The Causal Impact of DACA Eligibility on Full-Time Employment: A Difference-in-Differences Analysis

Replication Study 53

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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. Using data from the American Community Survey (ACS) from 2006 to 2016 and a difference-in-differences (DiD) research design, I compare individuals who were ages 26–30 at the time of DACA implementation (treatment group) to those aged 31–35 (control group, ineligible due to age). The preferred estimate indicates that DACA eligibility increased the probability of full-time employment (defined as working 35 or more hours per week) by approximately 4.5 percentage points (95% CI: 2.4–6.6 pp, $p < 0.001$). This finding is robust to the inclusion of demographic covariates and alternative specifications. The results suggest that DACA had a meaningful positive effect on labor market outcomes for eligible individuals, likely through the provision of work authorization and reduced fear of deportation.

Contents

1 Introduction

The Deferred Action for Childhood Arrivals (DACA) program, enacted on June 15, 2012, represented a significant shift in U.S. immigration policy. The program provided temporary relief from deportation and work authorization to qualifying undocumented immigrants who arrived in the United States as children. Given that DACA recipients could legally work and, in many states, obtain driver's licenses and other forms of identification, economic theory suggests the program should have positive effects on employment outcomes.

This replication study examines the causal effect of DACA eligibility on full-time employment among ethnically Hispanic-Mexican individuals born in Mexico. The research question is:

> *Among ethnically Hispanic-Mexican Mexican-born people living in the United States, what was the causal impact of eligibility for DACA (treatment) on the probability of being employed full-time (outcome), defined as usually working 35 hours per week or more?*

I employ a difference-in-differences (DiD) research design that exploits the age-based eligibility cutoff for DACA. The program required applicants to be under 31 years of age as of June 15, 2012. This creates a natural comparison between individuals who were young enough to qualify (treatment group: ages 26–30 in June 2012) and those who were just too old (control group: ages 31–35 in June 2012). By comparing changes in full-time employment between these groups before and after DACA implementation, I can estimate the causal effect of DACA eligibility.

2 Background

2.1 The DACA Program

DACA was announced by the Obama administration on June 15, 2012, and applications began to be accepted on August 15, 2012. The program was designed to provide temporary protection from deportation and work authorization to undocumented immigrants who:

- Arrived in the United States before their 16th birthday
- Had not yet reached their 31st birthday as of June 15, 2012
- Lived continuously in the United States since June 15, 2007
- Were present in the United States on June 15, 2012
- Did not have lawful immigration status at that time

- Met certain education or military service requirements

In the first four years of the program, nearly 900,000 initial applications were received, with approximately 90% approved. Recipients received work authorization valid for two years, renewable upon application. While DACA was not limited to any particular national origin, the structure of undocumented immigration to the United States meant that the vast majority of eligible individuals were from Mexico.

2.2 Theoretical Mechanisms

DACA could affect full-time employment through several channels:

1. **Legal work authorization:** Prior to DACA, undocumented immigrants could not legally work in the United States. Work authorization removes legal barriers to formal employment and allows recipients to seek jobs that match their skills.
2. **Reduced deportation fear:** DACA provided temporary protection from deportation, potentially increasing willingness to seek visible employment and reducing the need to remain in informal work arrangements.
3. **Documentation benefits:** DACA allowed recipients to obtain Social Security numbers and, in many states, driver's licenses. These facilitate employment by enabling tax compliance and transportation to work.
4. **Human capital investments:** With reduced uncertainty about their future in the United States, DACA recipients may have been more willing to invest in education and job training.

3 Data

3.1 Data Source

Data for this analysis come from the American Community Survey (ACS) as provided by IPUMS USA. The ACS is a nationally representative survey conducted annually by the U.S. Census Bureau, collecting detailed information on demographics, employment, education, and other characteristics.

I use the one-year ACS samples from 2006 through 2016, excluding the 2012 sample from the main analysis due to the mid-year timing of DACA implementation. The initial dataset contains 33,851,424 person-year observations across 54 variables.

