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 govt. policies:

  1. Lack of counterfactuals to estimate causal impacts of policies
     [Meyer 1995, Saez et al. 2012]

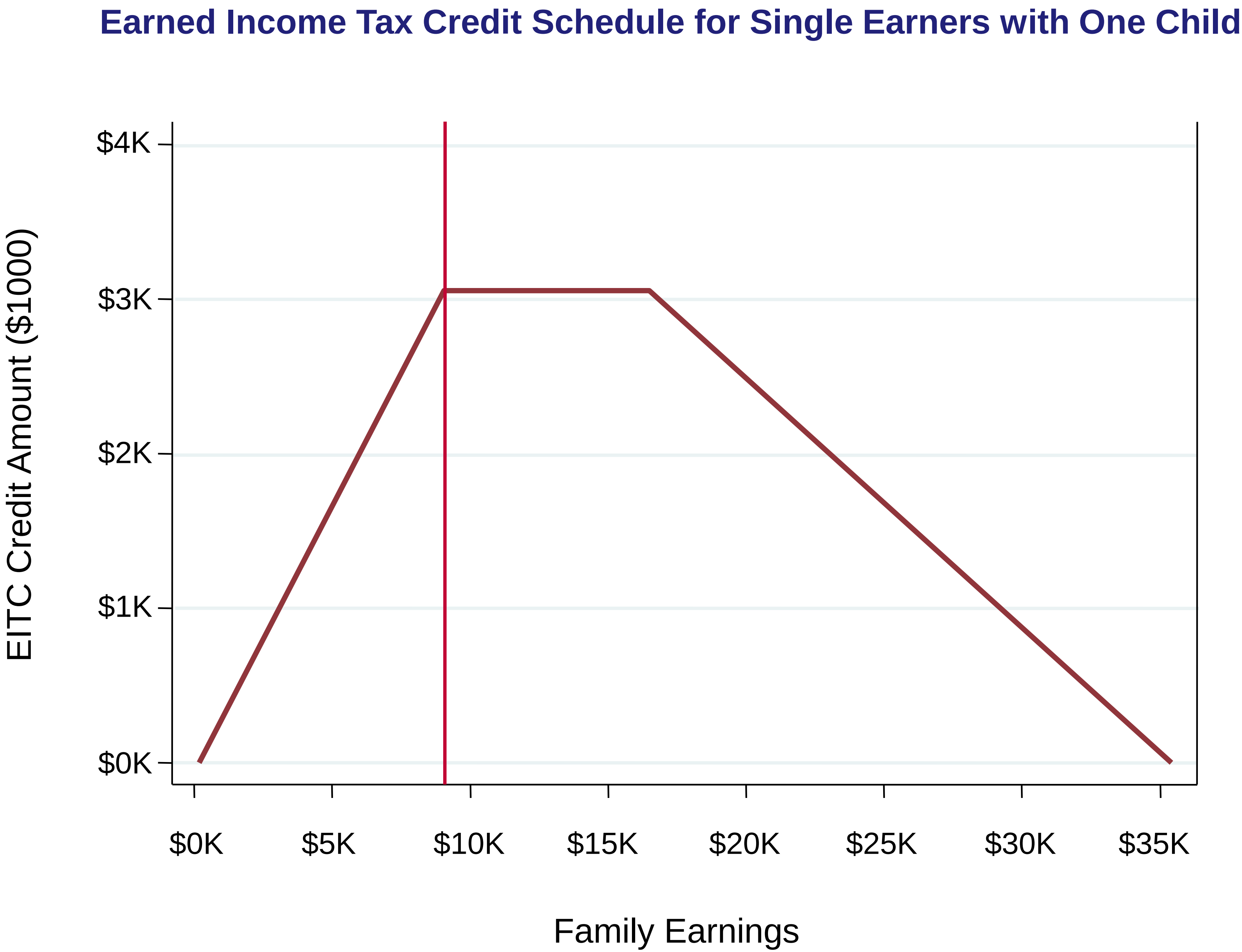
  2. Difficult to identify long run impacts from short-run responses to tax changes

     - 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 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.

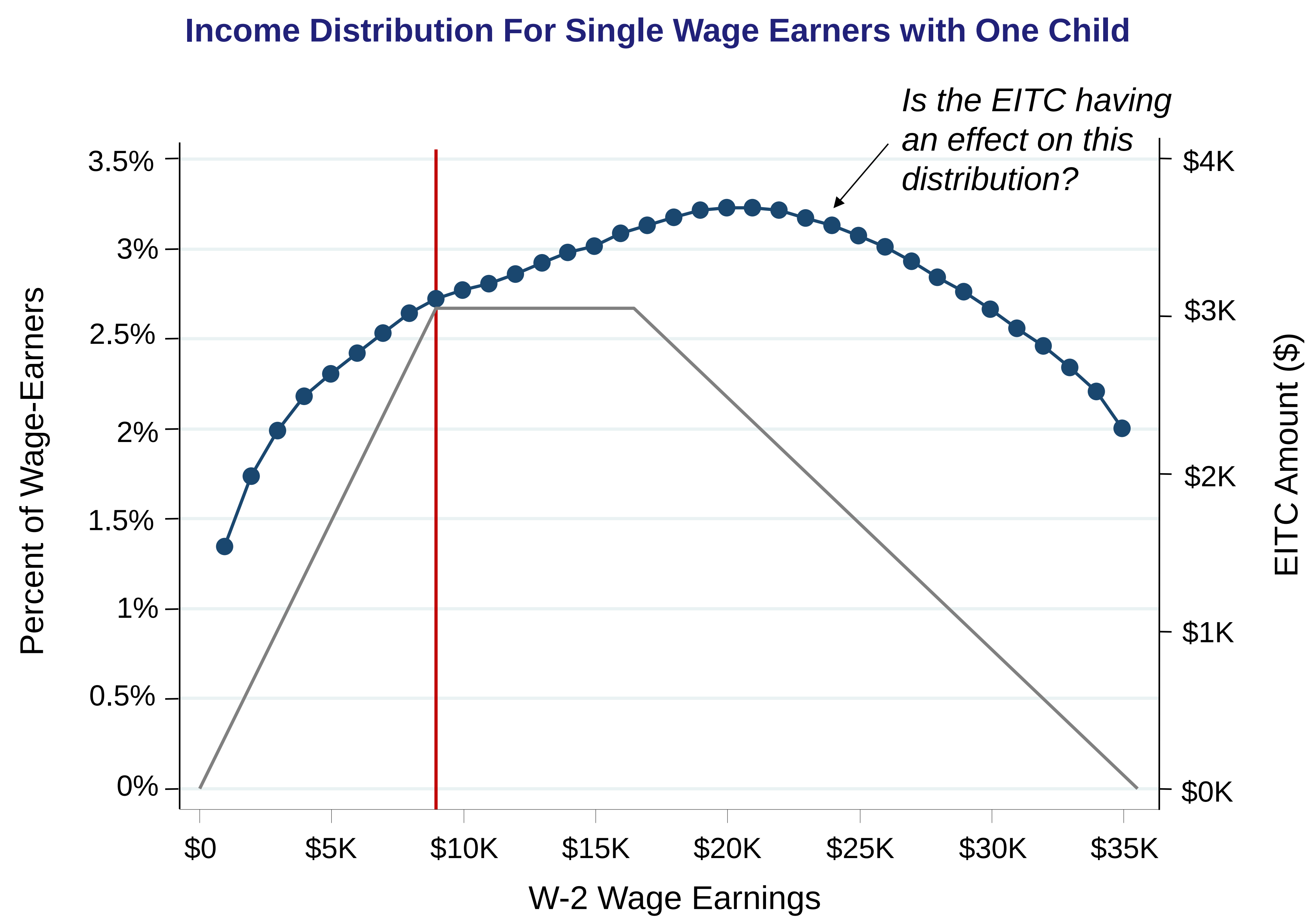


Earned Income Tax Credit Schedule for Single Earners with One Child
EITC Credit Amount ($1000)
$4K
$3K
$2K
$1K
$0K
$0K
$5K
$10K
$15K
$20K
$25K
$30K
$35K
Family Earnings

Relationship to Prior Work

- 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 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 2^{nd}-order on intensive but 1^{st} order on ext. margin → frictions attenuate intensive responses [Chetty 2012]

Income Distribution For Single Wage Earners with One Child



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

Outline

1. Conceptual Framework

2. Data and Institutional Background

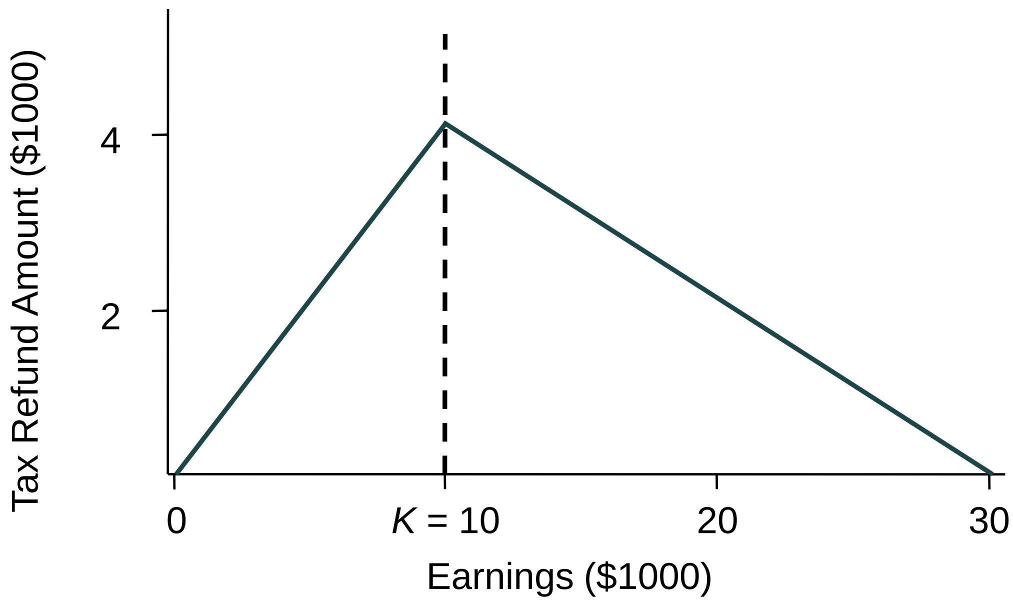
3. Proxy for Knowledge: Sharp Bunching via Self-Emp Income Manipulation

4. Uncover Wage Earnings Responses

5. Implications for Tax Policy

Stylized Model: Tax System

- Workers face a two-bracket income tax system $\tau = (\tau_1, \tau_2)$ and choose earnings z=wl 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 → bunching around K



Neighborhoods

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

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

- 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

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

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

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

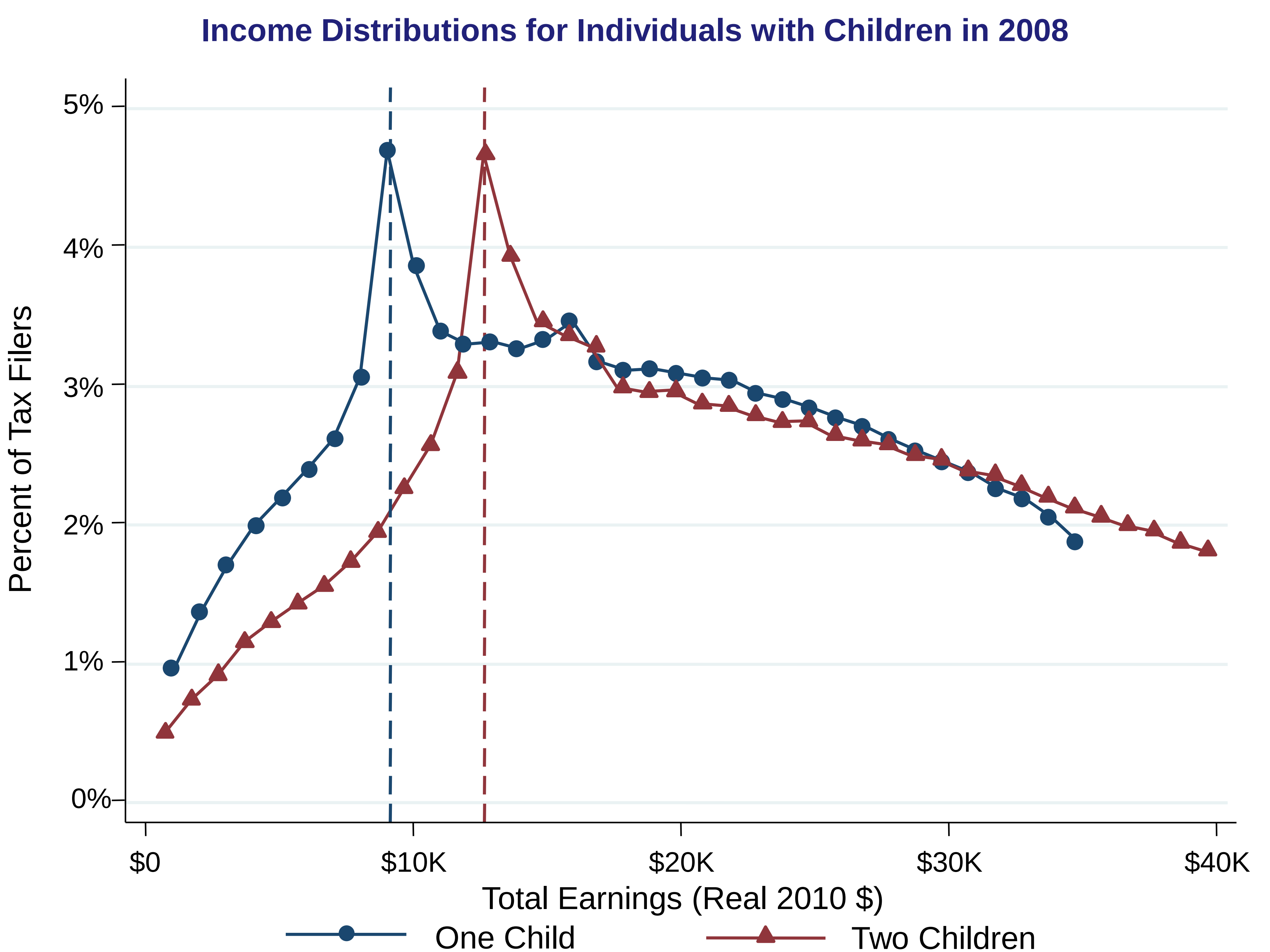
Summary Statistics for EITC Eligible Individuals

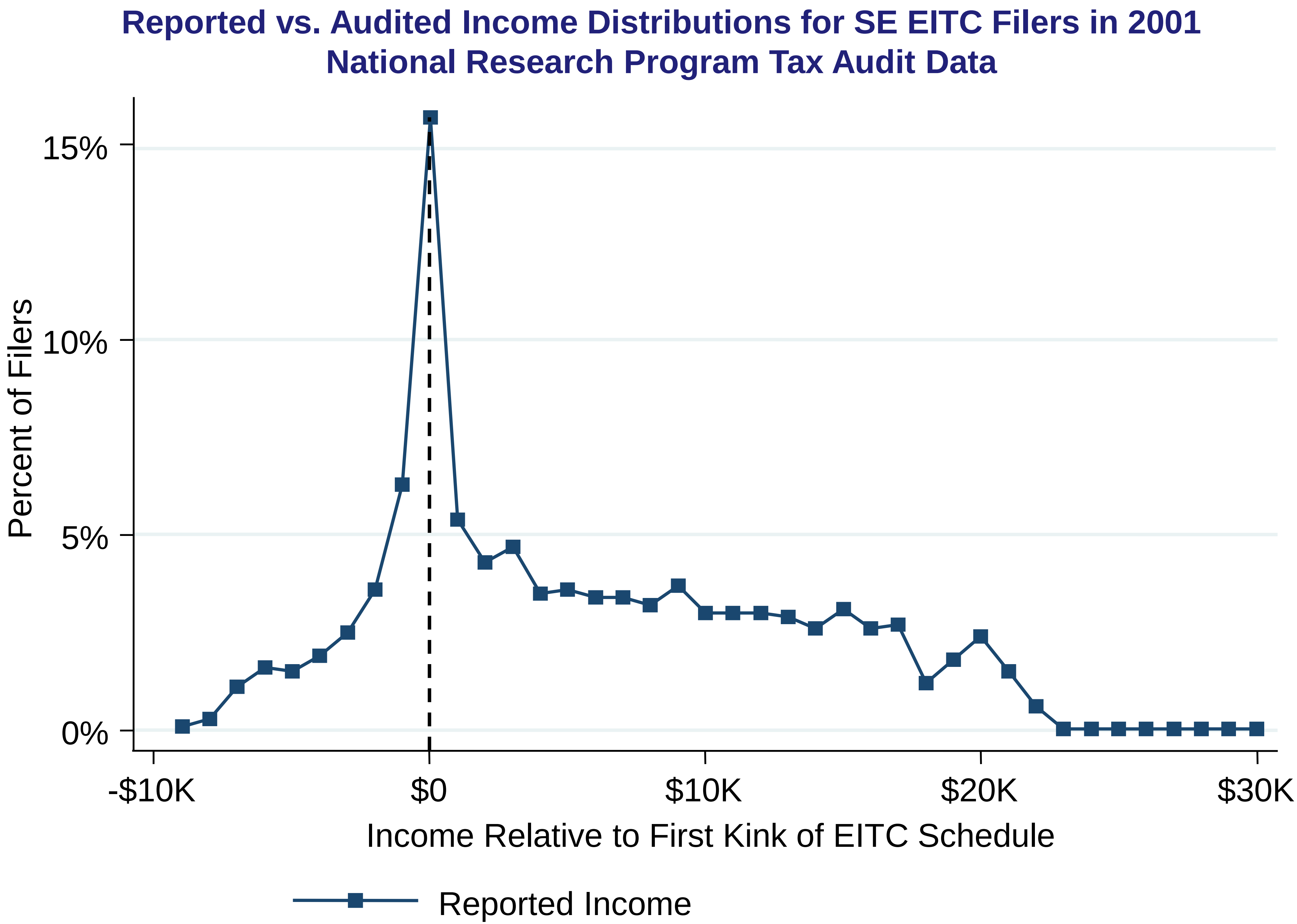
Variable	Mean (1)	Std. Dev. (2)
Income Measures		
Total Earnings	$20,091	$10,784
Wage Earnings	$18,308	$12,537
Self-Employment Income	$1,770	$6,074
Non-Zero Self-Emp. Income	19.6%	39.7%
Tax Credits		
EITC Refund Amount	$2,543	$1,454
Claimed EITC	88.9%	31.4%
Professionally Prepared Return	69.6%	46.0%
Demographics		
Age	37	13
Number of Children	1.7	0.8
Married	30.3%	45.9%
Female (for single filers)	73.0%	44.4%
Number of Observations	219,742,011	

Self Employment Income vs. Wage Earnings

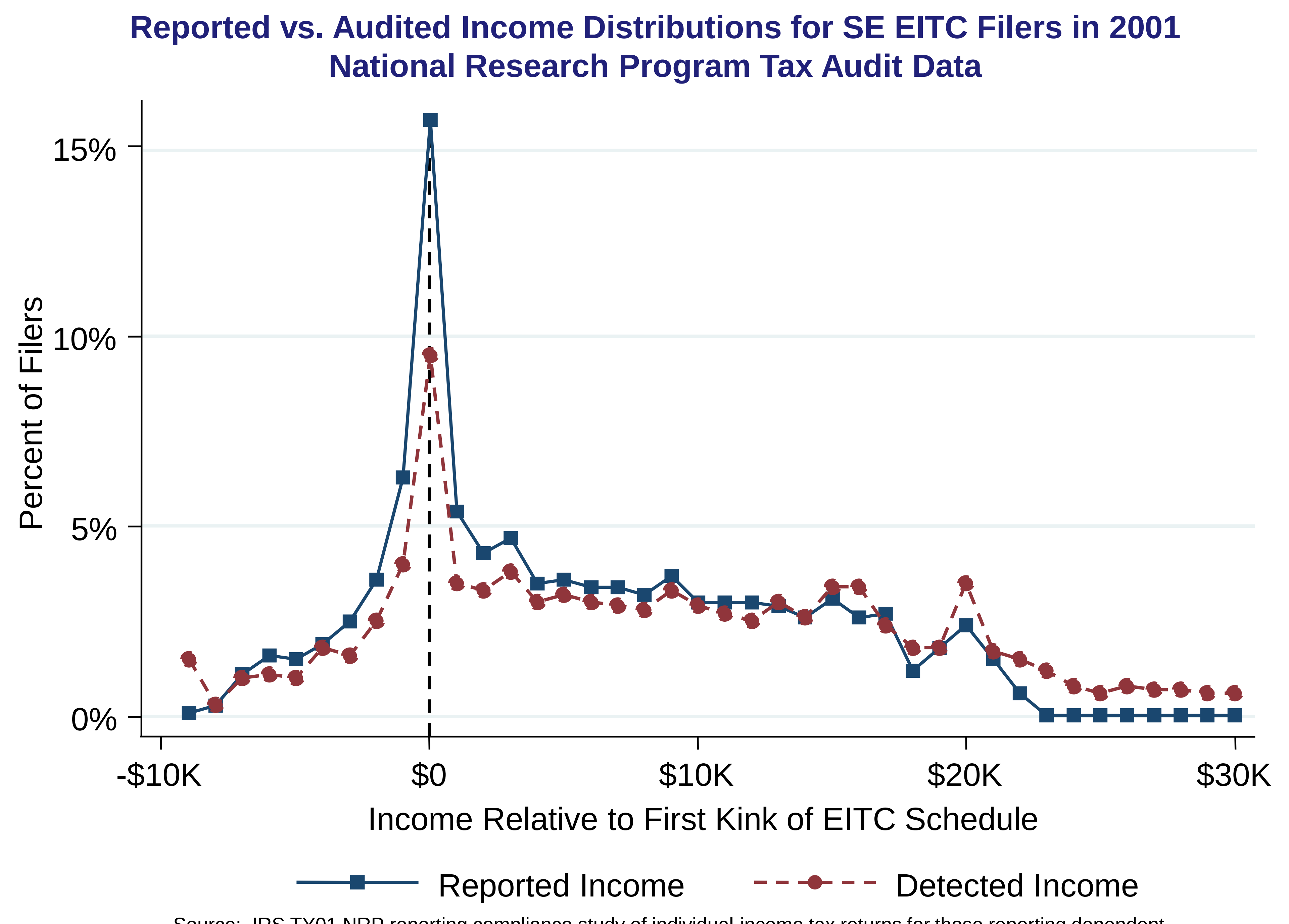
- To measure local knowledge, we rely on a critical distinction between wage earnings and self-employment income
- Self-employment income is self-reported → easy to manipulate
- Wage earnings are directly reported to IRS by employers
  - Therefore more likely to reflect "real" earnings behavior

