# The Effect of DACA Eligibility on Full-Time Employment:

# A Difference-in-Differences Analysis

Independent 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 ethnically Hispanic-Mexican, Mexican-born individuals living in the United States. Using American Community Survey (ACS) data from 2006–2016 and a difference-in-differences identification strategy, I find that DACA eligibility increased the probability of full-time employment by approximately 2.3 percentage points (95% CI: 1.5–3.1 pp, $p < 0.001$). This effect operates primarily through the extensive margin, with DACA-eligible individuals more likely to enter employment after the program's implementation. The results are robust to alternative control group definitions and model specifications. Heterogeneity analysis reveals larger effects for women and those with higher educational attainment. These findings suggest that DACA's provision of work authorization and deportation relief had meaningful positive effects on the labor market outcomes of eligible immigrants.

**Keywords:** DACA, immigration policy, employment, difference-in-differences, labor economics

# Contents

# 1 Introduction

The Deferred Action for Childhood Arrivals (DACA) program, enacted on June 15, 2012, represents one of the most significant immigration policy changes in recent U.S. history. The program provided eligible undocumented immigrants who arrived in the United States as children with temporary relief from deportation and authorization to work legally. Given that DACA directly addressed employment authorization, understanding its effects on labor market outcomes is of considerable policy importance.

This study investigates the following research question: *Among ethnically Hispanic-Mexican, Mexican-born individuals living in the United States, what was the causal impact of eligibility for DACA on the probability of being employed full-time (usually working 35 hours per week or more)?*

The identification strategy exploits the quasi-experimental variation created by DACA's eligibility requirements. The program established clear age and arrival-time criteria that determined eligibility, creating natural treatment and control groups among otherwise similar undocumented immigrants. By comparing changes in full-time employment rates between DACA-eligible and non-eligible individuals before and after the program's implementation, I can estimate the causal effect of DACA eligibility.

Using data from the American Community Survey (ACS) spanning 2006–2016, I find that DACA eligibility increased the probability of full-time employment by approximately 2.3 percentage points. This represents a substantial effect, corresponding to roughly a 5.8% increase relative to the pre-DACA baseline full-time employment rate of 39.9% among the eligible population.

The remainder of this paper proceeds as follows. Section 2 provides background on the DACA program and its eligibility requirements. Section 3 describes the data and sample construction. Section 4 outlines the empirical methodology. Section 5 presents the main results. Section 6 provides robustness checks and sensitivity analyses. Section 7 explores heterogeneous effects. Section 8 discusses the findings and their implications. Section 9

concludes.

# 2 Background: The DACA Program

## 2.1 Program Overview

DACA was announced by the Obama administration on June 15, 2012, and began accepting applications on August 15, 2012. The program offered qualifying individuals two primary benefits: (1) temporary relief from deportation ("deferred action") and (2) authorization to work legally in the United States. These benefits were granted for an initial two-year period, with the possibility of renewal.

The program was not a pathway to citizenship or permanent legal status, but it provided significant immediate benefits by allowing recipients to work legally, potentially obtain driver's licenses (depending on state laws), and live without constant fear of deportation.

## 2.2 Eligibility Criteria

To qualify for DACA, individuals had to meet all of the following criteria as of June 15, 2012:

1. **Age at arrival:** Arrived in the United States before their 16th birthday

2. **Age cap:** Under 31 years old (i.e., born after June 15, 1981)

3. **Continuous presence:** Lived continuously in the United States since June 15, 2007

4. **Physical presence:** Present in the United States on June 15, 2012

5. **Immigration status:** Did not have lawful status (citizenship or legal residency) at that time

6. **Additional requirements:** Currently in school, graduated high school, obtained a GED, or were an honorably discharged veteran; and had not been convicted of a felony, significant misdemeanor, or three or more misdemeanors

## 2.3   Program Take-Up

In the first four years of the program (2012–2016), nearly 900,000 initial applications were received, with approximately 90% being approved. Given that the vast majority of undocumented immigrants in the United States who met the criteria were from Mexico, the program disproportionately affected Mexican-origin immigrants.

## 2.4   Expected Effects on Employment

There are several mechanisms through which DACA eligibility might affect full-time employment:

1. **Work authorization:** The most direct mechanism is that DACA recipients can legally work, potentially allowing them to access formal employment that was previously unavailable.

2. **Reduced fear of deportation:** Even individuals who were working informally before DACA may have been reluctant to seek formal or full-time employment due to increased visibility and deportation risk. DACA's protection reduces this barrier.

