

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

## A Difference-in-Differences Analysis

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, Mexican-born individuals in the United States. Using American Community Survey data from 2006–2016 and a difference-in-differences identification strategy, I compare individuals aged 26–30 on June 15, 2012 (who were eligible for DACA) to those aged 31–35 (who were ineligible due to the age cutoff). The preferred specification, which includes state and year fixed effects along with demographic controls, estimates that DACA eligibility increased the probability of full-time employment by approximately 4.3 percentage points ( $SE = 0.011$ , 95% CI: [0.022, 0.064]). This effect is statistically significant at the 1% level. Robustness checks including pre-trend tests, placebo analyses, and heterogeneity analyses by gender support the validity of the findings.

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

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# 1 Introduction

The Deferred Action for Childhood Arrivals (DACA) program, implemented on June 15, 2012, represents one of the most significant immigration policy changes in recent U.S. history. The program provided temporary relief from deportation and work authorization for eligible undocumented immigrants who arrived in the United States as children. Given that DACA grants recipients legal authorization to work, an important policy question is whether and to what extent DACA eligibility affected employment outcomes among the eligible population.

This study investigates the causal effect of DACA eligibility on full-time employment among Hispanic-Mexican, Mexican-born non-citizens residing in the United States. The research design exploits the age-based eligibility cutoff: individuals had to be under 31 years old as of June 15, 2012, to qualify for the program. This creates a natural comparison between those who were just young enough to be eligible (the treatment group, aged 26–30) and those who were just too old (the control group, aged 31–35). By comparing changes in full-time employment rates between these groups before and after DACA implementation, I can estimate the causal effect of eligibility on employment outcomes.

The analysis uses data from the American Community Survey (ACS), a large nationally representative survey that provides detailed information on employment status, hours worked, demographic characteristics, and immigration-related variables. The sample is restricted to Hispanic-Mexican individuals born in Mexico who are non-citizens and who arrived in the United States before age 16—key criteria for DACA eligibility.

The main finding is that DACA eligibility is associated with an increase of approximately 4.3 percentage points in the probability of full-time employment. This effect is robust to the inclusion of various controls and fixed effects, and several specification checks support the validity of the parallel trends assumption underlying the difference-in-differences design.

## **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 allows eligible individuals to apply for a two-year renewable period of deferred action (protection from deportation) and eligibility for work authorization. To qualify, applicants must meet several criteria:

1. Were under age 31 as of June 15, 2012
2. Came to the United States before their 16th birthday
3. Have continuously resided in the United States since June 15, 2007
4. Were physically present in the United States on June 15, 2012
5. Had no lawful status on June 15, 2012
6. Are currently in school, have graduated from high school, have obtained a GED, or are honorably discharged veterans
7. Have not been convicted of a felony, significant misdemeanor, or three or more other misdemeanors

In the first four years of the program, nearly 900,000 initial applications were received, with approximately 90% approved. While the program is not specific to any nationality, the vast majority of DACA recipients are from Mexico due to the structure of undocumented immigration to the United States.

### **2.2 Theoretical Framework**

DACA could affect employment outcomes through several mechanisms. First, and most directly, DACA provides work authorization, allowing recipients to legally work in the United

States. Before DACA, undocumented individuals often worked in the informal sector with limited job opportunities. Work authorization expands the set of available jobs to include positions in the formal sector that require legal work status.

Second, DACA recipients can obtain state-issued identification, including driver's licenses in many states. This facilitates job search and can expand employment opportunities, particularly in areas with limited public transportation.

Third, protection from deportation may encourage greater labor market participation by reducing the risks associated with formal employment. Undocumented workers may have previously avoided visible employment due to fears of detection and deportation.

Fourth, DACA may affect human capital investments. While the education requirement ensures a baseline level of educational attainment, the prospect of legal work authorization may encourage recipients to pursue additional education or training, potentially improving their employment prospects.

These mechanisms suggest that DACA eligibility should increase employment rates among the eligible population, particularly full-time formal employment.

## 3 Data and Sample Construction

### 3.1 Data Source

The analysis uses data from the American Community Survey (ACS) provided by IPUMS USA. The ACS is an ongoing survey conducted by the U.S. Census Bureau that samples approximately 3.5 million households annually. The survey collects detailed information on demographic characteristics, employment status, income, education, and immigration-related variables.

I use ACS one-year samples from 2006 through 2016. The year 2012 is excluded from the analysis because DACA was implemented in the middle of that year (June 15, 2012), making it impossible to distinguish between pre- and post-treatment observations within

that year. This leaves six pre-treatment years (2006–2011) and four post-treatment years (2013–2016).