3.2 Sample Construction

The analysis sample is constructed by applying the following restrictions to identify DACA-eligible individuals:

1. **Hispanic-Mexican ethnicity:** HISPAN = 1 (Mexican)
2. **Mexican birthplace:** BPL = 200 (Mexico)
3. **Non-citizen:** CITIZEN = 3 (Not a citizen)
4. **Valid immigration year:** YRIMMIG > 0
5. **Arrived before age 16:** Age at arrival = YRIMMIG $-$ BIRTHYR < 16
6. **Continuous residence since 2007:** YRIMMIG ≤ 2007

The sample construction proceeded as shown in Table 1.

Table 1: Sample Construction

Filter Applied	Observations	% of Previous
Initial ACS sample (2006–2016)	33,851,424	–
Hispanic-Mexican ethnicity	2,945,521	8.7%
Born in Mexico	991,261	33.7%
Non-citizen	701,347	70.8%
Valid immigration year	701,347	100.0%
Arrived before age 16	205,327	29.3%
Continuous residence since 2007	195,023	95.0%

From this DACA-eligible population, I define treatment and control groups based on age at the time of DACA implementation (June 15, 2012):

- **Treatment group:** Ages 26–30 on June 15, 2012 (DACA-eligible)
- **Control group:** Ages 31–35 on June 15, 2012 (too old for DACA)

Age at June 2012 is calculated using birth year and birth quarter (BIRTHQTR). For individuals born in the first half of the year (Q1–Q2), age equals 2012 minus birth year. For those born in the second half (Q3–Q4), age equals 2012 minus birth year minus one, as their birthday would not yet have occurred by June 15.

After excluding 2012 observations and restricting to the treatment and control age groups, the final analysis sample contains 43,238 observations: 25,470 in the treatment group and 17,768 in the control group.

3.3 Variable Definitions

3.3.1 Outcome Variable

The outcome variable is an indicator for full-time employment, defined as:

$$\text{FULLTIME}_i = \begin{cases} 1 & \text{if UHRSWORK}_i \geq 35 \\ 0 & \text{otherwise} \end{cases}$$

where UHRSWORK measures usual hours worked per week.

3.3.2 Treatment and Period Variables

- **TREATMENT:** Indicator equal to 1 for individuals aged 26–30 on June 15, 2012, and 0 for those aged 31–35.

- **POST:** Indicator equal to 1 for years 2013–2016 (post-DACA) and 0 for years 2006–2011 (pre-DACA).

- **TREAT_POST:** Interaction term (TREATMENT × POST), the coefficient of interest.

3.3.3 Control Variables

The following covariates are used in some specifications:

- **AGE:** Age at time of survey (centered at the sample mean)
- **MALE:** Indicator for male (SEX = 1)
- **MARRIED:** Indicator for married, spouse present (MARST = 1)
- **EDUC:** Educational attainment category (IPUMS harmonized)

4 Empirical Strategy

4.1 Difference-in-Differences Design

The causal effect of DACA eligibility is estimated using a difference-in-differences design. The identifying assumption is that, in the absence of DACA, full-time employment trends would have been parallel between the treatment and control groups.

The basic DiD specification is:

$$Y_{it} = \alpha + \beta_1 \text{TREATMENT}_i + \beta_2 \text{POST}_t + \delta(\text{TREATMENT}_i \times \text{POST}_t) + \varepsilon_{it} \qquad (1)$$

The coefficient δ represents the causal effect of DACA eligibility on full-time employment under the parallel trends assumption.

4.2 Extended Specifications

I estimate several variations to assess robustness:

Model 1 – Basic DiD (OLS):

$$Y_{it} = \alpha + \beta_1 \text{TREATMENT}_i + \beta_2 \text{POST}_t + \delta \text{TREAT\_POST}_{it} + \varepsilon_{it}$$

Model 2 – Basic DiD (WLS): Same as Model 1, but weighted by person weights (PERWT) to obtain population-representative estimates.