2008 Federal EITC Schedule for a Single Filer with Children


Income Distributions for Individuals with Children in 2008
Percent of Tax Filers
5%
4%
3%
2%
1%
0%
$0
$10K
$20K
$30K
$40K
Total Earnings (Real 2010 $)
One Child
Two Children



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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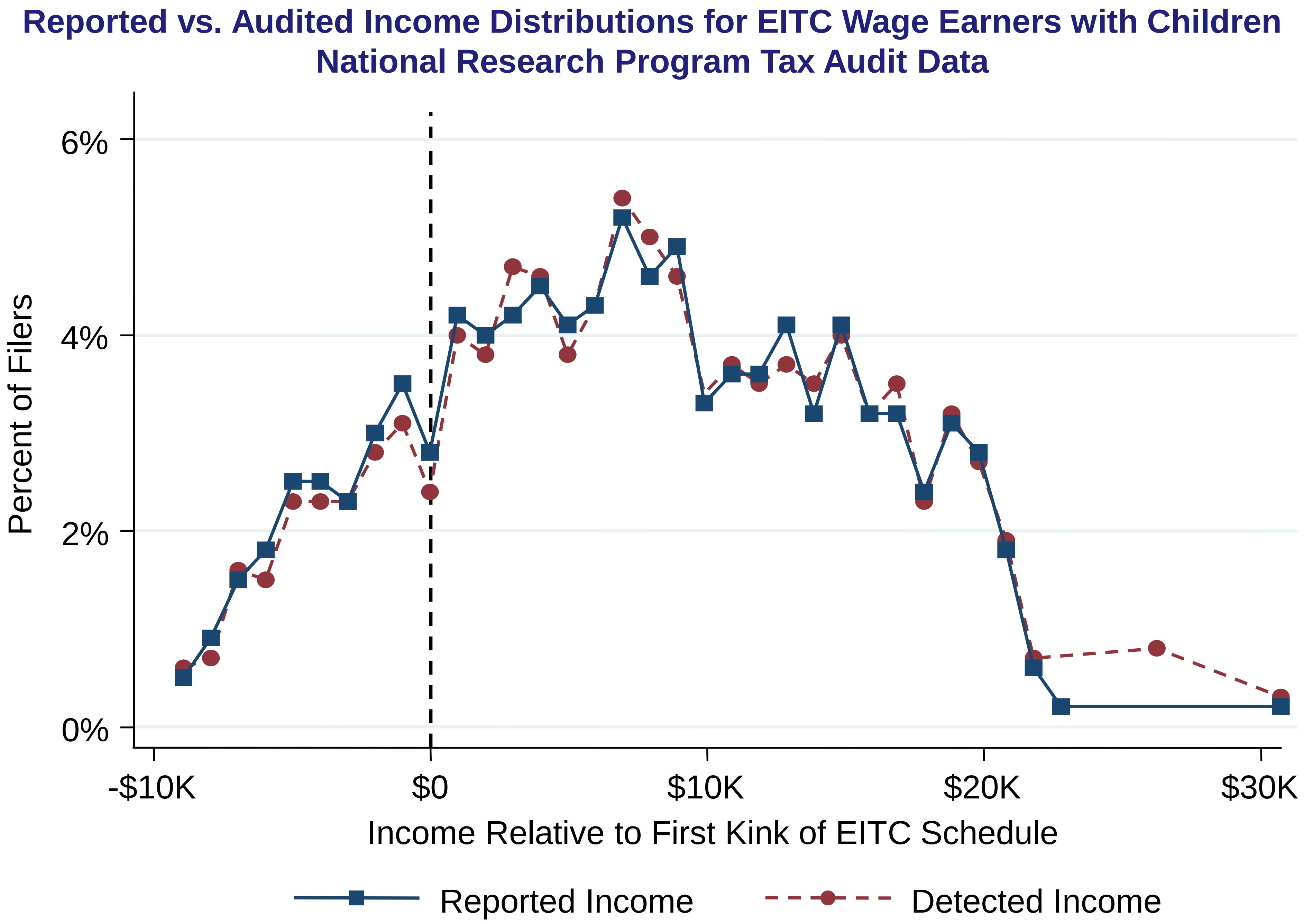


Source: IRS TY01 NRP reporting compliance study of individual income tax returns for those reporting dependent children; amounts reflect only what was detected by the auditors, weighted to population levels.

Empirical Implementation: Proxy for Knowledge

- We proxy for knowledge λ_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 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:

$$\phi_c = \theta_c \lambda_c$$

Empirical Implementation: Proxy for Knowledge

- 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

Identification Assumption 1: Tax Knowledge

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

$$\widehat{\Delta F} = F(z|\tau) - F(z|\tau, \phi_c = 0)$$

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

Identification Assumption 2: Counterfactuals

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

$$\widehat{\Delta F} = F(z|\tau) - F(z|\tau, \phi_c = 0)$$

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

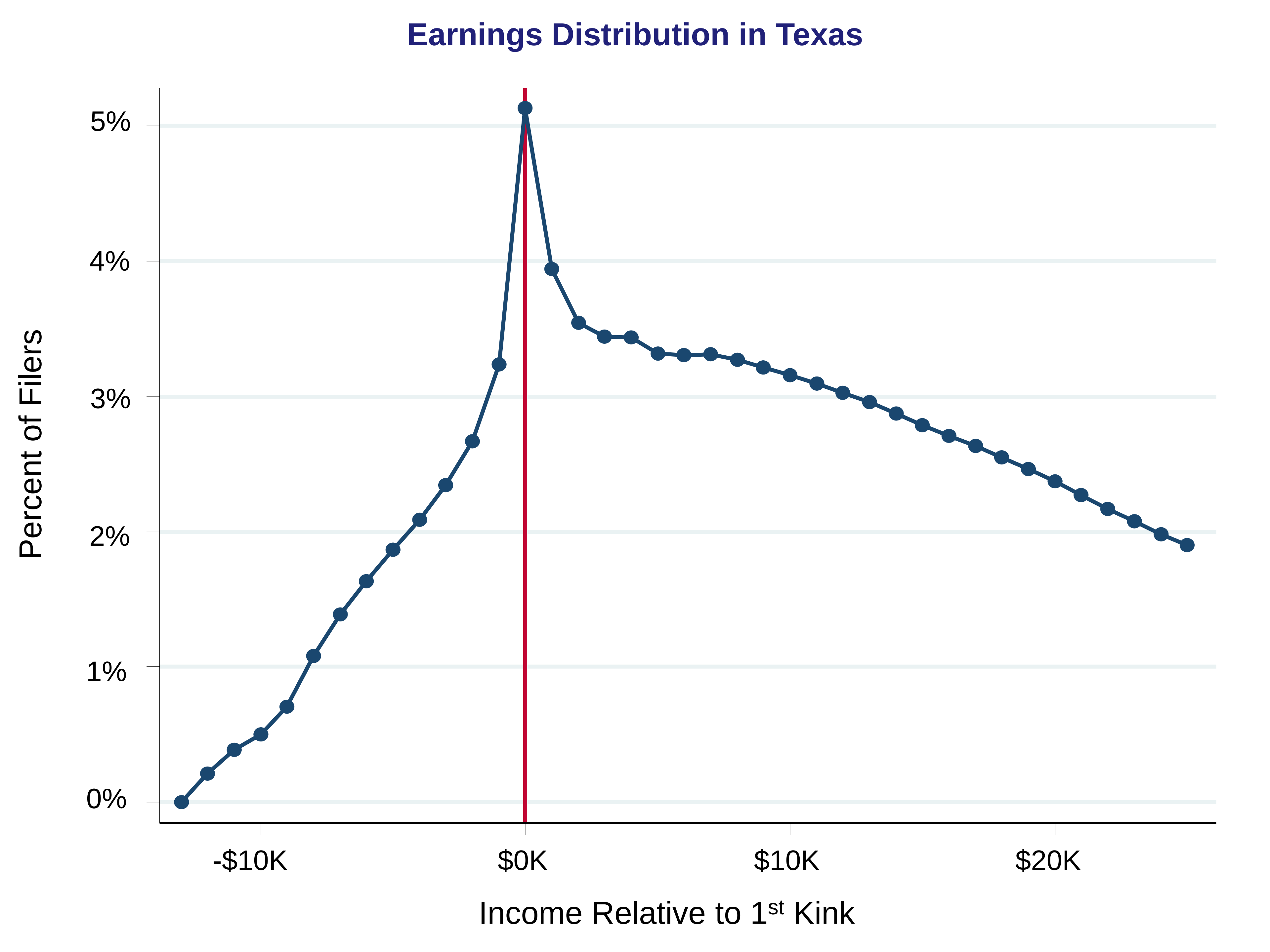
- Panel estimator: compare *changes* in aggregate earnings distribution around eligibility due to child birth with changes in $\phi_c = 0$ nbhds.

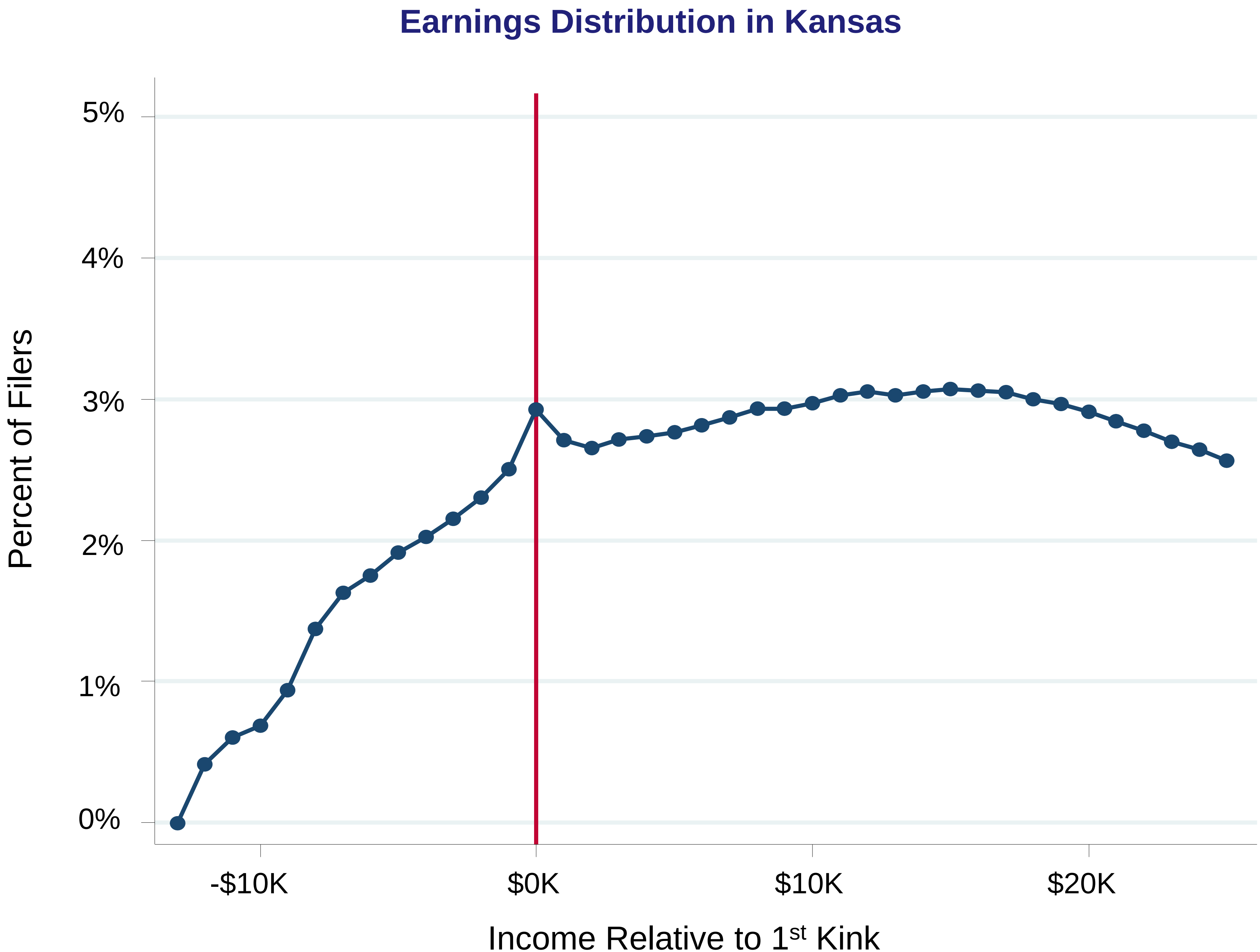
$$\widehat{\Delta F}_{DD} = [F_t(z|\tau) - F_t(z|\tau, \phi_c = 0)] - [F_{t-1}(z|\tau) - F_{t-1}(z|\tau, \phi_c = 0)]$$

Assumption 2b [Panel Identification] *Changes in skills when an individual becomes eligible for credit do not vary across cities with different λ_c*

Outline of Empirical Analysis

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

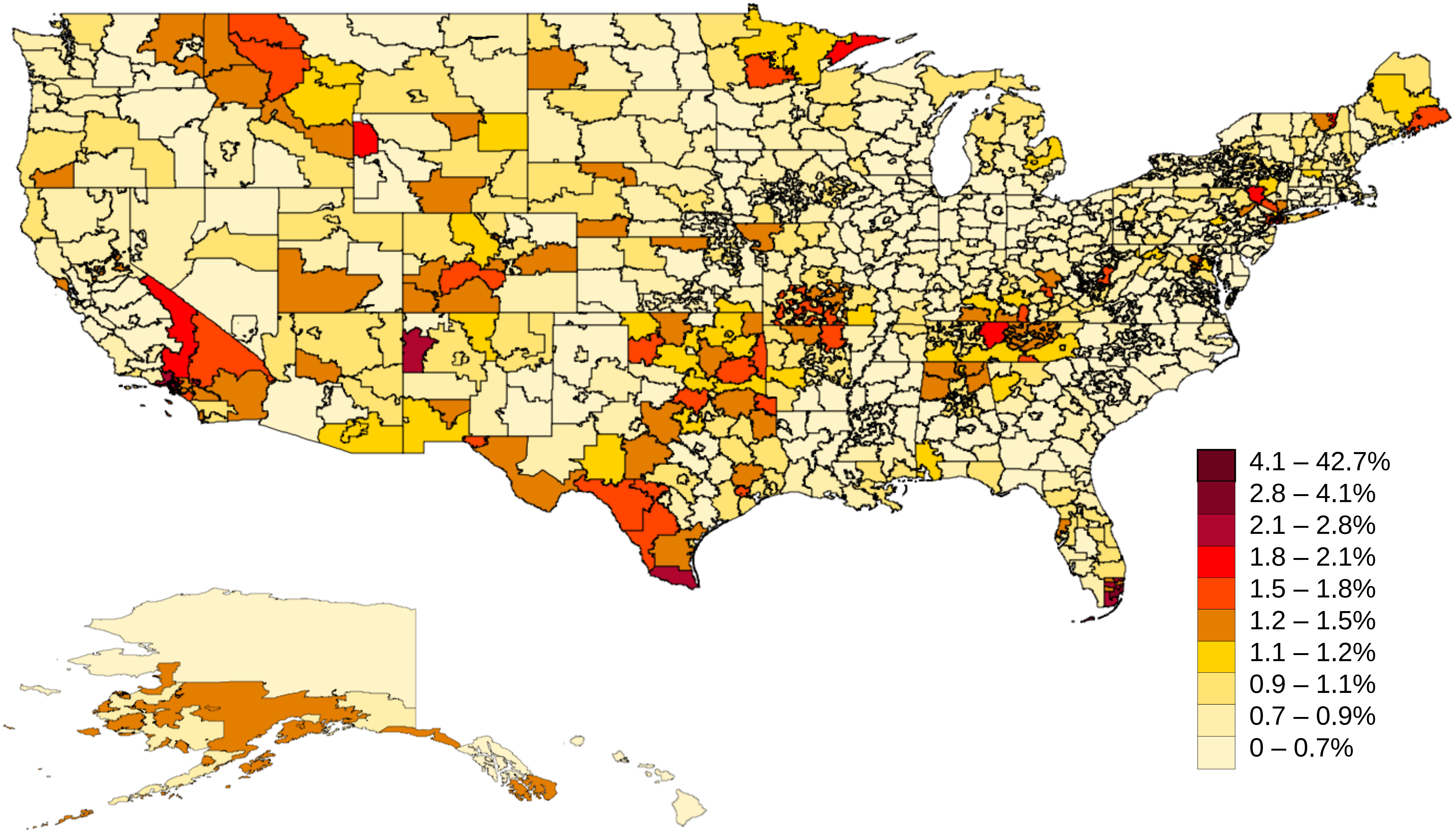

Earnings Distribution in Texas
5%
4%
3%
2%
1%
0%
Percent of Filers
-$10K
$0K
$10K
$20K
Income Relative to 1st Kink


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

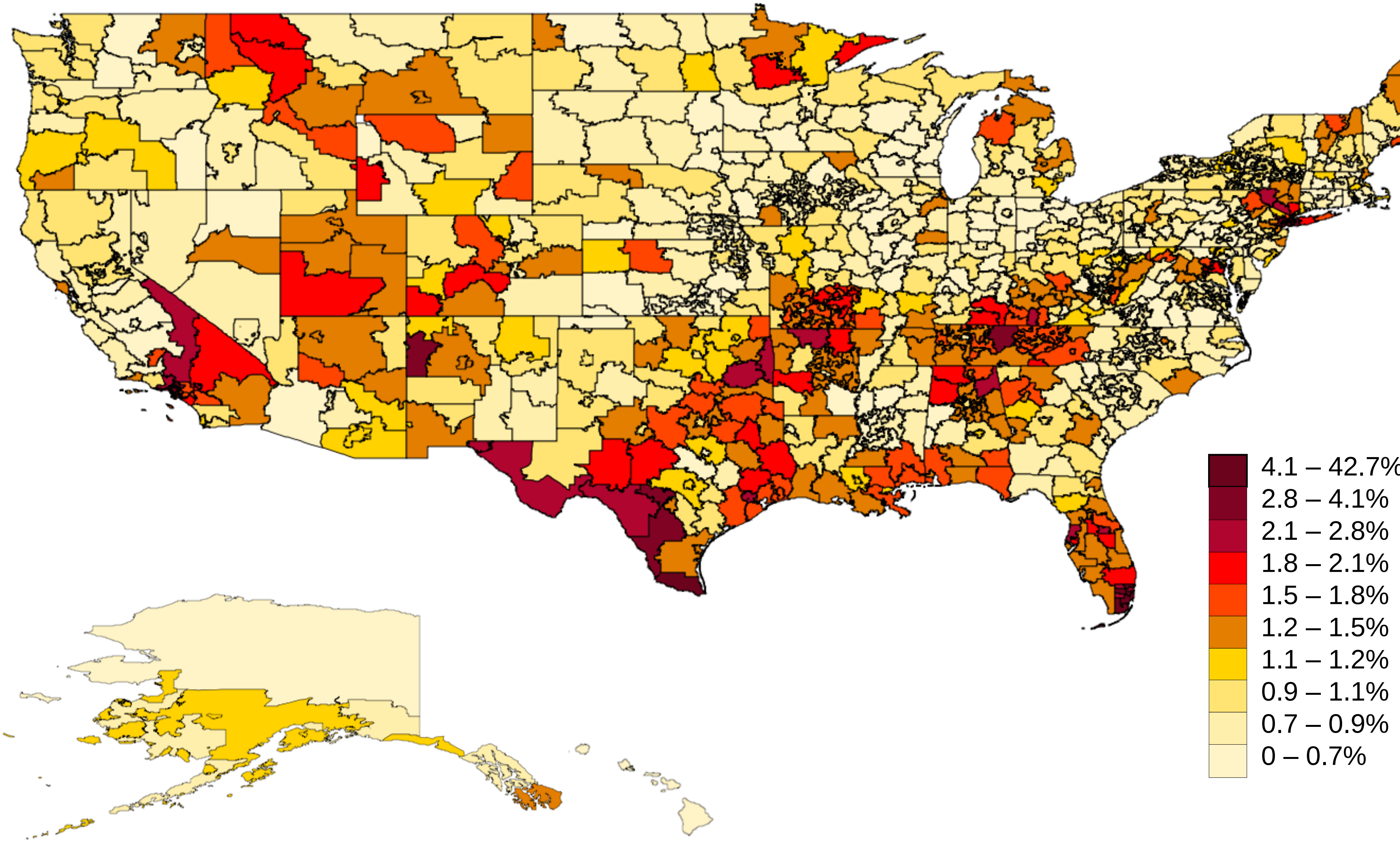
Neighborhood-Level Measure of Bunching

- Define a measure of "sharp bunching" in each neighborhood
  - Fraction of EITC-eligible tax filers who report income at first kink and have self-employment income
  - Measures fraction of individuals who manipulate reported income to maximize EITC refund in each neighborhood
- Begin by documenting spatial evolution of sharp bunching across U.S.