### 3.2 Sample Restrictions

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

1. **Hispanic-Mexican ethnicity:** Individuals must be of Hispanic-Mexican ethnicity ( $HISPAN = 1$ ). This captures the population most affected by DACA, as the majority of recipients are of Mexican origin.
2. **Born in Mexico:** Individuals must have been born in Mexico ( $BPL = 200$ ). Combined with the ethnicity restriction, this identifies Mexican immigrants.
3. **Non-citizen status:** Individuals must be non-citizens who have not received immigration papers ( $CITIZEN = 3$ ). This serves as a proxy for undocumented status, as the ACS does not directly identify documentation status.
4. **Arrived before age 16:** Individuals must have immigrated to the United States before their 16th birthday. This is calculated as  $YRIMMIG - BIRTHYR < 16$ .
5. **Continuous residence:** Individuals must have been in the United States since at least 2007, the requirement for continuous residence ( $YRIMMIG \leq 2007$ ).
6. **Age groups:** The treatment group consists of individuals aged 26–30 on June 15, 2012, and the control group consists of individuals aged 31–35 on the same date. Age is calculated using birth year and birth quarter to account for whether the individual's birthday had occurred by June 15.

### 3.3 Variable Definitions

#### 3.3.1 Outcome Variable

The primary outcome variable is **full-time employment**, defined as usually working 35 or more hours per week. This is measured using the UHRSWORK variable, which records the respondent's usual hours worked per week. The outcome is coded as a binary indicator:

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

I also examine employment (any) as an alternative outcome, defined as EMPSTAT = 1 (employed).

#### 3.3.2 Treatment Variables

The treatment indicator equals one for individuals in the treatment group (ages 26–30 on June 15, 2012) and zero for those in the control group (ages 31–35):

$$\text{Treated}_i = \mathbf{1}[\text{Age on June 15, 2012} \in \{26, 27, 28, 29, 30\}]$$

The post-treatment indicator equals one for observations from 2013–2016:

$$\text{Post}_t = \mathbf{1}[\text{Year} \geq 2013]$$

The key variable of interest is the interaction  $\text{Treated}_i \times \text{Post}_t$ .

#### 3.3.3 Control Variables

The analysis includes several control variables to improve precision and account for compositional differences between treatment and control groups:

- **Female:** Binary indicator for female gender ( $\text{SEX} = 2$ )
- **Married:** Binary indicator for married status ( $\text{MARST} \leq 2$ )
- **Education:** Categorical variables for education level:
  - Less than high school ( $\text{EDUC} < 6$ )
  - High school graduate ( $\text{EDUC} = 6$  or  $7$ )
  - Some college ( $\text{EDUC} = 8$  or  $9$ )
  - College or more ( $\text{EDUC} \geq 10$ )
- **Years in US:** Years since immigration ( $\text{YEAR} - \text{YRIMMIG}$ )
- **Metro:** Binary indicator for metropolitan residence ( $\text{METRO} \geq 2$ )

### 3.4 Final Sample

After applying all restrictions, the final sample contains **43,238** observations:

- Treatment group (ages 26–30): 25,470 observations
- Control group (ages 31–35): 17,768 observations
- Pre-period (2006–2011): 28,377 observations
- Post-period (2013–2016): 14,861 observations

## 4 Empirical Strategy

### 4.1 Difference-in-Differences Design

The identification strategy exploits the age-based eligibility cutoff for DACA. Individuals who were 30 years old or younger on June 15, 2012, were eligible for the program, while

those who were 31 or older were not. By comparing employment outcomes between these groups before and after DACA implementation, I can estimate the causal effect of DACA eligibility.

The basic difference-in-differences (DiD) estimator is:

$$\hat{\delta}_{DiD} = (\bar{Y}_{T,post} - \bar{Y}_{T,pre}) - (\bar{Y}_{C,post} - \bar{Y}_{C,pre}) \quad (1)$$

where  $\bar{Y}_{g,t}$  denotes the mean outcome for group  $g \in \{T, C\}$  (treatment, control) in period  $t \in \{pre, post\}$ .

This estimator provides an unbiased estimate of the treatment effect under the assumption that, in the absence of DACA, the treatment and control groups would have followed parallel trends in employment.

## 4.2 Regression Specification

The regression-based DiD specification allows for the inclusion of controls and fixed effects:

$$Y_{ist} = \alpha + \beta \cdot \text{Treated}_i + \gamma \cdot \text{Post}_t + \delta \cdot (\text{Treated}_i \times \text{Post}_t) + X'_{ist}\theta + \mu_s + \lambda_t + \varepsilon_{ist} \quad (2)$$

where:

- $Y_{ist}$  is the outcome for individual  $i$  in state  $s$  and year  $t$
- $\text{Treated}_i$  is the treatment group indicator
- $\text{Post}_t$  is the post-treatment period indicator
- $X_{ist}$  is a vector of individual-level controls
- $\mu_s$  are state fixed effects
- $\lambda_t$  are year fixed effects

- $\delta$  is the coefficient of interest—the DiD estimate

The coefficient  $\delta$  captures the differential change in the outcome for the treatment group relative to the control group after DACA implementation.

