# The Effect of DACA Eligibility on Full-Time Employment: A Difference-in-Differences Replication Study

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**Abstract**

This study examines the causal impact of eligibility for the Deferred Action for Childhood Arrivals (DACA) program on full-time employment among Hispanic-Mexican individuals born in Mexico and living in the United States. Using American Community Survey data from 2006–2016 and a difference-in-differences identification strategy, I compare individuals who were ages 26–30 at DACA implementation (treatment group) to those ages 31–35 (control group, ineligible due to age). The baseline difference-in-differences estimate suggests DACA eligibility increased full-time employment probability by approximately 5.9 percentage points. However, after controlling for demographic covariates and including year and state fixed effects, the estimated effect is reduced to approximately 2.0 percentage points and is no longer statistically significant at conventional levels ($p = 0.140$). Event study analysis provides suggestive evidence of positive post-treatment effects, though pre-treatment trends are not perfectly parallel. The results are sensitive to specification choices, with estimates ranging from 2.0 to 6.7 percentage points across models.

# Contents

# 1 Introduction

The Deferred Action for Childhood Arrivals (DACA) program, implemented on June 15, 2012, provided temporary relief from deportation and work authorization to undocumented immigrants who arrived in the United States as children. This landmark immigration policy affected approximately 800,000 individuals, predominantly of Mexican origin, and fundamentally changed their legal relationship with the U.S. labor market.

This replication study examines a central question in the DACA literature: **Did DACA eligibility causally increase the probability of full-time employment among eligible individuals?** Full-time employment (defined as usually working 35 or more hours per week) represents a meaningful labor market outcome that may be particularly sensitive to work authorization status, as undocumented workers often face barriers to formal, full-time employment.

The identification strategy exploits the age-based eligibility cutoff in DACA. To be eligible, individuals must not have turned 31 by June 15, 2012. This creates a natural comparison between those who were ages 26–30 at implementation (just eligible) and those who were ages 31–35 (just ineligible due to age, but otherwise meeting all criteria). By comparing changes in full-time employment between these groups before and after DACA implementation, I can estimate the causal effect of eligibility under the assumption of parallel trends.

The analysis uses American Community Survey (ACS) data from 2006–2016, focusing on Hispanic-Mexican individuals born in Mexico who are non-citizens and who arrived in the U.S. before age 16 and by 2007 (to satisfy DACA's residency requirements). The pre-treatment period spans 2006–2011, and the post-treatment period spans 2013–2016, with 2012 excluded as a transition year when DACA was implemented mid-year.

# 2 Background and Literature

## 2.1 The DACA Program

DACA was announced by President Obama on June 15, 2012, and applications began being accepted on August 15, 2012. The program offered two-year renewable deferred action (protection from deportation) and employment authorization to undocumented immigrants who met specific criteria:

1. Arrived in the United States before their 16th birthday
2. Had not yet turned 31 as of June 15, 2012
3. Continuously resided in the U.S. since June 15, 2007

4. Were physically present in the U.S. on June 15, 2012
5. Had no lawful status on June 15, 2012
6. Were enrolled in school, graduated from high school, obtained a GED, or were honorably discharged from the military
7. Had not been convicted of certain criminal offenses

In the first four years, nearly 900,000 initial applications were received, with approximately 90% approved. Given the demographics of undocumented immigration to the United States, the vast majority of DACA recipients were of Mexican origin.

## 2.2 Theoretical Mechanisms

DACA eligibility could affect employment through several channels:

- **Legal work authorization**: DACA recipients can legally work, potentially enabling access to formal employment, better jobs, and full-time positions
- **Reduced deportation fear**: Protection from deportation may increase willingness to seek visible employment
- **Improved job matching**: Work authorization and identification documents may improve matching with better employers
- **Human capital investment**: Greater security may encourage investment in skills and education
- **Driver's license access**: In many states, DACA enabled recipients to obtain driver's licenses, facilitating commutes and job access

## 2.3 Related Literature

Several studies have examined DACA's effects on various outcomes. The literature generally finds positive effects on labor market outcomes, though estimates vary. Studies have documented effects on employment, earnings, educational attainment, and other socioeconomic outcomes. This replication takes an independent approach to estimating the employment effect using the specified research design.

# 3 Data

## 3.1 Data Source

The analysis uses data from the American Community Survey (ACS) as provided by IPUMS USA. The ACS is a nationally representative survey conducted by the U.S. Census Bureau, collecting detailed demographic, social, economic, and housing information from approximately 3 million households annually.

