Labor Supply under Nonlinear Tax Programs: Evidence from the Interaction of EITC and Wage Shocks

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Abstract

Low-income households are especially vulnerable to economic shocks, and anti-poverty programs provide supplementary assistance. Many such programs feature nonlinear schedules with phase-ins, plateaus, and phase-outs that, theoretically, can amplify or dampen labor-supply responses to wage changes. This paper develops a theoretical framework for how nonlinear tax schedules shape labor supply incentives, focusing on the Earned Income Tax Credit (EITC), a leading U.S. program with a distinctly nonlinear design. Empirically, this paper proposes a commuting zone average treatment effect (CZATE) that aligns estimates with the equilibrium scope of local labor markets under economic shocks, and defines an envelope semi-elasticity to quantify these effects. Using three economic shocks—local booms, China trade shocks, and minimum-wage hikes—the analysis shows that a $100 increase in EITC generosity typically rotates the wage–employment slope by about 0.05–0.2 percentage points per 1% wage change, with larger rotations in downturn-type environments such as trade-exposed labor markets. These results suggest that nonlinear tax-transfer programs not only reduce inequality but also enhance macroeconomic resilience by shaping labor market decisions.

JEL Classification: J22, J31, J38, H24, H31.

Keywords: EITC, Labor Supply, Nonlinear Taxation, Employment, Commuting Zone Average Treatment Effect, Local Economic Booms, China Trade Shock, Minimum Wages.

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1 Introduction

Low-income households often face volatile earnings and limited liquid assets, so even modest wage fluctuations can shift both their capacity and incentive to work. Many safety-net programs embed nonlinear schedules—phase-ins, plateaus, and phase-outs—that change the slope of the budget constraint and thus how employment responds to wage changes. Examples include the Supplemental Nutrition Assistance Program (SNAP), Affordable Care Act premium tax credits (ACA), income-based rents in housing vouchers, and, centrally for this paper, the Earned Income Tax Credit (EITC). The EITC is large in scale—benefiting roughly one in five U.S. households and costing over $70 billion per year[1] and its schedule is explicitly nonlinear: benefits rise with earnings (phase-in), level off (plateau), and then decline (phase-out), generating sharp variation in implicit marginal tax rates. These features imply that a given wage change should elicit different labor supply responses across segments of the schedule. I formalize these predictions in a model and then test them empirically, asking whether the EITC's nonlinear structure amplifies or dampens wage shocks in practice and how effects vary with where EITC-eligible workers are concentrated in the income distribution.

I use EITC expansion in the 1990s to derive testable predictions on when the credit stabilizes or destabilizes employment responses. My theory predicts that when a large share of EITC-eligible individuals sits in the phase–in region of income distribution, wage shocks are amplified (destabilized); when a large body of these individuals locates in the phase–out region, shocks are dampened (stabilized). To test these predictions, I exploit three plausibly exogenous shocks that vary both in direction and in where they hit the earnings distribution. Two of these shocks are positive: (i) local economic booms raised household income broadly across commuting zones and thus affect workers throughout the entire wage distribution (Bartik, 1991a; Blanchard et al., 1992; Moretti, 2010; Allcott and Keniston, 2018); (ii) minimum–wage hikes raised household income almost exclusively at the very bottom and primarily affect low–wage, low–skill workers (Neumark and Wascher, 2006; Neumark, 2018). The third shock is a negative: China trade shock depressed wages in tradable manufacturing and hit low– and middle–skill workers (Autor et al., 2013, 2016). Empirically, I propose a commuting–zone average treatment effect (CZATE) to align my estimates with the equilibrium scope of the market under economic shocks. I summarize empirical findings using envelope semi–elasticity:

[1] Tax Policy Center, Historical EITC Parameters and Participation, https://taxpolicycenter.org/statistics/eitc-parameters

the percentage–point change in the employment rate induced by a 1% change in wages. In the regressions, the wage coefficients give the baseline semi–elasticity, and its interaction with EITC generosity gives the change in the policy–induced rotation. Taken together, my empirical analysis covers upward and downward wage movements and captures the response from distinct parts of the labor force in an equilibrium market. Investigating the impact of EITC in the framework offered this paper provides an opportunity to make a unified test of the effects of EITC on labor market decisions.

Consistent with the model implications, clustering of EITC-eligible individuals in phase–in region amplifies (destabilizes) wage shocks, and clutering of EITC-eligible individuals in phase–out region dampens (stabilizes) wage shocks. In broad booms where many eligibles lie on the plateau or phase–out region, greater EITC generosity stabilizes employment responses. Under adverse trade shocks, EITC destabilizes labor market, and the effects concentrate on single, low-education women who are disproportionately in phase–in region. In minimum–wage hikes, while the overall effect was muted, EITC amplified the effect of minimum wage policy on single women who were high school dropouts. In general, a $100 increase in generosity typically changes the wage–employment slope by about 0.05–0.20 percentage points per 1% wage change (decade–equivalent, 2017$), with larger rotations in downturn–type environments. My findings connect EITC incidence to automatic stabilizers: EITC program stabilizes individual labor market responses when wages rise and destabilizes the responses when wages fall at the bottom, shaping how local and sectoral shocks propagate through employment (e.g., Bitler and Hoynes, 2016; Finkelstein et al., 2019; Ganong and Noel, 2019).

This paper contributes to three margins and relates to three bodies of literature. First, I provide a unified envelope mapping that isolates policy-induced rotations of the wage–employment relationship and delivers a common metric—the employment semi-elasticity per 1% wage change—across heterogeneous empirical designs. Prior work on nonlinear tax schedules has identified behavioral responses at kinks and through bunching (Saez, 2002; Kleven, 2019), while the macro literature on automatic stabilizers has quantified stabilization primarily through calibrated wedges and aggregate elasticities (Auerbach and Feenberg, 2000; McKay and Reis, 2016; Farhi and Werning, 2016). This paper adds to current literature by translating institutional parameters into stabilizing or destabilizing rotations that are comparable across settings and directly tied to quasi-experimental variation.

Second, I enrich the wage–shock literature by bringing three canonical quasi–experiments into a single framework and placing their effects on a common semi–elasticity scale. Prior work studies local booms via shift–share designs (Bartik, 1991a; Blanchard et al., 1992; Moretti, 2010; Allcott and Keniston, 2018), import–competition shocks using ADH exposure (Autor et al., 2013, 2016), and minimum–wage changes in difference–in–differences with rich geography–time controls (Dube et al., 2010; Allegretto et al., 2011; Neumark, 2018). I harmonize identification and interpretation across these settings and test the model's sign prediction: nonlinear credits should stabilize responses to broad positive movements and destabilize responses when shocks concentrate at the bottom. This yields a cross–shock, cross–context comparison that is difficult to see when reading each literature in isolation.

Third, I contribute to the EITC literature by introducing a commuting–zone average treatment effect (CZATE) that complements ATT designs comparing eligibles to ineligibles (Eissa and Liebman, 1996; Meyer and Rosenbaum, 2001; Meyer, 2002; Hotz and Scholz, 2003; Nichols and Rothstein, 2015; Bastian, 2020). The CZATE aggregates exposure and outcomes at the local–market level, capturing both direct effects on eligibles and local general–equilibrium spillovers that are salient under geographically diffuse decadal shocks (Blanchard et al., 1992; Moretti, 2010; Autor et al., 2013). Empirically, it reproduces the qualitative ATT patterns with attenuated magnitudes—as expected for a broader equilibrium estimand—and clarifies how nonlinear policy design interacts with local adjustment.

The remainder of the paper proceeds as follows. Section 2 reviews the EITC's institutional details, maps statute to incentives, and builds the commuting–zone exposure index that defines the CZATE. Section 3 lays out the empirical strategy and presents evidence from three wage shocks—local booms, China import competition, and minimum-wage hikes—within a unified framework. Section 4 translates coefficients to a common "pp per 1% wage change" scale via envelope calculations and interprets rotations in light of the model. Section 5 addresses threats to identification and reports cross–cutting robustness and design variants. Section 6 concludes with implications for policy design and macro stabilization.

2 EITC Background, Incentive Mapping, and CZATE

This section provides the institutional context and the empirical object that underpins the paper's identification strategy. Section 2.1 reviews the Earned Income Tax Credit (EITC) and highlights the 1993 expansion that

supplies the main statutory variation. Section 2.2 translates that expansion into incentives using three figures: the level schedules in 1990 and 2000, their pointwise difference, and the derivative of that difference with respect to income. Section 2.3 aggregates these individual incentives using observed income distributions to generate population-level predictions by demographic group. Section 2.4 then constructs a commuting-zone (CZ) measure of policy exposure and defines the Commuting Zone Average Treatment Effect (CZATE), which I use for geographically diffuse decadal shocks.

2.1 Institutional background

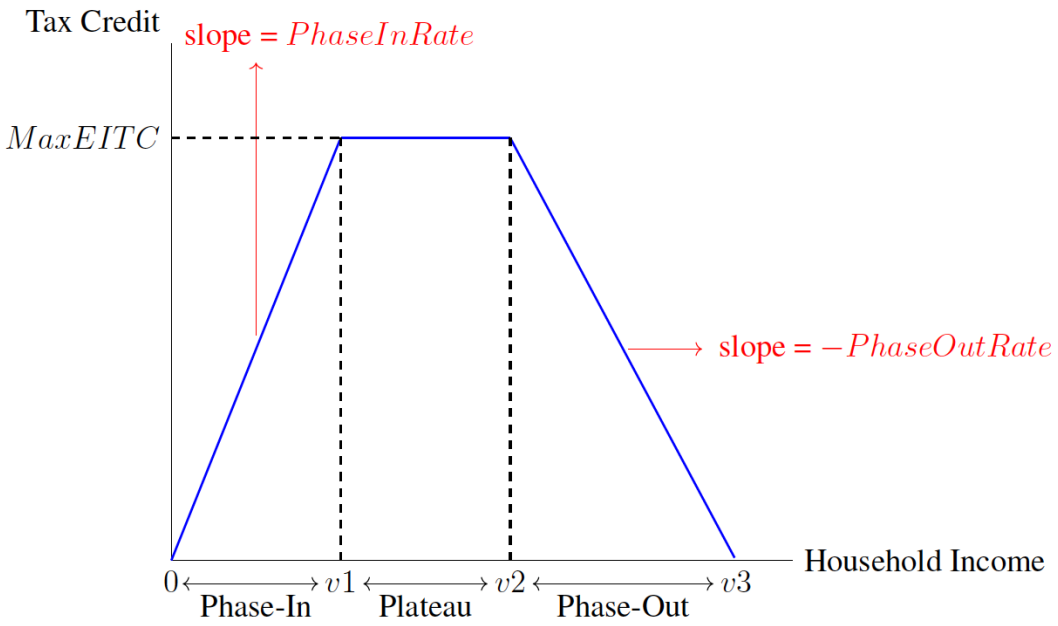
The EITC is the largest means-tested earnings subsidy for working households in the United States. Benefits are refundable and rise sharply with the number of qualifying children.[2] The schedule has three regions: a phase-in where benefits increase with earnings, a plateau where the maximum credit is received, and a phase-out where benefits decline with earnings. Figure 1 depicts this piecewise-linear structure in a generic year, labeling the three thresholds $\{v_1, v_2, v_3\}$ that delimit phase-in, plateau, and phase-out, and indicating that the local slope equals the phase-in rate in the first segment, zero on the plateau, and minus the phase-out rate in the final segment.

Table 1 reports one concrete set of statutory parameters (2017) by number of qualifying children. Reading the table alongside Figure 1 makes clear how higher phase-in rates and larger $MaxEITC$ shift up the first two segments of the schedule, while a steeper phase-out rate makes the last segment decline faster with income. These parameters are identical across marital statuses but increase steeply with the number of qualifying children. While Table 1 provides a snapshot, the schedule has evolved markedly over time. To situate these static parameters historically, I briefly summarize the major federal expansions and then show the resulting time series of the maximum credit.

Federal legislation in 1986–87, 1990, and especially 1993 substantially increased generosity, with further temporary enhancements in 2009 for three-child families. The 1986 reform broadened coverage and raised credits for families with children; the 1990 reform modestly increased phase-in rates and maximum benefits;

[2]For EITC, a "qualifying child" must meet: relationship (your child/stepchild/foster child, sibling/stepsibling, or their descendant), age (under 19; under 24 if full-time student; any age if permanently and totally disabled), residency (lived with you in the U.S. over half the year), joint-return (does not file a joint return unless only to claim a refund), and have a valid SSN. Source: IRS EITC rules (Pub. 596/Topic 601), `https://www.irs.gov/credits-deductions/individuals/earned-income-tax-credit`.

Figure 1: EITC Design



Notes — v_1, v_2, and v_3 denote the three EITC income thresholds, which vary by number of qualifying children (and over time via statute and indexation). In the phase-in region ($0 \leq y \leq v_1$), the credit increases with earnings at a constant rate ($PhaseInRate$); on the plateau ($v_1 < y \leq v_2$), the maximum credit is received; in the phase-out ($v_2 < y \leq v_3$), the credit declines linearly at the $PhaseOutRate$ until it reaches zero.

Table 1: EITC Parameters in 2017 by Number of Qualifying Children

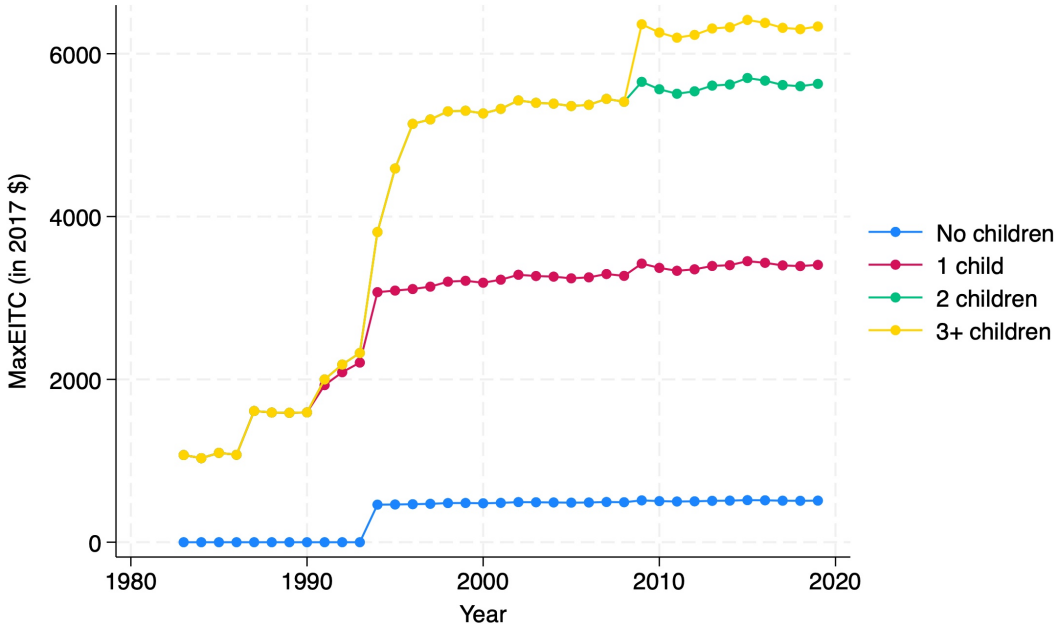
	0 Children	**1 Child**	**2 Children**	**3+ Children**
$MaxEITC$ (2017 $ per year)	6,670	10,000	14,040	14,040
$PhaseInRate$	0.0765	0.34	0.40	0.45
$PhaseOutRate$	0.0765	0.1598	0.2106	0.2106

and the 1993 expansion dramatically raised maximum credits—especially for families with two or more children—and widened eligibility. In 2009, benefits were temporarily increased for families with three or more children and marriage penalties were reduced.[3] Figure 2 shows these expansions in the time series of the statutory maximum credit: the large step-up after 1993 is visible for families with children, with an additional temporary bump in 2009 for 3+ children.

In what follows, I treat the 1993 expansion as the primary source of exogenous policy variation: it sharply raised the maximum credit and shifted outward the phase-in/plateau/phase-out thresholds for

[3]Tax Reform Act of 1986 (Pub. L. 99-514); Omnibus Budget Reconciliation Acts of 1990 and 1993 (Pub. L. 101-508; Pub. L. 103-66); American Recovery and Reinvestment Act of 2009 (Pub. L. 111-5).

Figure 2: Maximum EITC Benefit by Year and Number of Qualifying Children



Notes — Statutory maximum EITC benefit (2017 dollars) by number of qualifying children, 1980–2020. The three major step-ups are visible: after the Tax Reform Act of 1986, after the Omnibus Budget Reconciliation Acts of 1990 and 1993 (with a sharp increase in 1993, especially for 2+ children), and a temporary enhancement in 2009 for three-child families. Values drawn from TaxNotes historical EITC parameter tables.

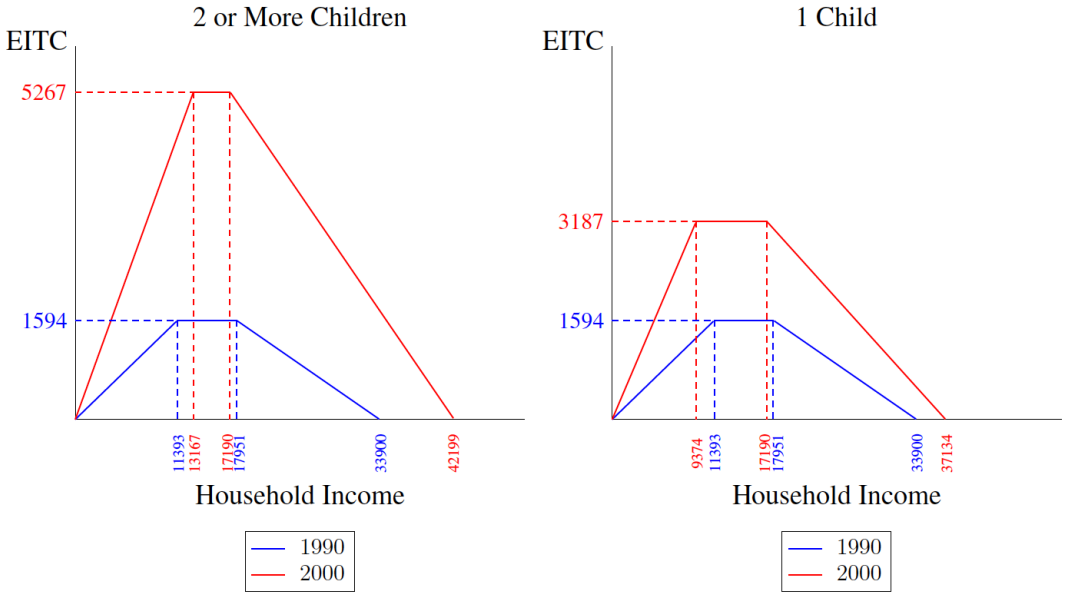
families with children, affecting a large share of working-age households. This reform generates meaningful cross-CZ dispersion in exposure through differences in family composition, and all empirical measures of generosity—including the CZ exposure index—are anchored on the 1990–2000 change implied by this expansion.

Two approaches are common in the literature. One constructs simulated (or weighted) benefits—often via TAXSIM—to estimate expected EITC dollars conditional on demographic or income distributions (e.g., Leigh 2010; Hoynes and Patel 2018); this connects directly to realized transfers but requires fixing baseline distributions to preserve exogeneity and can be sensitive to modeling choices (Kleven, 2024). The other relies on statutory parameters for a given family type and state–year (maximum credit and phase-in/out rates; e.g., Bastian and Michelmore 2018; Bastian and Jones 2021). I adopt the statutory approach and use the maximum possible credit as the baseline measure because it is transparent, comparable across settings, and preserves a policy-exogenous link between generosity and labor-supply incentives.