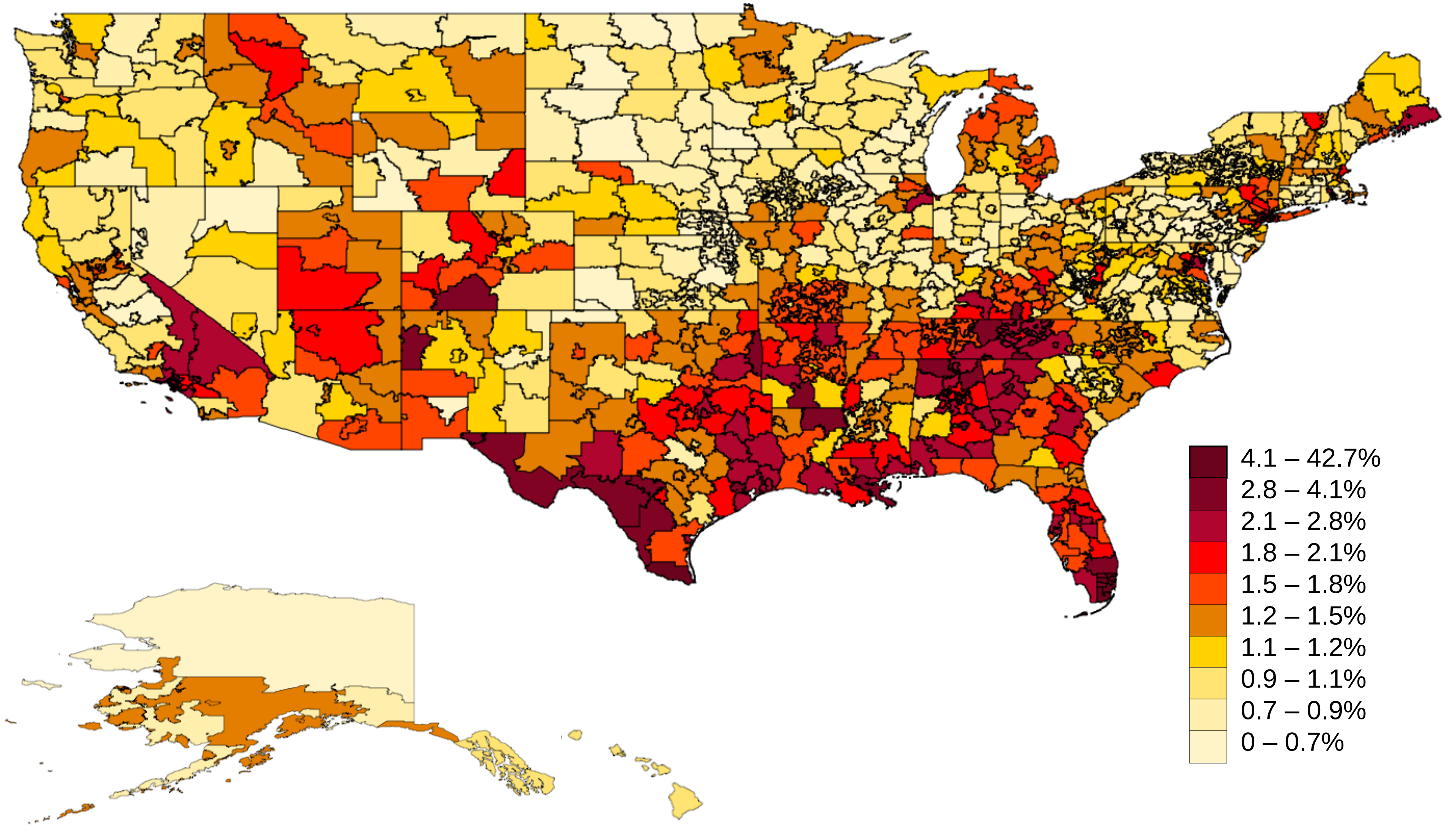
Fraction of Tax Filers Who Report SE Income that Maximizes EITC Refund in 1996



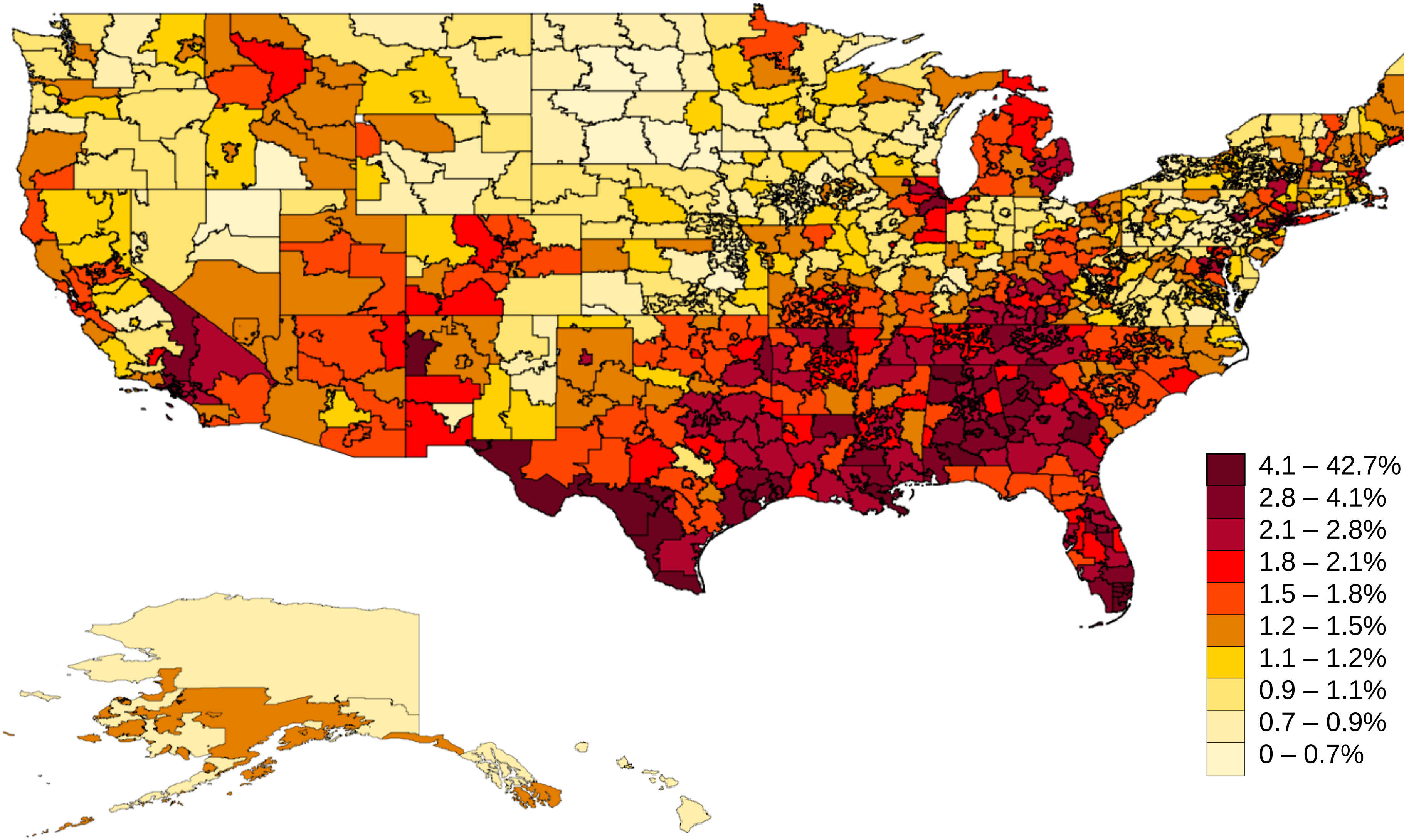
Fraction of Tax Filers Who Report SE Income that Maximizes EITC Refund in 1999



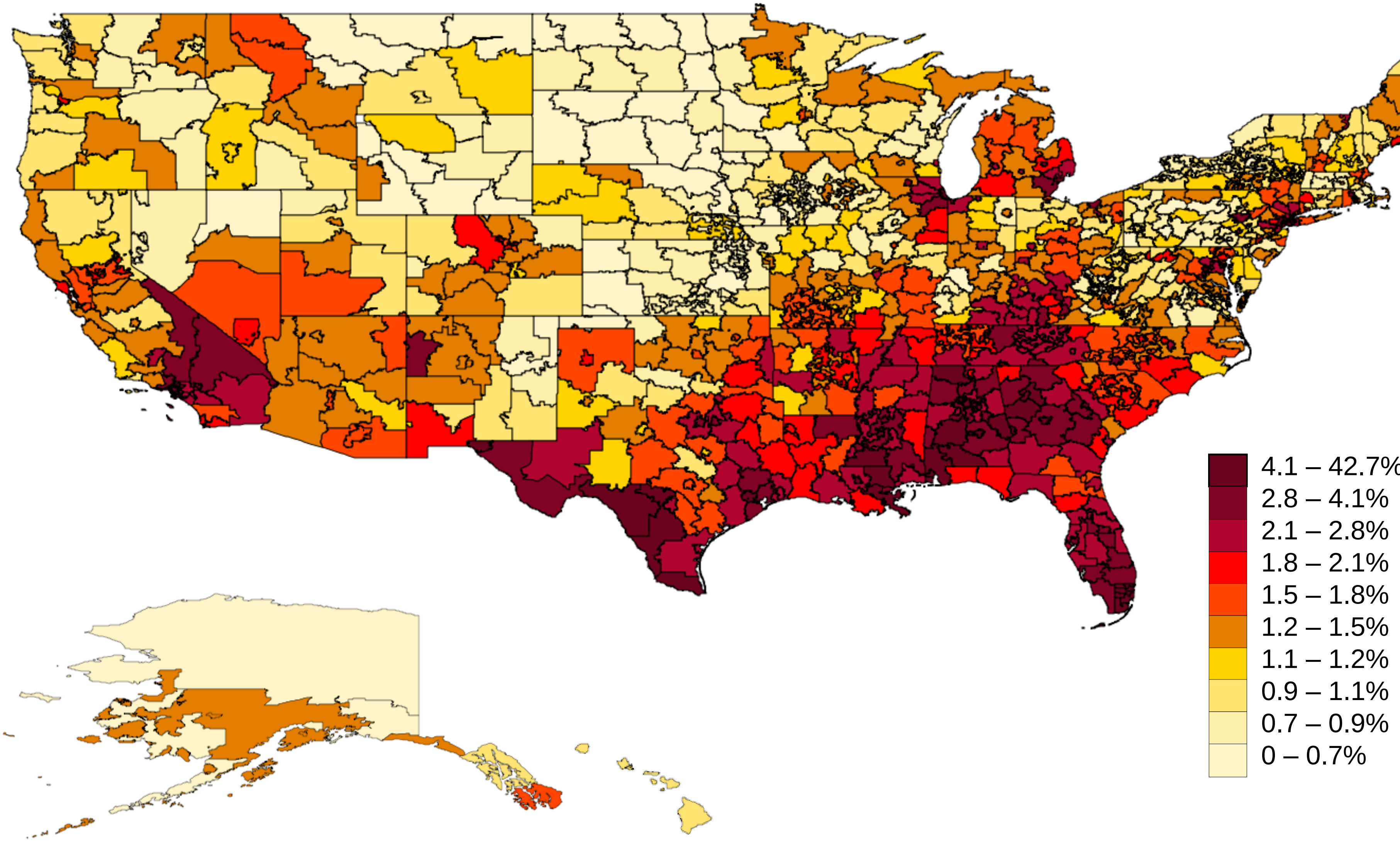
Fraction of Tax Filers Who Report SE Income that Maximizes EITC Refund in 2002

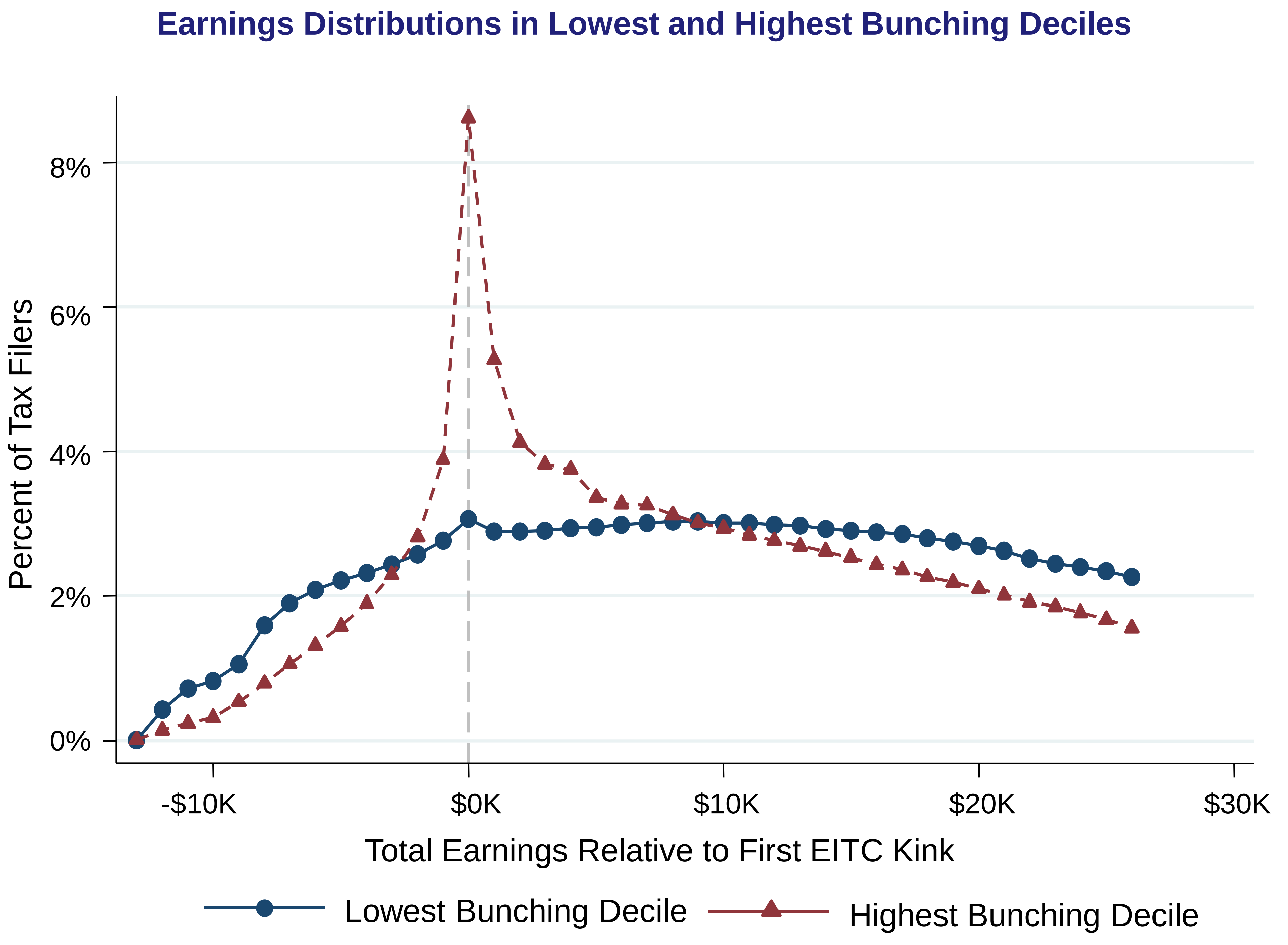


Fraction of Tax Filers Who Report SE Income that Maximizes EITC Refund in 2005



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
8%
6%
4%
2%
0%
-$10K
$0K
$10K
$20K
$30K
Total Earnings Relative to First EITC Kink
Lowest Bunching Decile
Highest Bunching Decile

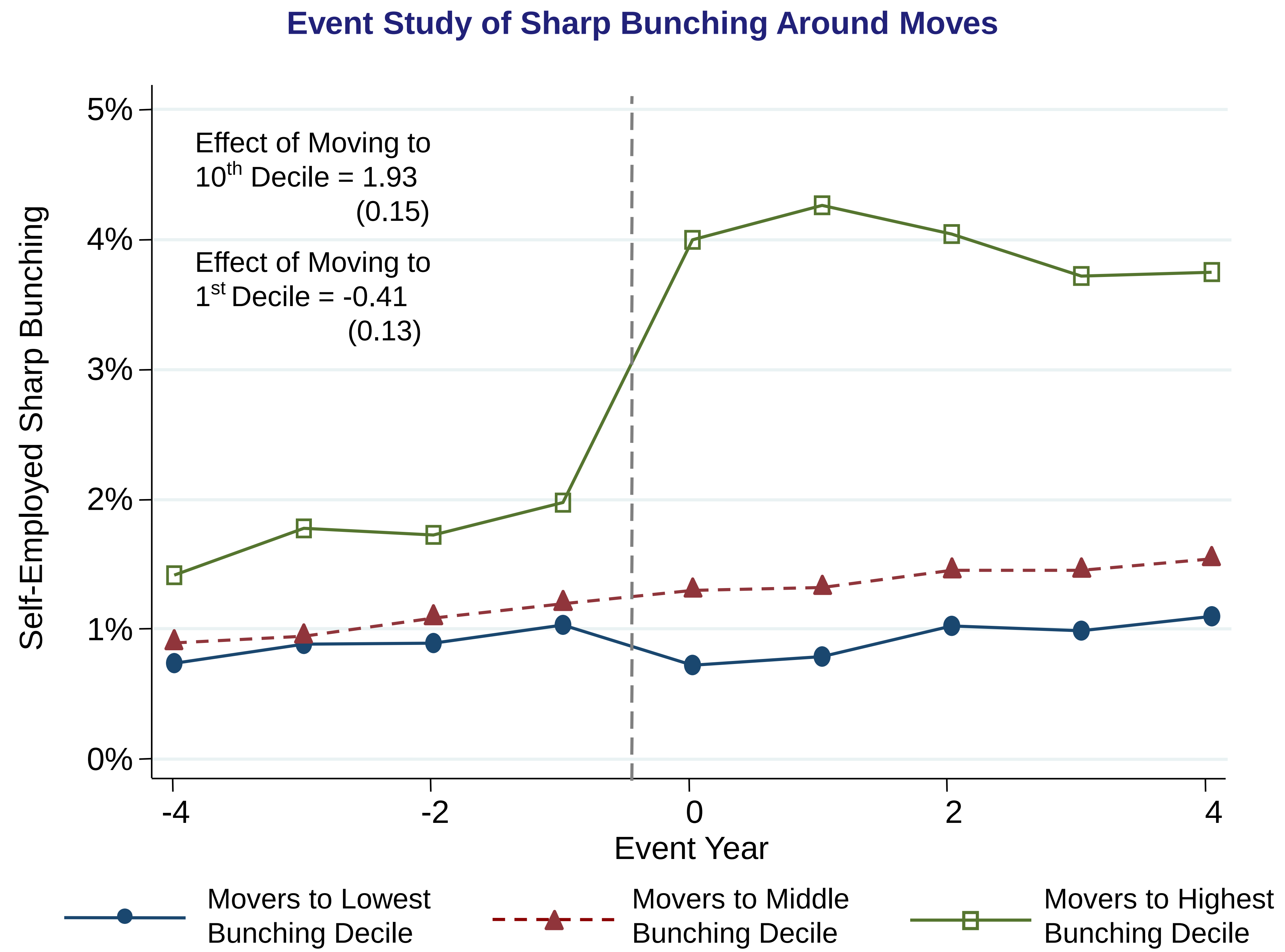
Outline of Empirical Analysis

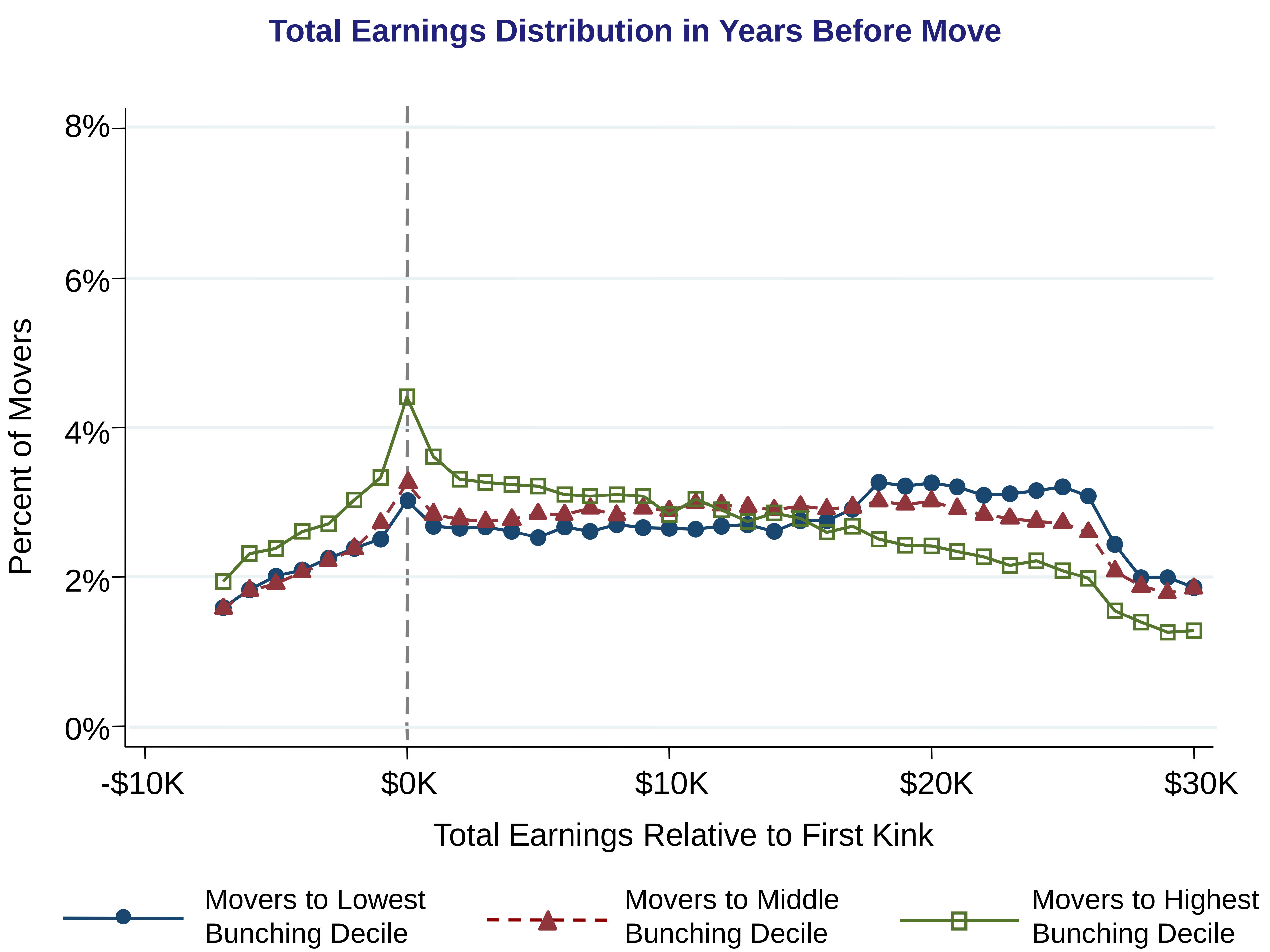
- Step 1: Document variation across neighborhoods in sharp bunching among self-employed