I use the one-year ACS files from 2006 through 2016, providing 11 years of cross-sectional data spanning periods before and after DACA implementation. The full dataset contains 33,851,424 person-observations across all years.

## 3.2 Key Variables

### 3.2.1 Outcome Variable

The outcome of interest is **full-time employment**, defined as usually working 35 or more hours per week. This is constructed using two IPUMS variables:

- `EMPSTAT`: Employment status (coded 1 if employed)
- `UHRSWORK`: Usual hours worked per week

An individual is classified as full-time employed if `EMPSTAT` $= 1$ AND `UHRSWORK` $\geq 35$.

### 3.2.2 Sample Selection Variables

To identify DACA-eligible individuals, I use:

- `HISPAN`: Hispanic origin (coded 1 for Mexican)
- `BPL`: Birthplace (coded 200 for Mexico)
- `CITIZEN`: Citizenship status (coded 3 for non-citizen)
- `YRIMMIG`: Year of immigration
- `BIRTHYR`: Birth year

### 3.2.3 Treatment Definition Variables

Treatment and control group assignment is based on age in June 2012:

- **Treatment**: Age 26–30 in 2012 (birth years 1982–1986)
- **Control**: Age 31–35 in 2012 (birth years 1977–1981)

#### 3.2.4 Control Variables

I include the following demographic covariates:

- `SEX`: Sex (female indicator)
- `MARST`: Marital status (married indicator)
- `EDUC`: Educational attainment (high school or more indicator)
- `AGE`: Age at time of survey
- `NCHILD`: Number of own children (has children indicator)
- `STATEFIP`: State of residence (for fixed effects)

### 3.3 Sample Construction

The analytic sample is constructed through the following steps:

1. Start with full ACS data: 33,851,424 observations
2. Restrict to Hispanic-Mexican ethnicity (`HISPAN` = 1) AND born in Mexico (`BPL` = 200): 991,261 observations
3. Restrict to non-citizens (`CITIZEN` = 3): 701,347 observations
4. Restrict to those who arrived before age 16: 205,327 observations
5. Restrict to those in U.S. since 2007 or earlier (`YRIMMIG` $\leq$ 2007): 195,023 observations
6. Restrict to treatment (ages 26–30 in 2012) or control (ages 31–35 in 2012) groups: 49,019 observations
7. Exclude transition year 2012 for main analysis: 44,725 observations

The final analytic sample contains 44,725 person-year observations, with 26,591 in the treatment group and 18,134 in the control group.

## 4 Empirical Strategy

### 4.1 Identification Strategy

I employ a difference-in-differences (DiD) design that exploits the age-based eligibility cutoff for DACA. The key identifying assumption is that, absent DACA, the treatment group (ages 26–30 in 2012) and control group (ages 31–35 in 2012) would have experienced parallel trends in full-time employment.

The basic DiD specification is:

$$Y_{it} = \alpha + \beta_1 \text{Treatment}_i + \beta_2 \text{Post}_t + \beta_3 (\text{Treatment}_i \times \text{Post}_t) + \epsilon_{it} \tag{1}$$

where:

- $Y_{it}$ is a binary indicator for full-time employment
- $\text{Treatment}_i$ indicates the individual was ages 26–30 in 2012
- $\text{Post}_t$ indicates the observation is from 2013–2016
- $\beta_3$ is the DiD coefficient of interest

## 4.2 Model Specifications

I estimate four main specifications with progressively richer controls:

**Model 1: Basic DiD**

$$Y_{it} = \alpha + \beta_1 \text{Treatment}_i + \beta_2 \text{Post}_t + \beta_3 \text{Treatment}_i \times \text{Post}_t + \epsilon_{it} \tag{2}$$

**Model 2: DiD with Demographic Covariates**

$$Y_{it} = \alpha + \beta_1 \text{Treatment}_i + \beta_2 \text{Post}_t + \beta_3 \text{Treatment}_i \times \text{Post}_t + X_{it}'\gamma + \epsilon_{it} \tag{3}$$

where $X_{it}$ includes female, married, high school education, age, age squared, and has children.

**Model 3: DiD with Covariates and Fixed Effects**

$$Y_{it} = \alpha + \beta_1 \text{Treatment}_i + \beta_3 \text{Treatment}_i \times \text{Post}_t + X_{it}'\gamma + \mu_t + \delta_s + \epsilon_{it} \tag{4}$$

where $\mu_t$ represents year fixed effects and $\delta_s$ represents state fixed effects.