2.2 From statute to incentive mapping

To make the incentive changes transparent, I first plot the statutory level schedules in 1990 (blue) and 2000 (red) for one-child and two-or-more–child households. Figure 3 overlays these two schedules so the reader can see the vertical lift (higher $MaxEITC$) and the rightward shift of the kink points between 1990 and 2000, especially pronounced for families with two or more children. In the subsequent analysis, these level shifts are the basis for mapping income ranges ("low/medium/high") to the phase-in/plateau/phase-out incentives implied by the expansion.

Figure 3: EITC Benefit Schedules in 1990 and 2000 by Number of Children

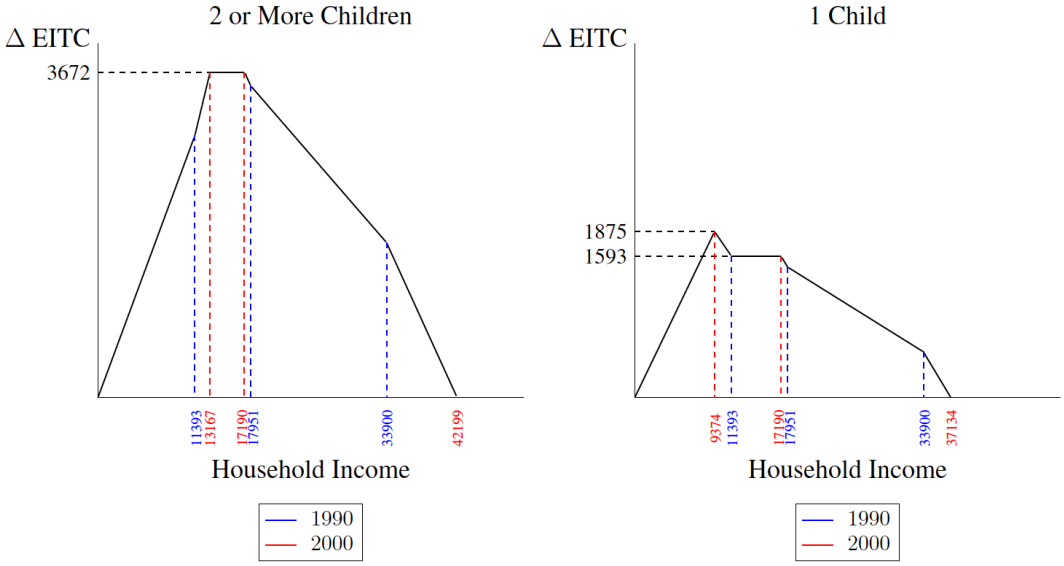


Notes — Each panel plots the statutory schedule in 1990 (blue) and 2000 (red) for one child (right) and two-or-more children (left). The 2000 schedule raises the maximum credit and shifts the phase-in/plateau/phase-out thresholds outward, especially for 2+ children. Dollar amounts are in 2017 dollars (Table 1).

The later schedule is uniformly above the earlier one over wide income ranges, and the kinks move rightward, especially for two-plus children. These level curves define the budget sets relevant for the work decision. Figure 4 then takes a pointwise difference between the two schedules, $\Delta\text{EITC}(y) = \text{EITC}_{2000}(y) - \text{EITC}_{1990}(y)$. Visually, it is simply the vertical gap between the red and blue lines in Figure 3 at each income y.

Local comparative statics are summarized by the slope of after-tax income with respect to earnings. Figure 5 plots the derivative of the 2000–1990 change with respect to income. Where the curve is positive (low

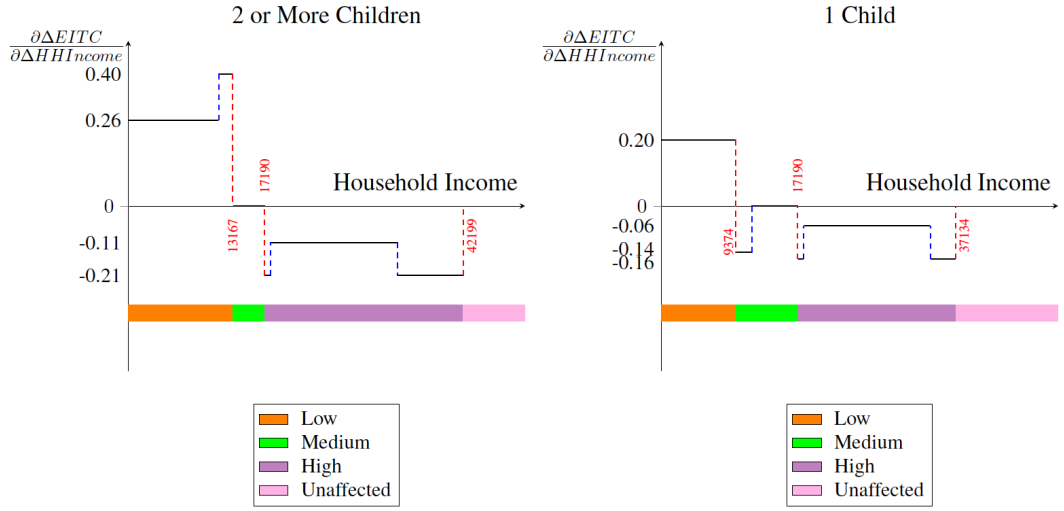
Figure 4: Change in EITC Schedule, 2000 vs. 1990, by Number of Children



Notes — The curve plots $\Delta\text{EITC}(y) = \text{EITC}_{2000}(y) - \text{EITC}_{1990}(y)$ at each income level. Equivalently, it is the red line minus the blue line in Figure 3. Increases are largest for 2+ children and around the phase-in and early plateau ranges. Dollar amounts are in 2017 dollars (Table 1).

range), a wage increase raises net income by more than dollar-for-dollar and amplifies employment responses; where it is near zero (medium), responses are roughly unchanged; where it is negative (high), the expansion dampens responses.

Figure 5: Derivative of the 2000–1990 EITC Change with Respect to Income



Notes — The slope is positive in the phase-in, flat on the plateau, and negative in the phase-out. Read this as how the expansion modifies the baseline wage–employment relationship: positive implies amplification, near zero implies neutrality, negative implies dampening. Dollar amounts and thresholds correspond to Figure 3 and Table 1.

Consistent with Figure 5, the resulting sign predictions for individual employment responses are:

Table 2: Theoretical Prediction on Employment for Household with 2 or More Children

	Household Income			
	Low	Medium	High	Unaffected
Positive Wage Shock	+	0	-	0
Negative Wage Shock	-	0	+	0

Notes — Predictions for households with one child are similar but less pronounced, as illustrated in Figure 5. The "Low," "Medium," and "High" ranges are defined using the sign of the derivative in Figure 5, which approximates the phase-in, plateau, and phase-out regions implied by the 1990–2000 expansion. "Unaffected" refers to households outside the eligible range.

In household survey data, I cannot place each person exactly on the statutory phase-in, plateau, or phase-out segments because doing so would require error-free information on filing status, the number of qualifying children, the level and timing of annual earnings, state supplements, and (for nonworkers) potential earnings.[4] To recover the qualitative incentives of the nonlinear schedule while preserving exogeneity, I use the 1990–2000 federal expansion as a mapping device and define three empirical income ranges based on Figure 5: a low range where the derivative of the 2000–1990 change is positive (phase-in proxy), a medium range where it is near zero (plateau proxy), and a high range where it is negative (phase-out proxy). Small misclassification near the boundaries does not alter the sign predictions; robustness checks with perturbed cutoffs and alternative child panels yield similar patterns.

2.3 From individual incentives to population predictions

Aggregating the signs in Table 2 using the observed working-household income distributions yields population-level predictions by group. I therefore weight these signs by the observed income distribution of working households in the 2000 Census, disaggregated by gender, marital status, and education.

Two features of Table 3 drive the population predictions. First, for most groups other than single women, the mass of eligibles lies in the high range, implying that phase-out forces tend to dominate. Second, single women—especially high-school dropouts—have a much larger mass in the low range. Hence, in broad local booms that lift wages across the distribution, the phase-out mechanism stabilizes the aggregate response

[4]Measurement error in any of these inputs can shift an individual across statutory thresholds; for nonworkers, potential earnings are unobserved by construction.

Table 3: Household Income Distribution by Demographic Groups

	Household Income (%)			
	Low	Medium	High	Unaffected
Overall (Percentage)	3.5	2.4	15.3	78.8
Single Men	3.5	2.8	17.3	76.4
High school dropouts	6.8	4.9	26.1	62.1
High school only	2.8	2.3	15.9	79.0
College graduates	1.3	1.2	7.8	89.7
Married Men	1.6	1.3	12.3	84.8
High school dropouts	5.7	4.3	31.3	58.8
High school only	1.4	1.1	12.8	84.8
College graduates	0.5	0.4	3.6	95.5
Single Women	11.4	6.7	27.0	54.9
High school dropouts	23.4	10.3	30.3	36.0
High school only	10.2	6.6	28.2	55.0
College graduates	3.6	2.5	15.4	78.5
Married Women	1.6	1.3	12.1	85.0
High school dropouts	6.0	4.4	32.2	57.4
High school only	1.4	1.2	12.4	85.0
College graduates	0.5	0.4	3.4	95.8

Notes — Data source: 2000 Census. "Low," "Medium," "High," and "Unaffected" correspond to the ranges defined by Figure 5. These distributions weight the individual signs to form population-level predictions.

for most groups (dampened wage–employment slope). Under adverse shocks like import competition that compress wages, the net response is ambiguous in general but clearly destabilizing for single low-education women (amplified movements). For minimum-wage increases that bind at the bottom, the phase-in mechanism amplifies responses among covered workers, while aggregate effects are muted where the low range is sparse.

A natural concern is negative selection: nonworkers may have lower potential wages than observed workers, which could place marginal entrants slightly to the right of where they would otherwise appear. Existing evidence suggests the bias is limited, with extensive-margin adjustments occurring broadly across the distribution and attrition inflating observed wages by about 10–13 percent; these magnitudes are too small to reclassify large numbers of households across the low/medium/high ranges. Accordingly, the working distribution is a reasonable proxy for population weighting.

2.4 Constructing CZ exposure and defining CZATE

The empirical analysis requires a policy-exogenous, CZ-level measure of EITC generosity that can be interacted with wage shocks. I first define a year-t statutory exposure index using predetermined family-size composition:

$$\text{MaxEITC}_{i,t} \equiv \sum_{s\in\{0,1,2,3+\}} \text{share}_{is,1980} \cdot C_{s,t},$$

where $\text{share}_{is,1980}$ is CZ i's 1980 share of households with s qualifying children, and $C_{s,t}$ denotes the statutory national maximum federal EITC for s qualifying children in year t. Using 1980 (rather than 1990) shares treats exposure as predetermined with respect to 1990s policy changes and local adjustments in fertility, marriage, or migration, supporting exogeneity of $\text{MaxEITC}_{i,t}$.

The decadal change in exposure, which underpins the long-difference designs, is therefore

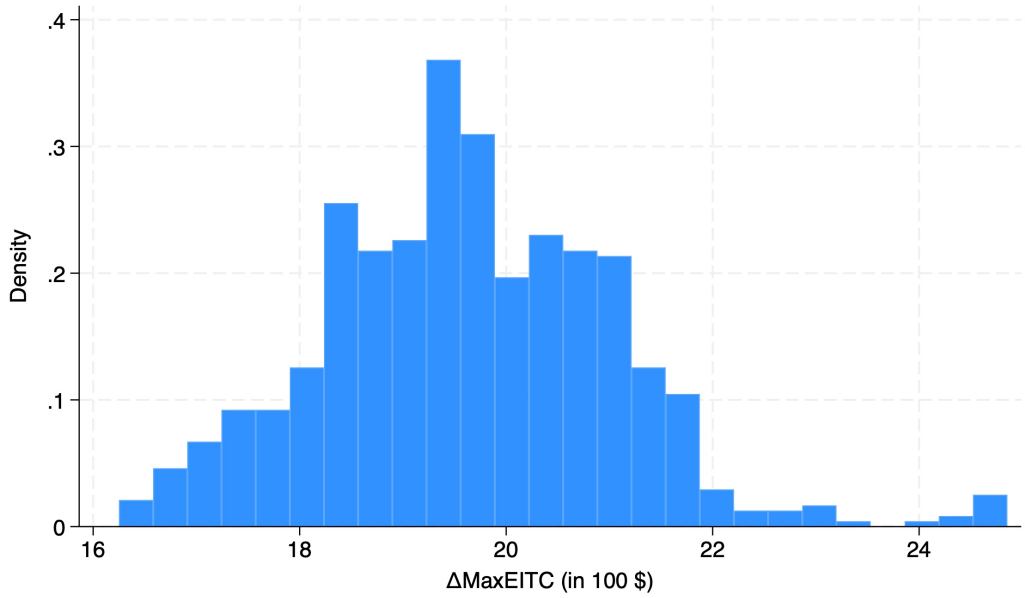
$$\Delta\text{MaxEITC}_i \equiv \text{MaxEITC}_{i,2000} - \text{MaxEITC}_{i,1990} = \sum_{s\in\{0,1,2,3+\}} \text{share}_{is,1980} \cdot \underbrace{\left(C_{s,2000} - C_{s,1990}\right)}_{\Delta C_s^{1990-2000}},$$

so that the change equals the 1980 parity mix reweighted by national statutory changes over 1990–2000. In practice I report and scale $\Delta\text{MaxEITC}_i$ in hundreds of 2017 dollars.

To summarize the cross-sectional variation used for identification, I compute the CZ-average maximum credit in 1990 and 2000 and plot the distribution of $\Delta\text{MaxEITC}_{cz}$ (Figure 6). Dispersion arises mechanically from differences in baseline family composition: CZs with larger shares of multi-child families experience larger increases, reflecting the 1993 expansion as the dominant driver of the 1990s change.

These ingredients motivate the Commuting Zone Average Treatment Effect (CZATE): the causal effect of statutory EITC generosity on CZ-level employment responses to wage shocks at the geographic unit where those shocks arise and equilibrate. Aggregation to CZs embeds policy parameters within a local labor-market equilibrium, relaxes the requirement that ineligibles form a valid counterfactual for eligibles, and parallels the commuting-zone aggregation widely used in the trade-exposure literature. I use this CZATE framework in the local-boom and China-shock sections, where shocks are geographically diffuse and unfold over a decade. In contrast, the minimum wage varies at high frequency and binds at the very bottom of the distribution, so I switch there to a two-way fixed effects individual-level difference-in-differences that targets an ATT for potentially bound workers. With this construction in place, subsequent sections do not need to

Figure 6: Distribution of CZ Exposure: $\Delta MaxEITC_{cz}$, 1990–2000



Notes — $\Delta MaxEITC_{cz}$ is the change in the CZ-average statutory maximum EITC benefit from 1990 to 2000, measured in hundreds of 2017 dollars. Most CZs experienced increases of roughly \$1,800–\$2,200 (2017\$), with a right tail in places where multi-child families are especially prevalent.

reintroduce the EITC schedule; all interactions use the CZ exposure defined here. A formal comparison of the CZATE estimand with individual-level ATT designs used in the EITC literature, and implications for interpretation, appears in Appendix A.1 (Comparability of EITC Results). In the next section, I apply the CZATE framework to three wage shocks to test the model's predictions.

3 Empirical Strategy and Evidence from Three Wage Shocks

This section brings the theoretical predictions to the data using three canonical wage shocks that differ in both direction and where they hit the earnings distribution: broad-based local economic booms, the adverse China trade shock, and policy-induced minimum-wage hikes. For each setting, I interact exogenous wage movements with CZ-level EITC exposure (Section 2) or, where appropriate, individual-level exposure, and estimate how EITC generosity rotates the wage–employment relationship. The design choices align each estimand with the shock's equilibrium scope: a CZATE for decade-long, geographically diffuse shocks (booms, trade) and an individual-level ATT for high-frequency, bottom-tail policy changes (minimum wages). I

maintain common outcome definitions, mean-centering conventions, and control sets to place coefficients on a comparable semi-elasticity scale.

3.1 Local Economic Booms

This subsection tests the model's stabilization prediction using broad-based local economic booms, with 1990 Commuting Zones (CZs) as the unit of analysis. These booms raise wages across much of the local distribution.[5] At the individual level (Table 2; Section 2.2), a positive wage shock amplifies employment in the low range, leaves it roughly unchanged in the medium range, and dampens it in the high range, with no effect for ineligibles. Aggregating to the population (Section 2.3), the eligible mass is empirically larger in the high range than in the low range, so the phase-out mechanism dominates and booms stabilize the aggregate response by dampening the otherwise positive wage–employment slope. The key empirical prediction is a negative interaction between EITC exposure and wage growth in the employment equation.

3.1.1 Data and Descriptive Patterns

This subsection draws on standard U.S. micro and administrative sources at the commuting–zone (CZ) level for 1990–2000. Employment outcomes come from the American Community Survey (ACS) microdata, aggregated to CZs using person weights. Wage measures are taken from the Quarterly Census of Employment and Wages (QCEW) and expressed in 2017 dollars using the Bureau of Economic Analysis (BEA) Personal Consumption Expenditures (PCE) price index. Additional covariates include industry composition from the QCEW, local unemployment rates from the Bureau of Labor Statistics (BLS) Local Area Unemployment Statistics (LAUS), state gross domestic product per capita from the BEA GDP by State series, and population counts from the National Bureau of Economic Research (NBER) population files. Federal Earned Income Tax Credit (EITC) parameters are compiled from Tax Notes (Tax Analysts).[6] For the construction of all control variables, refer to Autor et al. (2013).

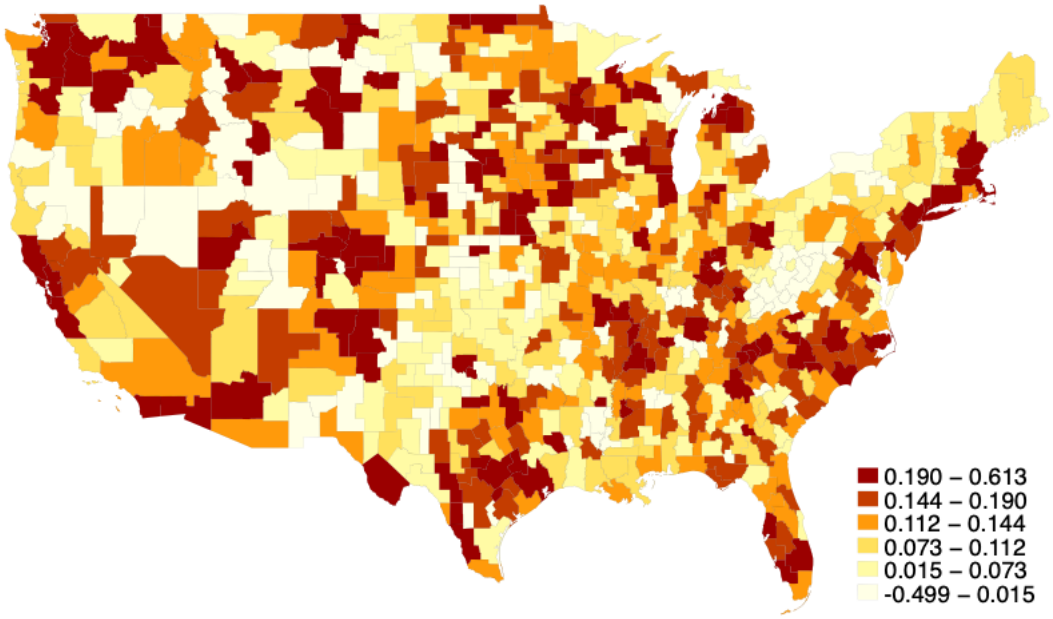
Wage growth varied markedly across CZs during the 1990s. Figure 7 maps CZ-level wage growth and shows clusters of faster growth in the Upper Midwest and Great Plains (e.g., the Dakotas, Nebraska, Iowa,

[5] See Section 1 and references therein, including Bartik (1991a); Blanchard et al. (1992); Moretti (2010); Allcott and Keniston (2018).