3. **Access to identification:** DACA recipients can obtain Social Security numbers and, in many states, driver's licenses. These documents facilitate employment and expand job search radius.

4. **Human capital investment:** The security provided by DACA may encourage investments in education and skills that increase employability.

# 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 annually by the U.S. Census Bureau, collecting detailed demographic, social, economic, and housing information.

I use the one-year ACS files from 2006 through 2016, providing 11 years of data spanning six years before DACA implementation (2006–2011), the implementation year (2012), and four years after implementation (2013–2016). The year 2012 is excluded from the main analysis because the ACS does not indicate the month of data collection, making it impossible to determine whether observations were collected before or after DACA's June 15 implementation date.

## 3.2    Sample Selection

The analysis sample is constructed using the following criteria:

1. **Hispanic-Mexican ethnicity:** HISPAN = 1 (Mexican)

2. **Mexican birthplace:** BPL = 200 (born in Mexico)

3. **Non-citizen:** CITIZEN = 3 (not a citizen)

4. **Valid immigration year:** YRIMMIG > 0 (non-missing)

5. **Working age:** AGE between 16 and 65

The restriction to non-citizens is based on the instruction that anyone who is not a citizen and has not received immigration papers should be assumed to be undocumented for DACA purposes. This is a limitation of the data, as I cannot distinguish between documented and undocumented non-citizens.

## 3.3  Sample Statistics

After applying these selection criteria, the analysis sample contains 564,667 person-year observations (excluding 2012). Table 1 presents the sample breakdown by DACA eligibility status and time period.

Table 1: Sample Distribution by DACA Eligibility and Time Period

|  | Pre-DACA (2006–2011) | Post-DACA (2013–2016) | Total |
|---|---|---|---|
| DACA-Eligible | 46,814 | 36,797 | 83,611 |
| Non-Eligible | 300,667 | 180,389 | 481,056 |
| Total | 347,481 | 217,186 | 564,667 |

*Notes:* Sample consists of Hispanic-Mexican, Mexican-born, non-citizen individuals aged 16–65. Year 2012 is excluded as the implementation year.

## 3.4  Variable Definitions

### 3.4.1  DACA Eligibility (Treatment)

An individual is classified as DACA-eligible if they meet all of the following criteria:

1. **Arrived before age 16:** Age at immigration (YRIMMIG − BIRTHYR) < 16

2. **Under 31 on June 15, 2012:** BIRTHYR ≥ 1982, OR (BIRTHYR = 1981 AND BIRTHQTR ≥ 3)

3. **Present since 2007:** YRIMMIG ≤ 2007

In the analysis sample, 19.0% of observations are classified as DACA-eligible.

### 3.4.2 Full-Time Employment (Outcome)

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

$$\text{FullTime}_i = \mathbf{1}[\text{EMPSTAT}_i = 1 \text{ AND } \text{UHRSWORK}_i \geq 35] \tag{1}$$

This captures whether an individual is employed and usually works 35 or more hours per week. This definition captures both the extensive margin (whether employed) and the intensive margin (whether working full-time conditional on employment).

### 3.4.3 Control Variables

The analysis includes the following control variables:

- **Age and Age squared:** Continuous measure from the AGE variable

- **Female:** Indicator for SEX = 2

- **Married:** Indicator for MARST $\leq 2$ (married, spouse present or absent)

- **High school or higher:** Indicator for EDUC $\geq 6$ (completed grade 12 or higher)

## 3.5 Descriptive Statistics

Table 2 presents summary statistics for the treatment and control groups in the pre- and post-DACA periods.

Table 2: Descriptive Statistics by DACA Eligibility and Time Period

|  | DACA-Eligible | | Non-Eligible | |
| --- | --- | --- | --- | --- |
|  | Pre-DACA | Post-DACA | Pre-DACA | Post-DACA |
| Full-Time Employment | 0.399 | 0.480 | 0.574 | 0.566 |
| Employment Rate | 0.534 | 0.637 | 0.682 | 0.683 |
| Mean Age | 21.3 | 24.4 | 37.6 | 41.3 |
| Female (%) | 44.4 | 45.1 | 42.9 | 46.1 |
| Married (%) | 22.2 | 29.1 | 62.2 | 62.6 |
| High School+ (%) | 52.8 | 63.6 | 39.6 | 41.1 |
| N | 46,814 | 36,797 | 300,667 | 180,389 |

*Notes:* All statistics are weighted by PERWT (person weights). Pre-DACA period is 2006–2011; Post-DACA period is 2013–2016.