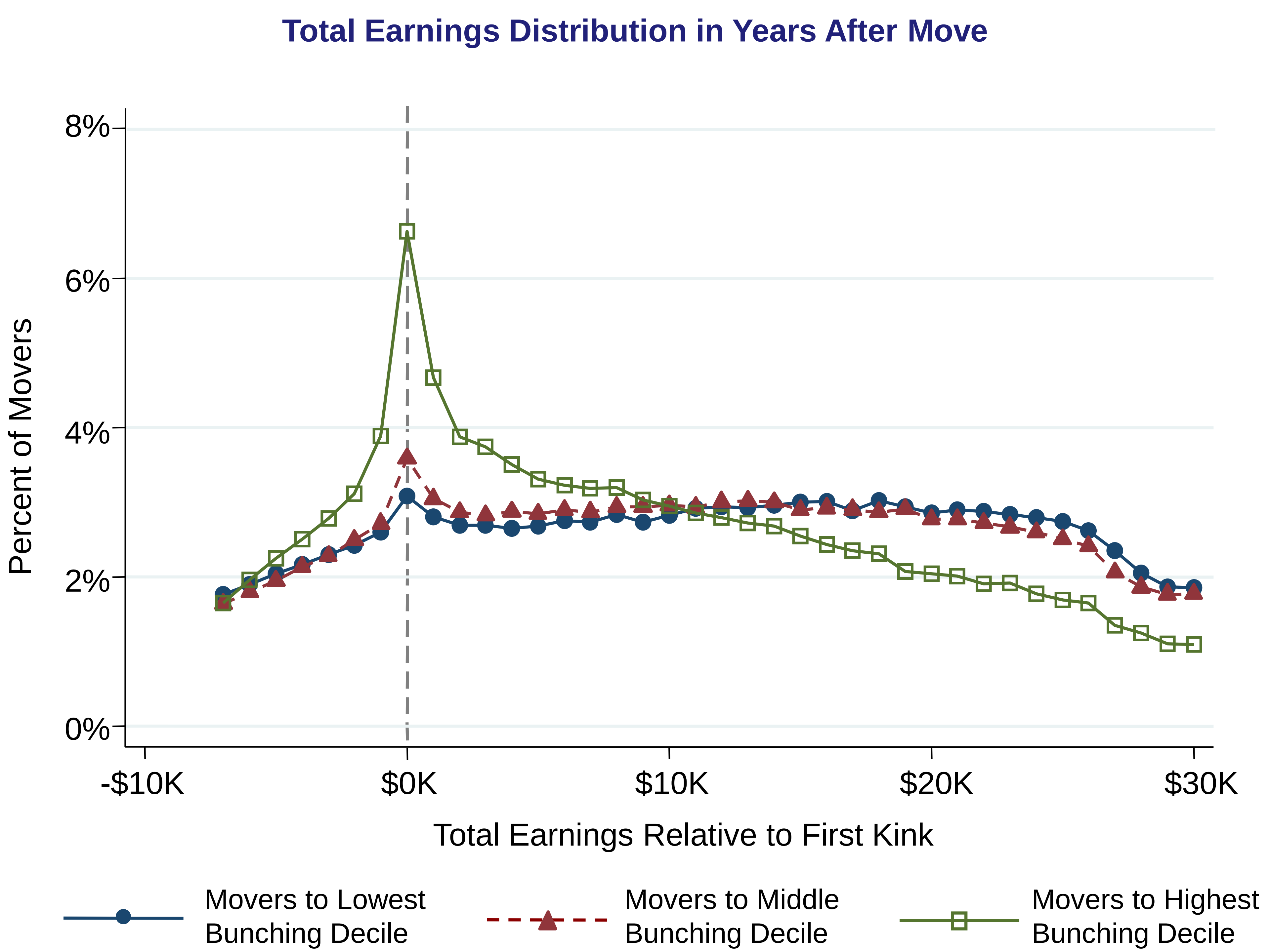
- Step 2: Establish that variation in sharp bunching across neighborhoods is driven by differences in knowledge about EITC schedule

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

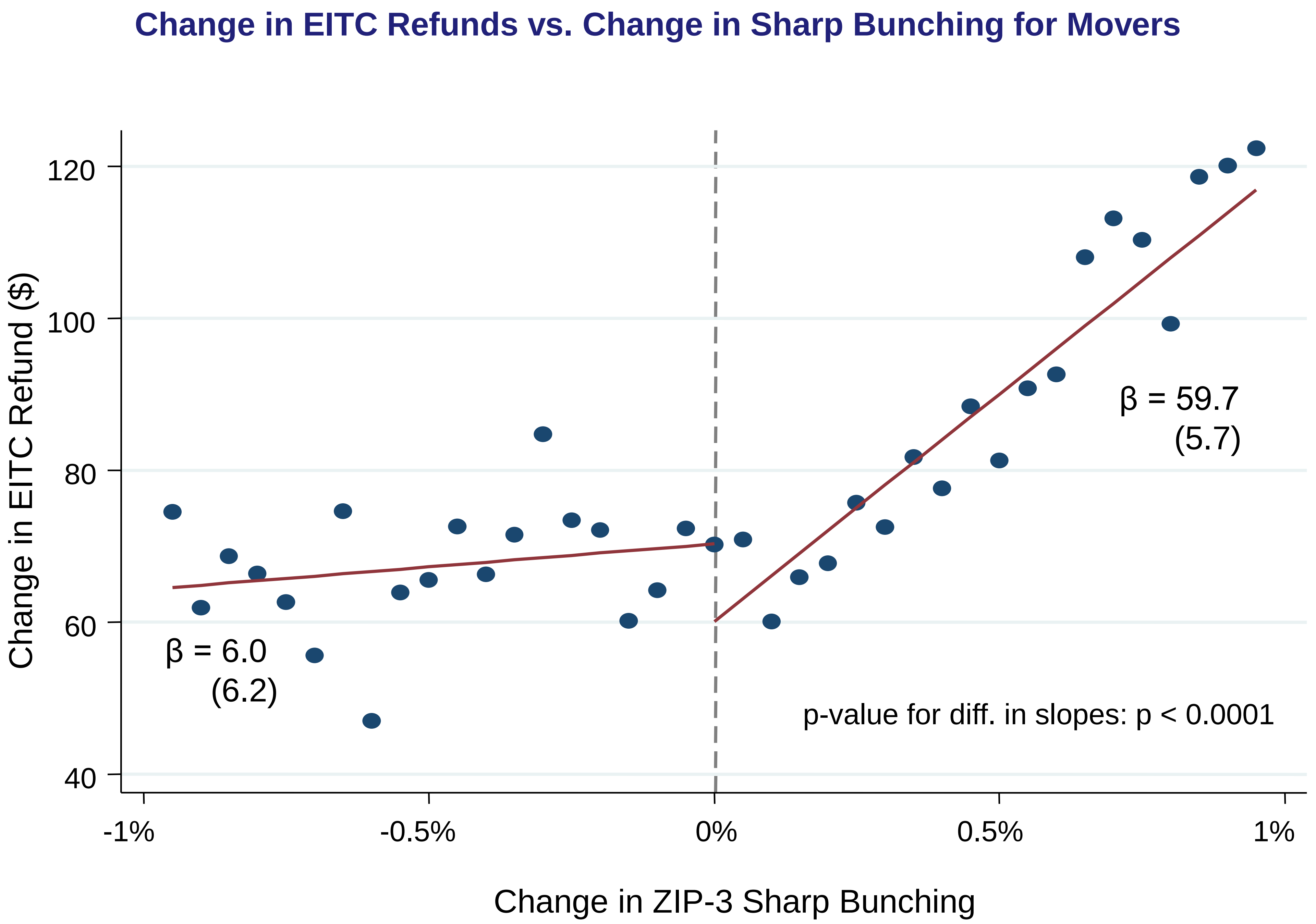

Event Study of Sharp Bunching Around Moves
Self-Employed Sharp Bunching
5%
4%
3%
2%
1%
0%
-4
-2
0
2
4
Event Year
Effect of Moving to
10th Decile = 1.93
(0.15)
Effect of Moving to
1st Decile = -0.41
(0.13)
Movers to Lowest Bunching Decile
Movers to Middle Bunching Decile
Movers to Highest Bunching Decile


Total Earnings Distribution in Years Before Move
8%
6%
4%
2%
0%
Percent of Movers
-$10K
$0K
$10K
$20K
$30K
Total Earnings 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
8%
6%
4%
2%
0%
Percent of Movers
-$10K
$0K
$10K
$20K
$30K
Total Earnings Relative to First Kink
Movers to Lowest Bunching Decile
Movers to Middle Bunching Decile
Movers to Highest Bunching Decile

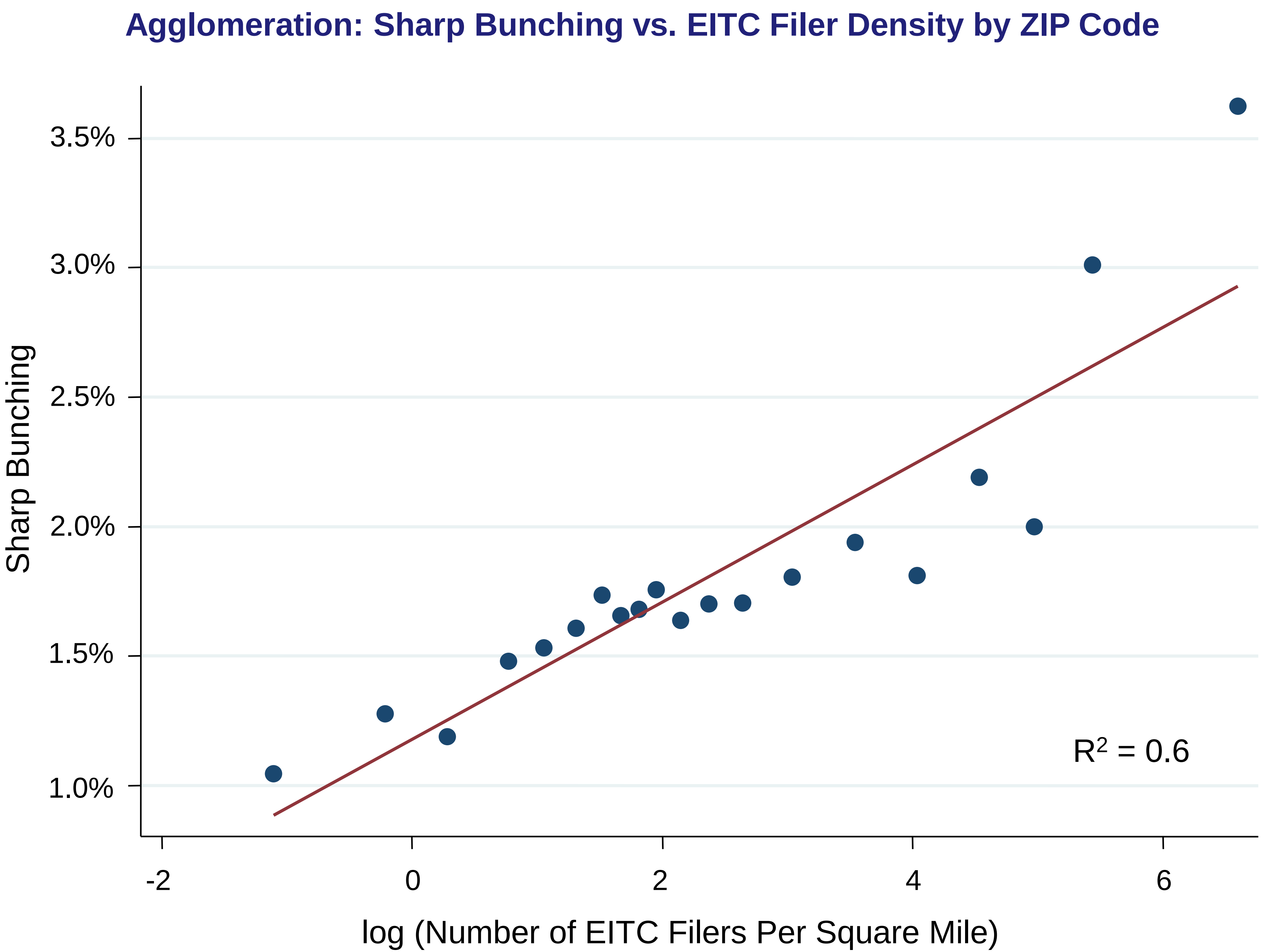
Learning and Memory

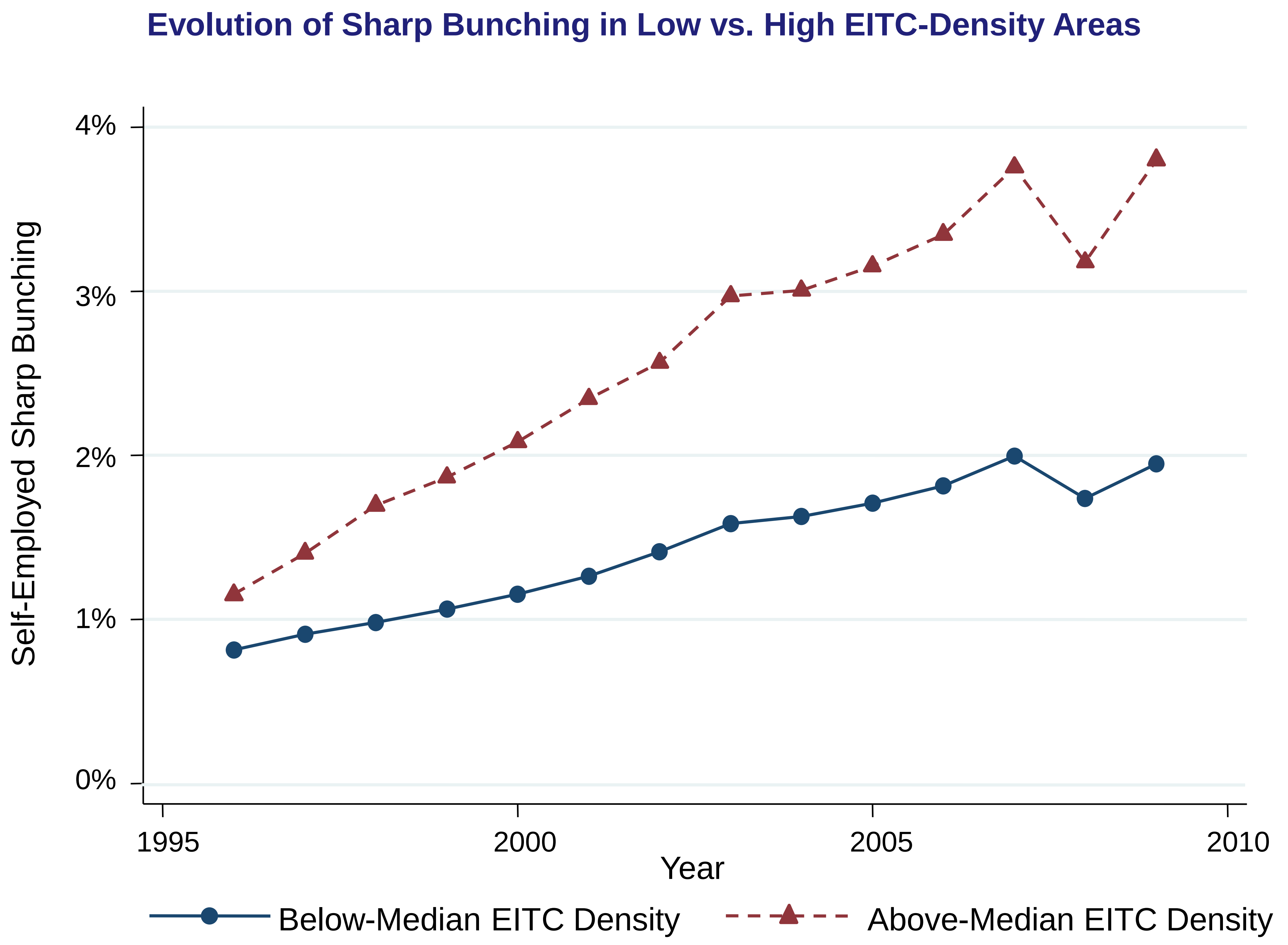
- Knowledge model predicts asymmetric impact of moving:
  - Moving to a higher-bunching neighborhood should raise EITC refund
  - Moving to a lower-bunching should not affect EITC refund

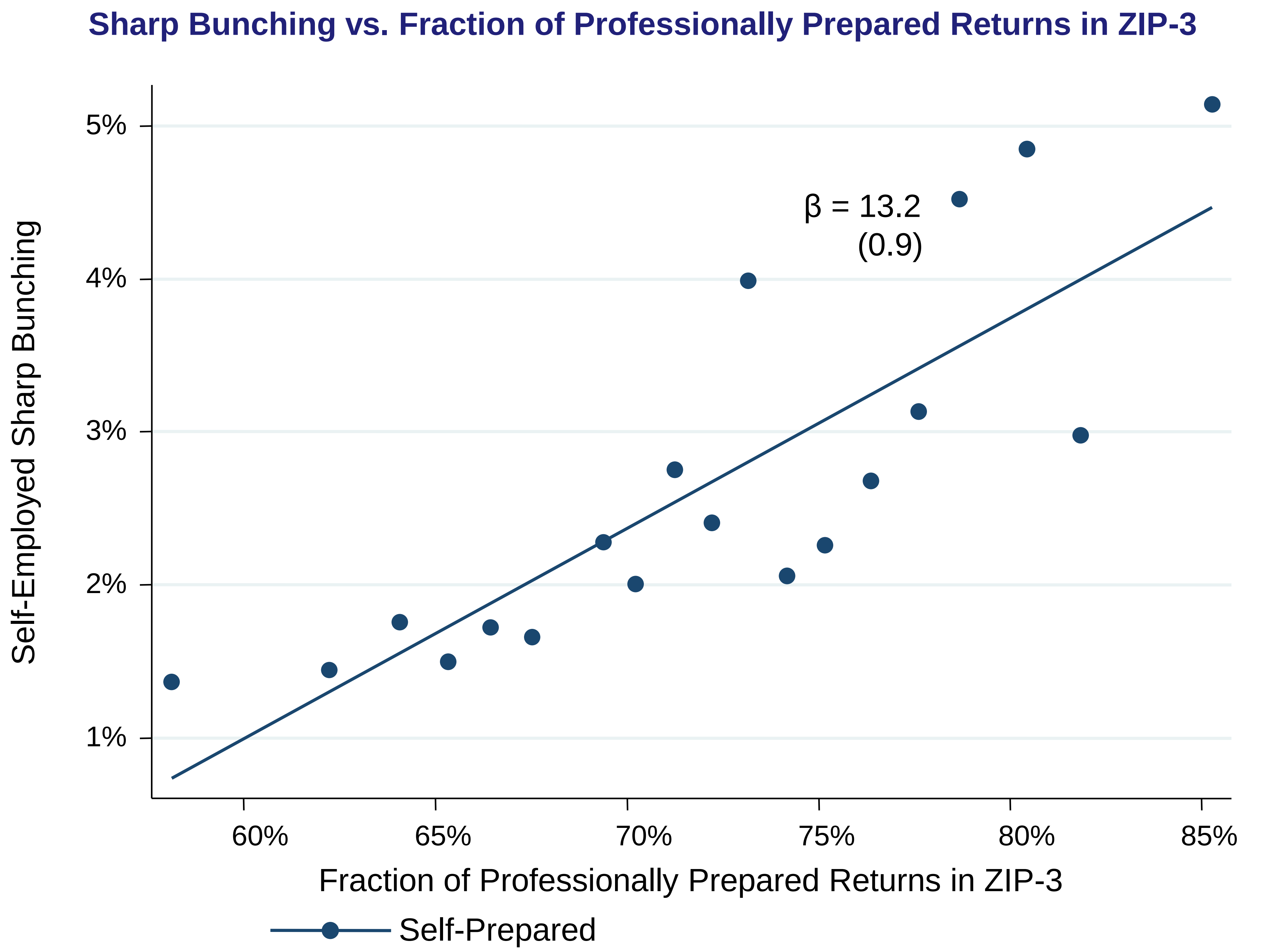

Change in EITC Refunds vs. Change in Sharp Bunching for Movers
Change in EITC Refund ($)
120
100
80
60
40
-1%
-0.5%
0%
0.5%
1%
Change in ZIP-3 Sharp Bunching
β = 6.0
(6.2)
β = 59.7
(5.7)
p-value for diff. in slopes: p < 0.0001