**Model 4: Weighted DiD with Fixed Effects**

Same specification as Model 3, but weighted by person weights (`PERWT`) to produce population-representative estimates.

All models use heteroskedasticity-robust (HC1) standard errors.

## 4.3 Robustness Checks

I conduct several robustness checks:

1. **Placebo test**: Estimate DiD using only pre-treatment years (2006–2011) with a fake treatment date of 2009

2. **Bandwidth sensitivity**: Estimate with narrower age bandwidth (27–29 vs. 32–34)

3. **Including 2012**: Re-estimate including the transition year 2012 in the post-period

## 4.4 Event Study

To examine the parallel trends assumption and dynamic effects, I estimate an event study specification:

$$Y_{it} = \alpha + \beta_1 \text{Treatment}_i + \sum_{j \neq 2011} \gamma_j \cdot \mathbf{1}[\text{Year} = j] + \sum_{j \neq 2011} \delta_j \cdot (\text{Treatment}_i \times \mathbf{1}[\text{Year} = j]) + X_{it}'\gamma + \epsilon_{it} \tag{5}$$

where 2011 is the reference year (last pre-treatment year). The coefficients $\delta_j$ trace out the year-specific treatment effects.

# 5 Results

## 5.1 Descriptive Statistics

Table 1 presents summary statistics for the analytic sample by treatment group and time period.

Table 1: Summary Statistics by Treatment Group and Period

| | Control (Ages 31–35) | | Treatment (Ages 26–30) | |
|---|---|---|---|---|
| | Pre-DACA | Post-DACA | Pre-DACA | Post-DACA |
| Full-time Employment Rate | 0.577 | 0.570 | 0.537 | 0.589 |
| | (0.494) | (0.495) | (0.499) | (0.492) |
| Female | 0.432 | 0.421 | 0.439 | 0.411 |
| Married | 0.531 | 0.513 | 0.373 | 0.436 |
| High School or More | 0.545 | 0.584 | 0.626 | 0.662 |
| Mean Age | 29.3 | 34.7 | 24.2 | 29.2 |
| Observations | 11,916 | 6,218 | 17,410 | 9,181 |

*Notes*: Standard deviations in parentheses for continuous/binary outcome. Pre-DACA includes years 2006–2011; Post-DACA includes years 2013–2016.

Several patterns emerge from the descriptive statistics:

- The treatment group has a lower pre-treatment full-time employment rate (53.7%) compared to the control group (57.7%)
- Both groups have similar gender composition (approximately 43% female)
- The treatment group has lower marriage rates in the pre-period (37.3% vs. 53.1%), reflecting their younger age
- The treatment group has higher educational attainment (62.6% vs. 54.5% with high school or more)
- Full-time employment increased by 5.3 percentage points for the treatment group (53.7% to 58.9%) while slightly declining by 0.7 percentage points for the control group (57.7% to 57.0%)

## 5.2 Simple Difference-in-Differences

The simple 2×2 DiD calculation yields:

$$\begin{aligned}
\text{DiD} &= (\bar{Y}_{T,post} - \bar{Y}_{T,pre}) - (\bar{Y}_{C,post} - \bar{Y}_{C,pre}) \\
&= (0.589 - 0.537) - (0.570 - 0.577) \\
&= 0.053 - (-0.007) \\
&= 0.059
\end{aligned}$$

This suggests DACA eligibility increased full-time employment probability by approximately 5.9 percentage points.

## 5.3 Regression Results

Table 2 presents the main regression results.

Table 2: Difference-in-Differences Estimates of DACA Effect on Full-Time Employment

| | (1) Basic DiD | (2) + Covariates | (3) + Year/State FE | (4) Weighted |
|---|---|---|---|---|
| Treatment × Post | 0.0592*** | 0.0672*** | 0.0199 | 0.0321** |
| | (0.0100) | (0.0127) | (0.0135) | (0.0163) |
| Treatment | −0.0403*** | 0.0077 | 0.0114 | 0.0108 |
| | (0.0068) | (0.0097) | (0.0104) | (0.0130) |
| Post | −0.0065 | −0.0090 | — | — |
| | (0.0081) | (0.0077) | | |
| Female | — | −0.2591*** | −0.2535*** | −0.2553*** |
| | | (0.0063) | (0.0064) | (0.0077) |
| Married | — | 0.0710*** | 0.0711*** | 0.0762*** |
| | | (0.0066) | (0.0066) | (0.0079) |
| HS or More | — | 0.0282*** | 0.0309*** | 0.0256*** |
| | | (0.0060) | (0.0060) | (0.0072) |
| Year FE | No | No | Yes | Yes |
| State FE | No | No | Yes | Yes |
| Weighted | No | No | No | Yes |
| Observations | 44,725 | 44,725 | 44,725 | 44,725 |
| R-squared | 0.0015 | 0.0732 | 0.0787 | 0.0828 |

*Notes*: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. The outcome is a binary indicator for full-time employment (working 35+ hours per week). All models include an intercept. Models 3 and 4 absorb the Post indicator through year fixed effects.

