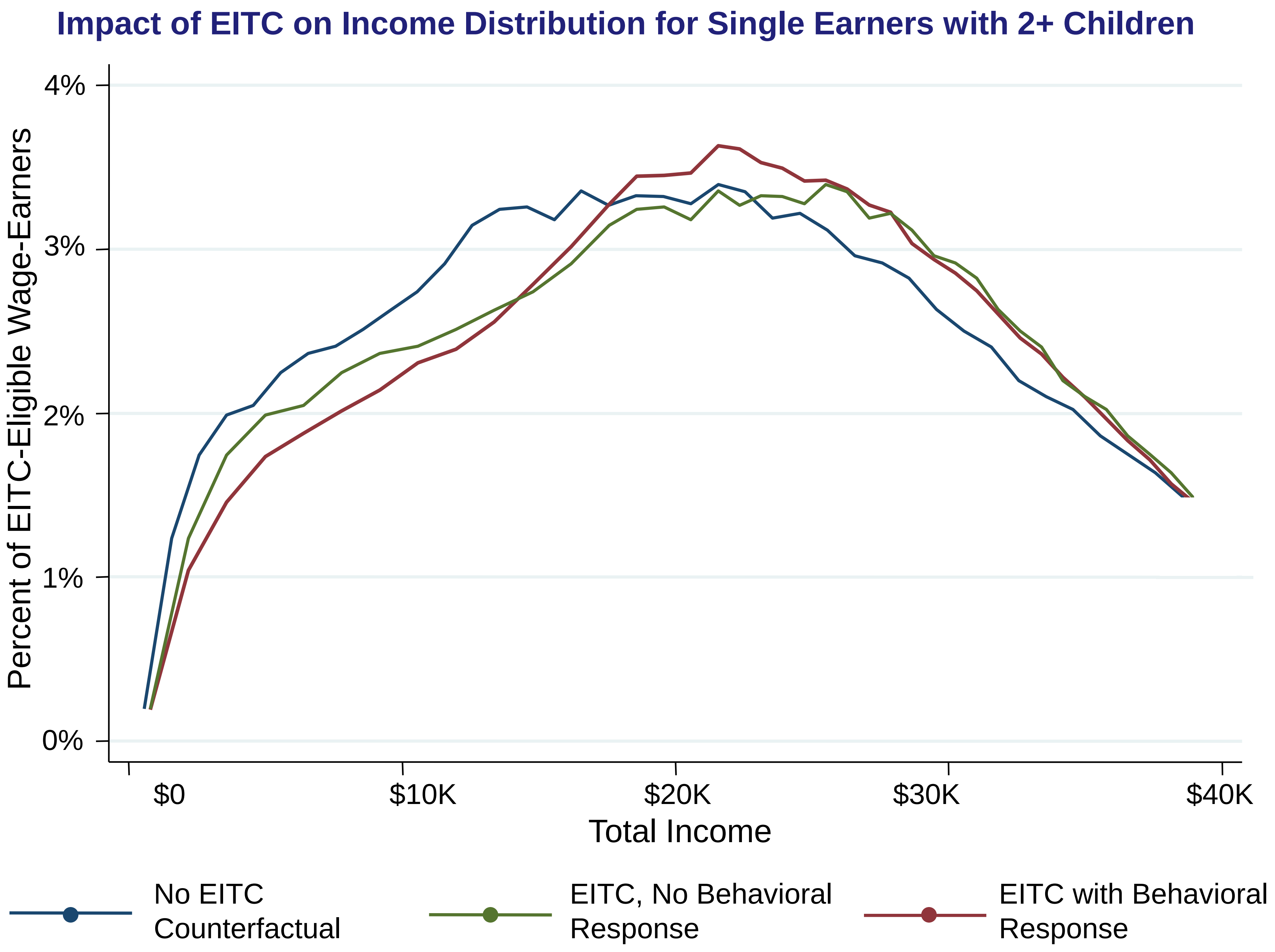
- Our estimates can be used to characterize impact of EITC on income distribution taking into account behavioral responses

- Use neighborhoods with little self-employment bunching as counterfactual for earnings distribution without EITC



Impact of EITC on Income Distribution for Single Earners with 2+ Children
Percent of EITC-Eligible Wage-Earners
4%
3%
2%
1%
0%
$0
$10K
$20K
$30K
$40K
Total Income
No EITC
Counterfactual


Impact of EITC on Income Distribution for Single Earners with 2+ Children
4%
3%
2%
1%
0%
Percent of EITC-Eligible Wage-Earners
$0
$10K
$20K
$30K
$40K
Total Income
No EITC Counterfactual
EITC, No Behavioral Response