Cross-Sectional Correlations

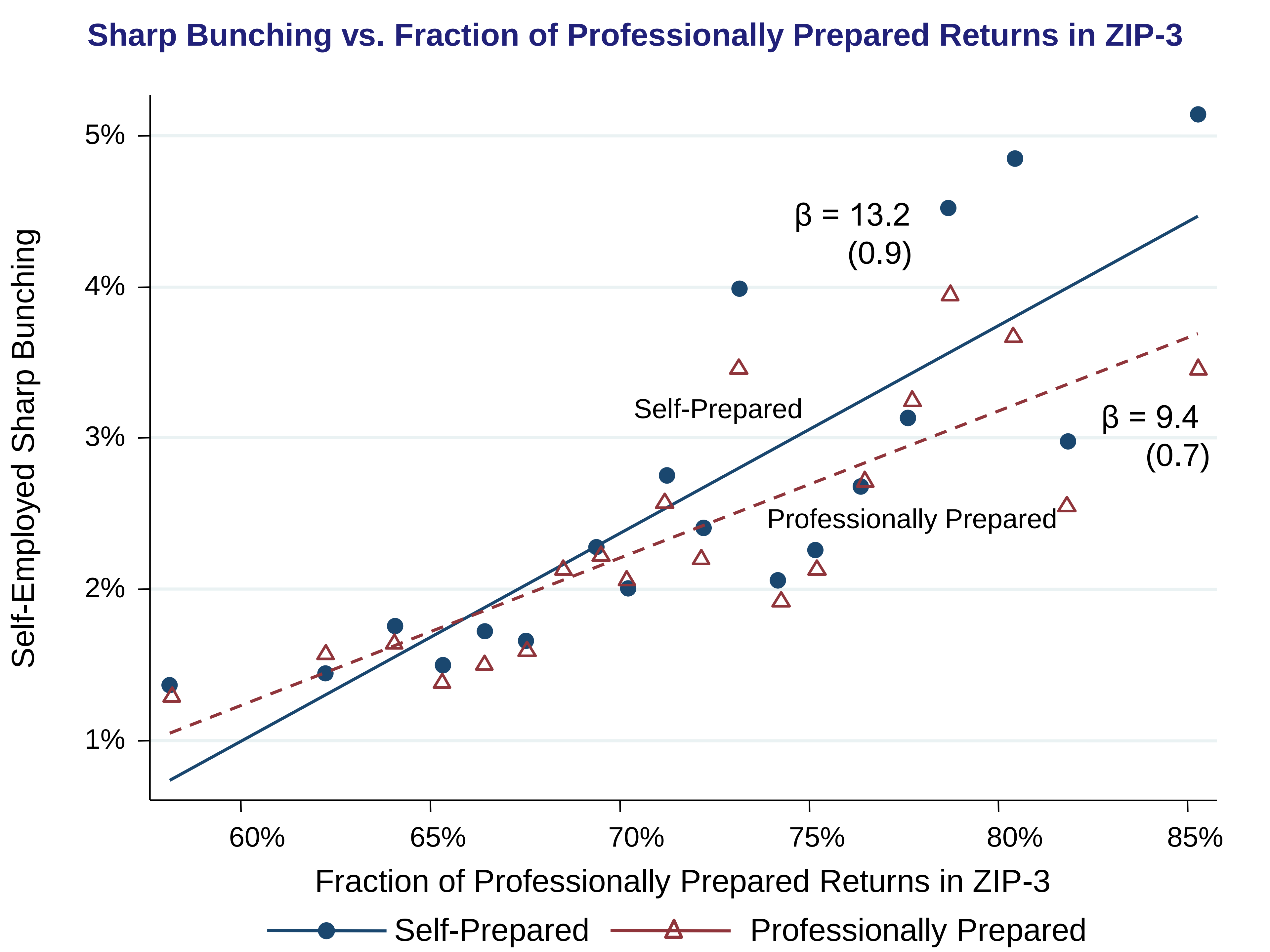
- What drives the variation in sharp bunching across neighborhoods?
  - Evaluate predictive power of proxies for information, tax compliance, and other variables


Agglomeration: Sharp Bunching vs. EITC Filer Density by ZIP Code
Sharp Bunching
3.5%
3.0%
2.5%
2.0%
1.5%
1.0%
-2
0
2
4
6
log (Number of EITC Filers Per Square Mile)
R2 = 0.6

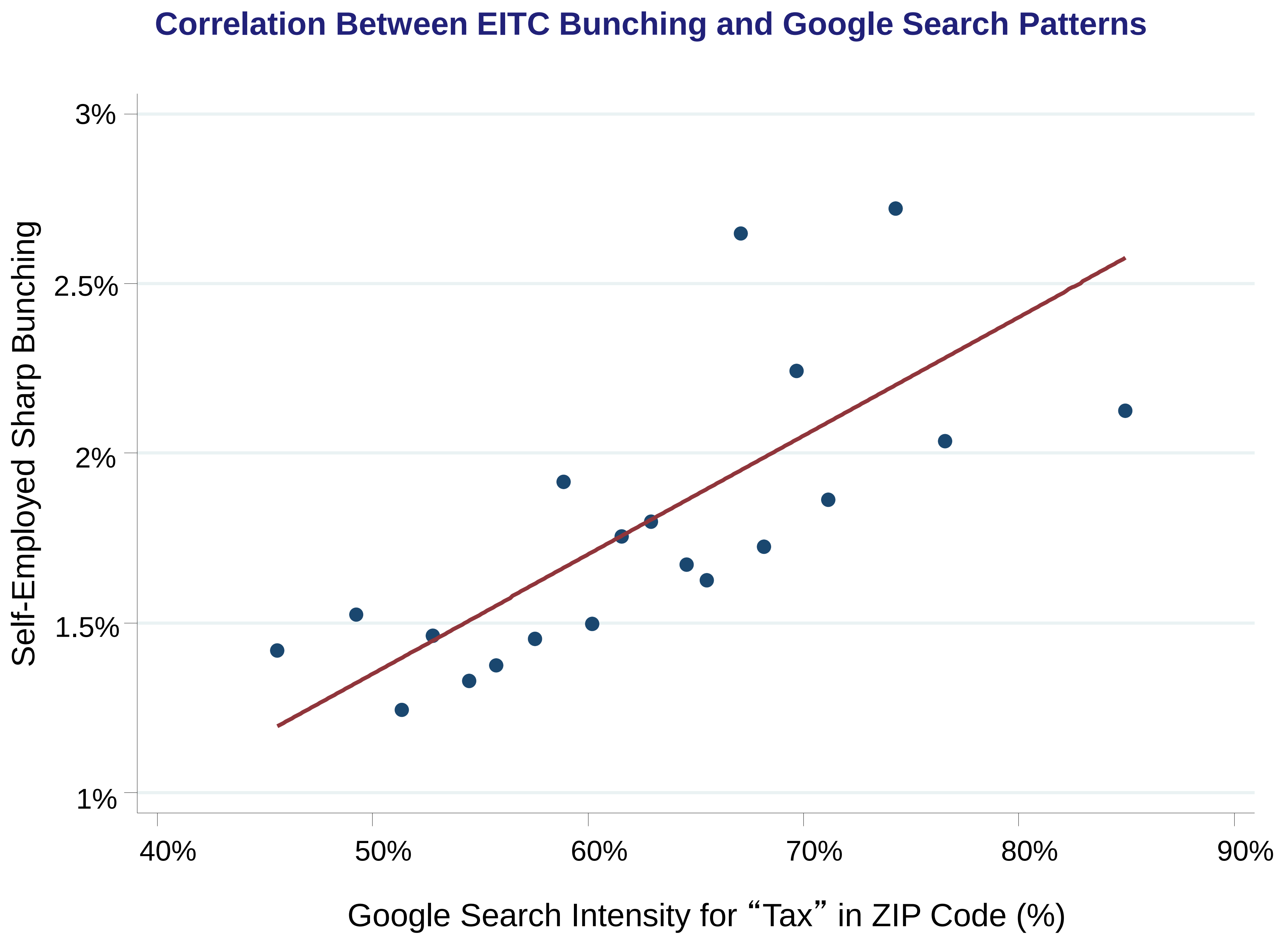

Evolution of Sharp Bunching in Low vs. High EITC-Density Areas
4%
3%
2%
1%
0%
Self-Employed Sharp Bunching
1995
2000
2005
2010
Year
Below-Median EITC Density
Above-Median EITC Density



Sharp Bunching vs. Fraction of Professionally Prepared Returns in ZIP-3
Self-Employed Sharp Bunching
5%
4%
3%
2%
1%
β = 13.2
(0.9)
60%
65%
70%
75%
80%
85%
Fraction of Professionally Prepared Returns in ZIP-3
Self-Prepared



Sharp Bunching vs. Fraction of Professionally Prepared Returns in ZIP-3
Self-Employed Sharp Bunching
5%
4%
3%
2%
1%
β = 13.2
(0.9)
β = 9.4
(0.7)
Self-Prepared
Professionally Prepared
60%
65%
70%
75%
80%
85%
Fraction of Professionally Prepared Returns in ZIP-3
Self-Prepared
Professionally Prepared



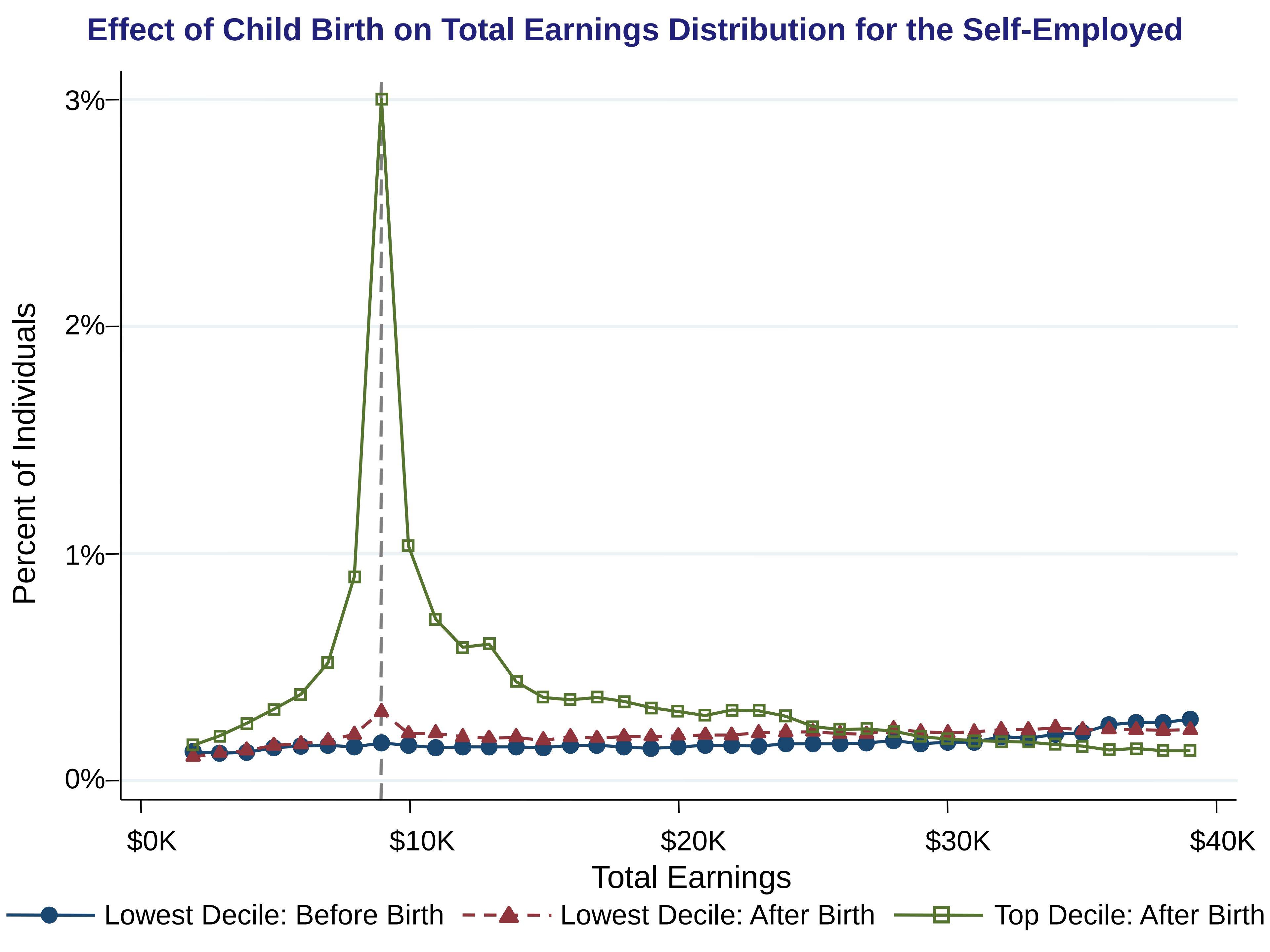
Correlation Between EITC Bunching and Google Search Patterns
Self-Employed Sharp Bunching
3%
2.5%
2%
1.5%
1%
40%
50%
60%
70%
80%
90%
Google Search Intensity for “Tax” in ZIP Code (%)

Cross-Sectional Correlates of Sharp Bunching

	Dep. Var.: Sharp Bunching Rate in ZIP-3 (%)							
EITC Filer Density in ZIP-3	1.93	1.82			0.44	0.69		
	(0.05)	(0.05)			(0.06)	(0.06)		
Fraction of Tax Prepared Returns in ZIP-3			9.86		3.02	3.46		
			(1.48)		(0.51)	(0.56)		
Google Search Intensity				0.30	0.14	0.19		
				(0.05)	(0.03)	(0.03)		
State EITC							**0.07**	
							(0.05)	
State Non-Compliance Rate								**-1.51**
								(5.32)
Demographic Controls		x			x	x		
State Fixed Effects						x		
Year	2000	2000	2008	2008	2008	2008	2000	2000
R-squared	0.603	0.798	0.169	0.032	0.728	0.848	**0.105**	**0.002**
Number of Observations	873	873	883	875	870	870	886	51

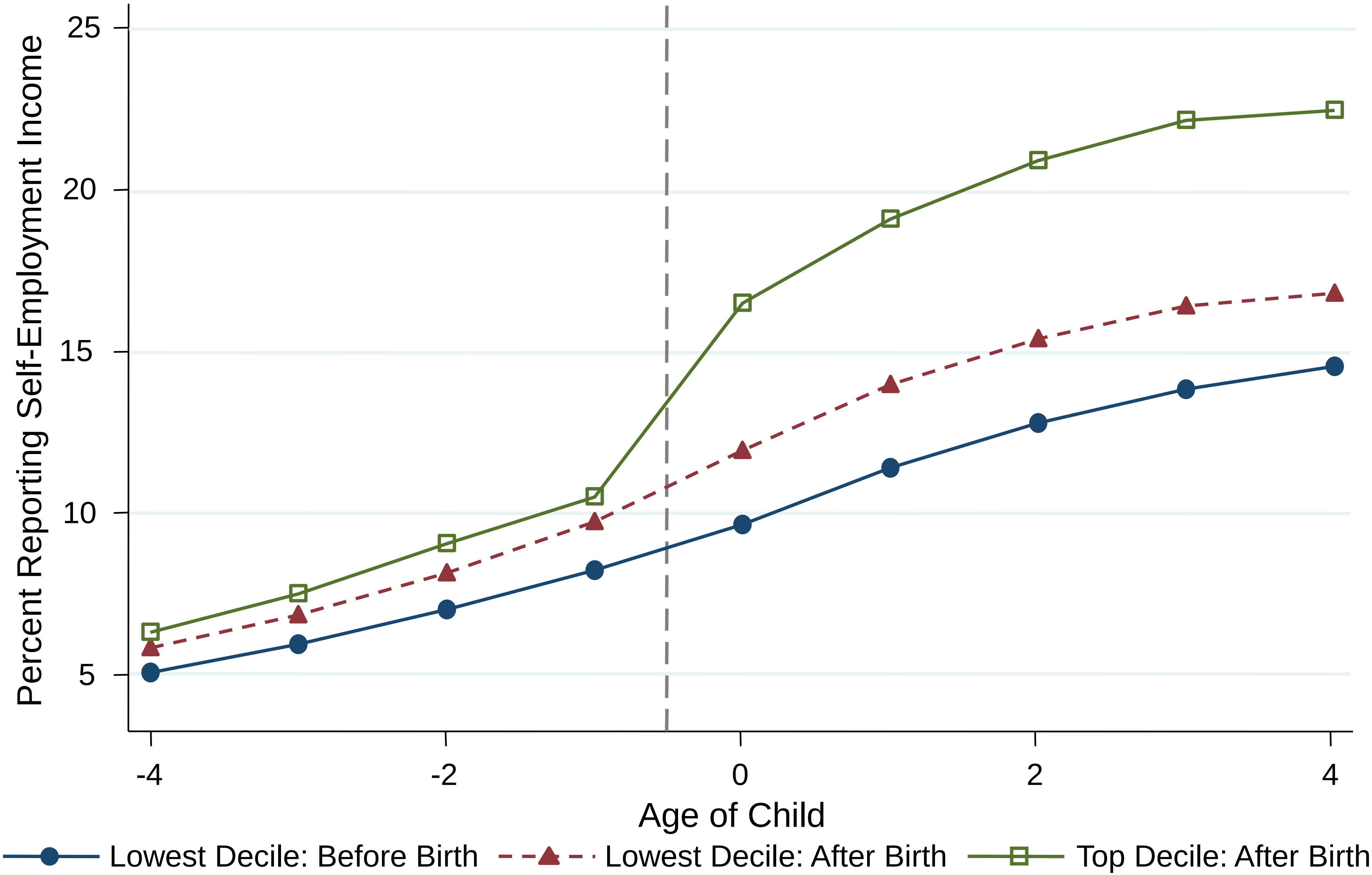
Perceptions of EITC in Low-Bunching Areas

- 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 → substantial change in EITC incentives



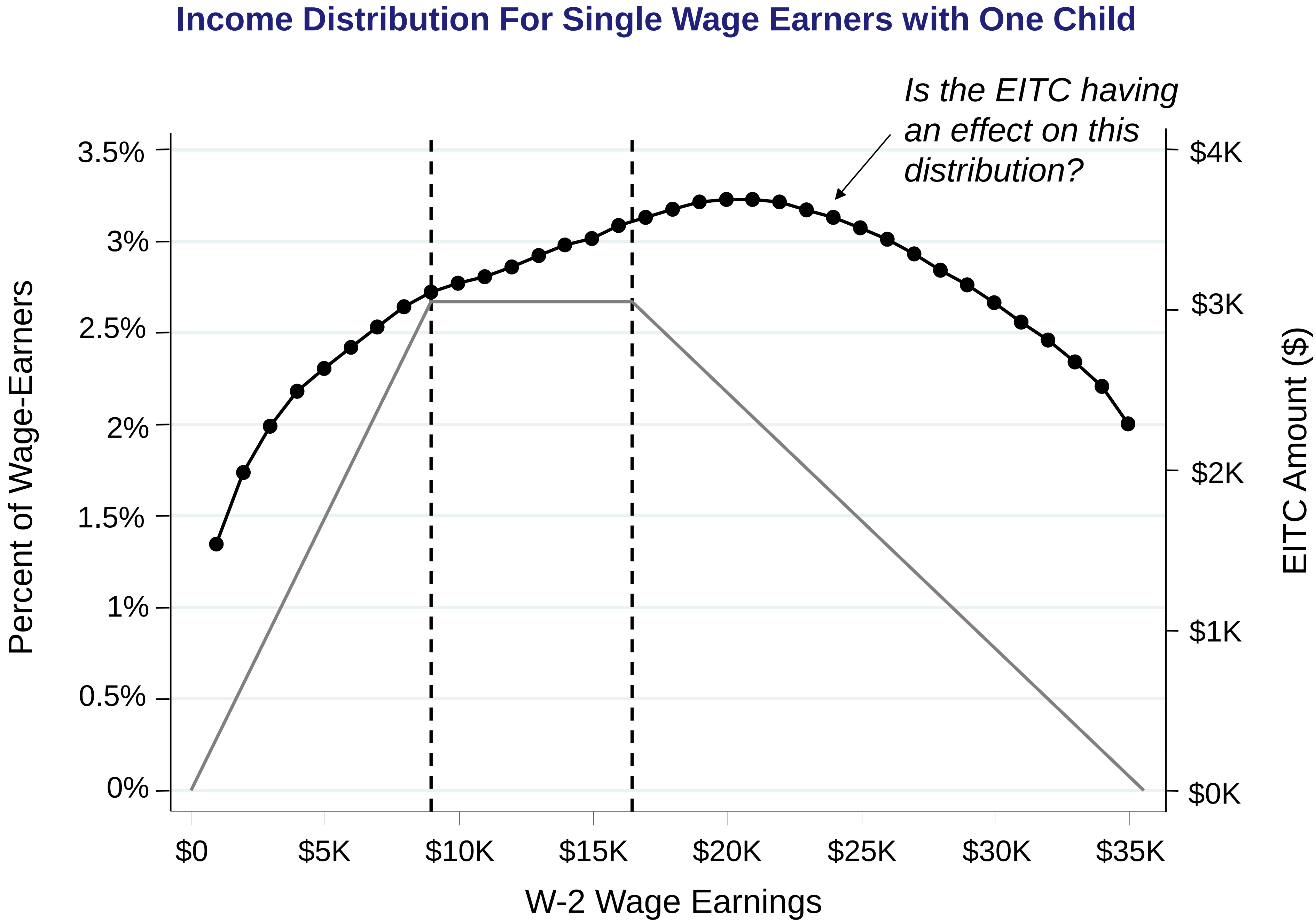
Effect of Child Birth on Total Earnings Distribution for the Self-Employed
3%
2%
1%
0%
Percent of Individuals
$0K
$10K
$20K
$30K
$40K
Total Earnings
Lowest Decile: Before Birth
Lowest Decile: After Birth
Top Decile: After Birth