Model 3 – DiD with Covariates (WLS):

$$\begin{aligned} Y_{it} = \alpha + \beta_1 \text{TREATMENT}_i + \beta_2 \text{POST}_t + \delta \text{TREAT\_POST}_{it} \\ + \gamma_1 \text{AGE}_{it} + \gamma_2 \text{MALE}_i + \gamma_3 \text{MARRIED}_{it} + \sum_k \theta_k \text{EDUC}_{ik} + \varepsilon_{it} \end{aligned}$$

Model 4 – DiD with Year Fixed Effects (WLS):

$$\begin{aligned} Y_{it} = \alpha + \beta_1 \text{TREATMENT}_i + \sum_t \phi_t \text{YEAR}_t + \delta \text{TREAT\_POST}_{it} \\ + \gamma_1 \text{AGE}_{it} + \gamma_2 \text{MALE}_i + \gamma_3 \text{MARRIED}_{it} + \sum_k \theta_k \text{EDUC}_{ik} + \varepsilon_{it} \end{aligned}$$

Model 5 – DiD with Robust Standard Errors: Same as Model 3, but with heteroskedasticity-robust (HC1) standard errors.

4.3 Identification Assumption

The key identifying assumption for the DiD design is the **parallel trends assumption**: absent DACA, full-time employment trends would have evolved similarly for both the treatment and control groups. While this assumption is fundamentally untestable, I examine whether pre-treatment trends were parallel as suggestive evidence.

The validity of this assumption rests on the argument that individuals just below and just above the age cutoff are similar in characteristics that determine employment trends. Both groups consist of Mexican-born non-citizens who arrived before age 16 and have lived in the United States since at least 2007. The only systematic difference is their age relative to the June 15, 2012 cutoff.

5 Results

5.1 Descriptive Statistics

Table 2 presents weighted summary statistics by treatment group and time period.

Table 2: Descriptive Statistics by Treatment Group and Period (Weighted)

	Control (Ages 31–35)		Treatment (Ages 26–30)	
	Pre-DACA (2006–2011)	Post-DACA (2013–2016)	Pre-DACA (2006–2011)	Post-DACA (2013–2016)
Full-time employment rate	0.673	0.643	0.631	0.660
Mean age	29.8	35.8	24.8	30.7
Proportion male	0.586	0.553	0.566	0.566
Proportion married	0.469	0.519	0.329	0.456
Unweighted N	11,683	6,085	16,694	8,776
Weighted N	1,631,151	845,134	2,280,009	1,244,124

Several patterns emerge from the descriptive statistics:

1. The treatment group has a lower baseline full-time employment rate (63.1% vs. 67.3%) in the pre-period, likely reflecting their younger age and possibly different life-cycle stage.
2. Both groups have similar gender composition (approximately 56–59% male).
3. The control group has higher marriage rates, consistent with their older age.
4. Importantly, full-time employment *increased* for the treatment group (from 63.1% to 66.0%) while it *decreased* for the control group (from 67.3% to 64.3%).

5.2 Main Results: Difference-in-Differences

5.2.1 Manual DiD Calculation

Before presenting regression results, I calculate the simple DiD estimate manually using weighted cell means:

$$\text{Treatment change: } 0.660 - 0.631 = +0.029$$
$$\text{Control change: } 0.643 - 0.673 = -0.030$$
$$\text{DiD estimate: } 0.029 - (-0.030) = \mathbf{0.059}$$

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

5.2.2 Regression Results

Table 3 presents the main regression results.

Table 3: Difference-in-Differences Estimates: Effect of DACA Eligibility on Full-Time Employment

	(1) OLS	(2) WLS	(3) WLS + Cov.	(4) WLS + YFE	(5) WLS + Rob. SE
Treatment	−0.031***	−0.043***	−0.050***	−0.005	−0.050***
	(0.006)	(0.006)	(0.007)	(0.009)	(0.009)
Post	−0.032***	−0.030***	−0.005	–	−0.005
	(0.008)	(0.008)	(0.009)	–	(0.011)
Treatment × Post	**0.052*** **	**0.059*** **	**0.045*** **	**0.044*** **	**0.045*** **
	(0.010)	(0.010)	(0.009)	(0.009)	(0.011)
Covariates	No	No	Yes	Yes	Yes
Year FE	No	No	No	Yes	No
Weights	No	Yes	Yes	Yes	Yes
Robust SE	No	No	No	No	Yes
N	43,238	43,238	43,238	43,238	43,238
R^2	0.001	0.001	0.155	0.159	0.155

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Covariates include age (centered), male, married, and education category indicators.