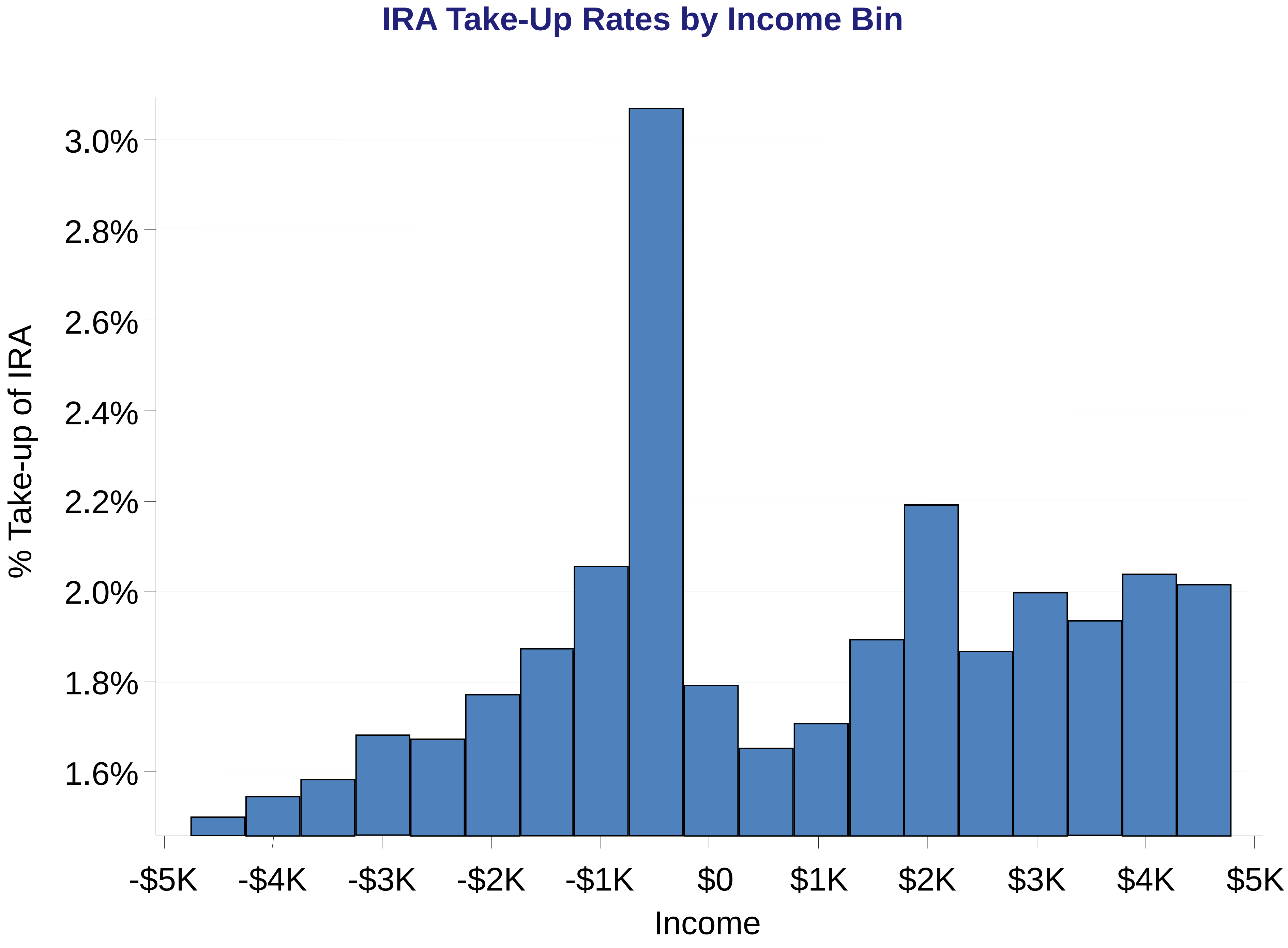
Impact of EITC on Income Distribution for Single Earners with 2+ Children
4%
3%
2%
1%
0%
Percent of EITC-Eligible Wage-Earners
$0
$10K
$20K
$30K
$40K
Total Income
No EITC Counterfactual
EITC, No Behavioral Response
EITC with Behavioral Response