[6] `https://www.taxnotes.com/research/federal/reference-tables/earned-income-tax-credit/1x7ym`

Minnesota) and in interior belts through the lower Mississippi Valley, Appalachia, and parts of the inland South. By contrast, many CZs along the Pacific and Atlantic coasts—including much of coastal California, the Northeast corridor, and parts of the Mid-Atlantic—fall in lower growth bins, with similarly modest growth in portions of the Mountain West. The map also reveals sizable within-state dispersion (e.g., across Texas; between California's Central Valley and coastal metros; and between upstate and downstate New York), indicating that variation in CZ wage growth is not purely regional but occurs at a finer geographic scale.

Figure 7: Wage Growth, 1990–2000 (Commuting Zone 1990)



Notes: Each polygon is a 1990 Commuting Zone. Colors show $\Delta \ln W_i = \ln(\bar{W}_{i,2000}) - \ln(\bar{W}_{i,1990})$ from ACS microdata, deflated to 2017 dollars. Bins in the legend are log points (e.g., $0.185 \approx 18.5\%$); darker shades denote faster growth. The map displays the contiguous United States. In the regressions, $\Delta \ln W_i$ is scaled by 100 so that coefficients can be read as percentage-point changes in employment per 1% wage change.

3.1.2 Identification Strategy

Using the CZATE framework and exposure measure from Section 2, define

$$\mathcal{G}\{\text{single men},\ \text{married men},\ \text{single women},\ \text{married women}\}.$$

For each $g \in \mathcal{G}$, estimate

$$\Delta Y_{gi,1990\text{–}2000} = \alpha_g + \beta_{1g}\,\text{MaxEITC}_i + \beta_{2g}\,\Delta \ln W_i + \beta_{3g}\,(\text{MaxEITC}_i \times \Delta \ln W_i) + \gamma_g' X_{i,1990} + \varepsilon_{gi}. \quad (1)$$

where MaxEITC_i is the CZ exposure defined in Section 2 and $\Delta \ln W_i$ is fixed–share CZ wage growth,

$$\Delta \ln W_i \equiv \sum_k \text{share}_{ik,1990} \left[\ln \bar{W}_{ik,2000} - \ln \bar{W}_{ik,1990} \right],$$

with $\text{share}_{ik,1990}$ the 1990 industry shares and $\bar{W}_{ik,t}$ QCEW average wages.

To address endogeneity of $\Delta \ln W_i$, use a Bartik/shift–share instrument

$$Z_i^W \equiv \sum_k \text{share}_{ik,1990} \left[\ln \bar{W}_{k,2000,\text{US}\setminus i} - \ln \bar{W}_{k,1990,\text{US}\setminus i} \right],$$

and instrument the interaction with the product $\text{MaxEITC}_i \times Z_i^W$. Estimation proceeds by 2SLS using $\{Z_i^W,\ \text{MaxEITC}_i \times Z_i^W\}$ as excluded instruments for $\{\Delta \ln W_i,\ \text{MaxEITC}_i \times \Delta \ln W_i\}$.

Regressors are mean–centered within each g cell. Specifications are CZ–weighted by population with standard errors clustered by state. The control vector $X_{i,1990}$ includes baseline CZ demographics and labor–market covariates (female shares, occupation/industry mix, education and race shares, the 1990 unemployment rate, Census–division fixed effects, and 1990–2000 local GDP growth).[7] Sanderson–Windmeijer partial F statistics indicate relevant first stages.

3.1.3 Results

Table 4 reports CZ–level 2SLS estimates by gender and marital status. Three facts emerge. First, $\widehat{\beta}_{1g}$ is positive and statistically significant for women (single and married) and for married men, indicating that CZs more exposed to EITC expansions saw larger decade-long employment gains, abstracting from wage growth. Second, because regressors are mean–centered, $\widehat{\beta}_{2g}$ gives the wage–employment semi–elasticity at mean exposure; it is small and positive for men and near zero to modestly negative for women. For magnitudes and the mapping to semi–elasticities, see Section **??**. Third, the interaction $\widehat{\beta}_{3g}$ is negative and precisely estimated for single men (-0.077) and single women (-0.075), and negative but imprecise for married women (-0.034) and married men (-0.013). Consistent with the stabilization mechanism, greater EITC exposure dampens the employment response to wage growth—most clearly for singles.

Heterogeneity by education aligns with these patterns (Tables 5–6). For single men, the interaction is negative across all education groups and statistically significant, with larger magnitudes for lower education.

[7] Controls follow Autor et al. (2013).

Table 4: Effect of EITC on Employment Response to Percentage Point Change in Wage by Gender and Marital Status

	Employment Rate			
	(1)	(2)	(3)	(4)
	Single Men	Married Men	Single Women	Married Women
MaxEITC(in 100 $)	0.031	0.215*	0.336**	0.328*
	(0.168)	(0.125)	(0.167)	(0.188)
ΔlnW_i	0.023	0.021	-0.024	-0.046
	(0.022)	(0.017)	(0.022)	(0.043)
MaxEITC $\times$ ΔlnW_i	-0.077***	-0.013	-0.075***	-0.034
	(0.025)	(0.019)	(0.021)	(0.028)
Observations	722	722	722	722
Mean of 1990 Employment Rate	72.7	90.9	68.0	66.8
R^2	0.700	0.824	0.736	0.828
First-stage diagnostics				
SW cond. F: ΔlnW_i	15.32	11.68	15.16	11.43
SW cond. F: MaxEITC $\times$ ΔlnW_i	36.45	37.85	30.35	36.71

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC$\times\Delta lnW_i$, instrumented by Z_i^W and MaxEITC$\times Z_i^W$. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

For married men, interactions are small and imprecise. For single women, the interaction is strongly negative for high-school–only and modestly negative for college graduates, with imprecision among high-school dropouts. For married women, interactions are near zero and imprecise across education groups. This distribution of effects matches the empirical composition in Table 3 and the stabilization mechanism derived from the theory.

3.2 China Trade Shock

Moving from broad positive movements to a concentrated negative shock, I examine the rise in Chinese import penetration between 1990 and 2000, which compressed wages in tradable manufacturing and among low- to mid-skill workers.[8] In the model (Table 2; Section 2.2), a negative wage shock reduces employment in the low range, is near zero in the medium range, and raises it in the high range. Aggregating (Section 2.3), groups with eligibility mass in the high range can exhibit stabilization (dampened declines), whereas where the low range is dense—most notably single women without a high-school diploma—the phase-in margin dominates and responses destabilize (amplified declines). Thus, relative to booms, the key prediction flips sign

[8]See Section 1 and, e.g., Autor et al. (2013, 2016).

Table 5: Effect of EITC on Employment Response to Percentage Point Change in Wage by Education Level – Men Only

Panel A. Single Men			
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	0.516	-0.052	-0.259
	(0.39)	(0.16)	(0.17)
ΔlnW_i	0.035	-0.027	0.067***
	(0.07)	(0.04)	(0.02)
MaxEITC $\times$ ΔlnW_i	-0.096**	-0.074**	-0.046*
	(0.04)	(0.03)	(0.02)
Observations	722	722	722
Mean of 1990 Employment Rate	55.1	75.7	87.8
R^2	0.526	0.632	0.367
First-stage diagnostics			
SW cond. F: ΔlnW_i	18.67	18.71	34.54
SW cond. F: MaxEITC $\times$ ΔlnW_i	31.78	37.55	46.43
Panel B. Married Men			
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	0.710	0.135	0.145
	(0.48)	(0.11)	(0.09)
ΔlnW_i	0.015	0.019	-0.002
	(0.06)	(0.03)	(0.01)
MaxEITC $\times$ ΔlnW_i	-0.095	0.015	0.016
	(0.10)	(0.02)	(0.01)
Observations	722	722	722
Mean of 1990 Employment Rate	79.5	91.8	96.6
R^2	0.547	0.768	0.533
First-stage diagnostics			
SW cond. F: ΔlnW_i	19.35	13.66	24.58
SW cond. F: MaxEITC $\times$ ΔlnW_i	20.05	39.13	62.94

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC is constructed using 1980 child-share weights and is treated as exogenous. Endogenous regressors are ΔlnW_i and MaxEITC$\times\Delta lnW_i$, instrumented by Z_i^W and MaxEITC$\times Z_i^W$, respectively. Standard errors are heteroskedasticity-robust and clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

where exposure is bottom-concentrated: the EITC–import interaction in the employment equation should be negative in low-range–dense cells and closer to zero or stabilizing elsewhere.

Table 6: Effect of EITC on Employment Response to Percentage Point Change in Wage by Education Level – Women Only

Panel C. Single Women

	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	0.838**	0.326*	-0.325*
	(0.40)	(0.17)	(0.17)
ΔlnW_i	0.071	-0.087***	0.024
	(0.08)	(0.02)	(0.03)
MaxEITC $\times$ ΔlnW_i	-0.013	-0.066***	-0.040*
	(0.07)	(0.02)	(0.02)
Observations	722	722	722
Mean of 1990 Employment Rate	43.3	71.4	89.2
R^2	0.509	0.702	0.354
First-stage diagnostics			
SW cond. F: ΔlnW_i	19.84	19.16	28.55
SW cond. F: MaxEITC $\times$ ΔlnW_i	21.45	33.07	39.25

Panel D. Married Women

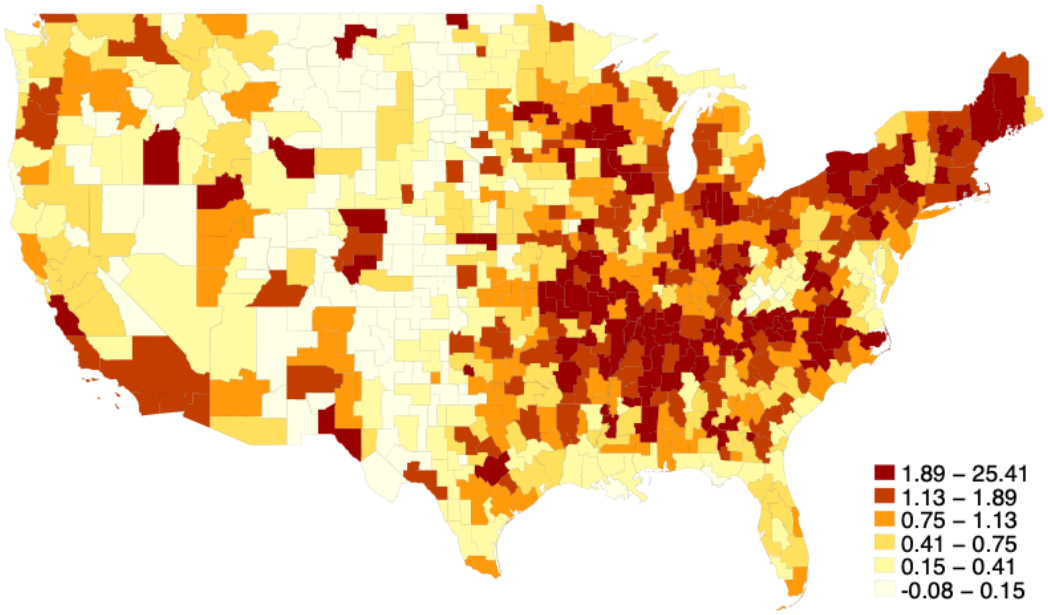
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	0.812**	0.198	0.122
	(0.33)	(0.19)	(0.15)
ΔlnW_i	0.075	-0.062	-0.084***
	(0.09)	(0.05)	(0.03)
MaxEITC $\times$ ΔlnW_i	0.009	-0.028	0.016
	(0.08)	(0.03)	(0.02)
Observations	722	722	722
Mean of 1990 Employment Rate	46.2	67.9	80.6
R^2	0.481	0.777	0.518
First-stage diagnostics			
SW cond. F: ΔlnW_i	22.40	13.41	24.01
SW cond. F: MaxEITC $\times$ ΔlnW_i	16.92	41.52	53.82

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC is constructed using 1980 child-share weights and is treated as exogenous. Endogenous regressors are ΔlnW_i and MaxEITC$\times\Delta lnW_i$, instrumented by Z_i^W and MaxEITC$\times Z_i^W$, respectively. Standard errors are heteroskedasticity-robust and clustered by state. First-stage diagnostics SW cond. F are reported in the table.

3.2.1 Data and Descriptive Patterns

The sample, outcome construction, and controls parallel Section 3.1. Import-exposure is measured using the Autor et al. (2013) shift–share: 1990 CZ industry employment shares interacted with Chinese export growth by industry.

Figure 8: China Import Penetration Exposure, 1990–2000 (Commuting Zone 1990)



Notes — Each polygon is a 1990 Commuting Zone. Shading reflects ADH-style import-penetration exposure IP_i^{cu}: 1990 CZ industry employment shares interacted with subsequent Chinese export growth to the United States by industry. Darker shades denote larger exposure increases. The legend reports bins of the exposure index. In estimation, IP_i^{cu} is instrumented with $Z_i^{IP} \equiv IP_i^{co}$, constructed using Chinese exports to other high-income destinations; see Section 3.2.2.

Figure 8 shows the geographic pattern: the highest exposure clusters across the Eastern manufacturing belt—New England through the Mid-Atlantic, the Ohio–Indiana–Michigan corridor, western Pennsylvania into Appalachia—and extends into the Carolinas and portions of the inland South. By contrast, much of the Mountain West and upper Great Plains fall into lower exposure bins, with visible within-state dispersion in large states (e.g., California, Texas, New York), indicating substantial identifying variation both across and within regions.

3.2.2 Identification and Estimation

The specification mirrors equation (1), replacing wage growth with ADH import penetration:

$$\Delta Y_{gi,1990\text{–}2000} = \alpha_g + \beta_{1g}\,\text{MaxEITC}_i + \beta_{2g}\,IP_i^{cu} + \beta_{3g}\big(\text{MaxEITC}_i \times IP_i^{cu}\big) + \gamma_g' X_{i,1990} + \varepsilon_{gi}. \tag{2}$$

Here, IP_i^{cu} is exposure to Chinese exports to the United States. Following ADH, I instrument IP_i^{cu} with $Z_i^{IP} \equiv IP_i^{co}$, constructed from Chinese exports to other high-income destinations, and use $\text{MaxEITC}_i \times Z_i^{IP}$ as the product instrument for the interaction. The control vector $X_{i,1990}$, centering, weights, clustering, and diagnostics match Section 3.1. Sanderson–Windmeijer partial F-statistics in Tables 7–9 indicate strong first stages for both IP_i^{cu} and $\text{MaxEITC}_i \times IP_i^{cu}$.

3.2.3 Results

Table 7 reports CZ-level 2SLS estimates by gender and marital status. The level effect of MaxEITC_i is positive for women (single and married) and imprecisely positive for men, echoing the boom setting. The direct effect of import exposure, $\widehat{\beta}_{2g}$, is most negative and precisely estimated for married women (-0.498, $p < 0.05$), with smaller and imprecise effects elsewhere. The interaction $\widehat{\beta}_{3g}$ is negative across all four columns but imprecisely estimated in these pooled sex–marital cells, consistent with theory's ambiguous population sign when eligibles span both low and high ranges.

Education splits sharpen the pattern (Tables 8–9). Among single women without a high-school diploma, the interaction is large and precisely negative ($\widehat{\beta}_3 \approx -1.087,\ p < 0.01$), implying that greater EITC exposure amplifies employment declines from import penetration in the group most likely to be in the low range. For single women with only a high-school degree and for married women and men across education cells, interaction estimates are smaller and imprecise, consistent with thinner low-range mass and offsetting forces in the high range.

3.3 Minimum Wage Hikes

This subsection examines a third, conceptually distinct test of the model: state and federal minimum-wage hikes. Unlike local booms or import exposure—both demand shocks—the minimum wage is a policy-set price floor that lifts pay primarily at the very bottom of the distribution. Empirically, once rich geography–time

Table 7: Effect of EITC on Employment Effect of China Trade Shock by Gender and Marital Status

	Employment Rate			
	(1)	(2)	(3)	(4)
	Single Men	Married Men	Single Women	Married Women
MaxEITC(in 100 $)	0.077	0.198	0.389**	0.347*
	(0.180)	(0.132)	(0.165)	(0.178)
IP^{cu}	-0.013	-0.077	-0.340	-0.498**
	(0.211)	(0.152)	(0.281)	(0.198)
MaxEITC $\times$ IP^{cu}	-0.009	-0.037	-0.403	-0.067
	(0.171)	(0.086)	(0.246)	(0.158)
Observations	722	722	722	722
Mean of 1990 Employment Rate	72.7	90.9	68.0	66.8
R^2	0.692	0.815	0.734	0.823
First-stage diagnostics				
SW cond. F: IP^{cu}	22.83	20.18	25.95	20.38
SW cond. F: MaxEITC $\times$ IP^{cu}	65.20	65.18	70.47	65.52

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are IP^{cu} and MaxEITC$\times IP^{cu}$, instrumented by IP^{co} and MaxEITC$\times IP^{co}$. SEs clustered by state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

controls are included, average employment effects are small to near zero (e.g., Dube et al., 2010; Allegretto et al., 2011; Neumark, 2018). When quantities move little, the first-order impact of a minimum-wage change is to raise observed wages for potentially bound workers, so for the purpose of my semi-elasticity mapping it can be treated as an exogenous wage shock concentrated in the low range of the schedule. In the framework summarized by Table 2, a positive wage shock at the bottom amplifies individual employment responses in the low range (phase-in), is roughly neutral on the plateau, and dampens in the phase-out. Aggregating to the population, groups most exposed to the wage floor (notably lower-education single women) have a dense low-range mass, so the phase-in mechanism should dominate for them: minimum-wage hikes destabilize the population response by steepening the otherwise modest wage–employment slope. By contrast, for groups less exposed to the floor, effects should be muted.

3.3.1 Data and Descriptive Patterns

I use March CPS microdata to construct an individual panel aggregated to state–year cells for 1991–2006, restricting to ages 19–55, excluding the incarcerated, and retaining observations with positive reported wages when employed. The outcome is a 0/1 employment indicator scaled by 100 (percentage points). The

Table 8: Effect of EITC on Employment Effect of China Trade Shock by Education Level - Men Only

Panel A. Single Men			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
$MaxEITC$(in 100 $)	0.541	0.011	-0.283
	(0.39)	(0.15)	(0.19)
IP^{cu}	0.285	-0.279	0.361
	(0.43)	(0.22)	(0.31)
$MaxEITC \times IP^{cu}$	-0.215	0.075	-0.114
	(0.39)	(0.15)	(0.23)
Observations	722	722	722
Mean of 1990 Employment Rate	55.1	75.7	87.8
R^2	0.533	0.642	0.346
First-stage diagnostics			
SW cond. F: IP^{cu}	30.66	33.06	70.09
SW cond. F: MaxEITC $\times$ IP^{cu}	84.07	63.70	56.45
Panel B. Married Men			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
$MaxEITC$(in 100 $)	0.745	0.098	0.127
	(0.51)	(0.11)	(0.08)
IP^{cu}	0.026	-0.199	0.175
	(0.49)	(0.12)	(0.14)
$MaxEITC \times IP^{cu}$	0.119	-0.018	-0.116
	(0.30)	(0.07)	(0.08)
Observations	722	722	722
Mean of 1990 Employment Rate	79.5	91.8	96.6
R^2	0.575	0.768	0.543
First-stage diagnostics			
SW cond. F: IP^{cu}	28.88	26.15	48.37
SW cond. F: MaxEITC $\times$ IP^{cu}	103.68	65.63	51.75

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC is constructed using 1980 child-share weights and is treated as exogenous. Endogenous regressors are IP^{cu} and MaxEITC$\times IP^{cu}$, instrumented by IP^{co} and MaxEITC$\times IP^{co}$. SEs clustered by state.