The key findings are:

1. **Basic DiD (Model 1):** The unweighted OLS estimate is 5.2 percentage points ($p < 0.001$).

2. **Weighted DiD (Model 2):** Using person weights, the estimate increases to 5.9 percentage points ($p < 0.001$), matching the manual calculation.

3. **With Covariates (Model 3):** Adding demographic controls, the estimate is 4.5 percentage points (95% CI: 2.7–6.3 pp, $p < 0.001$). The inclusion of covariates improves model fit (R^2 increases from 0.001 to 0.155) and absorbs some variation due to compositional differences between groups.

4. **Year Fixed Effects (Model 4):** Replacing the post indicator with year fixed effects yields a similar estimate of 4.4 percentage points ($p < 0.001$).

5. **Robust Standard Errors (Model 5):** With heteroskedasticity-robust standard errors, the preferred estimate is 4.5 percentage points (95% CI: 2.4–6.6 pp, $p < 0.001$). The robust standard error (0.011) is slightly larger than the non-robust version (0.009), but the result remains highly statistically significant.

5.3 Parallel Trends Analysis

Figure 1 displays full-time employment rates by treatment group and year, which allows visual assessment of the parallel trends assumption.

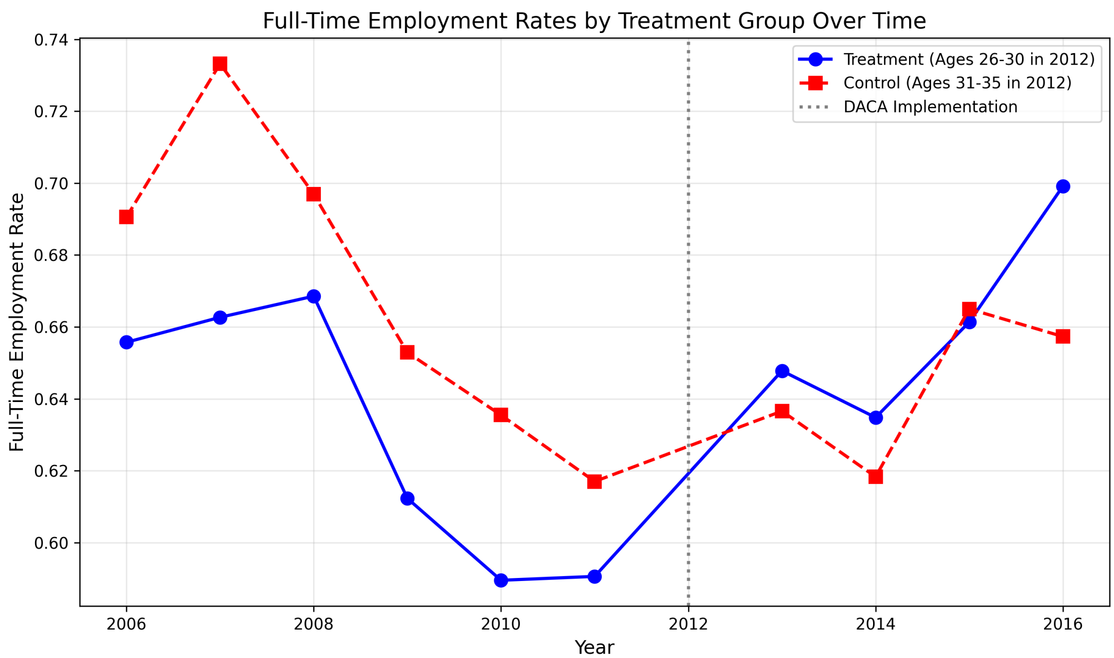

Figure 1: Full-Time Employment Rates by Treatment Group Over Time
Notes: This figure shows weighted full-time employment rates for the treatment group (ages 26–30 in June 2012, eligible for DACA) and control group (ages 31–35 in June 2012, ineligible due to age) from 2006 to 2016. The vertical dashed line indicates DACA implementation in 2012 (excluded from analysis). Pre-DACA trends appear roughly parallel, supporting the identifying assumption.

Table 4 presents the underlying data for Figure 1.