Tax Policy Implications

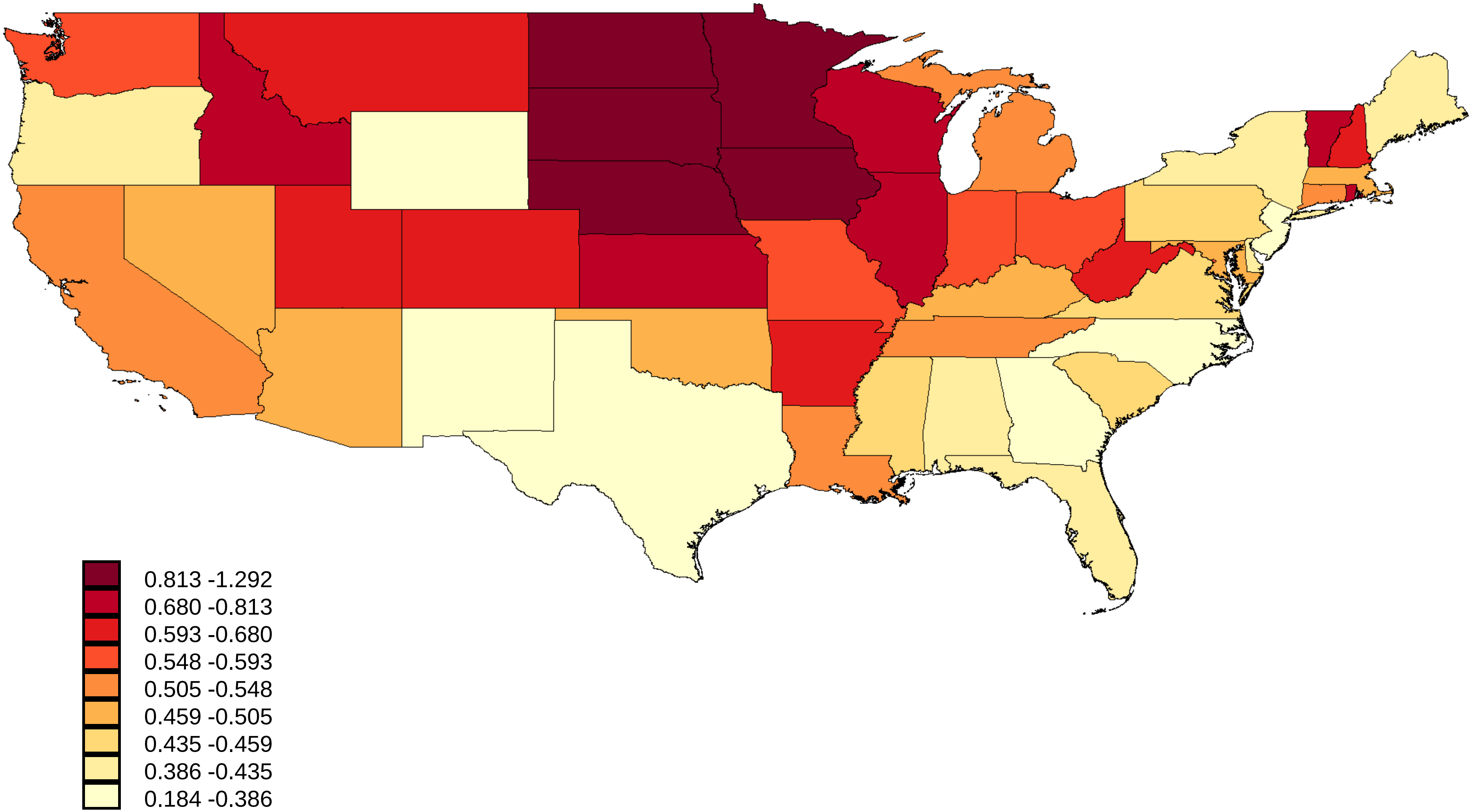
- Our estimates imply that average EITC refund amount for wage-earners is **7%** ($140) larger due to behavioral responses
  - 40% of aggregate response from the top 10% of neighborhoods
- Response primarily due to an intensive-margin increase in earnings coming from the phase-in region
- In neoclassical model, generating an increase of 7% in refund amount would require an intensive margin elasticity of 0.2