The results reveal substantial sensitivity to specification:

**Model 1 (Basic DiD)**: The simple DiD estimate is 0.0592, suggesting DACA eligibility increased full-time employment probability by 5.9 percentage points ($p < 0.001$).

**Model 2 (With Covariates)**: Adding demographic controls increases the estimate to 0.0672 (6.7 percentage points, $p < 0.001$). This increase suggests that covariate differences between groups were masking some of the treatment effect.

**Model 3 (With Fixed Effects)**: Adding year and state fixed effects substantially reduces the estimate to 0.0199 (2.0 percentage points), which is no longer statistically significant at conventional levels ($p = 0.140$). The 95% confidence interval ranges from −0.007 to 0.046.

**Model 4 (Weighted)**: Using person weights yields an estimate of 0.0321 (3.2 percentage points, $p = 0.049$), marginally significant at the 5% level.

The dramatic reduction in the estimate when adding fixed effects suggests that time-varying factors correlated with both treatment status and employment (such as macroeconomic conditions affecting different age groups differently) may have been confounding the simpler specifications.

## 5.4 Event Study Results

Figure ?? and Table 3 present the event study results, with 2011 as the reference year.

Table 3: Event Study Estimates (Reference Year: 2011)

| Year | Coefficient | Std. Error | p-value |
|---|---|---|---|
| *Pre-Treatment Period* | | | |
| 2006 | −0.0232 | 0.0190 | 0.221 |
| 2007 | −0.0080 | 0.0191 | 0.674 |
| 2008 | 0.0150 | 0.0194 | 0.440 |
| 2009 | −0.0045 | 0.0199 | 0.822 |
| 2010 | 0.0038 | 0.0197 | 0.845 |
| *Post-Treatment Period* | | | |
| 2013 | 0.0470** | 0.0203 | 0.021 |
| 2014 | 0.0445** | 0.0204 | 0.029 |
| 2015 | 0.0488** | 0.0207 | 0.019 |
| 2016 | 0.0600*** | 0.0209 | 0.004 |

*Notes*: Coefficients represent the interaction between treatment group and year indicators, relative to 2011. Controls include female, married, and high school education. *** $p<0.01$, ** $p<0.05$.

The event study results provide mixed support for the parallel trends assumption:

- Pre-treatment coefficients (2006–2010) are generally small and statistically insignificant
- There is no clear pre-trend, though some year-to-year variation exists
- Post-treatment coefficients (2013–2016) are consistently positive and statistically significant
- The effect appears relatively stable across post-treatment years, ranging from 4.5 to 6.0 percentage points
- There is some suggestion of a growing effect over time (2016 shows the largest coefficient)

The pre-treatment coefficients, while not individually significant, do show some variation (ranging from $-0.023$ to 0.015), which raises some concerns about the parallel trends assumption.

## 5.5 Robustness Checks

Table 4 presents results from robustness checks.

Table 4: Robustness Checks

| Specification | Coefficient | Std. Error | p-value |
|---|---|---|---|
| Main specification (Model 2) | 0.0672 | 0.0127 | 0.000 |
| Placebo test (fake 2009 treatment) | 0.0066 | 0.0111 | 0.552 |
| Narrower age bandwidth (27–29 vs. 32–34) | 0.0468 | 0.0121 | 0.000 |
| Including 2012 in post-period | 0.0482 | 0.0087 | 0.000 |

*Notes*: All specifications include controls for female, married, and high school education.

**Placebo test**: Using only pre-DACA years (2006–2011) with a fake treatment date of 2009 yields an estimate of 0.0066 ($p = 0.552$), close to zero and not significant. This supports the identifying assumption that there were no differential trends prior to DACA.

**Narrower bandwidth**: Restricting to ages 27–29 vs. 32–34 (closer to the eligibility cutoff) yields an estimate of 0.0468 ($p < 0.001$). This is somewhat smaller than the main estimate but remains significant.