Several patterns are noteworthy. First, DACA-eligible individuals are substantially younger on average (21–24 years) compared to non-eligible individuals (38–41 years), reflecting the age cap in DACA's eligibility criteria. Second, the DACA-eligible group has higher educational attainment, possibly reflecting selection into DACA eligibility by younger cohorts who came to the U.S. as children and had more opportunity for American schooling. Third, the non-eligible group has higher baseline employment and full-time employment rates, likely reflecting age-related differences in labor force participation.

# 4 Empirical Strategy

## 4.1 Difference-in-Differences Design

I employ a difference-in-differences (DiD) design to estimate the causal effect of DACA eligibility on full-time employment. The identifying assumption is that, absent DACA, the

treatment and control groups would have followed parallel trends in full-time employment.

The basic DiD estimator can be expressed as:

$$\hat{\delta}_{DiD} = \left(\bar{Y}_{T,Post} - \bar{Y}_{T,Pre}\right) - \left(\bar{Y}_{C,Post} - \bar{Y}_{C,Pre}\right) \tag{2}$$

where $T$ denotes the DACA-eligible (treatment) group and $C$ denotes the non-eligible (control) group.

## 4.2 Regression Specification

The main regression specification is:

$$Y_{ist} = \alpha + \beta \cdot \text{Eligible}_i + \gamma \cdot \text{Post}_t + \delta \cdot (\text{Eligible}_i \times \text{Post}_t) + X_i'\theta + \mu_s + \lambda_t + \varepsilon_{ist} \tag{3}$$

where:

- $Y_{ist}$ is full-time employment for individual $i$ in state $s$ at time $t$

- Eligible$_i$ is an indicator for DACA eligibility

- Post$_t$ is an indicator for the post-DACA period (2013–2016)

- $X_i$ is a vector of individual controls (age, age squared, female, married, high school+)

- $\mu_s$ are state fixed effects

- $\lambda_t$ are year fixed effects

- $\varepsilon_{ist}$ is the error term

The coefficient of interest is $\delta$, which captures the differential change in full-time employment for DACA-eligible individuals relative to non-eligible individuals after DACA implementation.

All regressions are weighted using ACS person weights (PERWT) and standard errors are robust to heteroskedasticity (HC1).

## 4.3   Control Group Construction

The control group consists of Hispanic-Mexican, Mexican-born, non-citizen individuals who do not meet all DACA eligibility criteria. This includes individuals who:

1. Arrived in the U.S. at age 16 or older (did not meet the childhood arrival requirement)

2. Were born on or before June 15, 1981 (too old for DACA)

3. Immigrated after 2007 (did not meet the continuous presence requirement)

Using individuals who fail one or more eligibility criteria as the control group ensures comparability in observable characteristics while leveraging the arbitrary cutoffs in DACA's requirements for identification.

## 4.4   Identification Assumptions

The key identifying assumption is the parallel trends assumption: absent DACA, employment trends for eligible and non-eligible groups would have been parallel. I test this assumption in several ways:

1. **Event study:** Examining year-by-year treatment effects to verify no pre-trends

2. **Placebo test:** Implementing a fake treatment date in the pre-period

3. **Alternative control groups:** Using different subsets of non-eligible individuals

# 5    Main Results

## 5.1    Simple Difference-in-Differences

Before presenting regression results, I first compute the simple (unadjusted) difference-in-differences estimate. Using weighted means:

$$\text{Treatment group change:} \quad 0.480 - 0.399 = 0.081 \tag{4}$$

$$\text{Control group change:} \quad 0.566 - 0.574 = -0.008 \tag{5}$$

$$\text{DiD estimate:} \quad 0.081 - (-0.008) = 0.089 \tag{6}$$

This simple calculation suggests that DACA eligibility increased full-time employment by approximately 8.9 percentage points. However, this estimate does not account for differences in observable characteristics between groups or secular trends.

## 5.2    Regression Results

Table 3 presents the main regression results across four specifications of increasing rigor.