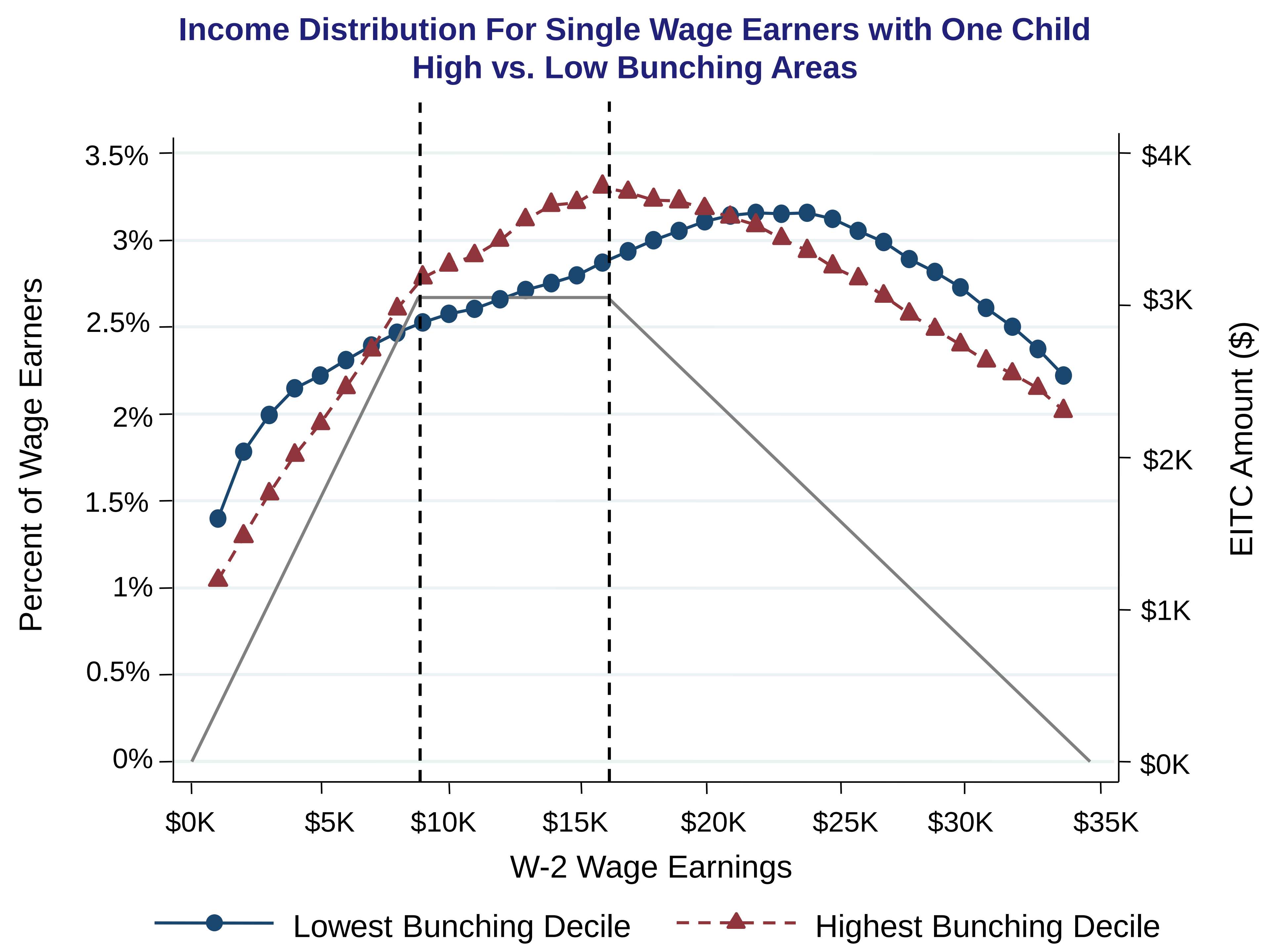
Fraction of Individuals Reporting Self-Employment Income Around Child Birth

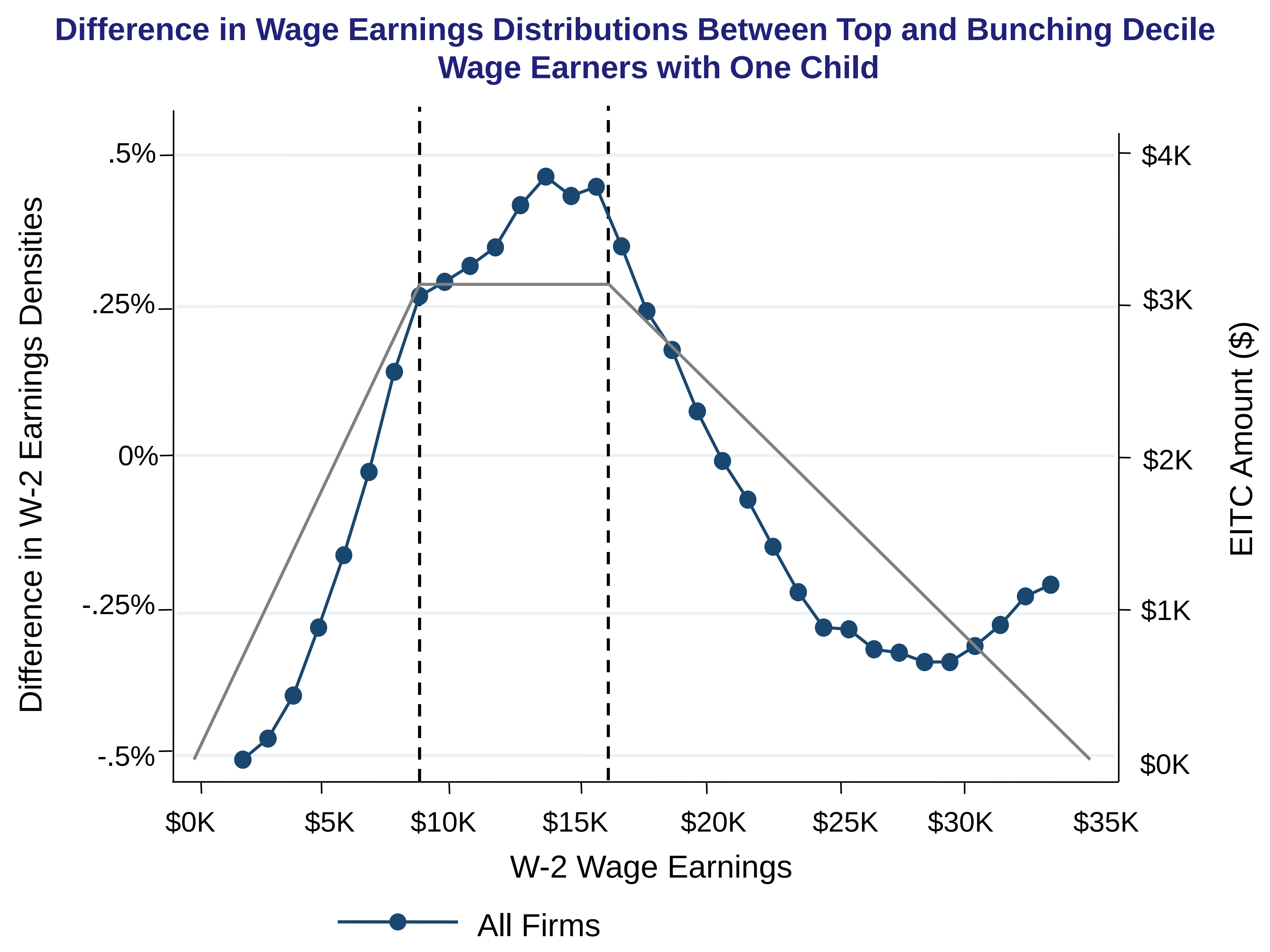


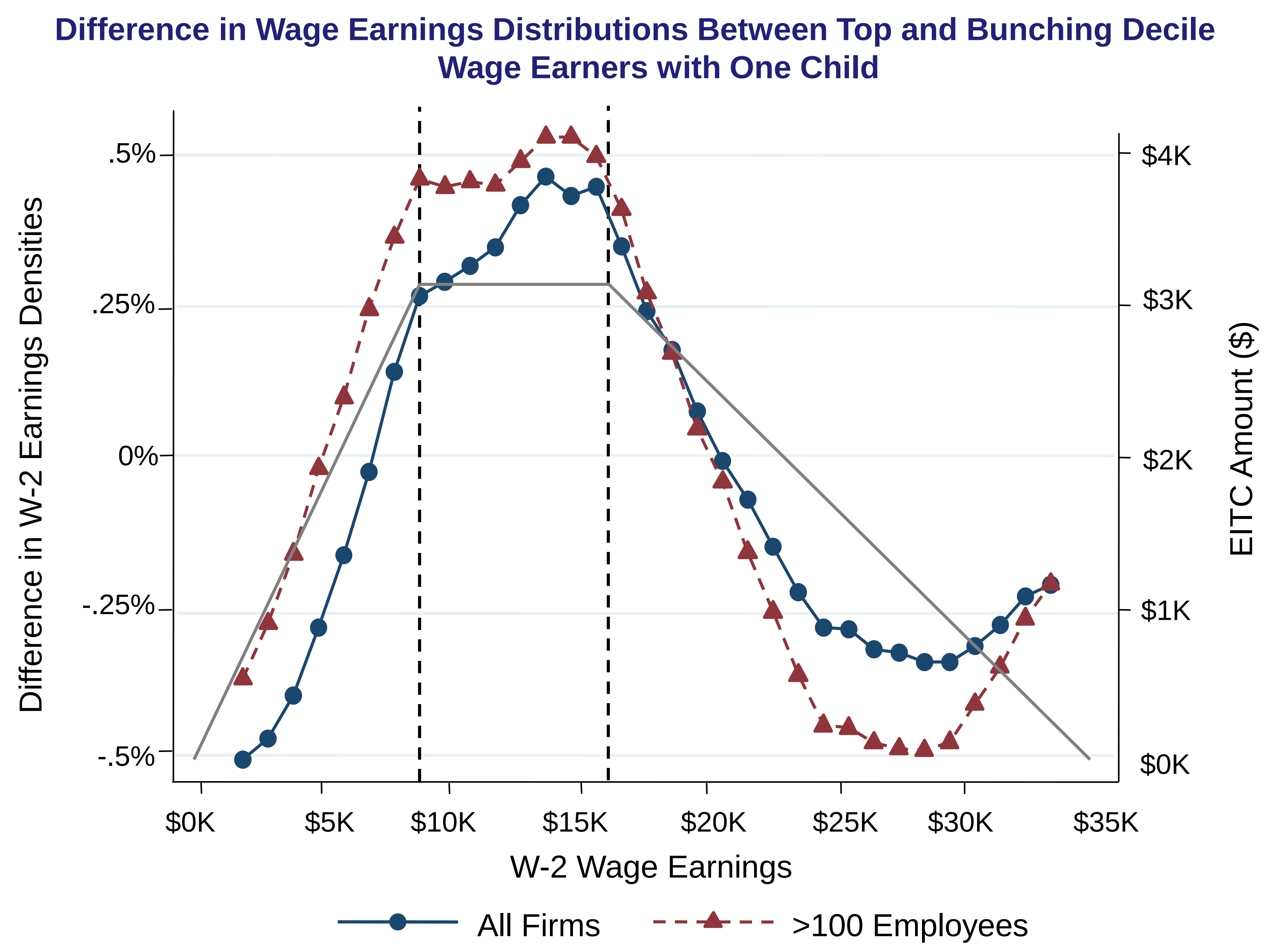
Outline of Empirical Analysis

- 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

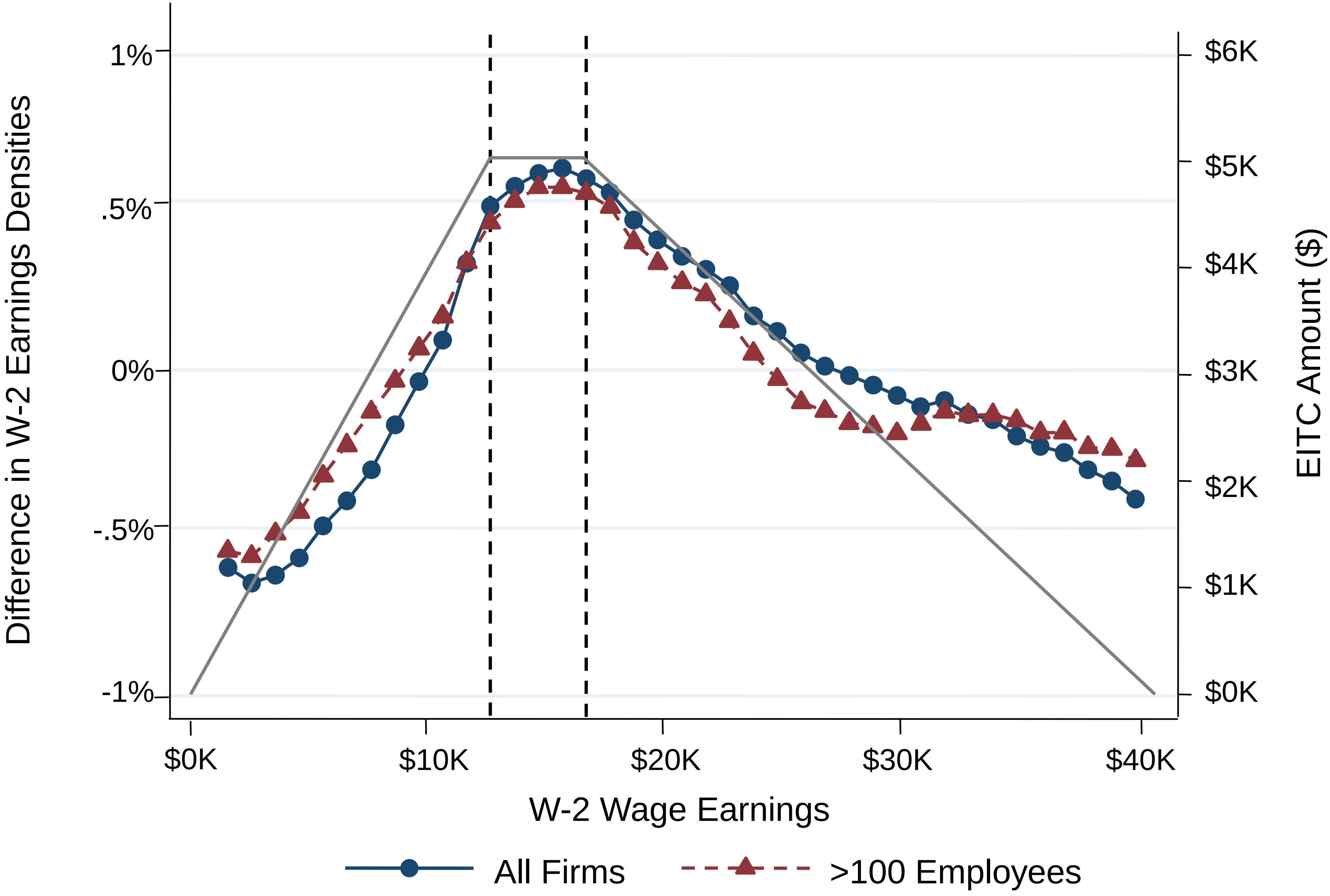

Income Distribution For Single Wage Earners with One Child
Is the EITC having an effect on this distribution?
Percent of Wage-Earners
3.5%
3%
2.5%
2%
1.5%
1%
0.5%
0%
EITC Amount ($)
$4K
$3K
$2K
$1K
$0K
$0
$5K
$10K
$15K
$20K
$25K
$30K
$35K
W-2 Wage Earnings

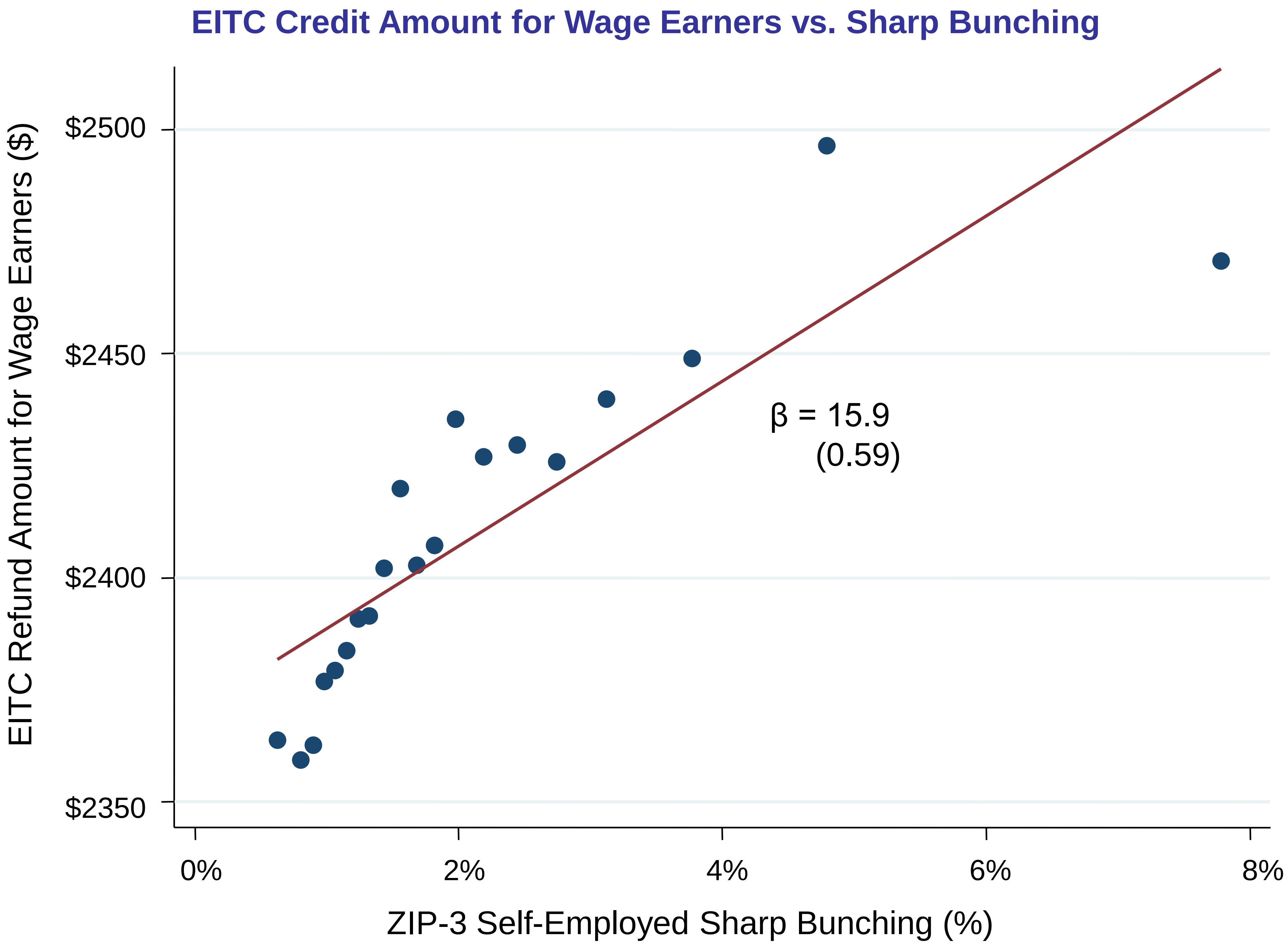

Income Distribution For Single Wage Earners with One Child
High vs. Low Bunching Areas
Percent of Wage Earners
3.5%
3%
2.5%
2%
1.5%
1%
0.5%
0%
$4K
$3K
$2K
$1K
$0K
EITC Amount ($)
$0K
$5K
$10K
$15K
$20K
$25K
$30K
$35K
W-2 Wage Earnings
Lowest Bunching Decile
Highest Bunching Decile


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


Difference in Wage Earnings Distributions Between Top and Bunching Decile
Wage Earners with One Child
Difference in W-2 Earnings Densities
.5%
.25%
0%
-.25%
-.5%
EITC Amount ($)
$4K
$3K
$2K
$1K
$0K
$0K
$5K
$10K
$15K
$20K
$25K
$30K
$35K
W-2 Wage Earnings
All Firms
>100 Employees