**Including 2012**: Including the transition year in the post-period yields an estimate of 0.0482 ($p < 0.001$), similar to the narrow bandwidth estimate. This is expected since 2012 is only a partial treatment year.

## 5.6 Heterogeneity Analysis

Table 5 presents estimates by subgroup.

Table 5: Heterogeneous Treatment Effects

| Subgroup | Coefficient | Std. Error | p-value | N |
|---|---|---|---|---|
| *By Sex* | | | | |
| Males | 0.0568*** | 0.0120 | 0.000 | 25,334 |
| Females | 0.0387*** | 0.0145 | 0.008 | 19,391 |
| *By Education* | | | | |
| Less than High School | 0.0266* | 0.0142 | 0.061 | 17,683 |
| High School or More | 0.0759*** | 0.0125 | 0.000 | 27,042 |

*Notes*: Each row represents a separate regression estimated on the indicated subsample. Controls include marital status and education (where applicable). *** p<0.01, ** p<0.05, * p<0.10.

The heterogeneity analysis reveals:

**By sex**: Males show a larger effect (5.7 percentage points) compared to females (3.9 percentage points), though both are statistically significant. This may reflect gender differences in labor force participation patterns.

**By education**: The effect is much larger for those with high school education or more (7.6 percentage points) compared to those with less than high school (2.7 percentage points, marginally significant). This suggests DACA may have particularly benefited more educated individuals, possibly by enabling them to access jobs matching their qualifications.

# 6 Discussion

## 6.1 Summary of Findings

This study provides evidence on the effect of DACA eligibility on full-time employment among Hispanic-Mexican individuals born in Mexico. The main findings are:

1. The simple difference-in-differences estimate suggests DACA eligibility increased full-time employment probability by approximately 5.9 percentage points
2. Adding demographic covariates increases the estimate to 6.7 percentage points
3. However, adding year and state fixed effects substantially reduces the estimate to 2.0 percentage points, which is no longer statistically significant
4. The population-weighted estimate with fixed effects is 3.2 percentage points (marginally significant)
5. Event study analysis shows positive and significant effects in all post-treatment years, with no clear pre-trend
6. The placebo test supports the identifying assumption
7. Effects are larger for males and for those with higher education

## 6.2 Interpretation of Results

The sensitivity of results to specification deserves careful interpretation. The baseline estimates (Models 1–2) of 5.9–6.7 percentage points may be upward biased if time-varying factors differentially affected the treatment and control groups. For example, the Great Recession and subsequent recovery may have affected different age groups differently, or there may be age-specific trends in full-time employment that confound the simple DiD comparison.

The preferred specification (Model 3) with year and state fixed effects yields a smaller, insignificant estimate. This could indicate:

- The true effect is smaller than simpler models suggest
- Fixed effects absorb too much variation, reducing statistical power
- The treatment effect is partially captured by the fixed effects if it operates through state-level or year-specific channels

The event study provides perhaps the most informative view: pre-treatment coefficients are generally small and insignificant (supporting parallel trends), while post-treatment coefficients are consistently positive and significant (suggesting a real effect). The event study estimates of 4.5–6.0 percentage points in post-treatment years suggest a meaningful positive effect.

## 6.3 Limitations

Several limitations should be noted:

1. **Identification concerns**: The control group (ages 31–35) may not perfectly satisfy the parallel trends assumption. Older workers may have different employment dynamics than younger workers.
2. **Sample definition**: I cannot directly identify DACA recipients or even definitively identify undocumented status. The assumption that non-citizen Mexican immigrants who arrived as children are undocumented is imperfect.
3. **Measurement**: The outcome (usual hours worked) may not capture recent changes in employment status. Full-time employment is a blunt measure that doesn't capture job quality.
4. **Repeated cross-section**: ACS is not panel data, so I cannot track individuals over time or control for individual fixed effects.
5. **External validity**: Results may not generalize to other immigrant groups or other policy contexts.

## 6.4 Comparison to Literature

My estimates are broadly consistent with the existing literature on DACA's labor market effects, though comparisons are complicated by differences in outcomes, samples, and identification strategies. The finding that effects are larger for more educated individuals is consistent with the hypothesis that DACA enabled better job matching for individuals whose human capital was previously underutilized.

# 7 Conclusion

This study estimates the causal effect of DACA eligibility on full-time employment using a difference-in-differences design. The results suggest DACA had a positive effect on full-time employment, though the magnitude and statistical significance depend on specification. The baseline DiD estimate of approximately 5.9 percentage points is reduced to approximately 2.0 percentage points (not statistically significant) when year and state fixed effects are included.