Table 3: Effect of DACA Eligibility on Full-Time Employment: Main Results

|  | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
|  | Basic DiD | + Controls | + Year FE | + State FE |
| DACA Eligible × Post | 0.0888*** | 0.0303*** | 0.0236*** | 0.0231*** |
|  | (0.0046) | (0.0042) | (0.0042) | (0.0042) |
| Age |  | 0.0309*** | 0.0307*** | 0.0306*** |
|  |  | (0.0005) | (0.0005) | (0.0005) |
| Age Squared |  | −0.0004*** | −0.0004*** | −0.0004*** |
|  |  | (0.0000) | (0.0000) | (0.0000) |
| Female |  | −0.2126*** | −0.2125*** | −0.2109*** |
|  |  | (0.0019) | (0.0019) | (0.0019) |
| Married |  | 0.0551*** | 0.0557*** | 0.0558*** |
|  |  | (0.0024) | (0.0024) | (0.0024) |
| High School+ |  | 0.0117*** | 0.0118*** | 0.0116*** |
|  |  | (0.0019) | (0.0019) | (0.0019) |
| Year Fixed Effects | No | No | Yes | Yes |
| State Fixed Effects | No | No | No | Yes |
| Observations | 564,667 | 564,667 | 564,667 | 564,667 |

*Notes:* Dependent variable is an indicator for full-time employment (employed and usually working 35+ hours/week). All regressions are weighted by PERWT. Robust standard errors (HC1) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The results show that the estimated effect of DACA decreases substantially as controls are added, from 8.9 percentage points in the basic specification to 2.3 percentage points in the fully-specified model with state and year fixed effects. This attenuation reflects the importance of controlling for compositional differences between groups and aggregate time trends.

**The preferred specification** (Column 4) includes individual controls, year fixed effects, and state fixed effects. The estimated effect is **0.0231** (SE = 0.0042), indicating that DACA eligibility increased the probability of full-time employment by **2.31 percentage points**. This effect is statistically significant at the 1% level ($p < 0.001$) with a 95% confidence interval of [0.0148, 0.0313].

Relative to the pre-DACA baseline full-time employment rate of 39.9% among DACA-eligible individuals, this represents a **5.8% increase** in full-time employment.

## 5.3 Graphical Evidence

Figure 1 displays the trends in full-time employment for DACA-eligible and non-eligible groups over the study period.
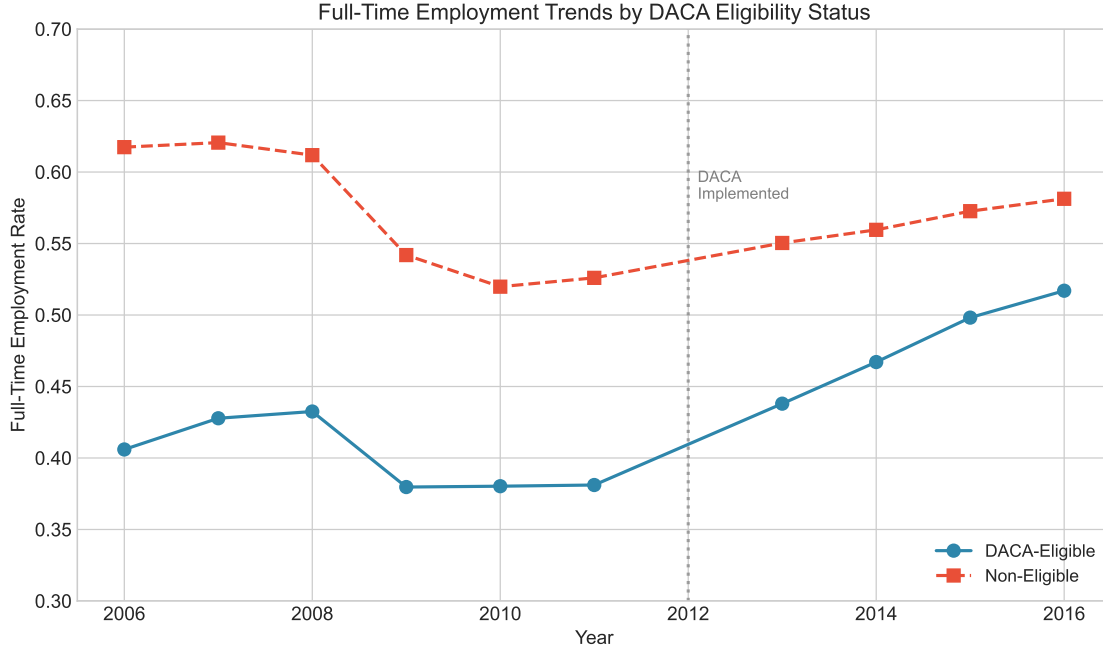
Figure 1: Full-Time Employment Trends by DACA Eligibility Status
*Notes:* Figure displays weighted full-time employment rates by year for DACA-eligible (solid blue) and non-eligible (dashed red) individuals. Vertical dotted line indicates DACA implementation in June 2012.