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




EITC Credit Amount for Wage Earners vs. Sharp Bunching
EITC Refund Amount for Wage Earners ($)
$2500
$2450
$2400
$2350
β = 15.9
(0.59)
0%
2%
4%
6%
8%
ZIP-3 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

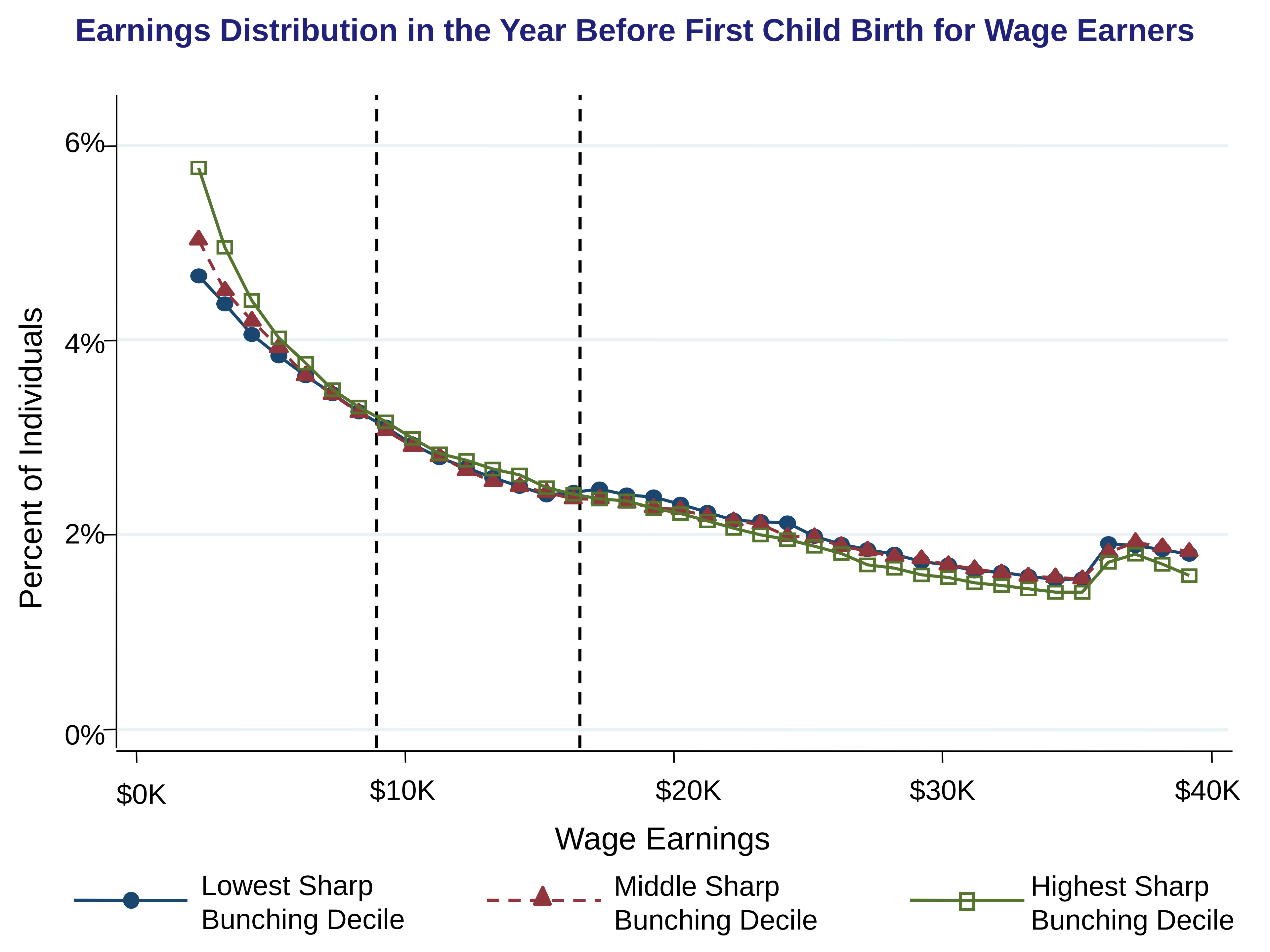
- Step 4: Compare impacts of changes in EITC subsidies on earnings across low vs. high knowledge nbhds. to account for omitted variables

Child Birth Research Design

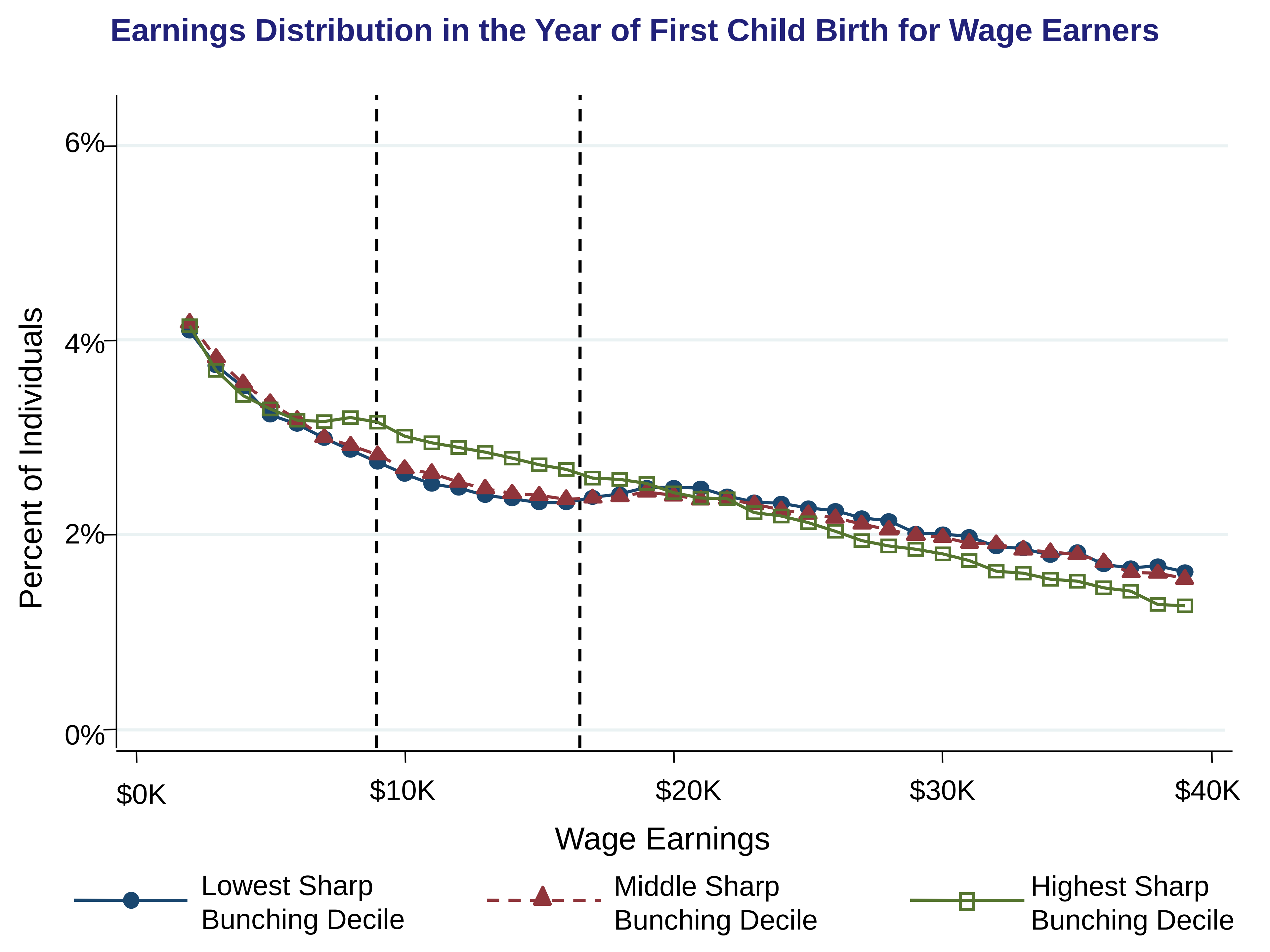
- Cross-sectional differences in income distributions could be biased by omitted variables

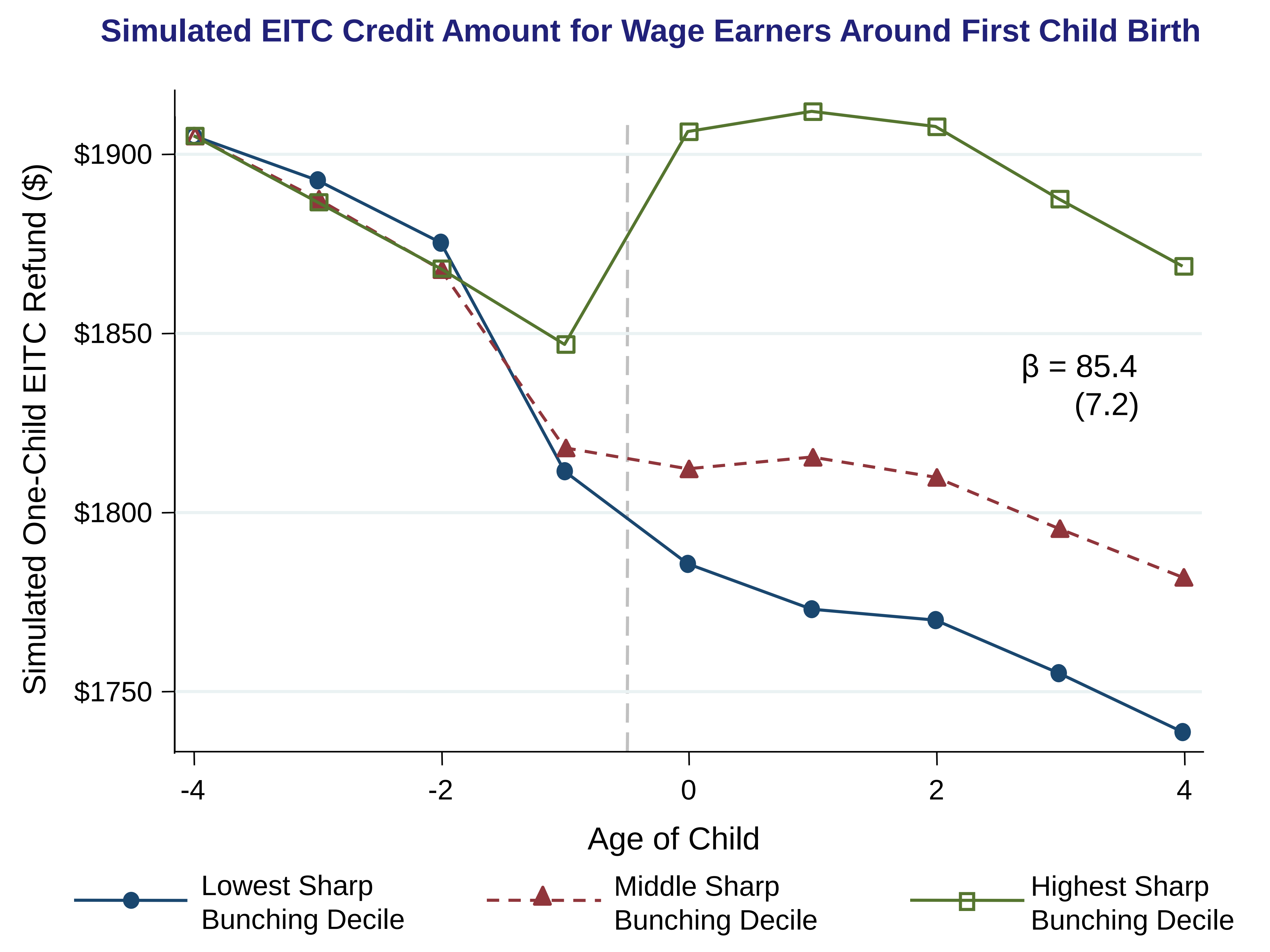
- To identify causal impacts of EITC, need variation in tax incentives
  - Use child birth as an instrument for EITC eligibility
  - Birth affects labor supply directly, but cross-neighborhood comparisons provide good counterfactuals

- 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
6%
4%
2%
0%
$0K
$10K
$20K
$30K
$40K
Wage Earnings
Lowest Sharp Bunching Decile
Middle Sharp Bunching Decile
Highest Sharp Bunching Decile


Earnings Distribution in the Year of First Child Birth for Wage Earners
6%
4%
2%
0%
Percent of Individuals
$0K
$10K
$20K
$30K
$40K
Wage Earnings
Lowest Sharp Bunching Decile
Middle Sharp Bunching Decile
Highest Sharp Bunching Decile

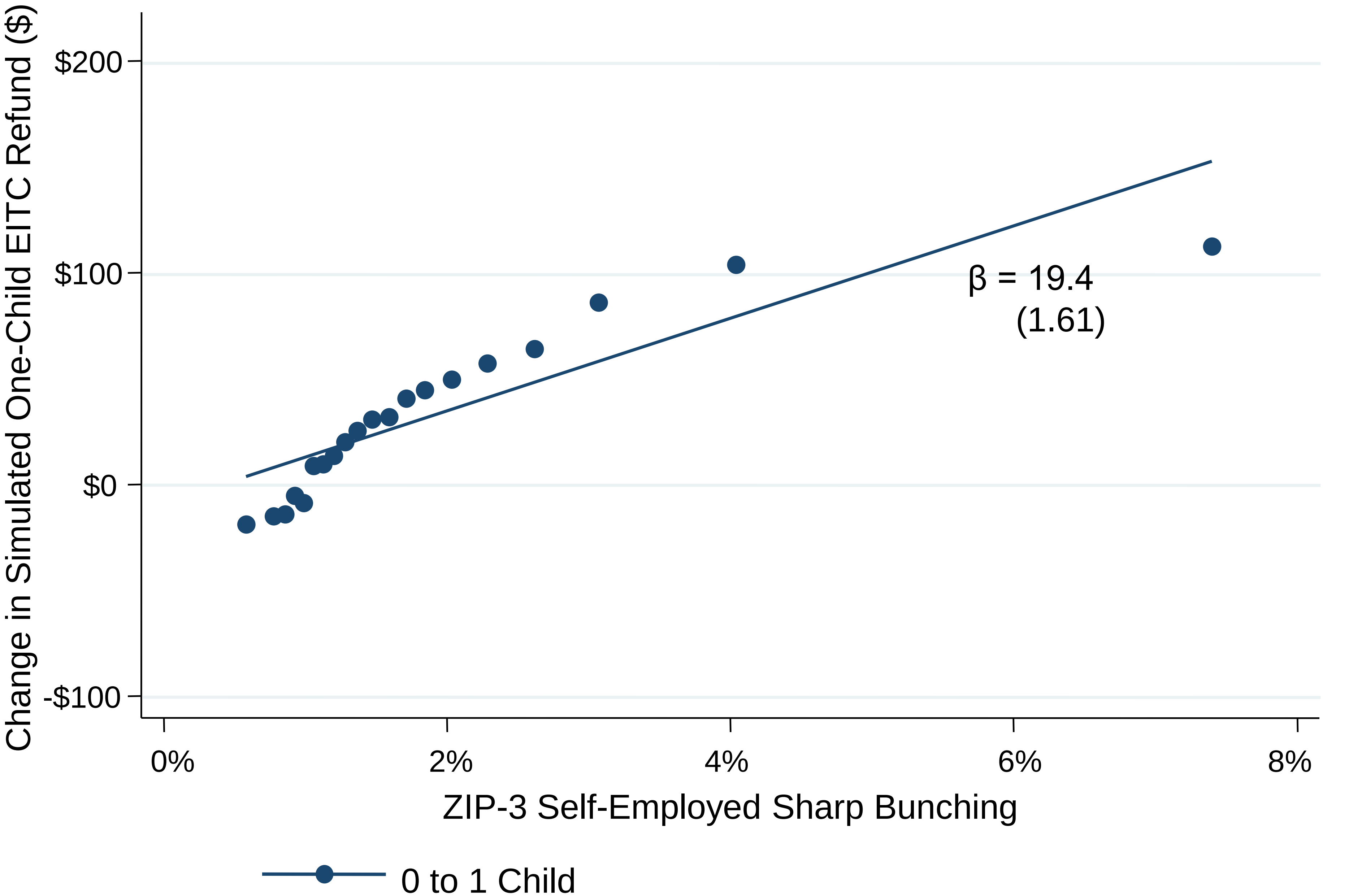


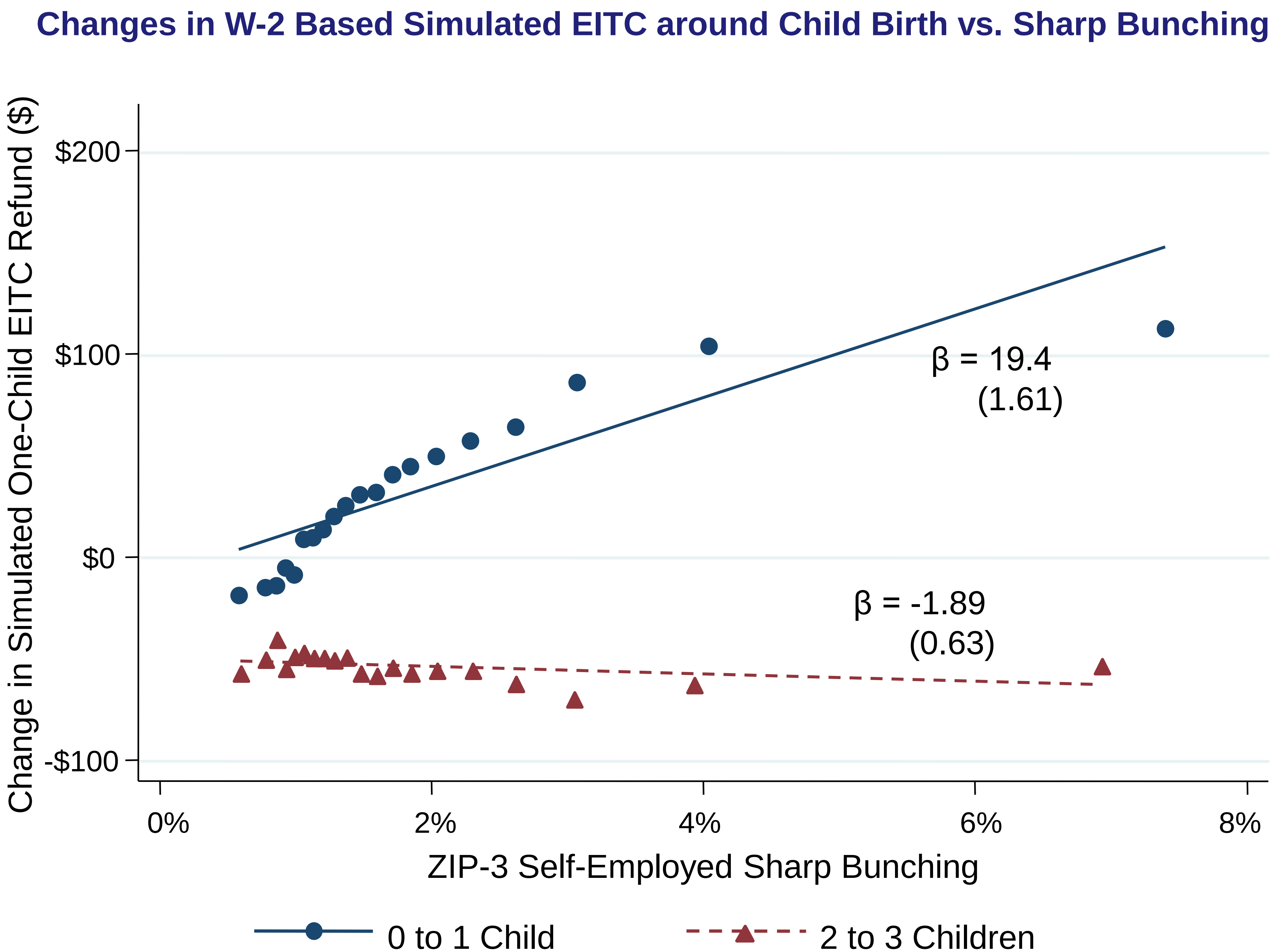
Simulated EITC Credit Amount for Wage Earners Around First Child Birth
Simulated One-Child EITC Refund ($)
$1900
$1850
$1800
$1750
β = 85.4
(7.2)
-4
-2
0
2
4
Age of Child
Lowest Sharp
Bunching Decile
Middle Sharp
Bunching Decile
Highest Sharp
Bunching Decile