Neighborhood Effects: Other Applications

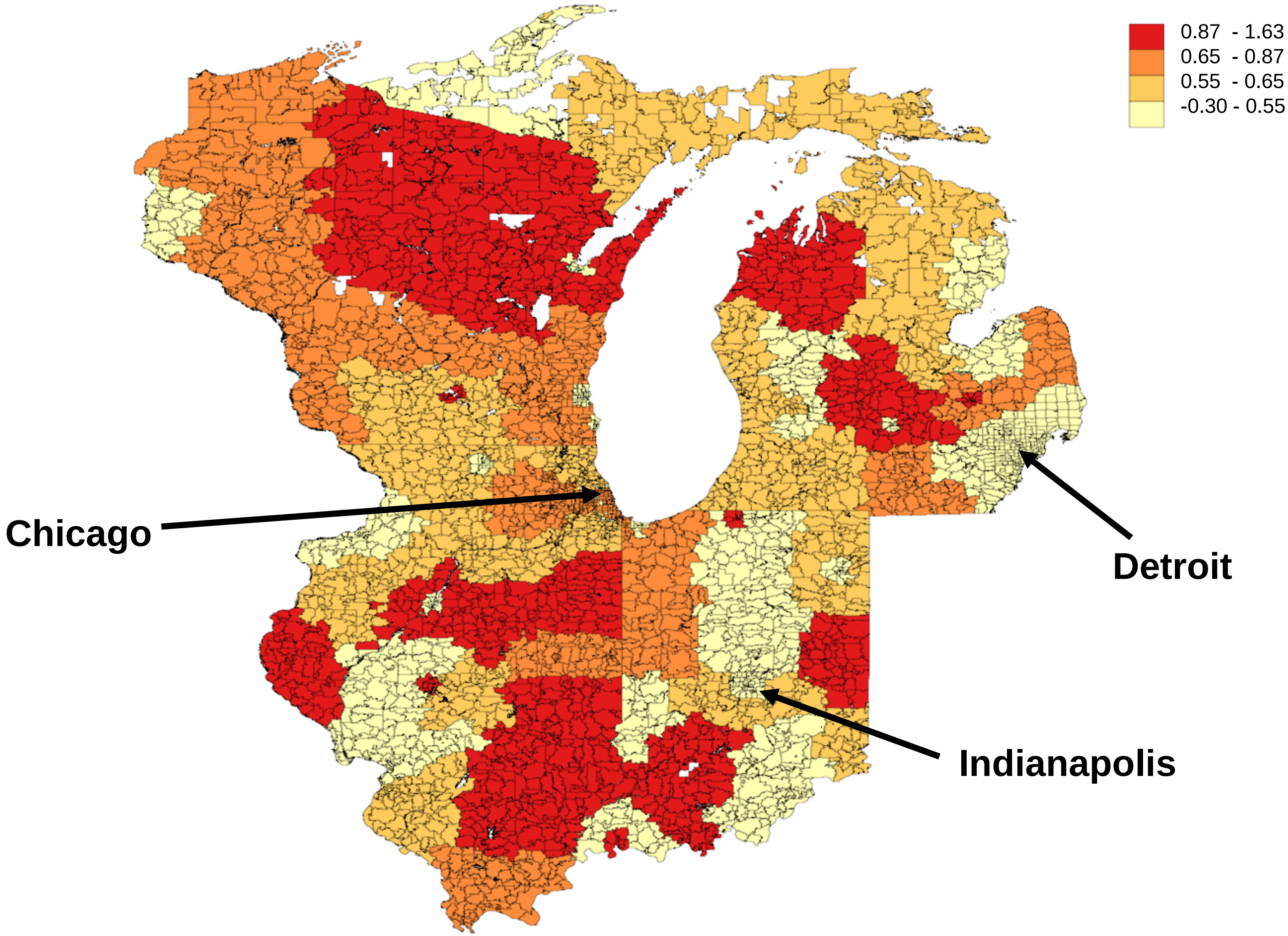
- Neighborhood effects could be used to uncover impacts of many policies
- Example: Saver's Credit
  - Saver's Credit provides up to a 100% subsidy to save in an IRA for low-income households
  - Eligibility based on discontinuous income thresholds
  - Previous work has documented modest impacts of saver's credit on IRA contributions in aggregate [Duflo et al. 2006, 2007; Ramnath 2011]