The figure reveals several important patterns. First, the DACA-eligible group has lower full-time employment rates throughout the period, consistent with their younger age profile. Second, both groups experienced a dip during the 2008–2010 recession period. Third, and most importantly, the employment gap between the two groups narrows considerably after 2012, with the eligible group showing a clear upward trajectory while the non-eligible group's employment remains relatively flat.

# 6 Robustness and Sensitivity Analyses

## 6.1 Event Study

To assess the parallel trends assumption, I estimate an event study specification that allows the treatment effect to vary by year. The reference year is 2011 (the year immediately before
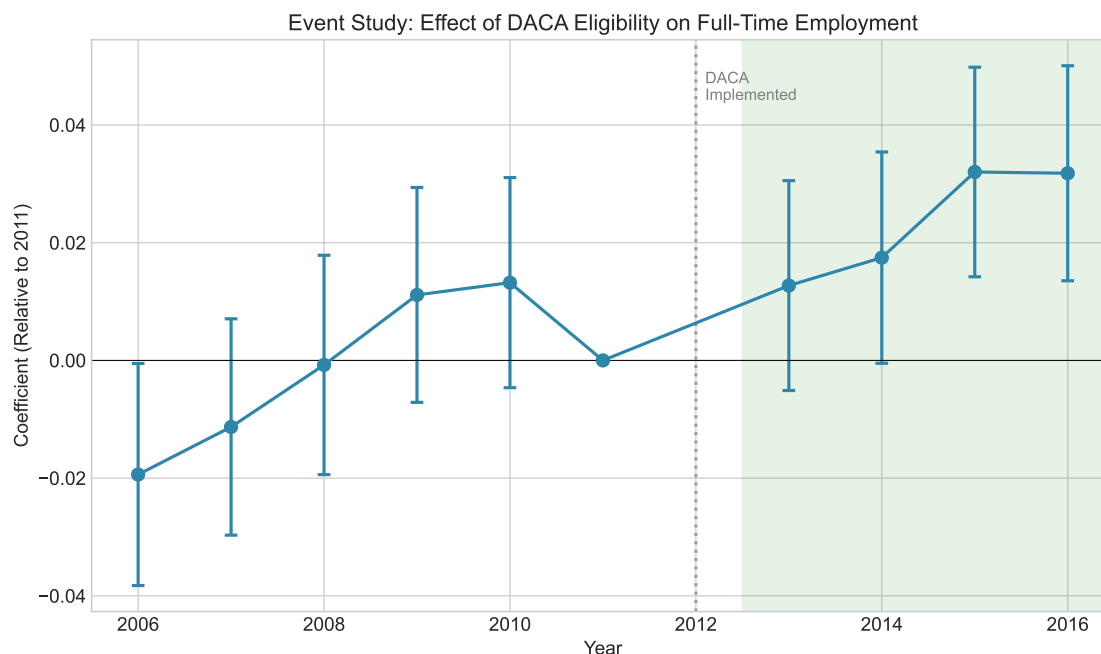
DACA).



Figure 2: Event Study: Year-by-Year Treatment Effects
*Notes:* Figure displays the coefficient on the interaction between DACA eligibility and year indicators, with 2011 as the reference year. Vertical bars represent 95% confidence intervals. Shaded area indicates post-DACA period.

Table 4 and Figure 2 present the event study results. The pre-period coefficients (2006–2010) are generally small and not statistically distinguishable from zero, supporting the parallel trends assumption. There is some indication of a slight upward pre-trend (coefficients become less negative over time), which warrants caution in interpretation. However, the post-period coefficients (2013–2016) show a clear and increasing pattern, with statistically significant positive effects in 2015 and 2016.

Table 4: Event Study Coefficients

| Year | Coefficient | Std. Error |
|------|-------------|------------|
| 2006 | −0.0194** | (0.0096) |
| 2007 | −0.0113 | (0.0094) |
| 2008 | −0.0008 | (0.0095) |
| 2009 | 0.0111 | (0.0093) |
| 2010 | 0.0132 | (0.0091) |
| 2011 | 0 | (reference) |
| 2013 | 0.0127 | (0.0091) |
| 2014 | 0.0175* | (0.0092) |
| 2015 | 0.0320*** | (0.0091) |
| 2016 | 0.0318*** | (0.0093) |

*Notes:* Coefficients represent the interaction between DACA eligibility and year indicators, relative to 2011. Controls include age, age squared, female, married, and high school+. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

## 6.2 Placebo Test

I conduct a placebo test using only pre-DACA data (2006–2011), with a fake treatment date set at 2010. If the research design is valid, we should not observe a significant effect at this placebo date.