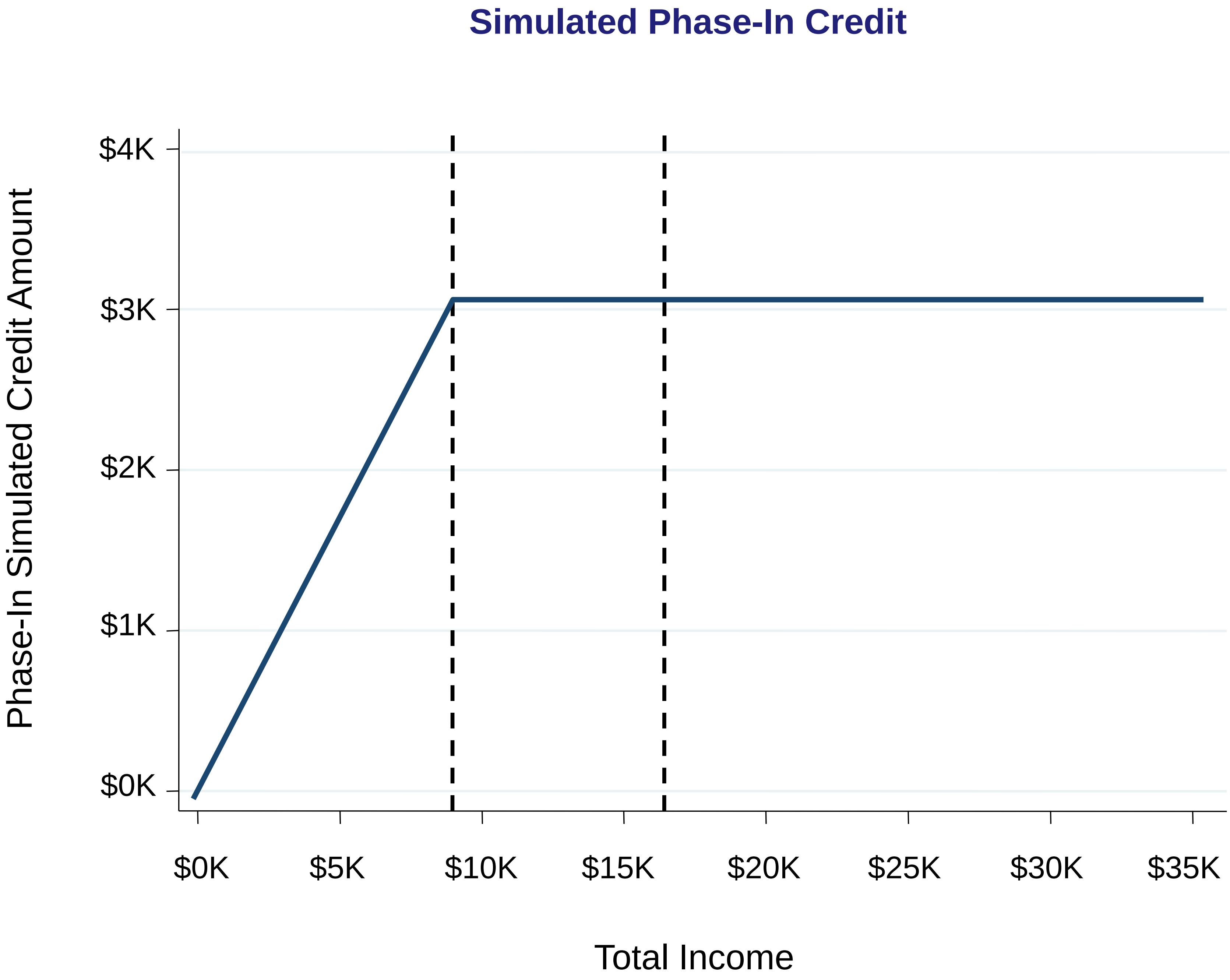
Composition of Wage Earnings Responses

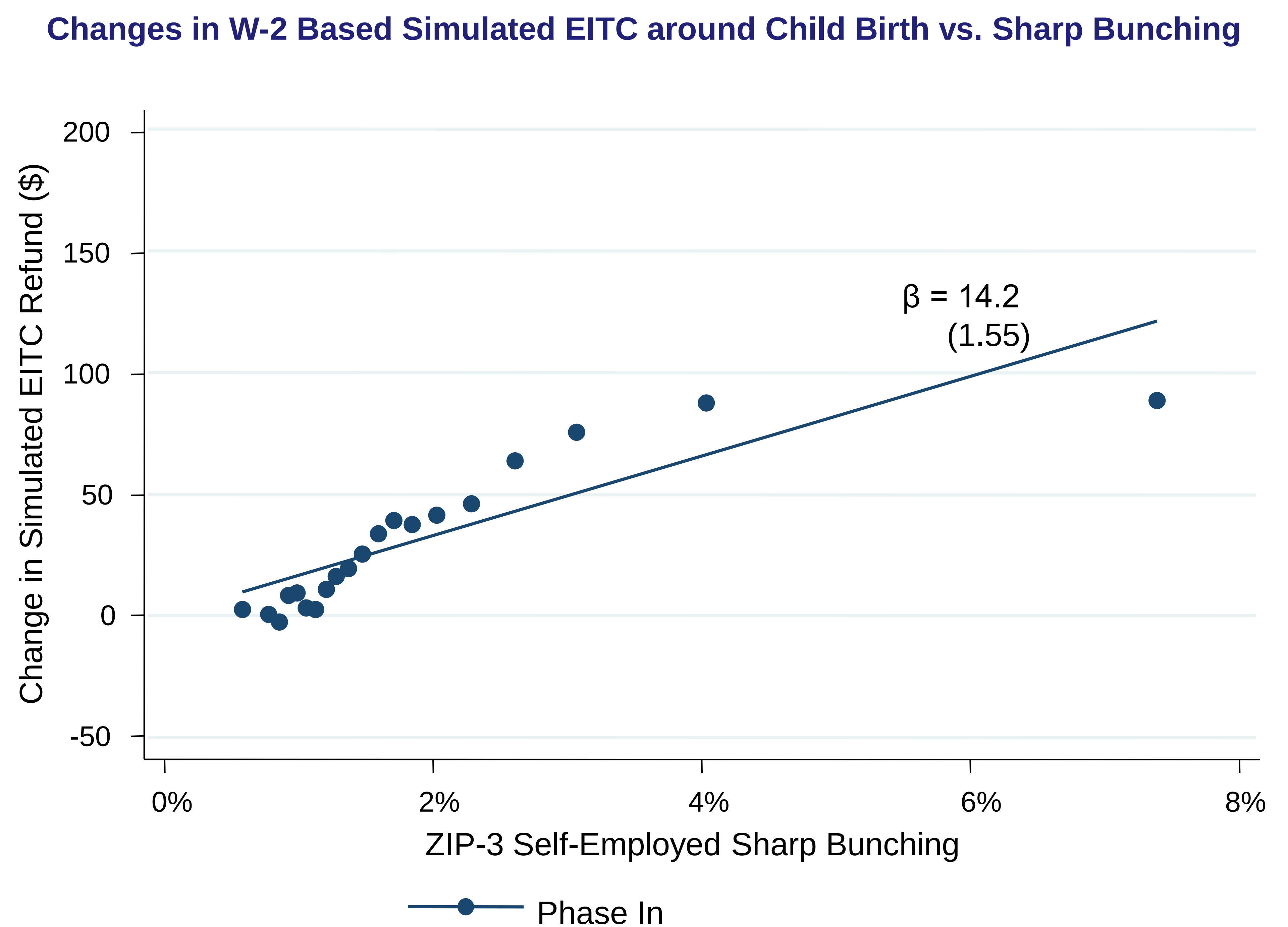
- Where is the increase in EITC refunds coming from?
  - Phase-in, phase-out, or extensive margin?
  - Important for understanding welfare consequences of EITC
- Compare change in simulated EITC amount (with 1 child) from year -1 to year 0 across low and high information areas

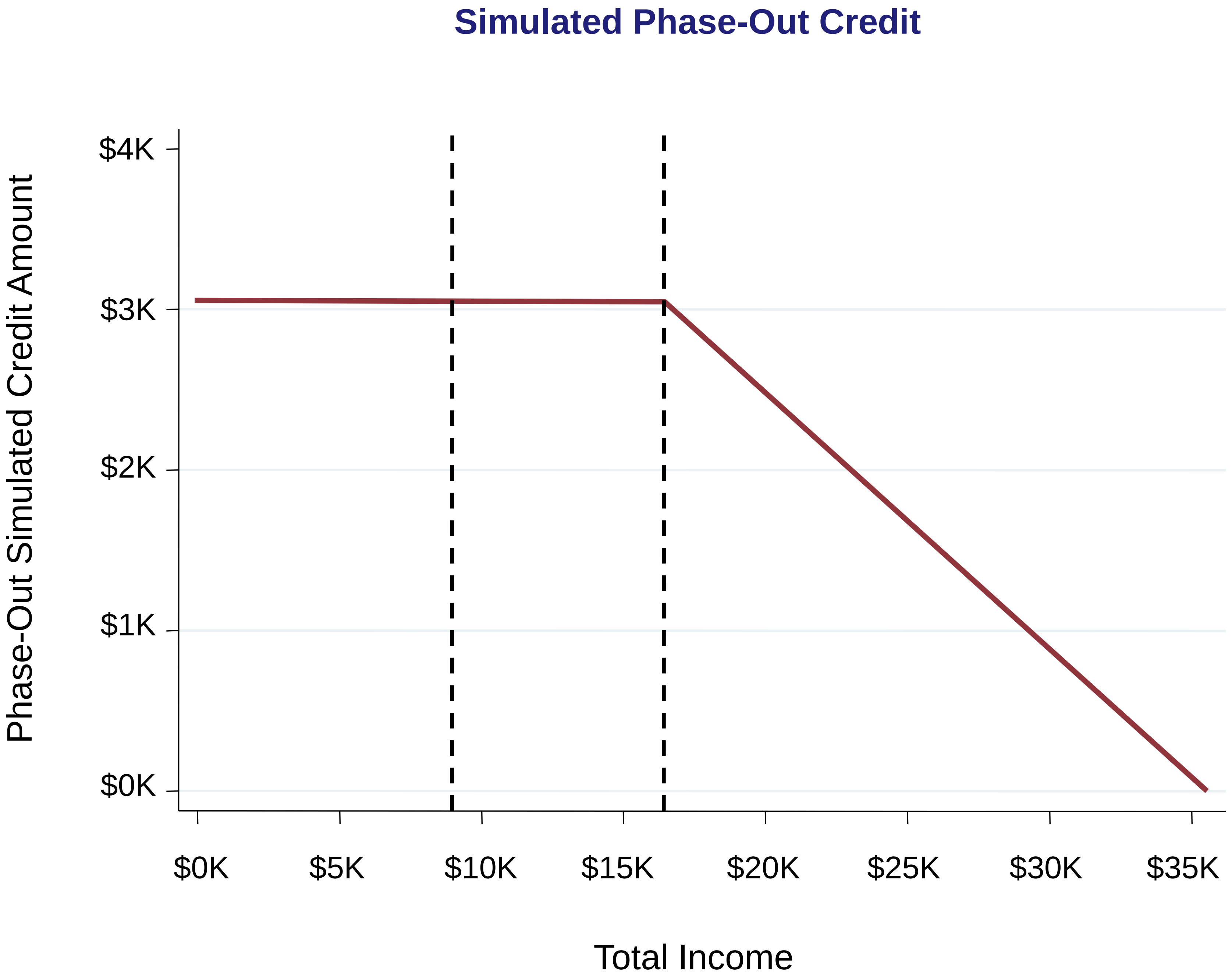
Changes in W-2 Based Simulated EITC around Child Birth vs. Sharp Bunching

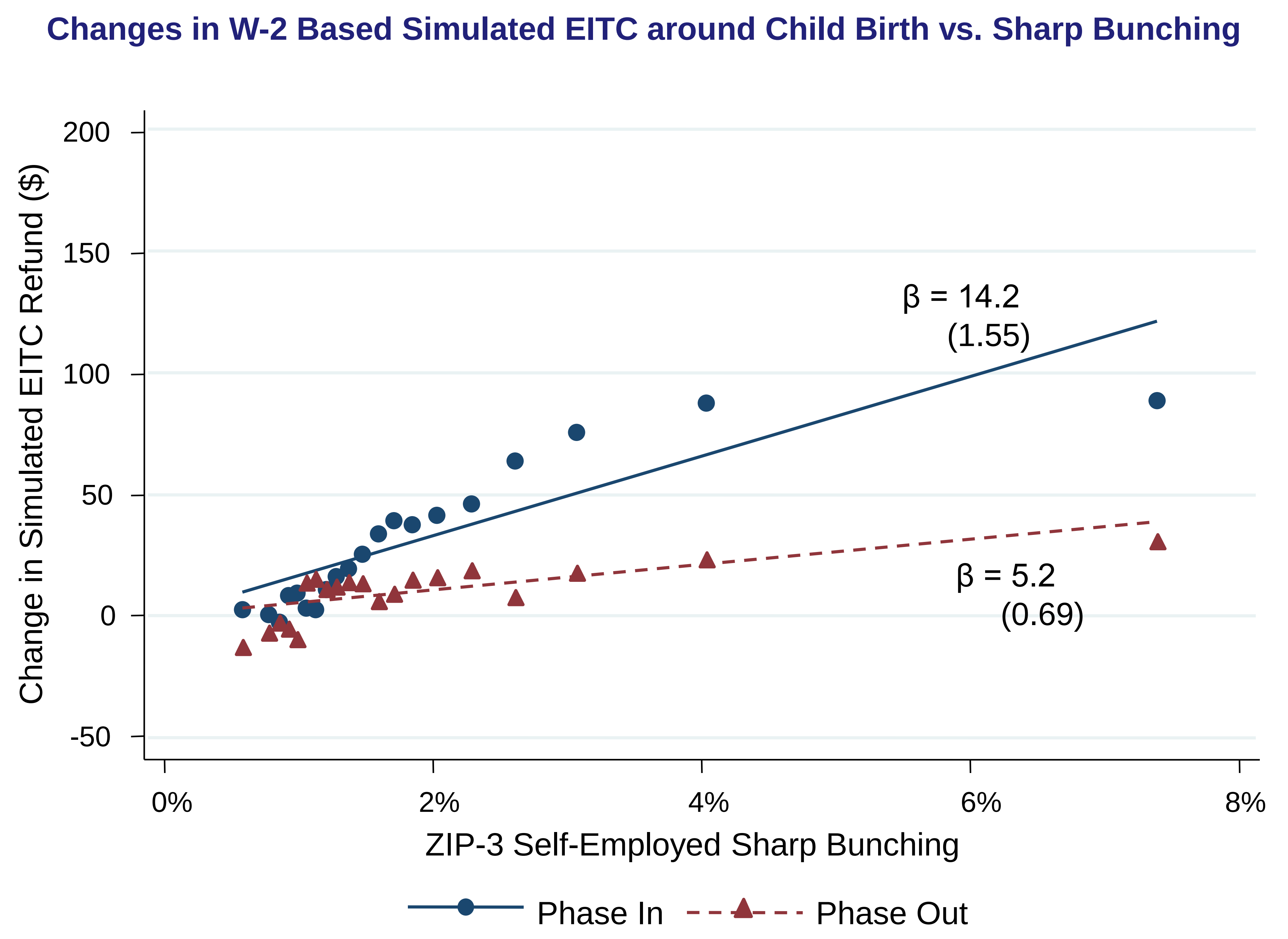



Changes in W-2 Based Simulated EITC around Child Birth vs. Sharp Bunching
Change in Simulated One-Child EITC Refund ($)
$200
$100
$0
-$100
β = 19.4
(1.61)
β = -1.89
(0.63)
0%
2%
4%
6%
8%
ZIP-3 Self-Employed Sharp Bunching
0 to 1 Child
2 to 3 Children

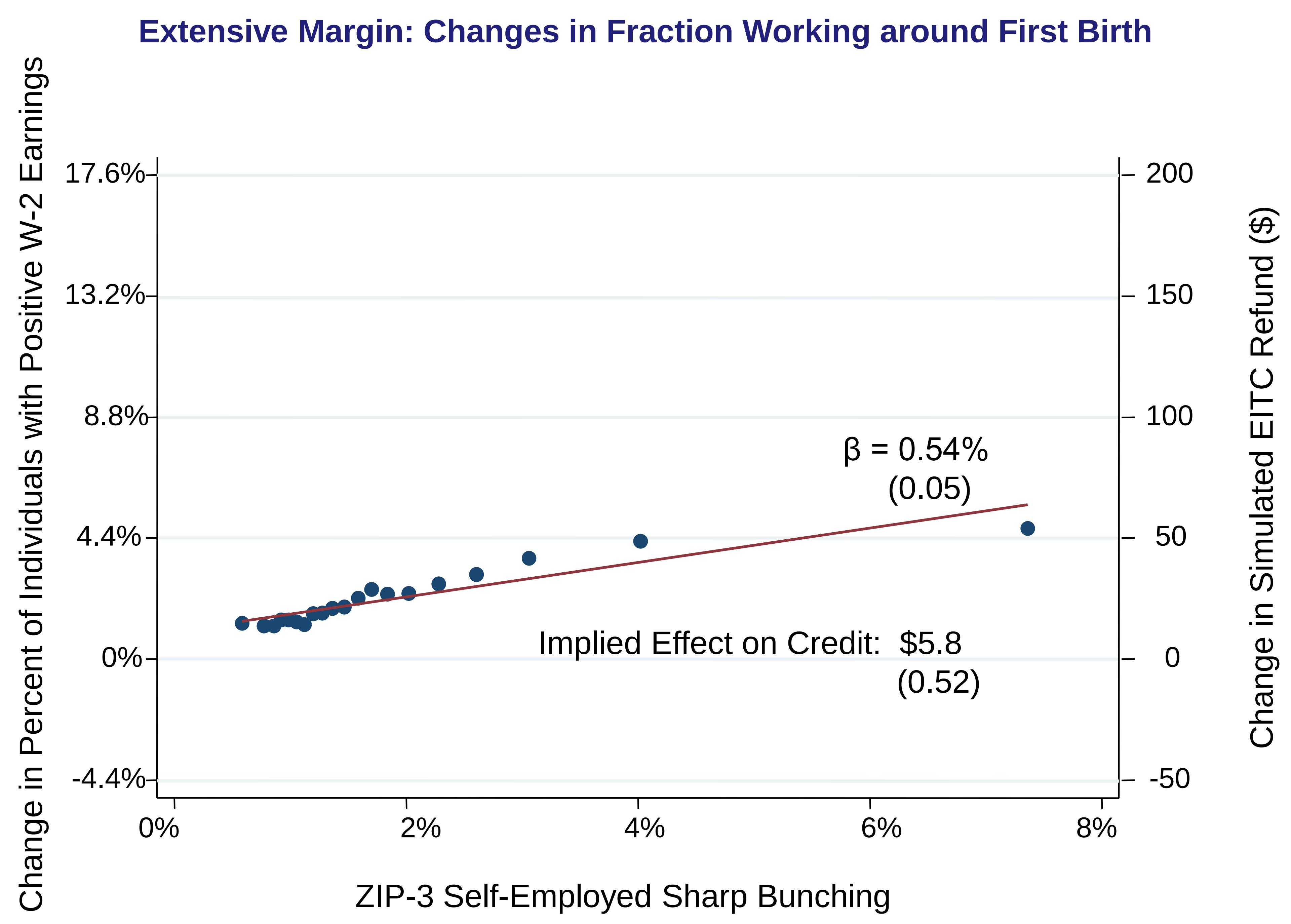

Simulated Phase-In Credit
Phase-In Simulated Credit Amount
$4K
$3K
$2K
$1K
$0K
$0K
$5K
$10K
$15K
$20K
$25K
$30K
$35K
Total Income


Changes in W-2 Based Simulated EITC around Child Birth vs. Sharp Bunching
β = 14.2
(1.55)
Change in Simulated EITC Refund ($)
200
150
100
50
0
-50
0%
2%
4%
6%
8%
ZIP-3 Self-Employed Sharp Bunching
Phase In


Simulated Phase-Out Credit
Phase-Out Simulated Credit Amount
$4K
$3K
$2K
$1K
$0K
$0K
$5K
$10K
$15K
$20K
$25K
$30K
$35K
Total Income



Changes in W-2 Based Simulated EITC around Child Birth vs. Sharp Bunching
Change in Simulated EITC Refund ($)
200
150
100
50
0
-50
β = 14.2
(1.55)
β = 5.2
(0.69)
0%
2%
4%
6%
8%
ZIP-3 Self-Employed Sharp Bunching
Phase In
Phase Out



Extensive Margin: Changes in Fraction Working around First Birth
Change in Percent of Individuals with Positive W-2 Earnings
17.6%
13.2%
8.8%
4.4%
0%
-4.4%
200
150
100
50
0
-50
Change in Simulated EITC Refund ($)
β = 0.54%
(0.05)
Implied Effect on Credit: $5.8
(0.52)
0%
2%
4%
6%
8%
ZIP-3 Self-Employed Sharp Bunching

Impact of EITC on Wage Earnings

	Baseline Specification	Large Firms Only	With ZIP-3 Fixed Effects	Placebo Test: 3rd Child
Dependent Variable:	Simulated EITC Refund			
ZIP-3 Sharp Bunching	\$19.4	\$14.4	\$34.7	-\$1.89
	(1.61)	(1.14)	(3.20)	(0.63)

Impact of EITC on Wage Earnings

Dependent Variable:	Phase-in vs. Phase-out		Extensive Margin	
	Sim. Phase-in Credit	Sim. Phase-out Credit	Positive W-2 Earnings	Number of Jobs (W-2's)
ZIP-3 Sharp Bunching	\$14.2	\$5.2	0.54%	**0.017**
	(1.55)	(0.69)	(0.05)	**(0.002)**

Tax Policy Implications

- 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

	Percent of EITC-Eligible Households Below Threshold			
	50% of Poverty Line	100% of Poverty Line	150% of Poverty Line	200% of Poverty Line
No EITC Counterfactual	**13.2%**	31.3%	53.8%	77.1%
EITC, No Behavioral Response	**8.9%**	21.4%	41.6%	70.8%
EITC, with Avg. Behavioral Response	**8.2%**	21.0%	42.0%	71.3%
EITC with Top Decile Behavioral Response	**6.7%**	20.2%	42.6%	72.1%

Elasticity Estimates Based on Change in EITC Refunds Around Birth of First Child

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

Conclusion

- 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