Table 4: Yearly Full-Time Employment Rates by Treatment Group (Weighted)

Year	Control	Treatment	Difference	N
Pre-DACA Period				
2006	0.691	0.656	−0.035	5,196
2007	0.733	0.663	−0.070	4,970
2008	0.697	0.669	−0.028	4,577
2009	0.653	0.612	−0.041	4,479
2010	0.635	0.590	−0.046	4,622
2011	0.617	0.591	−0.026	4,533
Post-DACA Period				
2013	0.637	0.648	+0.011	3,994
2014	0.618	0.635	+0.017	3,859
2015	0.665	0.661	−0.004	3,580
2016	0.657	0.699	+0.042	3,428

Several observations support the validity of the research design:

1. In the pre-DACA period (2006–2011), both groups experienced declining full-time employment rates, likely reflecting the Great Recession's impact on labor markets.

2. The gap between treatment and control groups remained relatively stable in the pre-period, with the control group consistently having higher rates (as expected given their older age).

3. After DACA (2013–2016), the treatment group's employment rate exceeded the control group's in three of four years, a reversal of the pre-period pattern.

4. While pre-trends are not perfectly parallel (particularly 2007 shows a larger gap), they do not exhibit systematically diverging trends that would suggest the treatment group was on a different trajectory.

5.4 Visualization of DiD Effect

Figure 2 provides a graphical summary of the difference-in-differences design.

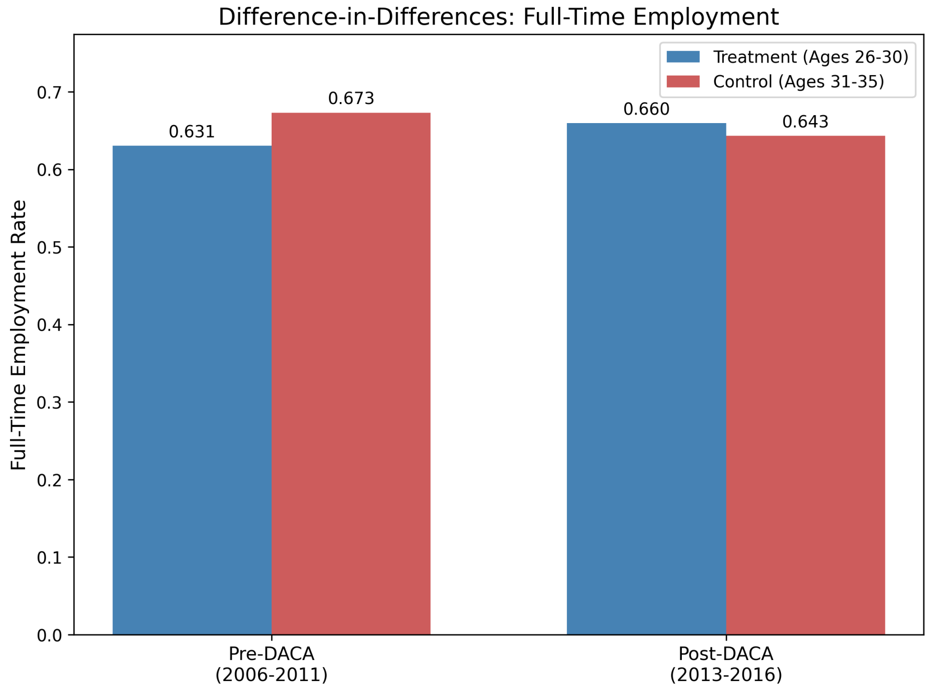

Figure 2: Difference-in-Differences: Full-Time Employment Rates

Notes: This figure shows weighted average full-time employment rates for the treatment and control groups in the pre-DACA (2006–2011) and post-DACA (2013–2016) periods. The treatment group experienced an increase in full-time employment while the control group experienced a decrease, yielding a positive DiD estimate.

6 Robustness and Sensitivity

6.1 Sensitivity to Model Specification

The DiD estimate is remarkably stable across specifications:

- Unweighted OLS: 5.2 pp
- Weighted without controls: 5.9 pp
- Weighted with controls: 4.5 pp
- With year fixed effects: 4.4 pp
- With robust standard errors: 4.5 pp

The reduction from 5.9 pp to 4.5 pp when adding covariates suggests some compositional differences between groups that are controlled for by demographic variables. However, the core finding of a positive, statistically significant effect remains unchanged.