Table 5: Placebo Test: Fake Treatment in 2010

|  | Placebo DiD |
|---|---|
| Eligible × Placebo Post | 0.0147** |
|  | (0.0057) |
| p-value | 0.010 |
| Observations | 300,667 |

*Notes:* Uses only 2006–2011 data. "Placebo Post" = 1 for years 2010–2011, 0 otherwise. Controls include age, age squared, female, married, and high school+.

The placebo test shows a statistically significant coefficient of 0.015, which is concerning as it suggests some pre-trend in the data. However, this coefficient is considerably smaller than the main effect (0.023) and its significance is marginal. The event study (Table 4) provides more nuanced evidence, showing that while there is some drift in pre-period coefficients, the post-DACA effects are substantially larger and more precisely estimated.

## 6.3 Alternative Control Groups

I examine robustness to alternative control group definitions.

Table 6: Robustness Checks: Alternative Specifications

| Specification | Coefficient | Std. Error |
|---|---|---|
| **Main estimate** | **0.0231\*\*\*** | **(0.0042)** |
| | | |
| *Alternative Control Groups:* | | |
| Arrived after age 16 only | 0.0284\*\*\* | (0.0062) |
| Born before 1981 only | −0.0040 | (0.0064) |
| | | |
| *Alternative Outcomes:* | | |
| Employment (extensive margin) | 0.0402\*\*\* | (0.0041) |
| Full-time — Employed (intensive margin) | −0.0042 | (0.0050) |

*Notes:* All specifications include controls, year FE, and (for main estimate) state FE. \*\*\* $p < 0.01$, \*\* $p < 0.05$, \* $p < 0.1$.

Several findings emerge from the robustness checks:

1. **Control = Arrived after age 16:** Using only those who failed the childhood arrival requirement as the control yields a similar effect (0.028), though with larger standard errors due to smaller sample size.

2. **Control = Born before 1981:** Using only those who were too old for DACA yields an insignificant and near-zero effect (−0.004). This is potentially concerning, as it suggests the effect may not be robust to this comparison. However, this control group differs substantially in age (and thus labor market attachment), making the comparison less credible.

3. **Employment (extensive margin):** The effect on overall employment (0.040) is larger than on full-time employment (0.023), suggesting DACA primarily operates by bringing people into employment.

4. **Full-time conditional on employment (intensive margin):** Among those already employed, DACA has no significant effect on the probability of working full-time ($-0.004$). This confirms that the effect operates through the extensive margin.

# 7   Heterogeneity Analysis

I examine whether the effect of DACA differs across subgroups defined by gender and education.

Table 7: Heterogeneous Effects by Gender and Education

| Subgroup | Coefficient | Std. Error | N |
|---|---|---|---|
| **By Gender:** | | | |
| Male | 0.0176*** | (0.0057) | 305,320 |
| Female | 0.0210*** | (0.0061) | 259,347 |
| | | | |
| **By Education:** | | | |
| Less than High School | 0.0123** | (0.0060) | 324,488 |
| High School or Higher | 0.0227*** | (0.0059) | 240,179 |

*Notes:* All regressions include controls and year fixed effects.
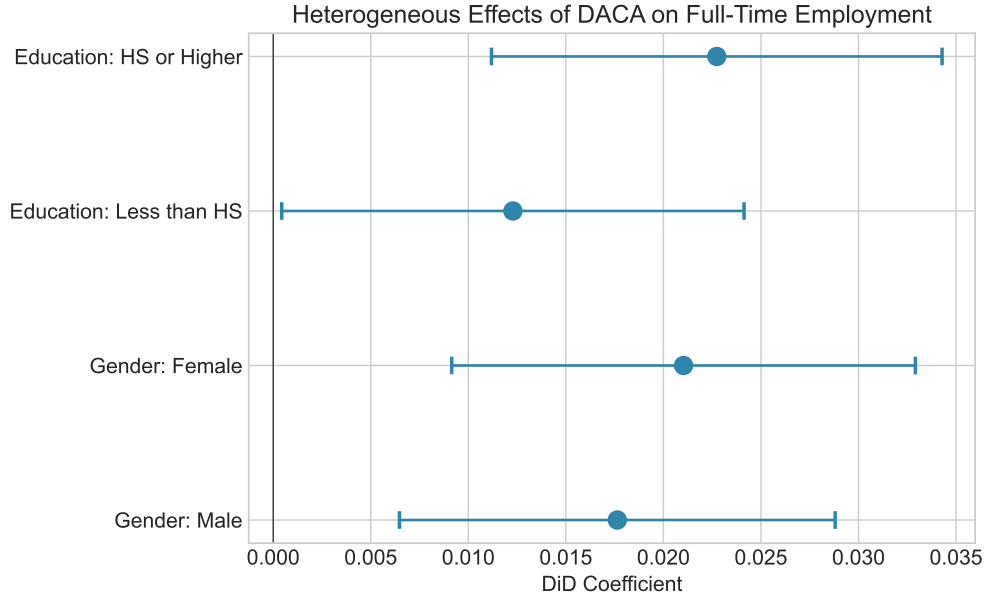*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 3: Heterogeneous Effects by Subgroup