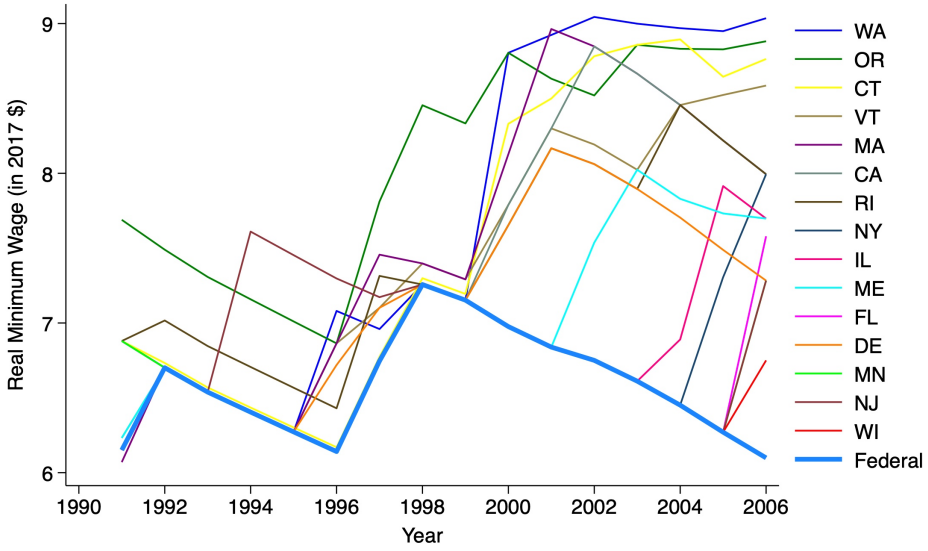
Table 9: Effect of EITC on Employment Effect of China Trade Shock by Education Level - Women Only

Panel C. Single Women			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	0.658	0.407***	-0.236
	(0.40)	(0.14)	(0.18)
IP^{cu}	-0.751	-0.613**	0.806***
	(0.65)	(0.30)	(0.27)
MaxEITC × IP^{cu}	-1.087***	-0.206	-0.230
	(0.40)	(0.24)	(0.21)
Observations	722	722	722
Mean of 1990 Employment Rate	43.3	71.4	89.2
R^2	0.472	0.725	0.353
First-stage diagnostics			
AP F: IP^{cu}	28.86	35.62	94.82
AP F: MaxEITC × IP^{cu}	94.62	67.34	73.38
Panel D. Married Women			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	0.797**	0.179	0.208
	(0.33)	(0.18)	(0.16)
IP^{cu}	-0.032	-0.741***	-0.192
	(0.69)	(0.23)	(0.32)
MaxEITC × IP^{cu}	0.138	-0.124	0.096
	(0.28)	(0.18)	(0.14)
Observations	722	722	722
Mean of 1990 Employment Rate	46.2	67.9	80.6
R^2	0.481	0.764	0.495
First-stage diagnostics			
SW cond. F: IP^{cu}	29.98	26.38	51.54
SW cond. F: MaxEITC × IP^{cu}	92.03	65.13	59.58

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC is constructed using 1980 child-share weights and is treated as exogenous. Endogenous regressors are IP^{cu} and MaxEITC×IP^{cu}, instrumented by IP^{co} and MaxEITC×IP^{co}. SEs clustered by state.

policy variable is the log of the real state minimum wage (2017 dollars), taken from FRED (underlying U.S. DOL/BLS series). State–year covariates include BEA state GDP per capita, the BLS LAUS unemployment rate, the top marginal state income–tax rate from NBER TAXSIM, the maximum AFDC/TANF cash benefit for a benchmark family from the Urban Institute WRD, and indicators for AFDC waivers and TANF implementation. All nominal values are deflated using the BEA PCE price index.

Figure 9: Minimum Wage by Year and State, 1991–2006



Notes — Real (2017$) minimum wages by state; unlabeled states track the federal path.

Figure 9 shows substantial cross–state and over–time variation generated by three federal increases (1991, 1996, 1997) and staggered state hikes, providing the usual difference–in–differences leverage.

3.3.2 Identification Strategy

The empirical design is a two–way fixed–effects (TWFE) difference–in–differences model with an interaction between EITC generosity and the minimum wage:

$$\begin{aligned} Y_{ist} = \beta_1 \,\mathrm{MaxEITC}_{it} + \beta_2 \,\ln \mathrm{MinW}_{st} + \beta_3 \big(\mathrm{MaxEITC}_{it} \times \ln \mathrm{MinW}_{st}\big) \\ + X_{it}\phi + U_{st}\eta + \delta_s + \delta_t + \nu_{ist}, \end{aligned} \tag{3}$$

where Y_{ist} is employment ($\times 100$), $\mathrm{MaxEITC}_{it}$ is the statutory maximum federal EITC for individual i's inferred filing/child status (2017$; in $1,000), and $\ln \mathrm{MinW}_{st}$ is the log real state minimum wage. Both policy

variables are mean–centered; β_3 is the interaction of interest. Individual controls X_{it} follow Bastian and Jones (2021) (age, race, education, number of children, indicator for children under five, SNAP participation). U_{st} collects state–year covariates listed above. I include state and year fixed effects, interact the number of children with state dummies, weight by ASEC weights, and cluster standard errors by state. Robustness checks (Appendix) add state–specific linear trends and Census–division–by–period fixed effects and implement parity–anchored designs parallel to Sections 3.1–3.2.

The CZATE design in Sections 3.1–3.2 exploits low-frequency, geographically diffuse shocks using decade-long differences across CZs. Minimum wages, by contrast, change at high frequency with staggered, state-specific timing and primarily affect workers at the wage floor. Collapsing these year-by-year changes into a single long difference would dilute the identifying variation and confound distinct episodes with unrelated decade trends; moreover, most CZs lie entirely within one state, leaving little cross-sectional variation at the CZ level in any given year. Because the mechanism is concentrated at the bottom tail, the relevant estimand is the individual ATT: how employment among potentially bound workers shifts when the minimum wage rises, as a function of EITC generosity. I therefore estimate a TWFE difference-in-differences at the individual level, which preserves high-frequency policy variation, aligns the estimand with exposure, and complements the CZATE evidence for the other shocks.

A further motivation is equilibrium scope. Local booms and import competition plausibly trigger broad general-equilibrium adjustments—reallocation across industries, migration, and local demand spillovers (e.g., Blanchard et al., 1992; Bartik, 1991a; Moretti, 2010; Autor et al., 2013, 2016)—so a CZATE is informative in those settings. Minimum-wage changes, by contrast, target the lower tail of the wage distribution, and the literature typically finds small average employment effects once rich geography–time controls are included, suggesting limited spillovers at the CZ scale.[9] Consistent with this view, minimum-wage adjustments mainly reprice labor at the bottom rather than shifting broader relative prices or input costs, further limiting CZ-level general-equilibrium feedback (see, among others, Dube et al., 2010; Allegretto et al., 2011; Neumark, 2018). In that environment, the individual-level average treatment effect on the treated (ATT) for potentially bound workers is the more relevant object. A formal comparison of CZATE and ATT for my designs appears in Appendix A.1 (Comparability of EITC Results).

[9]See, e.g., Dube et al. (2010); Allegretto et al. (2011); Neumark (2018).

3.3.3 Results

Table 10 reports TWFE estimates by gender and marital status. The interaction $\widehat{\beta}_3$ is positive across groups but statistically significant only for single women, which is precisely where the model predicts a dominant phase–in margin. Tables 11 and 12 split by education. Among men, interactions are small and imprecise. Among single women, the positive interaction is concentrated among lower–education cells (significant for high–school only), consistent with minimum–wage hikes destabilizing the population response in groups with dense mass in the low range. For married women, interactions are near zero and imprecise across education. Patterns are stable in the main and Appendix specifications (state trends, division–by–period effects, parity–based designs, dropping early transition years).

Table 10: Minimum Wage × EITC: Employment by Gender and Marital Status (TWFE DiD)

	Employment (pp)			
	Single Men	Married Men	Single Women	Married Women
MaxEITC (in $1,000)	0.699	0.357**	2.116***	0.597**
	(0.554)	(0.177)	(0.401)	(0.241)
ln MinW	7.055	0.638	-6.153	-6.295
	(7.012)	(1.697)	(7.463)	(4.527)
MaxEITC × ln MinW	0.621	0.591	5.214***	0.406
	(1.763)	(0.977)	(1.609)	(0.956)
Observations	110,587	202,100	127,533	213,216
Mean of outcome (pp)	76.6	90.4	73.1	68.1
R^2	0.125	0.102	0.247	0.111

Notes — March CPS 1991–2006. Outcome is 100×employment indicator (percentage points). MaxEITC is the statutory maximum federal credit for the individual's inferred filing/child status (2017$), scaled in $1,000; ln Min wage is the log real state minimum wage (2017$). Both policy variables are mean–centered within the estimation sample. Specifications include state and year fixed effects; individual controls (age, race, education, number of children, indicator for children under five, SNAP participation); state–year covariates (unemployment, GDP per capita, welfare generosity for a three–child family, top marginal tax rate, welfare reform and AFDC waiver indicators); and interactions of number of children with state dummies. ASEC weights used; standard errors clustered by state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.3.4 Event Study for Single Women

The TWFE estimates above indicate a positive EITC–minimum–wage interaction concentrated among single women, especially at lower education levels. To assess dynamics, check for pretrends, and gauge persistence in a setting where the wage floor binds intermittently, I estimate an event-study that interacts EITC generosity

Table 11: Minimum Wage × EITC: Men by Education (TWFE DiD)

Panel A. Single Men			
	High School Dropouts	High School Only	College Graduates
MaxEITC (in $1,000)	0.635	0.880	0.913
	(1.454)	(0.709)	(1.181)
ln MinW	0.864	12.088	-1.913
	(20.643)	(9.025)	(10.205)
MaxEITC × ln MinW	5.394	-0.371	-5.371
	(4.537)	(1.531)	(4.433)
Observations	18,910	69,313	22,364
Mean of outcome (pp)	57.8	77.8	88.2
R^2	0.134	0.077	0.046
Panel B. Married Men			
	High School Dropouts	High School Only	College Graduates
MaxEITC (in $1,000)	0.217	0.679**	-0.177
	(0.613)	(0.257)	(0.211)
ln MinW	-4.412	0.107	2.061
	(13.800)	(2.301)	(2.002)
MaxEITC × ln MinW	3.797	-0.279	1.050
	(2.792)	(1.447)	(0.976)
Observations	27,933	117,480	56,687
Mean of outcome (pp)	77.9	90.4	95.7
R^2	0.135	0.063	0.040

Notes — Specification, controls, weights, and clustering as in Table 10. Education is the highest completed degree. Coefficients are percentage–point changes in employment. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

with year dummies in the single–women sample, separately by education. This design complements the average DiD coefficients by tracing the timing of the response around the 1996–1997 federal hikes and subsequent real erosion, providing a sharper test of the "low–range amplification" mechanism and a built–in pretrend diagnostic:

I examine dynamics for the group most likely to be at the wage floor by interacting EITC generosity with year dummies in the sample of single women, estimating separate models by education:

$$Y_{ist} = \sum_j \alpha_j \mathbf{1}\{t = j\} + \beta \,\text{MaxEITC}_{it} + \sum_{j \neq -1} \gamma_j \big[\mathbf{1}\{t = j\} \times \text{MaxEITC}_{it}\big] + X_{it}\phi + U_{st}\eta + \delta_s + \delta_t + \varepsilon_{ist},$$

Table 12: Minimum Wage × EITC: Women by Education (TWFE DiD)

Panel C. Single Women

	High School Dropouts	High School Only	College Graduates
MaxEITC (in $1,000)	2.797***	1.992***	1.367**
	(0.831)	(0.469)	(0.609)
ln MinW	-10.904	-1.662	-14.796**
	(17.088)	(10.028)	(6.655)
MaxEITC × ln MinW	6.404	5.725***	1.655
	(5.076)	(1.517)	(2.116)
Observations	21,397	80,568	25,568
Mean of outcome (pp)	41.1	75.3	90.2
R^2	0.179	0.163	0.060

Panel D. Married Women

	High School Dropouts	High School Only	College Graduates
MaxEITC (in $1,000)	-0.770	0.923***	0.834
	(0.962)	(0.260)	(0.564)
ln MinW	-15.454*	-0.409	-14.911**
	(8.157)	(7.159)	(6.286)
MaxEITC × ln MinW	2.086	-0.165	0.974
	(3.509)	(1.369)	(1.946)
Observations	27,390	135,511	50,315
Mean of outcome (pp)	42.9	68.9	77.7
R^2	0.103	0.068	0.075

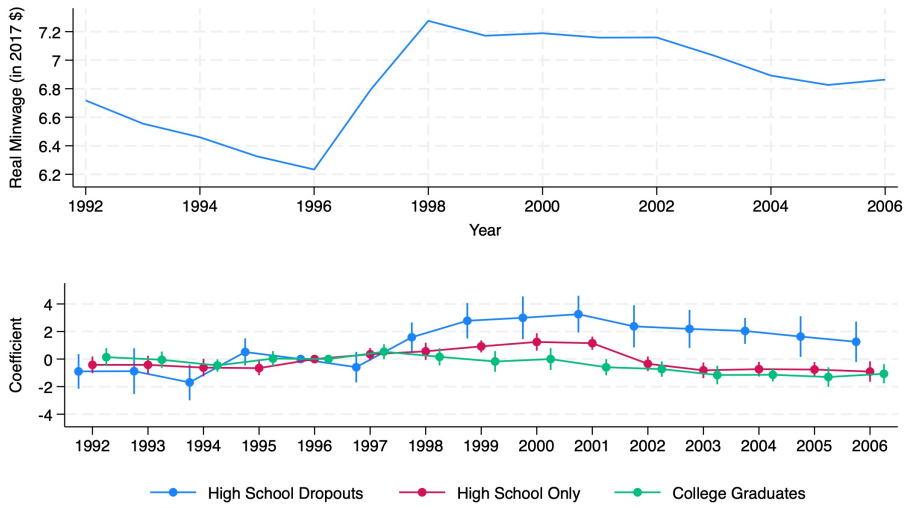
Notes — Specification, controls, weights, and clustering as in Table 10. Education is the highest completed degree. Coefficients are percentage–point changes in employment. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

where year -1 is 1996, the last year before the federal minimum–wage hikes. The coefficients γ_j are therefore changes, relative to 1996, in the employment response (in percentage points) to a $1,000 increase in EITC generosity, conditional on the controls and fixed effects used in Table 10.

Figure 10 presents two panels. The top panel plots the path of the real minimum wage, which falls through 1996, jumps in 1997–1998 with the federal increases, and then gradually erodes in real terms. The bottom panel reports the estimated γ_j by education. Coefficients are close to zero and statistically indistinguishable across education groups in the pre-period 1992–1996, indicating no differential pretrends in EITC responsiveness. Beginning in 1998, responsiveness rises sharply for high–school dropouts to roughly 2–3 percentage points per $1,000, with a smaller increase for high–school graduates and little movement for college graduates. This pattern matches the model's prediction that when the wage floor binds, more low-education single women lie in the low range of the EITC schedule, so EITC generosity amplifies the

wage–employment link. After 2001, as the real minimum wage drifts down, the dropout coefficients attenuate toward zero and the high–school–only effects fade, consistent with fewer workers remaining bound by the floor.

Figure 10: Responsiveness to EITC Around Minimum Wage Hikes (Single Women)



Notes — Event–time coefficients for the interaction of EITC generosity with year dummies; baseline year is 1996 (the year before the federal hike). Models include the controls and fixed effects from Table 10; vertical bars are 95% confidence intervals clustered by state.

4 Envelope Calculations and Theoretical Interpretation

4.1 Baseline semi–elasticities across shocks

At mean EITC exposure (regressors mean–centered), the CZATE boom estimates imply semi–elasticities of 0.023 (single men), 0.021 (married men), −0.024 (single women), and −0.046 (married women) (Table 4); these instrumented equilibrium responses align with evidence of weak male wage responsiveness and with secondary–earner effects for women (e.g., Blundell and MaCurdy, 1999; Blanchard et al., 1992; Mincer, 1962; Heckman, 1978; Blau and Kahn, 2007a; Juhn and Potter, 2006; Bradbury and Katz, 2008). For the China trade shock, converting ADH coefficients using a one–standard–deviation–matched wage pass–through yields 0.007 (single men), 0.044 (married men), 0.193 (single women), and 0.283 (married women) (see Appendix A.2 (Calculating Envelope Semi-Elasticity)); relative to regional–adjustment benchmarks of 0.05–0.15 pp per 1% wage change, men's responses are small to moderate while women's—especially married

women's—are larger, consistent with persistent, concentrated trade contractions and greater extensive–margin responsiveness among women (e.g., Autor et al., 2013, 2016; Mincer, 1962; Heckman, 1978; Blundell and MaCurdy, 1999; Blau and Kahn, 2007b; Keane, 2011). For minimum–wage changes, the TWFE design implies 0.0073 (single men), −0.0042 (married men), −0.0142 (single women), and 0.0062 (married women), in line with the literature's near–zero averages under rich geography–time controls (e.g., Dube et al., 2010; Allegretto et al., 2011; Neumark, 2018).

Across these settings—decade–long CZATE estimates for booms and trade, and a high–frequency individual ATT for minimum wages—the pattern points to a common mechanism: by altering the slope of the after–tax budget, the EITC rotates the wage–employment relationship, with the sign depending on where eligibles sit on the schedule. The remainder of this section formalizes and unifies that interpretation. Section 4.2 specifies the work decision and the EITC geometry; Section 4.3 derives the structural envelope semi–elasticity linking a 1% wage change to extensive–margin employment; and Section 4.4 maps the estimated EITC–shock interactions onto a common "pp per 1% wage change" scale via a marginal policy semi–elasticity (MPSE), enabling direct comparison of rotations across booms, trade, and minimum–wage contexts.

I study how the employment rate responds to wage changes, and how that response varies with EITC generosity. Intuitively, the EITC tilts the after–tax budget line: amplification in phase–in (credit rises with earnings), near neutrality on the plateau, and dampening in phase–out (credit is clawed back).