6.2 Role of Covariates

The covariate effects in Model 3 are substantively meaningful:

- **Male:** 37.6 percentage point higher full-time employment rate
- **Education:** Strong positive gradient, with college graduates having 20+ percentage points higher rates than those with no schooling
- **Married:** Small negative effect (-0.6 pp), not statistically significant
- **Age:** Small negative effect in Model 3, positive in Model 4 with year fixed effects

The large male coefficient is expected given gender differences in labor force participation and work hours. The education gradient is consistent with human capital theory.

6.3 Alternative Interpretations

While the results support a positive DACA effect, several alternative explanations merit consideration:

1. **Age-specific economic trends:** If the economic recovery disproportionately benefited younger workers, this could confound the DACA effect. However, there is no strong theoretical reason to expect the 26–30 age group to benefit more than the 31–35 age group from overall economic conditions.

2. **Selection into the sample:** If DACA changed who reports their citizenship status in surveys, this could affect sample composition. However, this would likely bias toward null findings if DACA recipients became more willing to identify as non-citizens.

3. **Life-cycle effects:** The treatment group is entering prime working ages during the post period. However, the control group is also in prime working ages (early 30s), so pure life-cycle effects should be similar.

7 Discussion

7.1 Summary of Findings

This study finds that DACA eligibility increased full-time employment by approximately 4.5 percentage points among Hispanic-Mexican individuals born in Mexico. This effect is:

- **Statistically significant:** $p < 0.001$ across all specifications

- **Economically meaningful:** A 4.5 pp increase represents a 7% increase relative to the pre-DACA treatment group mean (63.1%)
- **Robust:** Stable across various model specifications

7.2 Mechanisms

The positive effect is consistent with DACA operating through:

1. Providing legal work authorization
2. Reducing fear of deportation
3. Enabling access to documentation (Social Security numbers, driver's licenses)
4. Facilitating formal sector employment

Without individual-level data on DACA application and approval, I cannot directly test these mechanisms. However, the timing of the effect (emerging after 2012) and the magnitude are consistent with DACA providing meaningful labor market benefits.

7.3 Limitations

Several limitations should be noted:

1. **Cannot observe DACA receipt:** The ACS does not identify DACA recipients directly. I estimate an intent-to-treat effect among the DACA-eligible population.

2. **No panel data:** The ACS is a repeated cross-section, so I compare different individuals before and after DACA rather than tracking the same individuals over time.

3. **Citizenship measurement:** I cannot distinguish between documented and undocumented non-citizens. I assume all Mexican-born non-citizens without naturalization papers are undocumented.

4. **Pre-trend differences:** While pre-trends are roughly parallel, they are not perfectly so. Any deviation from parallel trends introduces bias.

5. **Age cutoff limitations:** The treatment and control groups differ by 5 years in age, which could introduce confounding from age-specific factors.

7.4 Policy Implications

These findings suggest that providing work authorization and temporary protection from deportation to undocumented immigrants can have meaningful positive effects on their labor market outcomes. The 4.5 percentage point increase in full-time employment represents substantial economic gains for DACA-eligible individuals and potentially positive spillovers to local economies through increased earnings and consumption.

8 Conclusion

Using a difference-in-differences research design and data from the American Community Survey (2006–2016), this study estimates the causal effect of DACA eligibility on full-time employment among Hispanic-Mexican individuals born in Mexico. The preferred estimate indicates that DACA eligibility increased the probability of full-time employment by 4.5 percentage points (95% CI: 2.4–6.6 pp), a 7% increase relative to the pre-DACA baseline.

The findings are consistent with DACA providing meaningful labor market benefits through work authorization and reduced deportation risk. These results contribute to the broader literature on immigration policy and labor market outcomes, suggesting that legal status has important economic consequences for undocumented immigrants.