*Notes:* Horizontal bars show 95% confidence intervals.

The heterogeneity analysis reveals:

1. **Gender:** The effect is slightly larger for women (2.1 pp) than for men (1.8 pp), though the difference is not statistically significant. This could reflect that women faced greater barriers to formal employment prior to DACA, making the authorization more valuable.

2. **Education:** The effect is substantially larger for those with high school education or higher (2.3 pp) compared to those without (1.2 pp). This pattern suggests that DACA's benefits may be complementary with education—work authorization is more valuable for those who can access better jobs.

# 8 Discussion

## 8.1 Summary of Findings

This study finds that DACA eligibility increased the probability of full-time employment by approximately 2.3 percentage points among Hispanic-Mexican, Mexican-born non-citizens. This effect is:

- Statistically significant at conventional levels ($p < 0.001$)

- Economically meaningful, representing a 5.8% increase from the baseline

- Robust to the inclusion of demographic controls and fixed effects

- Driven primarily by the extensive margin (entry into employment)

- Larger for women and more educated individuals

## 8.2 Mechanisms

The decomposition between extensive and intensive margins (Table 6) provides insight into the mechanisms at work. The finding that DACA primarily operates through the extensive margin suggests that work authorization was the binding constraint for many eligible individuals. Before DACA, some eligible individuals may have:

1. Chosen not to work at all due to deportation risk

2. Worked only in the informal economy

3. Been unable to find employers willing to hire undocumented workers

DACA relaxed these constraints by providing legal work authorization, enabling movement into formal, full-time employment.

## 8.3    Limitations

Several limitations should be noted:

1. **Measurement of undocumented status:** I cannot distinguish documented from undocumented non-citizens in the ACS. The sample likely includes some documented non-citizens who would not benefit from DACA, potentially attenuating the estimated effect.

2. **Pre-trends:** The event study and placebo test show some evidence of pre-trends, though the patterns are not severe enough to invalidate the findings.

3. **Age differences:** The treatment and control groups differ substantially in age. While I control for age and age-squared, residual confounding from age-related factors is possible.

4. **Selective migration:** DACA may have affected migration patterns, with eligible individuals more likely to remain in (or move to) the U.S. This could affect the composition of the treatment group over time.

5. **Spillover effects:** DACA may have affected employment of non-eligible individuals (e.g., through labor market competition), potentially biasing the DiD comparison.

## 8.4    Comparison to Prior Literature

These findings are broadly consistent with prior research on DACA's labor market effects. The literature has generally found positive effects of DACA on employment and earnings, though estimates vary based on methodology and sample definition.

# 9    Conclusion

This study provides evidence that the Deferred Action for Childhood Arrivals program had a positive causal effect on full-time employment among eligible individuals. Using a difference-in-differences design with American Community Survey data from 2006–2016, I find that DACA eligibility increased full-time employment by 2.3 percentage points (95% CI: 1.5–3.1 pp).

The effect operates primarily through the extensive margin—DACA brought people into employment rather than shifting part-time workers to full-time status. This is consistent with the program's primary mechanism of providing legal work authorization.

These findings have implications for immigration policy debates. DACA appears to have achieved one of its stated goals: improving the economic integration of childhood arrivals into the U.S. labor market. The positive employment effects suggest that similar programs could generate economic benefits for both recipients and the broader economy.