4.2 Setup and Work Decision

Let w denote the hourly wage, h annual hours (normalized to one for extensive–margin analysis), and $y = wh$ pre–tax earnings. The EITC schedule is $T(y;\theta)$, parameterized by generosity θ (e.g., the maximum credit and the phase–in/phase–out rates).[10] Net income when working is $c(y) = y + T(y;\theta)$. Let $U(c)$ be utility when working and U_0 the reservation utility of non–work. A person works if $U(c(y)) \geq U_0$. With G the CDF of U_0 and g its density,

$$P = \Pr[U_0 \leq U(c(y))] = G\big(U(c(y))\big), \qquad Y \equiv 100 \cdot P \ \text{ (percentage points).}$$

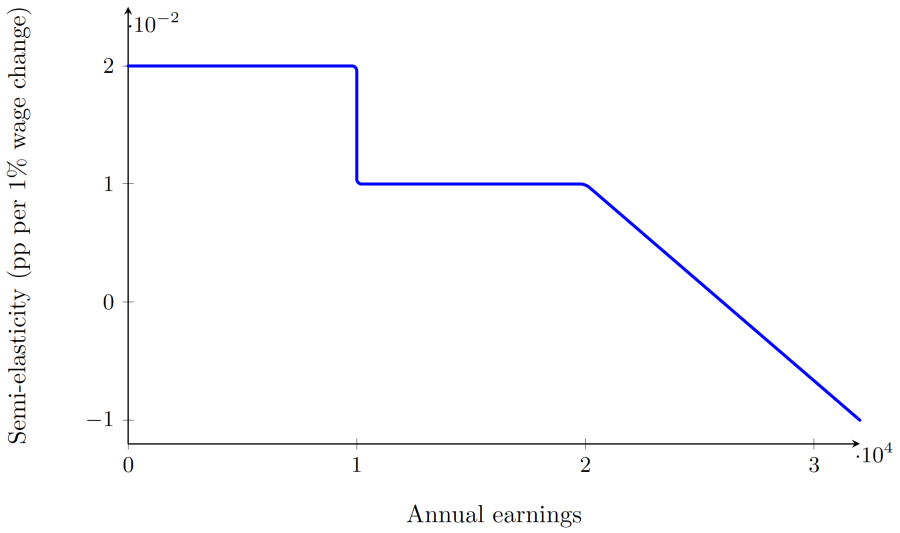
[10] Because T is a *benefit*, it adds to income; a tax would subtract.

Write the EITC marginal rate $\tau_m(y;\theta) \equiv \partial T(y;\theta)/\partial y$ (positive in phase–in, zero on the plateau, negative in phase–out). Because $c(y) = y + T(y;\theta)$, the slope of the after–tax budget is

$$\mathrm{NTR}(y;\theta) \equiv \frac{\partial c}{\partial y} = 1 + \tau_m(y;\theta).$$

4.3 Structural Envelope Semi–Elasticity (pp per 1% wage)

Figure 11: Schematic envelope semi–elasticity across the EITC schedule



Notes—The vertical axis is the extensive–margin envelope semi–elasticity (percentage–point change in employment per 1% wage change), and the horizontal axis is annual earnings (in $10,000s). The piecewise shape mirrors the EITC's geometry: high and roughly flat in phase–in (amplification), a discrete drop at the first kink, flat and smaller on the plateau (near neutrality), and then a linear decline through phase–out (dampening), crossing zero as implicit tax rates rise. The exact levels are illustrative; the theory pins down signs and relative magnitudes, while the empirical MPSEs below quantify rotations in the data.

Figure 11 visualizes the structural envelope semi–elasticity in Section 4.3. In phase–in, the positive EITC marginal rate steepens the after–tax budget line, yielding a high, approximately flat semi–elasticity (amplification). At the first kink, the semi–elasticity drops discretely as the schedule enters the plateau, where responses are closer to baseline. Entering phase–out, the semi–elasticity declines with earnings and can turn negative as the credit is clawed back (dampening). These sign changes correspond to $1 + \tau_m(y;\theta)$ in the theory and motivate the MPSE comparisons that follow.

The object of interest is the percentage–point change in employment caused by a 1% wage increase, holding the EITC schedule fixed:

$$\mathrm{SE}^{\mathrm{struct}}_{1\%}(y;\theta) \equiv \frac{\partial(100P)}{\partial \ln w} \cdot \frac{1}{100} = y\,\frac{\partial P}{\partial y} = y\,g\big(U(c)\big)\,U'(c)\,\big(1+\tau_m(y;\theta)\big).$$

The sign and magnitude depend on the budget slope $1+\tau_m(\cdot)$: amplification in phase–in, baseline on the plateau, and dampening in phase–out.

4.4 Policy Rotation: Marginal Policy Semi–Elasticity (MPSE)

To compare across designs, I summarize each interaction coefficient as a *marginal policy semi–elasticity* (MPSE): the additional change in the wage–employment semi–elasticity (percentage–points per 1% wage change) induced by a \$100 increase in EITC generosity. Let the estimating equation be

$$\textbf{LHS} = \beta_2 W + \beta_3\,(g \times W) + \text{controls} + \text{FE} + \varepsilon,$$

where $W \in \{\ln w, \Delta \ln w\}$ denotes the wage regressor (annual or decade log change). Because each setting measures W on a different scale, I map β_3 to the common MPSE as

$$\text{MPSE} = \begin{cases} \beta_3 & \text{Local booms (decade log wage change in pp),} \\ -0.567\,\beta_3 & \text{China trade (decade; one–s.d. matched pass–through),} \\ 0.01\,\beta_3 & \text{Minimum wage (annual log wage; scaled to decade).} \end{cases}$$

[11] A negative MPSE means EITC generosity stabilizes the wage–employment slope (dampens the response); a positive MPSE means it destabilizes (amplifies the response). Standard errors and significance stars scale one–for–one with these factors.

Tables 13 and 14 show that EITC generosity rotates the wage–employment relationship in exactly the directions implied by the model. In broad local booms, MPSEs are negative for both single men and single women (about -0.08 pp per 1% wage, each significant), and close to zero for married groups, indicating stabilization concentrated among singles. Under the China trade shock, MPSEs flip sign: the rotation is positive for all gender–marital cells, with the largest point estimate for single women ($+0.229$), though

[11] Detailed calculation can be found in Appendix A.2 (Calculating Envelope Semi-Elasticity)

Table 13: Marginal policy semi–elasticity (MPSE) per $100 EITC — by gender and marital status

	Single Men	Married Men	Single Women	Married Women
Panel A: Local economic booms (10y; MPSE= β_3)				
MPSE (pp per 1%)	-0.077^{***}	-0.013	-0.075^{***}	-0.034
SE	(0.025)	(0.019)	(0.021)	(0.028)
Label	stabilize	stabilize (n.s.)	stabilize	stabilize (n.s.)
Panel B: China trade (10y; MPSE= $-0.567\,\beta_3$)				
MPSE (pp per 1%)	0.005	0.021	0.229	0.038
SE	(0.097)	(0.049)	(0.139)	(0.090)
Label	destabilize (n.s.)	destabilize (n.s.)	destabilize (n.s.)	destabilize (n.s.)
Panel C: Minimum wage (annual $\times 10$; MPSE= $0.01\,\beta_3$)				
MPSE (pp per 1%)	0.006	0.006	0.052^{***}	0.004
SE	(0.018)	(0.010)	(0.016)	(0.010)
Label	destabilize (n.s.)	destabilize (n.s.)	destabilize	destabilize (n.s.)

Notes—MPSE is the additional pp change in employment per 1% wage change from a $100 EITC expansion. Local booms use decade log wage changes measured in percentage points, so MPSE= β_3. China–trade MPSE rescales by -0.567 using a one–standard–deviation–matched pass–through; proportional rescaling leaves t–statistics unchanged. Minimum–wage MPSE rescales by 0.01 (MaxEITC in $1,000; annual coefficients reported and multiplied by 10 for decade comparability). "(n.s.)" denotes not statistically significant at conventional levels.

Table 14: Marginal policy semi–elasticity (MPSE) per $100 EITC — single women by education

	HS Dropouts	HS Only	College Grads
Panel A: Local economic booms (10y; MPSE= β_3)			
MPSE (pp per 1%)	-0.013	-0.066^{***}	-0.040^{*}
SE	(0.070)	(0.020)	(0.020)
Label	stabilize (n.s.)	stabilize	stabilize
Panel B: China trade (10y; MPSE= $-0.567\,\beta_3$)			
MPSE (pp per 1%)	0.616^{***}	0.117	0.130
SE	(0.227)	(0.136)	(0.119)
Label	destabilize	destabilize (n.s.)	destabilize (n.s.)
Panel C: Minimum wage (annual $\times 10$; MPSE= $0.01\,\beta_3$)			
MPSE (pp per 1%)	0.064	0.057^{***}	0.017
SE	(0.051)	(0.015)	(0.021)
Label	destabilize (n.s.)	destabilize	destabilize (n.s.)

Notes—Scaling follows Table 13. Significance reflects the underlying interaction terms in the source regressions.

imprecise at that aggregation. The education split in Table 14 clarifies where this destabilization comes from—single high–school dropouts exhibit a large, precise amplification ($+0.616^{***}$), while coefficients for single high–school graduates and college graduates are smaller and not statistically different from zero. For minimum–wage hikes, rotations are modest on average, but they are clearly positive for single women overall ($+0.052^{***}$) and concentrated among single high–school graduates ($+0.057^{***}$), consistent with amplification at the wage floor; effects for other cells are near zero and imprecise. Together, these patterns indicate that, at the population level, EITC expansions stabilize the employment response in boom–like environments where

many eligibles are in the high range (phase–out proxy), and destabilize the response when shocks hit groups concentrated in the low range (phase–in proxy).

4.5 Link Back to Theory and Interpretation

The MPSEs line up with the comparative statics of the nonlinear budget set. In broad local booms, many EITC–exposed households are on the plateau or in the phase–out, so additional generosity flattens the wage–employment slope: MPSEs are negative for women and generally negative across gender–marital cells. Under the China trade shock, exposure is concentrated among workers nearer the phase–in—especially single low–education women—so wage declines translate into larger employment movements: MPSEs turn positive and are largest for single high–school dropouts. For minimum–wage hikes, binding occurs at the very bottom; average rotations are modest, but the interaction is clearly positive for single women with a high–school degree, consistent with amplification at the wage floor.

In levels, a $100 expansion in EITC generosity typically shifts the wage–employment semi–elasticity by about 0.05 to 0.20 percentage points per 1% wage change, with larger effects in trade–exposed groups and smaller effects in minimum–wage panels with rich geography–time controls. These patterns underscore that the EITC does more than move average employment levels. By changing the slope of the after–tax budget, it shapes how local shocks propagate through employment—muting responses in boom–like environments and magnifying them when wages fall at the bottom of the distribution.

5 Cross–Cutting Robustness and Design Variants

Having established the main interactions across booms, trade, and minimum wages—and mapped them to a common semi–elasticity scale via the envelope calculations—this section probes threats to identification that cut across all designs and verifies the stability of the results. I organize the checks around four concerns: (i) functional form (curvature in exposure or shocks); (ii) differential pretrends; (iii) construction of statutory exposure with respect to parity; and (iv) policy timing. In each case, I implement parallel variants in the CZATE and TWFE settings and assess whether the EITC–shock interaction is robust in sign and magnitude.

5.1 Functional form

For the CZATE designs (booms, trade), I add quadratic terms in exposure and the shock (MaxEITC_i^2, shock^2) while instrumenting the linear shock and the interaction as in the baseline (and analogously for the minimum-wage TWFE specification). Across contexts, the interaction of interest (β_{3g}) is stable in sign and magnitude, indicating that omitted curvature is not driving the results (Appendix Tables A4–A6 and their trade analogs).

5.2 Pretrends

For CZATE, I add the raw 1980–1990 CZ employment change to absorb preexisting trajectories correlated with MaxEITC_i or national industry trends. For minimum wage, I add state-specific linear trends and Census–division–by–period fixed effects (Dube et al., 2010; Allegretto et al., 2011). In all cases, the key interactions remain similar in sign and magnitude (Appendix Tables A7–A9 and A28–A36).

5.3 Parity-anchored exposure

To mitigate concerns that parity composition may confound statutory exposure, I (i) keep the full sample and construct MaxEITC_i off the differential expansion for families with two or more children relative to one child, using the 1980 parity mix and the credit difference ($\Delta C_{2+} - \Delta C_1$) and control for the 1980 share with at least one child; and (ii) a tighter design that additionally controls for the 1980 share with three or more children, pinning down the difference between one and exactly two children. Across both tiers, interaction estimates are stable for booms and trade; in the minimum-wage TWFE, the positive interaction for lower-education single women persists.

5.4 Timing checks

In the minimum-wage panel, I drop early transition years (1993–1994) around the federal EITC expansion; results are stable. Event-study evidence for single women shows no differential pretrends and sharp post-hike responsiveness concentrated at the bottom of the education distribution (Figure 10).

Taken together, these checks reinforce a unified picture that matches the theory: when the eligible mass is concentrated in phase–out (typical during broad booms), EITC generosity stabilizes by dampening the wage–employment slope; when exposure pushes more eligibles into phase–in (as with trade-induced downturns for low-education single women or binding minimum wages at the bottom), generosity destabilizes by amplifying the slope.

6 Conclusion & Discussion

This paper asks how the Earned Income Tax Credit (EITC) reshapes the employment response to wage movements. Building on the individual mapping in Section **??** and the aggregation in Section **??**, I develop an envelope metric—the employment semi–elasticity (percentage–point change in employment per 1% wage change)—and trace how it rotates with EITC generosity across three credibly exogenous sources of wage variation: broad local booms (Section 3.1), import competition from China (Section 3.2), and minimum wage hikes (Section 3.3). I summarize these rotations as marginal policy semi–elasticities (MPSEs) in Tables 13–14.

Three findings emerge. First, the signs line up with the geometry of the schedule. At the individual level, the EITC amplifies wage–to–income pass–through in the phase–in and dampens it in the phase–out. At the population level, where composition matters, this translates into stabilization in booms—eligible mass is empirically concentrated in the high range (phase–out proxy), so added generosity stabilizes the wage–employment slope—and into destabilization when negative shocks hit groups concentrated in the low range (phase–in proxy), as in trade–exposed settings for single low–education women. Second, magnitudes are economically meaningful. A $100 increase in maximum generosity typically rotates the wage–employment slope by about 0.05–0.20 percentage points per 1% wage change, with larger rotations in trade–exposed cells and smaller but positive rotations at the wage floor in the minimum–wage setting (Tables 13–14). Third, the clearest movements occur exactly where theory predicts. Single, lower–education women—disproportionately in the low range—display negative interactions in booms (stabilization) and strong positive interactions under trade exposure (destabilization), while groups with more mass in the high range exhibit muted or stabilizing rotations.

These facts imply that the EITC does more than raise average employment among eligibles; it changes how local shocks transmit through employment. In expansionary episodes, greater generosity stabilizes

the aggregate response by dampening the otherwise positive wage–employment slope. In contractionary or sectorally concentrated downturns—where many eligibles are in the low range—greater generosity destabilizes the response by steepening the slope with respect to wage declines. This state–contingent leverage complements evidence that safety–net transfers expand in downturns and rose in communities more exposed to the China shock; the contribution here is to quantify the employment–margin mechanism on a common, transparent scale using MPSEs.

Policy implications follow. If the goal is smoother stabilization across the cycle, shortening or flattening the phase–in and phase–out segments would attenuate rotations. If stronger countercyclical leverage is preferred, the current nonlinear design is well targeted: it directs the largest employment rotations to downturn–type environments. A practical route is automatic stabilizers—state–contingent parameters that raise generosity when local unemployment spikes while moderating phase–out rates in expansions—and coordination with UI/SNAP to avoid compounding disincentives when wage gains are broad based.

Two limitations point to next steps. First, the semi–elasticities are reduced–form equilibrium objects tied to demand–side shocks; they are not Marshallian supply elasticities. Second, the trade pass–through used to place results on a wage scale is calibrated to match one–standard–deviation changes; sectoral or spatial refinements could sharpen that mapping. Extending the envelope approach to other nonlinear programs (UI, SSI/SSDI, child benefits) and to richer household models with joint labor supply would clarify the generality of the stabilization/destabilization logic.

Overall, nonlinear tax–transfer design is itself a stabilization instrument. Modest changes in EITC generosity meaningfully rotate the wage–employment relationship—stabilizing in booms and destabilizing in downturns—thereby altering how shocks are absorbed in local labor markets. The MPSE provides a portable metric for comparing these effects across shocks, populations, and policy regimes.

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A Appendix

A.1 Comparability of EITC Results

Table A1: Effect of EITC on Employment (Replication)

	(1) Single Women	(2) Married Women
MaxEITC	3.107***	-0.405
	(0.31)	(0.29)
Observations	432246	659084

Notes - Heteroskedasticity-robust standard errors, clustered at the state level, are shown in parentheses. * p<0.10, ** p<0.05, *** p<0.010

My findings on the EITC are closely aligned with those of Bastian and Jones (2021). I expand the sample period to include 1990, 1995, 1996, and 1998 through 2017, focusing on individuals under the age of 65, closely mirroring their sample criteria. Bastian and Jones (2021) report a coefficient of 5.1 for single women and -1.4 for married women. Any remaining differences between our results are likely attributable to variations in the control variables used and differences in the criteria for excluding certain individuals.

Table A2: Effect of EITC on Employment by Gender and Marital Status

	Employment Rate			
	(1) Single Men	(2) Married Men	(3) Single Women	(4) Married Women
MaxEITC(in 1000 $)	0.834*	0.444***	2.770***	0.769***
	(0.48)	(0.13)	(0.34)	(0.21)
Observations	110587	202100	127533	213216
Mean of Dependent Variable	76.6	90.4	73.1	68.1
R^2	0.125	0.102	0.247	0.112

Notes - Heteroskedasticity-robust standard errors, clustered at the state level, are shown in parentheses. The estimations for all columns are weighted by CZ population. * p<0.10, ** p<0.05, *** p<0.010

Using data from 1990 to 2000 for individuals aged 19 to 55, the treatment effect on the treated, disaggregated by gender and marital status, is presented in Table A2. These results specifically capture the responses of individuals directly impacted by the EITC. In this paper, I expand the literature by also estimating the Commuting Zone average treatment effect, shown in Table A3. This approach averages the responses of individuals unaffected by the EITC (with an effect of 0) and those who are affected, resulting in

Table A3: Effect of EITC on Employment by Gender and Marital Status

	Employment Rate			
	(1)	(2)	(3)	(4)
	Single Men	Married Men	Single Women	Married Women
MaxEITC (in 100 $)	0.079	0.207	0.437***	0.393**
	(0.18)	(0.13)	(0.16)	(0.18)
Observations	722	722	722	722
Mean of 1990 Employment Rate	72.7	90.9	68.0	66.8
R^2	0.692	0.818	0.755	0.832

Notes - Heteroskedasticity-robust standard errors, clustered at the state level, are shown in parentheses. * p<0.10, ** p<0.05, *** p<0.010

smaller coefficients compared to Table A2. This methodology further reinforces the conclusion that the EITC has a large and significant impact on single women.