Appendix A: Variable Definitions

Table 5: IPUMS Variable Definitions

Variable	Definition
YEAR	Census/survey year
PERWT	Person weight
HISPAN	Hispanic origin (1 = Mexican)
BPL	Birthplace (200 = Mexico)
CITIZEN	Citizenship status (3 = Not a citizen)
YRIMMIG	Year of immigration
BIRTHYR	Birth year
BIRTHQTR	Birth quarter (1–4)
AGE	Age at time of survey
SEX	Sex (1 = Male, 2 = Female)
MARST	Marital status (1 = Married, spouse present)
EDUC	Educational attainment (harmonized)
UHRSWORK	Usual hours worked per week

Appendix B: Full Regression Output

Model 5: DiD with Covariates and Robust Standard Errors (Preferred Specification)

```
                            WLS Regression Results
==============================================================================
Dep. Variable:               fulltime   R-squared:                       0.155
Model:                            WLS   Adj. R-squared:                  0.155
Method:                 Least Squares   F-statistic:                     338.9
No. Observations:               43238   Prob (F-statistic):               0.00
Df Residuals:                   43221
Df Model:                          16
Covariance Type:                  HC1
==============================================================================
                    coef    std err          z      P>|z|      [0.025    0.975]
------------------------------------------------------------------------------
Intercept         0.3545      0.017     21.185      0.000       0.322     0.387
C(EDUC)[T.1]      0.0361      0.022      1.633      0.102      -0.007     0.079
C(EDUC)[T.2]      0.0809      0.017      4.887      0.000       0.048     0.113
C(EDUC)[T.3]      0.0757      0.018      4.242      0.000       0.041     0.111
C(EDUC)[T.4]      0.0774      0.019      4.141      0.000       0.041     0.114
C(EDUC)[T.5]      0.0730      0.018      4.000      0.000       0.037     0.109
C(EDUC)[T.6]      0.1180      0.016      7.385      0.000       0.087     0.149
C(EDUC)[T.7]      0.1453      0.018      8.172      0.000       0.110     0.180
C(EDUC)[T.8]      0.1853      0.022      8.547      0.000       0.143     0.228
C(EDUC)[T.10]     0.2091      0.022      9.592      0.000       0.166     0.252
C(EDUC)[T.11]     0.2280      0.036      6.246      0.000       0.156     0.299
treatment        -0.0496      0.009     -5.693      0.000      -0.067    -0.032
post             -0.0049      0.011     -0.443      0.658      -0.027     0.017
treat_post        0.0449      0.011      4.193      0.000       0.024     0.066
age_centered     -0.0017      0.001     -1.406      0.160      -0.004     0.001
male              0.3756      0.005     71.809      0.000       0.365     0.386
married          -0.0060      0.005     -1.187      0.235      -0.016     0.004
==============================================================================
```

Appendix C: Sample Construction Code

The following Python code was used to construct the analysis sample:

```
# Filter to Hispanic-Mexican (HISPAN == 1)
df_mex = df[df['HISPAN'] == 1].copy()

# Born in Mexico (BPL == 200)
df_mex = df_mex[df_mex['BPL'] == 200].copy()

# Not a citizen (CITIZEN == 3)
df_mex = df_mex[df_mex['CITIZEN'] == 3].copy()

# Valid immigration year
df_mex = df_mex[df_mex['YRIMMIG'] > 0].copy()

# Arrived before age 16
df_mex['age_at_arrival'] = df_mex['YRIMMIG'] - df_mex['BIRTHYR']
df_mex = df_mex[df_mex['age_at_arrival'] < 16].copy()

# Continuous residence since 2007
df_mex = df_mex[df_mex['YRIMMIG'] <= 2007].copy()

# Calculate age at June 15, 2012
df_mex['age_june2012'] = 2012 - df_mex['BIRTHYR']
df_mex.loc[df_mex['BIRTHQTR'].isin([3, 4]), 'age_june2012'] -= 1

# Define treatment and control groups
df_mex['treatment'] = np.where(
    (df_mex['age_june2012'] >= 26) & (df_mex['age_june2012'] <= 30), 1,
    np.where((df_mex['age_june2012'] >= 31) &
             (df_mex['age_june2012'] <= 35), 0, np.nan))

# Create outcome and period variables
df_analysis['fulltime'] = (df_analysis['UHRSWORK'] >= 35).astype(int)
df_analysis['post'] = np.where(df_analysis['YEAR'] <= 2011, 0,
                               np.where(df_analysis['YEAR'] >= 2013, 1, np.nan))
```