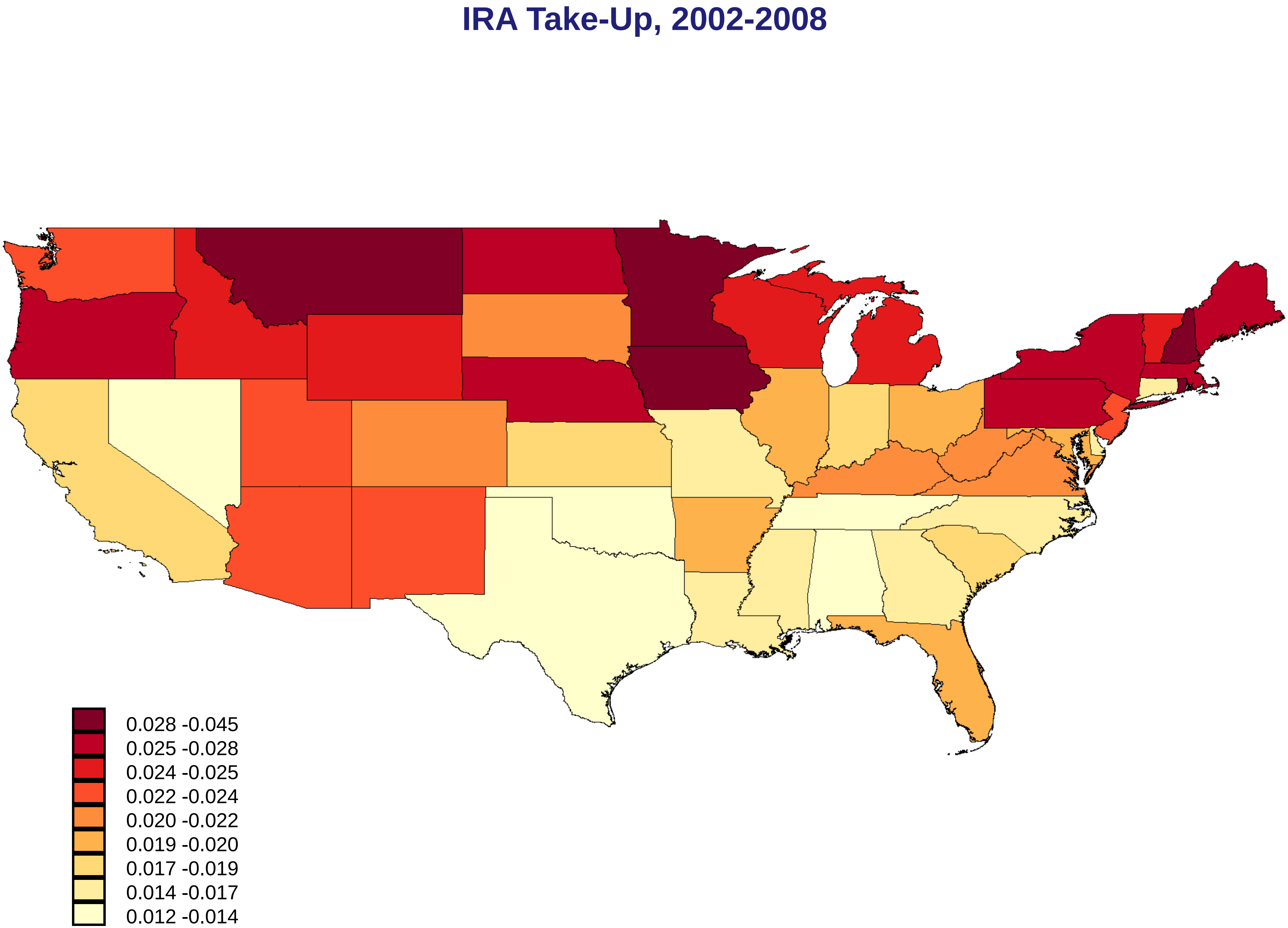

IRA Take-Up Rates by Income Bin
% Take-up of IRA
3.0%
2.8%
2.6%
2.4%
2.2%
2.0%
1.8%
1.6%
-$5K
-$4K
-$3K
-$2K
-$1K
$0
$1K
$2K
$3K
$4K
$5K
Income

Savers Credit Response, 2002-2008



Saver's Credit Response by 3-Digit Zip, 2002-2008 in Illinois, Indiana, Michigan, and Wisconsin




IRA Take-Up, 2002-2008
0.028 -0.045
0.025 -0.028
0.024 -0.025
0.022 -0.024
0.020 -0.022
0.019 -0.020
0.017 -0.019
0.014 -0.017
0.012 -0.014

Neighborhood Effects: Other Applications

- Future work could use neighborhood effects in response to saver's tax credit to analyze impacts of IRAs' on behavior
  - Compare effect of IRA eligibility change in areas with high vs. low saver's credit response
- Neighborhood effects could also be used to analyze other tax policies, e.g. impacts of social security on retirement
  - Classify areas based on response to a policy such as earnings test, as in Friedberg (1999)
  - Use low-response areas as a counterfactual to study the impact of changes in social security policies on retirement