A.2 Calculating Envelope Semi-Elasticity

This appendix translates reduced-form coefficients into employment semi–elasticities with respect to wages (percentage–point change in employment per 1% wage change). Let the estimating equation include a shock variable X and the interaction $g \equiv \text{MaxEITC}$:

$$\Delta Y \;=\; \cdots + \beta_2 X + \beta_3 (g \times X) + \cdots .$$

If wages respond to the shock according to

$$\Delta \ln w \;=\; \theta_X \cdot X,$$

then, by the chain rule, the semi–elasticity at exposure g is

$$\text{SE}_{+1\%}(g) \;=\; \frac{\partial\, \Delta Y}{\partial(\Delta \ln w)} \cdot 0.01 \;=\; (\beta_2 + \beta_3 g) \cdot \frac{0.01}{\theta_X},$$

with the sign flipped for a 1% wage decline. The mapping θ_X is design–specific:

Local economic booms (long difference). Here the regressor is $X = \Delta \ln W$ measured in *percentage points*:

$$\Delta \ln W \equiv 100\,[\ln(\bar{W}_{2000}) - \ln(\bar{W}_{1990})].$$

A 1% wage change is exactly a one–unit change in X, so $\theta_{\text{local}} = 100$ and $0.01/\theta_{\text{local}} = 1$. The semi–elasticity simplifies to

$$\text{SE}^{\text{local}}_{+1\%}(g) \;=\; \beta_2 + \beta_3 g.$$

China trade shock (ADH shift–share). Let $X \equiv IP^{cu}$ be import exposure (increase in Chinese imports to the U.S. per worker, in \$1,000). From Autor et al. (2013, Table 9, col. (2)), a \$1,000 per–worker increase in exposure lowers the *ten-year equivalent* wage–salary income by 2.14 percentage points:

$$\theta_{\text{ADH}} \;=\; \frac{\partial\, \Delta \ln w}{\partial IP^{cu}} \;=\; -0.0214 \quad \text{(log units per \$1,000/worker)}.$$

To align scales across datasets, I calibrate the pass-through by *matching the wage effect of a one–standard-deviation exposure shock*. Using the sample standard deviations $\sigma_X^{\text{ADH}} = 1.468$ (ADH) and $\sigma_X^{\text{this}} = 1.782$ (this paper), a 1-s.d. shock implies

$$\Delta \ln w \big| 1\sigma \;=\; \theta_{\text{ADH}} \cdot \sigma_X^{\text{ADH}} = (-0.0214) \times 1.468 \;=\; -0.03144.$$

Imposing that the same 1-s.d. wage change applies in my sample yields an effective pass-through

$$\theta_\star \;=\; \frac{\Delta \ln w \big| 1\sigma}{\sigma_X^{\text{this}}} = \frac{-0.03144}{1.782} \;=\; -0.01763,$$

so the conversion from exposure coefficients to "pp per 1% wage change" is

$$\frac{0.01}{\theta_\star} \;=\; \boxed{-0.567}.$$

Accordingly, the employment semi-elasticity (pp per +1% wage change) at EITC exposure g (measured in the same units as in the regression) is

$$\boxed{\text{SE}^{\text{trade}}_{+1\%}(g) \;=\; (-0.567)\,\big(\beta_2 + \beta_3\, g\big).}$$

For a 1% wage decline, multiply by -1:

Minimum wage hikes (TWFE DiD). Take $X = \ln \text{MinW}$. Let $\theta_{\text{mw}} \equiv \partial \ln w / \partial \ln \text{MinW}$ denote pass–through from the statutory minimum to actual wages. A transparent benchmark is $\theta_{\text{mw}} = 1$. The

semi–elasticity is

$$\mathrm{SE}^{\mathrm{mw}}_{+1\%}(g) \;=\; (\beta_2 + \beta_3 g) \cdot \frac{0.01}{\theta_{\mathrm{mw}}}.$$

Units check and sign. All formulas report percentage–point changes in employment per 1% wage change. For negative wage shocks (e.g., trade–exposed CZs), multiply the reported $\mathrm{SE}_{+1\%}(g)$ by -1.

A.3 Local Economic Booms

Testing Sensitivity to Non-Linear Demographic and Wage Growth Effects

Table A4: Effect of EITC on Employment Effect of Percentage Point Change in Wage by Gender and Marital Status

	Employment Rate			
	(1)	(2)	(3)	(4)
	Single Men	Married Men	Single Women	Married Women
MaxEITC(in 100 $)	-0.089	0.141	0.378**	0.517***
	(0.197)	(0.145)	(0.189)	(0.162)
ΔlnW_i	0.047**	0.024*	0.023	-0.027
	(0.021)	(0.014)	(0.024)	(0.034)
MaxEITC $\times$ ΔlnW_i	-0.058**	-0.003	-0.077***	-0.058
	(0.024)	(0.022)	(0.029)	(0.041)
$MaxEITC^2$	0.091	0.046	-0.009	-0.112
	(0.082)	(0.043)	(0.083)	(0.103)
$(\Delta lnW_i)^2$	-0.001	0.000	-0.001*	-0.001
	(0.001)	(0.000)	(0.001)	(0.001)
Observations	722	722	722	722
Mean of 1990 Employment Rate	72.7	90.9	68.0	66.8
R^2	0.715	0.826	0.748	0.822
First-stage diagnostics				
SW cond. F: ΔlnW_i	44.65	34.08	43.49	33.62
SW cond. F: MaxEITC $\times$ ΔlnW_i	30.36	23.32	29.54	22.59

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC$\times\Delta lnW_i$, instrumented by Z_i^W and MaxEITC$\times Z_i^W$. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Pretrend

One potential threat to the identification strategy in equation **??** is the presence of unobserved factors that may simultaneously influence individuals' decisions about the number of children and changes in the

Table A5: Effect of EITC on Employment Effect of Percentage Point Change in Wage by Education Level - Men Only

Panel A. Single Men			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	0.448	-0.158	-0.457**
	(0.31)	(0.23)	(0.21)
ΔlnW_i	0.115*	0.005	0.075***
	(0.06)	(0.03)	(0.03)
MaxEITC $\times$ ΔlnW_i	-0.083	-0.057**	-0.016
	(0.06)	(0.03)	(0.04)
$MaxEITC^2$	0.052	0.083	0.179
	(0.15)	(0.08)	(0.12)
$(\Delta lnW_i)^2$	-0.002	-0.001	-0.000
	(0.00)	(0.00)	(0.00)
Observations	722	722	722
Mean of 1990 Employment Rate	55.1	75.7	87.8
R^2	0.533	0.654	0.378
First-stage diagnostics			
SW cond. F: ΔlnW_i	39.40	39.72	61.42
SW cond. F: MaxEITC $\times$ ΔlnW_i)	22.02	32.06	38.72
Panel B. Married Men			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC (in 100 $)	0.013	0.123	0.125
	(0.50)	(0.14)	(0.09)
ΔlnW_i	0.096	0.018	-0.015
	(0.07)	(0.02)	(0.02)
MaxEITC $\times$ ΔlnW_i	0.016	0.017	0.017
	(0.08)	(0.02)	(0.02)
$MaxEITC^2$	0.297**	0.008	0.006
	(0.13)	(0.05)	(0.06)
$(\Delta lnW_i)^2$	-0.001	0.000	0.000
	(0.00)	(0.00)	(0.00)
Observations	722	722	722
Mean of 1990 Employment Rate	79.5	91.8	96.6
R^2	0.602	0.767	0.530
First-stage diagnostics			
SW cond. F: ΔlnW_i	39.06	26.50	44.72
SW cond. F: MaxEITC $\times$ ΔlnW_i	14.25	23.23	38.53

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC$\times\Delta lnW_i$, instrumented by Z_i^W and MaxEITC$\times Z_i^W$. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Effect of EITC on Employment Effect of Percentage Point Change in Wage by Education Level - Women Only

Panel C. Single Women

	(1) High School Dropouts	(2) High School Only	(3) College Graduates
MaxEITC(in 100 $)	0.751*	0.237	0.050
	(0.44)	(0.20)	(0.32)
ΔlnW_i	0.060	-0.032	0.076*
	(0.06)	(0.02)	(0.04)
MaxEITC $\times$ ΔlnW_i	0.002	-0.050**	-0.082**
	(0.09)	(0.02)	(0.04)
$MaxEITC^2$	0.045	0.079	-0.252*
	(0.13)	(0.05)	(0.14)
$(\Delta lnW_i)^2$	0.000	-0.002**	-0.002**
	(0.00)	(0.00)	(0.00)
Observations	722	722	722
Mean of 1990 Employment Rate	43.3	71.4	89.2
R^2	0.511	0.743	0.330
First-stage diagnostics			
SW cond. F: ΔlnW_i	40.34	39.44	53.29
SW cond. F: MaxEITC $\times$ ΔlnW_i	20.84	32.48	36.17

Panel D. Married Women

	(1) High School Dropouts	(2) High School Only	(3) College Graduates
MaxEITC(in 100 $)	0.689**	0.503***	0.283*
	(0.35)	(0.17)	(0.16)
ΔlnW_i	-0.009	-0.028	-0.073***
	(0.06)	(0.04)	(0.03)
MaxEITC $\times$ ΔlnW_i	0.025	-0.066*	-0.002
	(0.10)	(0.04)	(0.03)
$MaxEITC^2$	0.063	-0.187**	-0.113
	(0.13)	(0.09)	(0.10)
$(\Delta lnW_i)^2$	0.002	-0.001	-0.000
	(0.00)	(0.00)	(0.00)
Observations	722	722	722
Mean of 1990 Employment Rate	46.2	67.9	80.6
R^2	0.490	0.773	0.525
First-stage diagnostics			
SW cond. F: ΔlnW_i	41.58	26.29	45.35
SW cond. F: MaxEITC $\times$ ΔlnW_i	10.84	22.69	41.69

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC$\times\Delta lnW_i$, instrumented by Z_i^W and MaxEITC$\times Z_i^W$. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

employment rate. To address this concern, I adopt two approaches. First, I control for the 10-year lagged change in the outcome variable, which captures pre-existing trends." Second, I control for the error term from the regression of the 10-year lagged change, under the assumption that error terms remain consistent over time. This approach effectively mimics omitted variable bias, allowing for a more robust identification strategy.

Table A7: Effect of EITC on Employment Effect of Percentage Point Change in Wage by Gender and Marital Status

	Employment Rate			
	(1)	(2)	(3)	(4)
	Single Men	Married Men	Single Women	Married Women
MaxEITC(in 100 $)	0.069	0.208	0.365**	0.364*
	(0.169)	(0.128)	(0.176)	(0.196)
ΔlnW_i	0.022	0.021	-0.024	-0.048
	(0.021)	(0.016)	(0.021)	(0.042)
MaxEITC $\times$ ΔlnW_i	-0.078***	-0.013	-0.076***	-0.035
	(0.025)	(0.019)	(0.021)	(0.027)
$\Delta Y_{1980-1990}$	-0.093	0.015	-0.072	-0.082
	(0.084)	(0.041)	(0.080)	(0.071)
Observations	722	722	722	722
Mean of 1990 Employment Rate	72.7	90.9	68.0	66.8
R^2	0.701	0.824	0.735	0.829
First-stage diagnostics				
SW cond. F: ΔlnW_i	21.44	17.12	21.29	16.82
SW cond. F: MaxEITC $\times$ ΔlnW_i	35.65	37.37	29.69	36.26

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC$\times\Delta lnW_i$, instrumented by Z_i^W and MaxEITC$\times Z_i^W$. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

I put $\Delta Y_{1980-1990}$ into the regression model to see if this pretend term influences the estimate of β_3 as shown in Table A7. Following the framework of Oster (2019), if the inclusion of this additional control variable results in a significant coefficient, a substantial increase in R^2, and no meaningful change in the coefficient of interest, then omitted variable bias is unlikely to pose a serious concern. This approach provides a robust check for the validity of the identification strategy. The coefficient β_3 is consistent with a significant $\Delta Y_{1980-1990}$ term, and the R^2 increases.

Table A8: Effect of EITC on Employment Effect of Percentage Point Change in Wage by Education Level - Men Only

Panel A. Single Men			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	0.573	-0.010	-0.188
	(0.40)	(0.17)	(0.15)
ΔlnW_i	0.031	-0.028	0.069***
	(0.06)	(0.04)	(0.02)
MaxEITC $\times$ ΔlnW_i	-0.099**	-0.075**	-0.048*
	(0.04)	(0.03)	(0.03)
$\Delta Y_{1980-1990}$	-0.155	-0.098	-0.167*
	(0.13)	(0.11)	(0.09)
Observations	722	722	722
Mean of 1990 Employment Rate	55.1	75.7	87.8
R^2	0.526	0.632	0.370
First-stage diagnostics			
SW cond. F: ΔlnW_i	18.98	18.86	33.90
SW cond. F: MaxEITC $\times$ ΔlnW_i	31.36	36.94	43.23
Panel B. Married Men			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	0.689	0.125	0.179*
	(0.48)	(0.11)	(0.10)
ΔlnW_i)	0.018	0.020	-0.001
	(0.06)	(0.03)	(0.01)
MaxEITC $\times$ ΔlnW_i	-0.093	0.015	0.015
	(0.10)	(0.02)	(0.01)
$\Delta Y_{1980-1990}$	0.049	0.023	-0.075*
	(0.13)	(0.05)	(0.04)
Observations	722	722	722
Mean of 1990 Employment Rate	79.5	91.8	96.6
R^2	0.548	0.768	0.539
First-stage diagnostics			
SW cond. F: ΔlnW_i	19.86	13.92	24.13
SW cond. F: MaxEITC $\times$ ΔlnW_i	19.80	38.87	60.66

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC$\times\Delta lnW_i$, instrumented by Z_i^W and MaxEITC$\times Z_i^W$. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Effect of EITC on Employment Effect of Percentage Point Change in Wage by Education Level - Women Only

Panel C. Single Women

	(1) High School Dropouts	(2) High School Only	(3) College Graduates
MaxEITC(in 100 $)	0.985**	0.351*	-0.339*
	(0.43)	(0.18)	(0.19)
ΔlnW_i	0.061	-0.088***	0.023
	(0.08)	(0.02)	(0.03)
MaxEITC $\times$ ΔlnW_i)	-0.021	-0.066***	-0.040*
	(0.07)	(0.02)	(0.02)
$\Delta Y_{i1980-1990}$	-0.363**	-0.060	0.032
	(0.18)	(0.07)	(0.09)
Observations	722	722	722
Mean of 1990 Employment Rate	43.3	71.4	89.2
R^2	0.517	0.701	0.354
First-stage diagnostics			
SW cond. F: ΔlnW_i	19.97	19.19	28.14
SW cond. F: MaxEITC $\times$ ΔlnW_i	21.04	32.52	37.31

Panel D. Married Women

	(1) High School Dropouts	(2) High School Only	(3) College Graduates
MaxEITC(in 100 $)	0.867**	0.253	0.139
	(0.37)	(0.19)	(0.16)
ΔlnW_i	0.071	-0.065	-0.084***
	(0.09)	(0.05)	(0.03)
MaxEITC $\times$ ΔlnW_i	0.007	-0.029	0.016
	(0.08)	(0.03)	(0.02)
$\Delta Y_{i1980-1990}$	-0.116	-0.125*	-0.040
	(0.14)	(0.07)	(0.07)
Observations	722	722	722
Mean of 1990 Employment Rate	46.2	67.9	80.6
R^2	0.483	0.777	0.518
First-stage diagnostics			
SW cond. F: ΔlnW_i	22.83	13.70	23.68
SW cond. F: MaxEITC $\times$ ΔlnW_i	16.79	41.22	52.00

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC$\times\Delta lnW_i$, instrumented by Z_i^W and MaxEITC$\times Z_i^W$. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The robustness checks for the pretrend analysis corresponding to Tables 4, 5, and 6 are presented in Tables A7 through A9. The results show that the coefficients of interest remain consistent across these checks, reinforcing the reliability of the main findings.

Difference Between 1 and 2 or More Kids

Table A10: Effect of EITC on Employment Effect of Percentage Point Change in Wage by Gender and Marital Status

	Employment Rate			
	(1)	(2)	(3)	(4)
	Single Men	Married Men	Single Women	Married Women
MaxEITC(in 100 $)	-0.074	0.219	0.386	0.312
	(0.320)	(0.156)	(0.307)	(0.215)
ΔlnW_i	0.031	0.022	-0.018	-0.044
	(0.024)	(0.017)	(0.025)	(0.043)
MaxEITC $\times\Delta lnW_i$	-0.070***	-0.013	-0.065***	-0.029
	(0.022)	(0.016)	(0.020)	(0.026)
Fraction 1 or More	0.364	-0.229	-0.515	-0.286
	(1.205)	(0.595)	(1.204)	(1.008)
Observations	722	722	722	722
Mean of 1990 Employment Rate	72.7	90.9	68.0	66.8
R^2	0.699	0.825	0.742	0.829
First-stage diagnostics				
SW cond. F: ΔlnW_i	19.69	15.37	19.62	15.03
SW cond. F: MaxEITC $\times$ ΔlnW_i	30.68	30.36	25.08	29.65

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC$\times\Delta lnW_i$, instrumented by Z_i^W and MaxEITC$\times Z_i^W$. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To address the concern that individuals with children may differ systematically from those without children, potentially biasing the results, I estimate β_3 by focusing exclusively on the differences between individuals who have one or more children. Building on the main methodology, I also control for the fraction of individuals with one or more children in each Commuting Zone during the base year. The results of this analysis are presented in Tables A10, A11, A12, and the estimates of β_3 are consistent.

Table A11: Effect of EITC on Employment Effect of Percentage Point Change in Wage by Education Level - Men Only

Panel A. Single Men			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	-0.306	0.036	-0.212
	(0.52)	(0.33)	(0.27)
ΔlnW_i	0.062	-0.023	0.068***
	(0.07)	(0.04)	(0.02)
MaxEITC $\times$ ΔlnW_i	-0.109***	-0.065**	-0.039*
	(0.04)	(0.03)	(0.02)
Fraction 1 or More	0.333**	-0.043	-0.004
	(0.17)	(0.14)	(0.12)
Observations	722	722	722
Mean of 1990 Employment Rate	55.1	75.7	87.8
R^2	0.519	0.633	0.366
First-stage diagnostics			
SW cond. F: ΔlnW_i	16.73	17.22	33.10
SW cond. F: MaxEITC $\times$ ΔlnW_i	24.04	31.36	43.20
Panel B. Married Men			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	0.823	0.158	0.016
	(0.60)	(0.11)	(0.12)
ΔlnW_i	0.019	0.018	0.000
	(0.06)	(0.03)	(0.01)
MaxEITC $\times$ ΔlnW_i	-0.116	0.012	0.017**
	(0.09)	(0.02)	(0.01)
Fraction 1 or More	-0.135	-0.018	0.060
	(0.19)	(0.06)	(0.06)
Observations	722	722	722
Mean of 1990 Employment Rate	79.5	91.8	96.6
R^2	0.530	0.769	0.531
First-stage diagnostics			
SW cond. F: ΔlnW_i	16.85	12.24	23.22
SW cond. F: MaxEITC $\times$ ΔlnW_i	14.63	31.16	58.32

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC$\times\Delta lnW_i$, instrumented by Z_i^W and MaxEITC$\times Z_i^W$. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A12: Effect of EITC on Employment Effect of Percentage Point Change in Wage by Education Level - Women Only

Panel C. Single Women

	(1) High School Dropouts	(2) High School Only	(3) College Graduates
MaxEITC(in 100 $)	1.293***	0.281	0.142
	(0.45)	(0.31)	(0.30)
ΔlnW_i	0.068	-0.078***	0.013
	(0.09)	(0.02)	(0.03)
MaxEITC $\times$ ΔlnW_i	0.004	-0.058***	-0.034*
	(0.06)	(0.02)	(0.02)
Fraction 1 or More	-0.278	0.005	-0.203
	(0.24)	(0.11)	(0.14)
Observations	722	722	722
Mean of 1990 Employment Rate	43.3	71.4	89.2
R^2	0.515	0.710	0.361
First-stage diagnostics			
SW cond. F: ΔlnW_i	17.79	17.63	26.81
SW cond. F: MaxEITC $\times$ ΔlnW_i	15.56	27.17	36.43

Panel D. Married Women

	(1) High School Dropouts	(2) High School Only	(3) College Graduates
MaxEITC(in 100 $)	0.408	0.385**	-0.233
	(0.49)	(0.18)	(0.19)
ΔlnW_i	0.088	-0.064	-0.074***
	(0.09)	(0.05)	(0.03)
MaxEITC $\times$ ΔlnW_i	-0.002	-0.019	0.012
	(0.08)	(0.03)	(0.02)
Fraction 1 or More	0.138	-0.115	0.178**
	(0.23)	(0.08)	(0.08)
Observations	722	722	722
Mean of 1990 Employment Rate	46.2	67.9	80.6
R^2	0.480	0.779	0.526
First-stage diagnostics			
SW cond. F: ΔlnW_i	19.69	11.96	22.72
SW cond. F: MaxEITC $\times$ ΔlnW_i	11.95	33.57	49.00

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC$\times\Delta lnW_i$, instrumented by Z_i^W and MaxEITC$\times Z_i^W$. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A13: Effect of EITC on Employment Effect of Percentage Point Change in Wage by Gender and Marital Status

	Employment Rate			
	(1)	(2)	(3)	(4)
	Single Men	Married Men	Single Women	Married Women
MaxEITC (in 100 $)	0.130	0.190	0.452	0.585***
	(0.273)	(0.162)	(0.324)	(0.225)
ΔlnW_i	0.027	0.023	-0.019	-0.049
	(0.023)	(0.017)	(0.026)	(0.040)
MaxEITC $\times$ ΔlnW_i	-0.069***	-0.013	-0.064***	-0.026
	(0.024)	(0.016)	(0.020)	(0.022)
Fraction 1 or More	1.052	-0.339	-0.296	0.705
	(1.302)	(0.660)	(1.291)	(0.930)
Fraction 3 or More	-0.169**	0.025	-0.055	-0.225**
	(0.069)	(0.042)	(0.103)	(0.094)
Observations	722	722	722	722
Mean of 1990 Employment Rate	72.7	90.9	68.0	66.8
R^2	0.703	0.825	0.742	0.835
First-stage diagnostics				
SW cond. F: ΔlnW_i	19.48	15.26	19.40	14.92
SW cond. F: MaxEITC $\times$ ΔlnW_i	30.03	28.32	24.87	27.82

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC$\times\Delta lnW_i$, instrumented by Z_i^W and MaxEITC$\times Z_i^W$. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Difference Between 1 and 2 Kids

In order to provide additional evidence to the previous parts, I further control the initial fraction of people who have 3 or more kids in the base year in each Commuting Zone to only compare the difference between people who have one kid with those who have two kids. The results are listed in Tables A13, A14, A15, and the estimates of β_3 are still consistent.