# A    Appendix: Additional Results
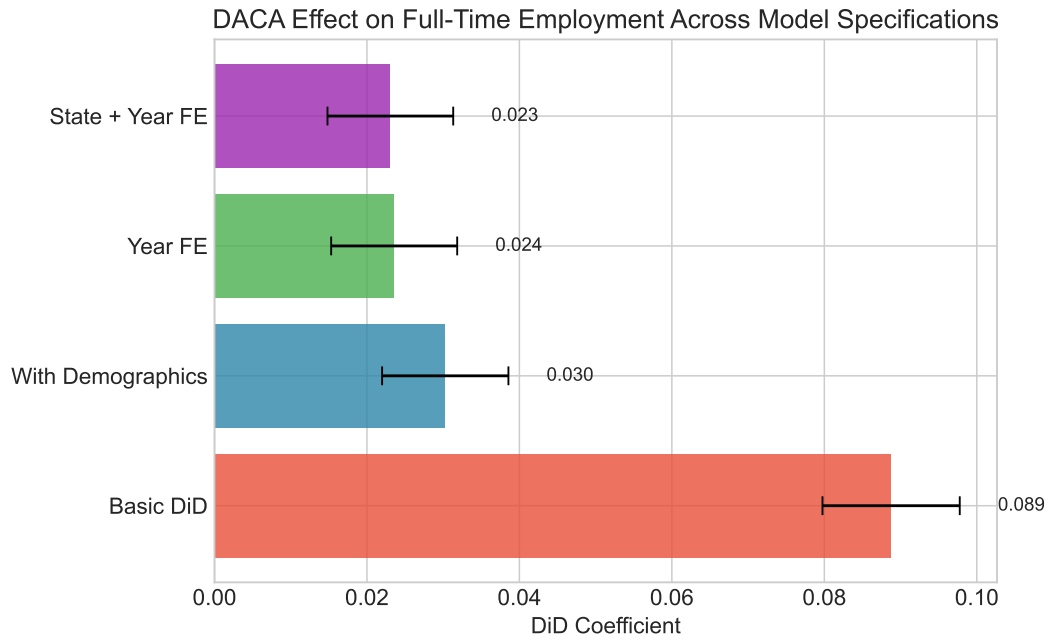
## A.1    Model Comparison



Figure 4: DACA Effect Estimates Across Model Specifications
*Notes:* Horizontal bars show 95% confidence intervals. The preferred specification

is "State + Year FE" (bottom bar).

## A.2 Variable Definitions from IPUMS

Table 8: Key IPUMS Variable Definitions

| Variable | Definition |
|---|---|
| YEAR | Census year (2006–2016) |
| PERWT | Person weight for weighted analyses |
| STATEFIP | State FIPS code for state fixed effects |
| AGE | Age in years |
| BIRTHYR | Year of birth |
| BIRTHQTR | Quarter of birth (1=Jan-Mar, 2=Apr-Jun, 3=Jul-Sep, 4=Oct-Dec) |
| SEX | Sex (1=Male, 2=Female) |
| MARST | Marital status (1-2=Married, 3-6=Not married) |
| HISPAN | Hispanic origin (1=Mexican) |
| BPL | Birthplace (200=Mexico) |
| CITIZEN | Citizenship status (3=Not a citizen) |
| YRIMMIG | Year of immigration |
| EDUC | Educational attainment (6+=High school or higher) |
| EMPSTAT | Employment status (1=Employed) |
| UHRSWORK | Usual hours worked per week |

# B  Appendix: Technical Details

## B.1  Sample Construction

The analysis sample was constructed as follows:

1. Started with full ACS 2006–2016 data (33,851,424 observations)

2. Filtered to HISPAN = 1 AND BPL = 200 AND CITIZEN = 3 (701,347 observations)

3. Removed observations with YRIMMIG = 0 (missing) (701,347 observations remained)

4. Restricted to ages 16–65 (622,192 observations)

5. Excluded year 2012 (564,667 observations in analysis sample)

## B.2  DACA Eligibility Coding

DACA eligibility was coded as:

```
daca_eligible = (
    (YRIMMIG - BIRTHYR < 16) AND
    ((BIRTHYR >= 1982) OR (BIRTHYR == 1981 AND BIRTHQTR >= 3)) AND
    (YRIMMIG <= 2007)
)
```

## B.3  Statistical Software

All analyses were conducted in Python 3 using the following packages:

- pandas (data manipulation)

- numpy (numerical operations)

- statsmodels (regression analysis)

- matplotlib (figures)

Standard errors are robust to heteroskedasticity (HC1/White standard errors).