Several findings are robust across specifications: the placebo test supports the identifying assumptions, effects appear larger for males and more educated individuals, and event study coefficients are consistently positive in post-treatment years.

The policy implications are that DACA likely had modest positive effects on labor market outcomes for eligible individuals. The work authorization and protection from deportation provided by DACA appears to have facilitated increased formal employment, particularly for more educated individuals. However, the sensitivity of results to specification choices suggests caution in drawing strong conclusions about the precise magnitude of effects.

Future research could address limitations of this study by using administrative data on DACA recipients, employing alternative identification strategies (such as regression discontinuity designs around the age cutoff), or examining other labor market outcomes such as wages, job quality, or occupational upgrading.

# A Appendix: Additional Tables and Figures

Table 6: Sample Size by Year and Treatment Group

| Year | Control | Treatment |
|---|---|---|
| 2006 | 1,956 | 2,748 |
| 2007 | 1,951 | 2,903 |
| 2008 | 2,056 | 2,928 |
| 2009 | 2,058 | 2,937 |
| 2010 | 1,949 | 3,001 |
| 2011 | 1,946 | 2,893 |
| 2013 | 1,634 | 2,463 |
| 2014 | 1,560 | 2,325 |
| 2015 | 1,491 | 2,200 |
| 2016 | 1,533 | 2,193 |
| Total | 18,134 | 26,591 |

*Notes*: Sample restricted to Hispanic-Mexican individuals born in Mexico, non-citizens who arrived before age 16 and by 2007, and who were ages 26–35 in 2012. Year 2012 excluded from main analysis.

Table 7: Full Model 3 Coefficient Estimates

| Variable | Coefficient | Std. Error |
|---|---|---|
| Treatment | 0.0114 | 0.0104 |
| Treatment × Post | 0.0199 | 0.0135 |
| Female | −0.2535*** | 0.0064 |
| Married | 0.0711*** | 0.0066 |
| HS or More | 0.0309*** | 0.0060 |
| Age | 0.0377*** | 0.0050 |
| Age$^2$ | −0.0005*** | 0.0001 |
| Has Children | −0.0266*** | 0.0063 |
| Year FE | Yes | |
| State FE | Yes | |
| Observations | 44,725 | |
| R-squared | 0.0787 | |

*Notes*: Robust standard errors. *** p<0.01. Year and state fixed effect coefficients not shown.

Table 8: Covariate Balance: Pre-Treatment Period

| Variable | Control | Treatment |
|---|---|---|
| Female | 0.432 | 0.439 |
| Married | 0.531 | 0.373 |
| HS or More | 0.545 | 0.626 |
| Mean Age | 29.3 | 24.2 |
| Full-time Employment | 0.577 | 0.537 |
| Observations | 11,916 | 17,410 |

*Notes*: Sample means for pre-treatment period (2006–2011).

# B Appendix: Variable Definitions

Table 9: IPUMS Variable Definitions and Codes Used

| Variable | Definition | Codes Used |
|---|---|---|
| YEAR | Survey year | 2006–2016 |
| PERWT | Person weight | Continuous |
| SEX | Sex | 1 = Male, 2 = Female |
| AGE | Age | Continuous |
| BIRTHYR | Birth year | Continuous |
| MARST | Marital status | 1,2 = Married |
| HISPAN | Hispanic origin | 1 = Mexican |
| BPL | Birthplace | 200 = Mexico |
| CITIZEN | Citizenship status | 3 = Non-citizen |
| YRIMMIG | Year of immigration | Continuous |
| EDUC | Education | $\geq$6 = HS or more |
| EMPSTAT | Employment status | 1 = Employed |
| UHRSWORK | Usual hours worked | $\geq$35 = Full-time |
| NCHILD | Number of children | $>$0 = Has children |
| STATEFIP | State FIPS code | State identifiers |

# C Appendix: Computational Details

All analysis was conducted using Python 3.x with the following packages:

- pandas (data manipulation)
- numpy (numerical operations)
- statsmodels (regression analysis)

The analysis script reads the ACS data in chunks to manage memory constraints (the full dataset contains over 33 million observations). Data filtering is applied during loading to reduce the working dataset size.

Standard errors are heteroskedasticity-robust (HC1) throughout. The linear probability model is used for computational convenience and interpretability; results are similar with logit/probit models.

All code is available in the accompanying analysis.py file.