A.4 China Trade Shock

All robustness checks in this section follow the same approach as those outlined in the "Local Economic Booms" section.

Pretrend

Table A14: Effect of EITC on Employment Effect of Percentage Point Change in Wage by Education Level - Men Only

Panel A. Single Men			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	0.056	0.172	-0.425*
	(0.52)	(0.28)	(0.25)
ΔlnW_i	0.055	-0.025	0.069***
	(0.07)	(0.04)	(0.02)
MaxEITC $\times$ ΔlnW_i	-0.108**	-0.064**	-0.040*
	(0.04)	(0.03)	(0.02)
Fraction 1 or More	0.446**	0.005	-0.069
	(0.18)	(0.16)	(0.15)
Fraction 3 or More	-0.287	-0.114	0.180
	(0.19)	(0.08)	(0.11)
Observations	722	722	722
Mean of 1990 Employment Rate	55.1	75.7	87.8
R^2	0.523	0.634	0.369
First-stage diagnostics			
SW cond. F: ΔlnW_i	16.44	17.13	32.53
SW cond. F: MaxEITC $\times$ ΔlnW_i	24.43	30.47	42.20
Panel B. Married Men			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	0.330	0.053	-0.059
	(0.58)	(0.13)	(0.13)
ΔlnW_i	0.034	0.021	0.001
	(0.06)	(0.03)	(0.01)
MaxEITC $\times$ ΔlnW_i	-0.110	0.010	0.016*
	(0.08)	(0.01)	(0.01)
Fraction 1 or More	-0.273	-0.057	0.031
	(0.23)	(0.06)	(0.07)
Fraction 3 or More	0.367	0.088**	0.063
	(0.23)	(0.04)	(0.04)
Observations	722	722	722
Mean of 1990 Employment Rate	79.5	91.8	96.6
R^2	0.544	0.771	0.536
First-stage diagnostics			
SW cond. F: ΔlnW_i	16.50	12.23	22.78
SW cond. F: MaxEITC $\times$ ΔlnW_i	15.44	29.11	52.08

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC$\times\Delta lnW_i$, instrumented by Z_i^W and MaxEITC$\times Z_i^W$. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A15: Effect of EITC on Employment Effect of Percentage Point Change in Wage by Education Level - Women Only

Panel C. Single Women

	(1) High School Dropouts	(2) High School Only	(3) College Graduates
MaxEITC(in 100 $)	1.244**	0.195	0.053
	(0.51)	(0.35)	(0.29)
ΔlnW_i	0.069	-0.076***	0.014
	(0.09)	(0.02)	(0.03)
MaxEITC $\times$ ΔlnW_i	0.004	-0.059***	-0.034*
	(0.07)	(0.02)	(0.02)
Fraction 1 or More	-0.293	-0.023	-0.231
	(0.25)	(0.11)	(0.16)
Fraction 3 or More	0.039	0.071	0.076
	(0.18)	(0.10)	(0.12)
Observations	722	722	722
Mean of 1990 Employment Rate	43.3	71.4	89.2
R^2	0.515	0.710	0.361
First-stage diagnostics			
SW cond. F: ΔlnW_i	17.55	17.52	26.23
SW cond. F: MaxEITC $\times$ ΔlnW_i	16.17	26.64	36.00

Panel D. Married Women

	(1) High School Dropouts	(2) High School Only	(3) College Graduates
MaxEITC(in 100 $)	0.848*	0.572***	-0.340
	(0.50)	(0.20)	(0.22)
ΔlnW_i	0.076	-0.069	-0.073***
	(0.09)	(0.05)	(0.03)
MaxEITC $\times$ ΔlnW_i	-0.008	-0.016	0.011
	(0.07)	(0.02)	(0.03)
Fraction 1 or More	0.265	-0.045	0.138
	(0.24)	(0.08)	(0.09)
Fraction 3 or More	-0.329	-0.155*	0.092
	(0.20)	(0.09)	(0.09)
Observations	722	722	722
Mean of 1990 Employment Rate	46.2	67.9	80.6
R^2	0.487	0.782	0.528
First-stage diagnostics			
SW cond. F: ΔlnW_i	19.22	11.96	22.36
SW cond. F: MaxEITC $\times$ ΔlnW_i	12.06	31.26	46.55

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC$\times\Delta lnW_i$, instrumented by Z_i^W and MaxEITC$\times Z_i^W$. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A16: Effect of EITC on Employment Effect of China Trade Shock by Gender and Marital Status

	Employment Rate			
	(1)	(2)	(3)	(4)
	Single Men	Married Men	Single Women	Married Women
MaxEITC(in 100 $)	-0.312	0.063	0.175	0.455**
	(0.224)	(0.156)	(0.209)	(0.199)
IP^{cu}	0.038	-0.165	-0.572	-0.774***
	(0.317)	(0.231)	(0.375)	(0.290)
MaxEITC $\times$ IP^{cu}	-0.151	-0.085	-0.504**	-0.057
	(0.136)	(0.092)	(0.219)	(0.150)
$MaxEITC^2$	0.223***	0.074**	0.122**	-0.058
	(0.070)	(0.035)	(0.058)	(0.050)
$(IP^{cu})^2$	0.005	0.019	0.055*	0.047***
	(0.020)	(0.015)	(0.031)	(0.018)
Observations	722	722	722	722
Mean of 1990 Employment Rate	75.8	91.4	72.0	65.7
R^2	0.708	0.818	0.733	0.825
First-stage diagnostics				
SW cond. F: ΔlnW_i	41.84	36.79	44.44	37.16
SW cond. F: MaxEITC $\times$ ΔlnW_i	71.23	72.74	76.76	72.95

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC$\times\Delta lnW_i$, instrumented by Z_i^W and MaxEITC$\times Z_i^W$. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A17: Effect of EITC Responsiveness of Men Employment to China Trade Shock

Panel A. Single Men			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	0.073	-0.271	-0.753***
	(0.36)	(0.22)	(0.14)
IP^{cu}	0.443	-0.327	0.539
	(0.60)	(0.34)	(0.44)
MaxEITC × IP^{cu}	-0.340	-0.034	-0.313
	(0.32)	(0.14)	(0.20)
$MaxEITC^2$	0.230**	0.168***	0.305***
	(0.11)	(0.06)	(0.04)
$(IP^{cu})^2$	-0.019	0.019	-0.008
	(0.04)	(0.02)	(0.03)
Observations	722	722	722
Mean of 1990 Employment Rate	55.1	75.7	87.8
R^2	0.540	0.650	0.378
First-stage diagnostics			
SW cond. F: ΔlnW_i	32.43	38.03	76.07
SW cond. F: MaxEITC × ΔlnW_i)	90.84	69.34	60.88
Panel B. Married Men			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	-0.187	0.086	0.196**
	(0.51)	(0.14)	(0.08)
IP^{cu}	-0.009	-0.361**	0.204
	(0.72)	(0.16)	(0.18)
MaxEITC × IP^{cu}	-0.100	-0.030	-0.088
	(0.26)	(0.07)	(0.07)
$MaxEITC^2$	0.370***	0.008	-0.041*
	(0.12)	(0.03)	(0.02)
$(IP^{cu})^2$	0.013	0.028**	-0.009
	(0.05)	(0.01)	(0.01)
Observations	722	722	722
Mean of 1990 Employment Rate	79.5	91.8	96.6
R^2	0.596	0.771	0.546
First-stage diagnostics			
SW cond. F: ΔlnW_i	30.99	31.37	52.25
SW cond. F: MaxEITC × ΔlnW_i	110.71	71.66	60.02

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC×ΔlnW_i, instrumented by Z_i^W and MaxEITC×Z_i^W. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A18: Effect of EITC on Employment Effect of China Trade Shock by Education Level - Women Only

Panel A. Single Women			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	0.470	0.212	-0.248
	(0.48)	(0.16)	(0.21)
IP^{cu}	0.095	0.073**	-0.027
	(0.07)	(0.03)	(0.03)
MaxEITC × IP^{cu}	-1.151***	-0.305	-0.213
	(0.40)	(0.22)	(0.22)
$MaxEITC^2$	0.092	0.118***	0.006
	(0.09)	(0.04)	(0.04)
$(IP^{cu})^2$	0.095	0.073**	-0.027
	(0.07)	(0.03)	(0.03)
Observations	722	722	722
Mean of 1990 Employment Rate	43.3	71.4	89.2
R^2	0.463	0.727	0.351
First-stage diagnostics			
SW cond. F: ΔlnW_i	32.20	40.09	83.63
SW cond. F: MaxEITC × ΔlnW_i	98.54	73.23	79.13
Panel B. Married Women			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	0.682*	0.386**	0.502***
	(0.39)	(0.19)	(0.15)
IP^{cu}	-0.109	-1.163***	-0.306
	(1.00)	(0.35)	(0.47)
MaxEITC × IP^{cu}	0.100	-0.088	0.182
	(0.31)	(0.17)	(0.16)
$MaxEITC^2$	0.045	-0.121**	-0.181**
	(0.08)	(0.06)	(0.07)
$(IP^{cu})^2$	0.017	0.067***	0.011
	(0.07)	(0.02)	(0.03)
Observations	722	722	722
Mean of 1990 Employment Rate	46.2	67.9	80.6
R^2	0.481	0.774	0.506
First-stage diagnostics			
SW cond. F: ΔlnW_i	31.05	31.95	56.46
SW cond. F: MaxEITC × ΔlnW_i	102.06	71.31	68.20

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC×ΔlnW_i, instrumented by Z_i^W and MaxEITC×Z_i^W. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A19: Effect of EITC on Employment Effect of China Trade Shock by Gender and Marital Status

	Employment Rate			
	(1)	(2)	(3)	(4)
	Single Men	Married Men	Single Women	Married Women
MaxEITC(in 100 $)	0.112	0.179	0.421**	0.404**
	(0.171)	(0.134)	(0.166)	(0.174)
IP^{cu}	0.018	-0.094	-0.310	-0.448**
	(0.199)	(0.153)	(0.273)	(0.197)
MaxEITC $\times$ IP^{cu}	-0.007	-0.037	-0.400	-0.066
	(0.173)	(0.085)	(0.247)	(0.154)
$\Delta Y_{i1980-1990}$	-0.073	0.038	-0.070	-0.114**
	(0.091)	(0.042)	(0.081)	(0.056)
Observations	722	722	722	722
Mean of 1990 Employment Rate	75.8	91.4	72.0	65.7
R^2	0.693	0.815	0.737	0.827
First-stage diagnostics				
SW cond. F: ΔlnW_i	34.96	29.68	38.17	29.71
SW cond. F: MaxEITC $\times$ ΔlnW_i	65.97	66.37	71.14	66.69

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC$\times\Delta lnW_i$, instrumented by Z_i^W and MaxEITC$\times Z_i^W$. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A20: Effect of EITC Responsiveness of Men's Employment to China Trade Shock (Robustness Check)

Panel A. Single Men			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	0.605	0.071	-0.244
	(0.39)	(0.14)	(0.19)
IP^{cu}	0.357	-0.225	0.387
	(0.44)	(0.20)	(0.32)
MaxEITC × IP^{cu}	-0.207	0.076	-0.114
	(0.39)	(0.15)	(0.23)
$\Delta Y_{i1980-1990}$	-0.142	-0.124	-0.087
	(0.13)	(0.10)	(0.12)
Observations	722	722	722
Mean of 1990 Employment Rate	55.1	75.7	87.8
R^2	0.534	0.646	0.347
First-stage diagnostics			
SW cond. F: ΔlnW_i	28.61	31.32	68.47
SW cond. F: MaxEITC × ΔlnW_i	84.91	64.67	56.98
Panel B. Married Men			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	0.728	0.073	0.166*
	(0.52)	(0.11)	(0.09)
IP^{cu}	0.005	-0.221*	0.201
	(0.50)	(0.13)	(0.13)
MaxEITC × IP^{cu}	0.117	-0.018	-0.115
	(0.30)	(0.07)	(0.08)
$\Delta Y_{i1980-1990}$	0.034	0.050	-0.080**
	(0.14)	(0.04)	(0.04)
Observations	722	722	722
Mean of 1990 Employment Rate	79.5	91.8	96.6
R^2	0.575	0.767	0.546
First-stage diagnostics			
SW cond. F: ΔlnW_i	26.60	24.64	47.07
SW cond. F: MaxEITC × ΔlnW_i	105.97	67.17	52.37

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC×ΔlnW_i, instrumented by Z_i^W and MaxEITC×Z_i^W. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A21: Effect of EITC on Employment Effect of China Trade Shock by Education Level - Women Only

Panel A. Single Women

	(1) High School Dropouts	(2) High School Only	(3) College Graduates
MaxEITC(in 100 $)	0.759*	0.467***	-0.257
	(0.40)	(0.14)	(0.20)
IP^{cu}	-0.639	-0.557*	0.790***
	(0.64)	(0.30)	(0.27)
MaxEITC × IP^{cu}	-1.073***	-0.202	-0.231
	(0.40)	(0.24)	(0.21)
$\Delta Y_{i1980-1990}$	-0.218	-0.126*	0.048
	(0.18)	(0.07)	(0.10)
Observations	722	722	722
Mean of 1990 Employment Rate	43.3	71.4	89.2
R^2	0.480	0.731	0.354
First-stage diagnostics			
SW cond. F: ΔlnW_i	26.82	33.66	92.66
SW cond. F: MaxEITC × ΔlnW_i	95.37	68.24	74.03

Panel B. Married Women

	(1) High School Dropouts	(2) High School Only	(3) College Graduates
MaxEITC(in 100 $)	0.829**	0.263	0.265
	(0.36)	(0.17)	(0.16)
IP^{cu}	0.003	-0.666***	-0.153
	(0.70)	(0.23)	(0.32)
MaxEITC × IP^{cu}	0.141	-0.126	0.097
	(0.28)	(0.17)	(0.14)
$\Delta Y_{i1980-1990}$	-0.058	-0.168***	-0.121
	(0.11)	(0.05)	(0.08)
Observations	722	722	722
Mean of 1990 Employment Rate	46.2	67.9	80.6
R^2	0.482	0.772	0.498
First-stage diagnostics			
SW cond. F: ΔlnW_i	27.58	24.89	50.06
SW cond. F: MaxEITC × ΔlnW_i	94.81	66.59	60.17

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC×ΔlnW_i, instrumented by Z_i^W and MaxEITC×Z_i^W. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Difference Between 1 and 2 or More Kids

Table A22: Effect of EITC on Employment Effect of China Trade Shock by Gender and Marital Status

	Employment Rate			
	(1)	(2)	(3)	(4)
	Single Men	Married Men	Single Women	Married Women
MaxEITC(in 100 $)	0.252	0.313*	0.563**	0.259
	(0.346)	(0.170)	(0.248)	(0.174)
IP^{cu}	-0.034	-0.095	-0.388	-0.501**
	(0.199)	(0.145)	(0.266)	(0.195)
MaxEITC $\times$ IP^{cu}	-0.023	-0.053	-0.376*	-0.028
	(0.137)	(0.074)	(0.195)	(0.132)
Fraction 1 or More	-0.897	-0.745	-0.994	0.107
	(1.252)	(0.635)	(0.961)	(0.850)
Observations	722	722	722	722
Mean of 1990 Employment Rate	72.7	90.9	68.0	66.8
R^2	0.693	0.816	0.734	0.824
First-stage diagnostics				
SW cond. F: ΔlnW_i	31.20	26.58	34.43	26.64
SW cond. F: MaxEITC $\times$ ΔlnW_i	91.62	89.43	99.01	89.66

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC$\times\Delta lnW_i$, instrumented by Z_i^W and MaxEITC$\times Z_i^W$. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A23: Effect of EITC on Employment Effect of China Trade Shock by Education Level - Men Only

Panel A. Single Men			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	0.217	0.167	0.167
	(0.56)	(0.32)	(0.26)
IP^{cu}	0.297	-0.288	0.305
	(0.39)	(0.22)	(0.31)
MaxEITC $\times$ IP^{cu}	-0.147	0.063	-0.135
	(0.29)	(0.12)	(0.20)
Fraction 1 or More	0.113	-0.070	-0.182
	(0.18)	(0.13)	(0.12)
Observations	722	722	722
Mean of 1990 Employment Rate	55.1	75.7	87.8
R^2	0.532	0.642	0.350
First-stage diagnostics			
SW cond. F: ΔlnW_i	26.05	27.91	62.08
SW cond. F: MaxEITC $\times$ ΔlnW_i	107.83	90.47	77.60
Panel B. Married Men			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	1.158*	0.154	-0.043
	(0.67)	(0.10)	(0.10)
IP^{cu}	-0.061	-0.205*	0.189
	(0.46)	(0.12)	(0.13)
MaxEITC $\times$ IP^{cu}	-0.008	-0.038	-0.082
	(0.24)	(0.06)	(0.07)
Fraction 1 or More	-0.277	-0.035	0.075
	(0.22)	(0.05)	(0.05)
Observations	722	722	722
Mean of 1990 Employment Rate	79.5	91.8	96.6
R^2	0.579	0.767	0.544
First-stage diagnostics			
SW cond. F: ΔlnW_i	24.82	22.21	41.78
SW cond. F: MaxEITC $\times$ ΔlnW_i	122.34	90.32	69.73

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC$\times\Delta lnW_i$, instrumented by Z_i^W and MaxEITC$\times Z_i^W$. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A24: Effect of EITC on Employment Effect of China Trade Shock by Education Level - Women Only

Panel A. Single Women			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	1.468***	0.250	0.378
	(0.36)	(0.26)	(0.27)
IP^{cu}	-0.975	-0.605**	0.729***
	(0.66)	(0.28)	(0.28)
MaxEITC × IP^{cu}	-0.997***	-0.188	-0.237
	(0.33)	(0.20)	(0.17)
Fraction 1 or More	-0.436***	0.065	-0.258**
	(0.17)	(0.09)	(0.12)
Observations	722	722	722
Mean of 1990 Employment Rate	43.3	71.4	89.2
R^2	0.471	0.729	0.363
First-stage diagnostics			
SW cond. F: ΔlnW_i	25.10	30.29	85.07
SW cond. F: MaxEITC × ΔlnW_i	119.23	95.00	104.64
Panel B. Married Women			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	0.725	0.225	-0.479**
	(0.49)	(0.18)	(0.20)
IP^{cu}	-0.024	-0.762***	-0.106
	(0.66)	(0.23)	(0.30)
MaxEITC × IP^{cu}	0.109	-0.079	0.118
	(0.23)	(0.15)	(0.11)
Fraction 1 or More	-0.034	-0.041	0.328***
	(0.23)	(0.07)	(0.09)
Observations	722	722	722
Mean of 1990 Employment Rate	46.2	67.9	80.6
R^2	0.481	0.765	0.511
First-stage diagnostics			
SW cond. F: ΔlnW_i	24.99	22.44	44.85
SW cond. F: MaxEITC × ΔlnW_i	111.77	88.94	80.17

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC×ΔlnW_i, instrumented by Z_i^W and MaxEITC×Z_i^W. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Difference Between 1 and 2 Kids

Table A25: Effect of EITC on Employment Effect of China Trade Shock by Gender and Marital Status

	Employment Rate			
	(1)	(2)	(3)	(4)
	Single Men	Married Men	Single Women	Married Women
MaxEITC(in 100 $)	0.448	0.289*	0.661***	0.520***
	(0.295)	(0.168)	(0.248)	(0.184)
IP^{cu}	-0.069	-0.091	-0.405	-0.548***
	(0.200)	(0.149)	(0.273)	(0.191)
MaxEITC $\times$ IP^{cu}	-0.023	-0.052	-0.375*	-0.032
	(0.135)	(0.074)	(0.194)	(0.131)
Fraction 1 or More	-0.102	-0.857	-0.618	1.294
	(1.536)	(0.745)	(1.173)	(0.839)
Fraction 3 or More	-0.177*	0.022	-0.086	-0.240**
	(0.098)	(0.048)	(0.107)	(0.097)
Observations	722	722	722	722
Mean of 1990 Employment Rate	72.7	90.9	68.0	66.8
R^2	0.695	0.816	0.734	0.828
First-stage diagnostics				
SW cond. F: ΔlnW_i	30.82	26.24	33.99	26.29
SW cond. F: MaxEITC $\times$ ΔlnW_i	90.31	88.06	97.39	88.34

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC$\times\Delta lnW_i$, instrumented by Z_i^W and MaxEITC$\times Z_i^W$. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.5 Minimum Wage Hikes

To address concerns about potential pre-treatment bias in the DID with TWFE method, I incorporate US Division and State-Specific Linear Trends, following the methodology of Dube et al. (2010) and Allegretto et al. (2011). The results are presented in Tables A28, A29, and A30. While the estimates for $lnMinwage$ may vary, the coefficient of interest, β_3, remains consistent, providing reassurance about the robustness of the main findings.

Table A26: Effect of EITC on Employment Effect of China Trade Shock by Education Level - Men Only

Panel A. Single Men			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	0.576	0.304	-0.049
	(0.55)	(0.27)	(0.25)
IP^{cu}	0.237	-0.314	0.337
	(0.40)	(0.22)	(0.32)
MaxEITC × IP^{cu}	-0.145	0.063	-0.132
	(0.30)	(0.12)	(0.21)
Fraction 1 or More	0.248	-0.011	-0.255*
	(0.21)	(0.16)	(0.15)
Fraction 3 or More	-0.307	-0.127	0.192
	(0.19)	(0.09)	(0.14)
Observations	722	722	722
Mean of 1990 Employment Rate	55.1	75.7	87.8
R^2	0.537	0.643	0.354
First-stage diagnostics			
SW cond. F: ΔlnW_i	25.76	27.58	61.29
SW cond. F: MaxEITC × ΔlnW_i	105.37	89.35	77.10
Panel B. Married Men			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	0.739	0.069	-0.106
	(0.55)	(0.11)	(0.11)
IP^{cu}	-0.005	-0.188	0.200
	(0.48)	(0.12)	(0.14)
MaxEITC × IP^{cu}	-0.011	-0.036	-0.080
	(0.24)	(0.06)	(0.07)
Fraction 1 or More	-0.420	-0.076	0.046
	(0.28)	(0.06)	(0.06)
Fraction 3 or More	0.335	0.081*	0.059
	(0.25)	(0.05)	(0.04)
Observations	722	722	722
Mean of 1990 Employment Rate	79.5	91.8	96.6
R^2	0.584	0.770	0.546
First-stage diagnostics			
SW cond. F: ΔlnW_i	24.69	21.92	41.19
SW cond. F: MaxEITC × ΔlnW_i	118.81	89.21	69.17

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC×ΔlnW_i, instrumented by Z_i^W and MaxEITC×Z_i^W. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A27: Effect of EITC on Employment Effect of China Trade Shock by Education Level - Women Only

Panel A. Single Women			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	1.501***	0.208	0.284
	(0.43)	(0.28)	(0.28)
IP^{cu}	-0.980	-0.597**	0.744***
	(0.66)	(0.28)	(0.28)
MaxEITC × IP^{cu}	-0.997***	-0.188	-0.236
	(0.33)	(0.20)	(0.18)
Fraction 1 or More	-0.424**	0.048	-0.291*
	(0.17)	(0.10)	(0.15)
Fraction 3 or More	-0.028	0.038	0.084
	(0.19)	(0.10)	(0.12)
Observations	722	722	722
Mean of 1990 Employment Rate	43.3	71.4	89.2
R^2	0.471	0.730	0.364
First-stage diagnostics			
SW cond. F: ΔlnW_i	24.76	29.93	83.55
SW cond. F: MaxEITC × ΔlnW_i	115.64	93.73	103.45
Panel B. Married Women			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 100 $)	1.126**	0.412**	-0.567***
	(0.57)	(0.18)	(0.22)
IP^{cu}	-0.086	-0.797***	-0.090
	(0.67)	(0.23)	(0.30)
MaxEITC × IP^{cu}	0.115	-0.084	0.119
	(0.22)	(0.15)	(0.11)
Fraction 1 or More	0.106	0.049	0.289***
	(0.23)	(0.07)	(0.09)
Fraction 3 or More	-0.318	-0.176*	0.083
	(0.22)	(0.09)	(0.11)
Observations	722	722	722
Mean of 1990 Employment Rate	46.2	67.9	80.6
R^2	0.485	0.767	0.512
First-stage diagnostics			
SW cond. F: ΔlnW_i	24.87	22.15	44.17
SW cond. F: MaxEITC × ΔlnW_i	108.50	87.88	79.53

Notes—2SLS at the CZ level with CZ-population weights, division fixed effects, and baseline 1990 covariates. Regressors are mean-centered within the estimating cell. MaxEITC uses 1980 child-share weights (treated as exogenous). Endogenous regressors are ΔlnW_i and MaxEITC×ΔlnW_i, instrumented by Z_i^W and MaxEITC×Z_i^W. Heteroskedasticity-robust SEs clustered by state. First-stage diagnostics SW cond. F are reported in the table. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A28: Effect of EITC on Employment Effect of Minimum Wage Hikes by Gender and Marital Status

	Employment Rate			
	(1)	(2)	(3)	(4)
	Single Men	Married Men	Single Women	Married Women
MaxEITC(in 1000 $)	0.733	0.379**	2.119***	0.588**
	(0.549)	(0.182)	(0.398)	(0.243)
ln MinW	8.052	-1.081	-7.951	-7.145*
	(7.002)	(1.615)	(6.748)	(4.222)
MaxEITC × ln MinW	0.580	0.424	5.025***	0.397
	(1.765)	(1.018)	(1.614)	(0.964)
US Division Specific Linear Trend	✓	✓	✓	✓
State Specific Linear Trend	✓	✓	✓	✓
Observations	110587	202100	127533	213216
Mean of Dependent Variable	76.6	90.4	73.1	68.1
R^2	0.125	0.102	0.248	0.111

Notes — March CPS 1991–2006. Outcome is 100×employment indicator (percentage points). MaxEITC is the statutory maximum federal credit for the individual's inferred filing/child status (2017$), scaled in $1,000; ln Min wage is the log real state minimum wage (2017$). Both policy variables are mean–centered within the estimation sample. Specifications include state and year fixed effects; individual controls (age, race, education, number of children, indicator for children under five, SNAP participation); state–year covariates (unemployment, GDP per capita, welfare generosity for a three–child family, top marginal tax rate, welfare reform and AFDC waiver indicators); and interactions of number of children with state dummies. ASEC weights used; standard errors clustered by state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A29: Effect of EITC on Employment Effect of Minimum Wage Hikes by Education Level - Men Only

Panel A. Single Men			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 1000 $)	0.525	0.936	0.923
	(1.460)	(0.704)	(1.190)
ln MinW	9.888	10.185	-0.740
	(22.958)	(8.617)	(12.671)
MaxEITC × ln MinW	5.953	-0.659	-4.753
	(4.635)	(1.533)	(4.473)
US Division Specific Linear Trend	✓	✓	✓
State Specific Linear Trend	✓	✓	✓
Observations	18910	69313	22364
Mean of Dependent Variable	57.8	77.8	88.2
R^2	0.137	0.078	0.048
Panel B. Married Men			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 1000 $)	0.204	0.703**	-0.164
	(0.591)	(0.268)	(0.212)
ln MinW	-0.311	-3.248	1.860
	(13.904)	(2.894)	(2.634)
MaxEITC × ln MinW	2.955	-0.390	0.970
	(2.837)	(1.534)	(0.976)
US Division Specific Linear Trend	✓	✓	✓
State Specific Linear Trend	✓	✓	✓
Observations	27933	117480	56687
Mean of Dependent Variable	77.9	90.4	95.7
R^2	0.138	0.063	0.041

Notes - Specification, controls, weights, and clustering as in Table A28. Education is the highest completed degree. Coefficients are percentage–point changes in employment. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A30: Effect of EITC on Employment Effect of Minimum Wage Hikes by Education Level - Women Only

Panel C. Single Women

	(1) High School Dropouts	(2) High School Only	(3) College Graduates
MaxEITC(in 1000 $)	2.699***	2.009***	1.435**
	(0.838)	(0.469)	(0.615)
ln MinW	-20.373	-3.455	-13.511*
	(21.460)	(8.939)	(7.050)
MaxEITC × ln MinW	6.252	5.471***	1.177
	(5.195)	(1.520)	(2.083)
US Division Specific Linear Trend	✓	✓	✓
State Specific Linear Trend	✓	✓	✓
Observations	21397	80568	25568
Mean of Dependent Variable	41.1	75.3	90.2
R^2	0.182	0.164	0.062

Panel D. Married Women

	(1) High School Dropouts	(2) High School Only	(3) College Graduates
MaxEITC(in 1000 $)	-0.687	0.896***	0.888
	(0.913)	(0.265)	(0.571)
ln MinW	-19.970**	0.440	-18.269***
	(9.084)	(6.888)	(6.262)
MaxEITC × ln MinW	1.545	0.069	0.627
	(3.383)	(1.422)	(2.099)
US Division Specific Linear Trend	✓	✓	✓
State Specific Linear Trend	✓	✓	✓
Observations	27390	135511	50315
Mean of Dependent Variable	42.9	68.9	77.7
R^2	0.104	0.068	0.076

Notes - Specification, controls, weights, and clustering as in Table A28. Education is the highest completed degree. Coefficients are percentage–point changes in employment. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Difference Between 1 and 2 or More Kids

Table A31: Effect of EITC on Employment Effect of Minimum Wage Hikes by Gender and Marital Status

	Employment Rate			
	(1)	(2)	(3)	(4)
	Single Men	Married Men	Single Women	Married Women
MaxEITC(in 1000 $)	-0.092	0.041	1.237***	0.107
	(0.67)	(0.16)	(0.33)	(0.25)
ln MinW	-126.636	-79.327***	-71.450	62.276
	(126.95)	(28.74)	(64.71)	(72.59)
MaxEITC × ln MinW	-3.695	1.494	10.134***	1.149
	(5.80)	(1.46)	(3.30)	(2.54)
Observations	21448	140401	54775	142359
Mean of Dependent Variable	75.7	91.4	66.5	65.4
R^2	0.143	0.115	0.287	0.110

Notes - March CPS 1991–2006. Outcome is 100×employment indicator (percentage points). MaxEITC is the statutory maximum federal credit for the individual's inferred filing/child status (2017$), scaled in $1,000; ln Min wage is the log real state minimum wage (2017$). Both policy variables are mean–centered within the estimation sample. Specifications include state and year fixed effects; individual controls (age, race, education, number of children, indicator for children under five, SNAP participation); state–year covariates (unemployment, GDP per capita, welfare generosity for a three–child family, top marginal tax rate, welfare reform and AFDC waiver indicators); and interactions of number of children with state dummies. ASEC weights used; standard errors clustered by state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To address the same concerns raised earlier, I restrict the sample to individuals with children, allowing for a direct comparison between those with one child and those with more than one. The results are presented in Tables A31, A32, and A33. It is important to note that for certain groups, such as single men, only a small proportion have children, leading to a very limited sample size and potentially noisy estimates. However, for most cases, the results remain robust and consistent with the main findings.

Table A32: Effect of EITC on Employment Effect of Minimum Wage Hikes by Education Level - Men Only

Panel A. Single Men			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 1000 $)	-0.857	-0.218	3.649**
	(2.28)	(0.87)	(1.81)
ln MinW	-4.297	22.857	-5.487
	(39.16)	(24.21)	(30.50)
MaxEITC × ln MinW	-13.798	1.768	-2.301
	(11.32)	(6.08)	(16.11)
Observations	5122	13906	2420
Mean of Dependent Variable	62.0	78.6	87.4
R^2	0.185	0.098	0.158
Panel B. Married Men			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 1000 $)	-0.400	0.194	-0.269
	(0.70)	(0.24)	(0.20)
ln MinW	-7.651	-1.735	2.747
	(13.03)	(3.79)	(3.41)
MaxEITC × ln MinW	14.756**	0.797	1.407
	(6.53)	(1.68)	(1.86)
Observations	19973	80736	39692
Mean of Dependent Variable	79.2	91.4	96.6
R^2	0.151	0.072	0.045

Notes - Specification, controls, weights, and clustering as in Table A31. Education is the highest completed degree. Coefficients are percentage–point changes in employment. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A33: Effect of EITC on Employment Effect of Minimum Wage Hikes by Education Level - Women Only

Panel C. Single Women

	(1) High School Dropouts	(2) High School Only	(3) College Graduates
MaxEITC(in 1000 $)	2.741**	0.900**	0.262
	(1.09)	(0.42)	(0.83)
ln MinW	-28.201	-3.393	-40.645**
	(17.42)	(9.92)	(15.14)
MaxEITC × ln MinW	6.766	13.969***	-1.799
	(9.49)	(3.82)	(7.50)
Observations	12421	36002	6352
Mean of Dependent Variable	37.6	71.5	89.4
R^2	0.205	0.207	0.125

Panel D. Married Women

	(1) High School Dropouts	(2) High School Only	(3) College Graduates
MaxEITC(in 1000 $)	-1.944*	0.354	0.495
	(1.14)	(0.39)	(0.52)
ln MinW	2.851	3.446	-12.214***
	(13.22)	(6.28)	(4.10)
MaxEITC × ln MinW	16.277**	0.536	-7.513*
	(6.95)	(2.18)	(4.21)
Observations	18824	90106	33429
Mean of Dependent Variable	40.9	66.6	73.8
R^2	0.117	0.074	0.066

Notes - Specification, controls, weights, and clustering as in Table A31. Education is the highest completed degree. Coefficients are percentage–point changes in employment. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Drop 1993 and 1994

Table A34: Effect of EITC on Employment Effect of Minimum Wage Hikes by Gender and Marital Status

	Employment Rate			
	(1)	(2)	(3)	(4)
	Single Men	Married Men	Single Women	Married Women
MaxEITC(in 1000 $)	0.874	0.478**	2.109***	0.698***
	(0.580)	(0.200)	(0.414)	(0.239)
ln MinW	11.897	-0.003	-6.002	-6.189
	(7.197)	(2.098)	(7.916)	(5.223)
MaxEITC × ln MinW	0.610	0.292	5.067***	0.483
	(1.955)	(0.935)	(1.628)	(1.078)
Observations	90508	162919	103967	171895
Mean of Dependent Variable	77.0	90.7	73.6	68.4
R^2	0.126	0.101	0.238	0.110

Notes - March CPS 1991–2006, except for 1993 and 1994. Outcome is 100×employment indicator (percentage points). MaxEITC is the statutory maximum federal credit for the individual's inferred filing/child status (2017$), scaled in $1,000; ln Min wage is the log real state minimum wage (2017$). Both policy variables are mean–centered within the estimation sample. Specifications include state and year fixed effects; individual controls (age, race, education, number of children, indicator for children under five, SNAP participation); state–year covariates (unemployment, GDP per capita, welfare generosity for a three–child family, top marginal tax rate, welfare reform and AFDC waiver indicators); and interactions of number of children with state dummies. ASEC weights used; standard errors clustered by state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In several policy analysis studies, researchers often exclude the years surrounding policy changes to reduce noise and account for potential delayed responses. Following this approach, I exclude the years 1993 and 1994, which immediately follow the EITC expansion, as part of a robustness check. The results, presented in Tables A34, A35, and A36, show that all coefficients of interest remain consistent, further supporting the robustness of the findings.

Table A35: Effect of EITC on Employment Effect of Minimum Wage Hikes by Education Level - Men Only

Panel A. Single Men			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 1000 $)	0.641	1.212*	0.853
	(1.565)	(0.714)	(1.082)
ln MinW	2.529	20.521**	-4.322
	(23.312)	(8.641)	(9.801)
MaxEITC × ln MinW	5.689	-0.748	-3.902
	(4.809)	(1.618)	(4.905)
Observations	15510	56672	18326
Mean of Dependent Variable	58.4	78.3	88.5
R^2	0.137	0.077	0.052
Panel B. Married Men			
	(1)	(2)	(3)
	High School Dropouts	High School Only	College Graduates
MaxEITC(in 1000 $)	0.657	0.736**	-0.070
	(0.635)	(0.279)	(0.219)
ln MinW	-0.964	-1.020	1.515
	(12.074)	(2.685)	(2.640)
MaxEITC × ln MinW	3.307	-0.659	1.025
	(2.798)	(1.461)	(1.058)
Observations	22719	94387	45813
Mean of Dependent Variable	78.6	90.7	95.8
R^2	0.135	0.062	0.043

Notes - Specification, controls, weights, and clustering as in Table A34. Education is the highest completed degree. Coefficients are percentage–point changes in employment. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A36: Effect of EITC on Employment Effect of Minimum Wage Hikes by Education Level - Women Only

Panel C. Single Women

	(1) High School Dropouts	(2) High School Only	(3) College Graduates
MaxEITC(in 1000 $)	2.754***	2.014***	1.099*
	(0.905)	(0.498)	(0.641)
ln MinW	-13.421	-0.842	-14.315*
	(18.144)	(10.842)	(8.126)
MaxEITC × ln MinW	6.173	5.357***	3.340
	(5.162)	(1.488)	(2.234)
Observations	17389	65603	20975
Mean of Dependent Variable	42.0	75.6	90.4
R^2	0.173	0.154	0.061

Panel D. Married Women

	(1) High School Dropouts	(2) High School Only	(3) College Graduates
MaxEITC(in 1000 $)	-0.507	0.982***	0.998*
	(0.958)	(0.266)	(0.559)
ln MinW	-10.349	0.665	-18.887***
	(10.873)	(7.782)	(6.611)
MaxEITC × ln MinW	1.192	-0.063	1.439
	(3.788)	(1.417)	(2.008)
Observations	22119	108782	40994
Mean of Dependent Variable	43.4	69.1	77.8
R^2	0.102	0.067	0.078

Notes - Specification, controls, weights, and clustering as in Table A34. Education is the highest completed degree. Coefficients are percentage–point changes in employment. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.