### 4.3 Estimation

All regressions are estimated using weighted least squares (WLS) with person weights (PERWT) to make the estimates representative of the population. Standard errors are robust to heteroskedasticity (HC1).

I estimate four specifications of increasing stringency:

1. Basic DiD without controls
2. DiD with year fixed effects
3. DiD with year fixed effects and individual controls
4. DiD with year and state fixed effects and individual controls (preferred specification)

### 4.4 Identification Assumptions

The key assumption for causal identification is the **parallel trends assumption**: in the absence of DACA, employment trends would have been similar for the treatment and control groups. This assumption is fundamentally untestable, but I provide evidence supporting its plausibility:

1. **Pre-trend test**: I test whether there were differential trends in employment between the treatment and control groups during the pre-treatment period.
2. **Placebo test**: I conduct a placebo analysis using only pre-treatment data, assigning a “fake” treatment date of 2009.

3. **Event study:** I estimate year-specific treatment effects to examine whether effects appear only after DACA implementation.

## 5 Results

### 5.1 Summary Statistics

Table 1 presents summary statistics for the treatment and control groups in the pre-period. The groups are similar along many dimensions, though the control group is mechanically older and has more years in the United States. The treatment group has a slightly lower rate of full-time employment in the pre-period (63.1% vs. 67.3%), is less likely to be married (37.7% vs. 51.8%), and has slightly more education at the high school level.

Table 1: Summary Statistics by Treatment Group (Pre-Period)

Variable	Treatment (26–30)	Control (31–35)	Difference
Full-time employment	0.631	0.673	-0.043
Employed (any)	0.753	0.788	-0.035
Female	0.434	0.414	0.020
Married	0.377	0.518	-0.141
Less than high school	0.387	0.471	-0.084
High school graduate	0.557	0.474	0.083
Some college	0.030	0.026	0.004
College or more	0.026	0.029	-0.002
Years in US	15.37	19.84	-4.47
Arrival age	9.39	9.95	-0.55
Metropolitan area	0.889	0.902	-0.013
N	16,694	11,683	—

Notes: Sample restricted to pre-period (2006–2011). All statistics are weighted using person weights. Treatment group includes individuals aged 26–30 on June 15, 2012; control group includes those aged 31–35.

## 5.2 Main Results

Table 2 presents the main difference-in-differences results. The simple DiD estimate (Model 1) shows that DACA eligibility increased full-time employment by 5.9 percentage points. This estimate remains similar when adding year fixed effects (Model 2: 5.7 percentage points).

When individual-level controls are added (Model 3), the estimate decreases to 4.4 percentage points, suggesting that some of the raw difference is attributable to compositional differences between groups. The preferred specification (Model 4), which includes both state

and year fixed effects along with controls, yields an estimate of **4.3 percentage points** (SE = 0.011).

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

	(1)	(2)	(3)	(4)
	Basic DiD	Year FE	+ Controls	+ State FE
Treated × Post	0.059*** (0.012)	0.057*** (0.012)	0.044*** (0.011)	0.043*** (0.011)
95% CI	[0.036, 0.082]	[0.035, 0.080]	[0.023, 0.065]	[0.022, 0.064]
Year FE	No	Yes	Yes	Yes
State FE	No	No	No	Yes
Controls	No	No	Yes	Yes
N	43,238	43,238	43,238	43,238
R <sup>2</sup>	0.006	0.011	0.144	0.161

Notes: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Robust standard errors in parentheses.

All regressions weighted using person weights. Controls include female, married, education categories (high school, some college, college+), and years in US. The dependent variable is a binary indicator for full-time employment (working 35+ hours per week).

The preferred estimate implies that DACA eligibility increased the probability of full-time employment by 4.3 percentage points. Relative to the pre-period mean for the treatment group (63.1%), this represents a 6.9% increase in full-time employment.

### 5.3 Simple Difference-in-Differences Calculation

The mechanics of the DiD estimate can be illustrated with the group means:

Table 3: Difference-in-Differences Calculation

	Pre (2006–2011)	Post (2013–2016)	Change
Treatment (26–30)	0.631	0.660	+0.029
Control (31–35)	0.673	0.643	-0.030
Difference	-0.043	+0.017	<b>+0.059</b>

The treatment group's full-time employment rate increased by 2.9 percentage points from the pre- to post-period, while the control group's rate decreased by 3.0 percentage points. The DiD estimate of 5.9 percentage points reflects the differential change between groups.

### 5.4 Robustness Checks

#### 5.4.1 Pre-Trend Test

A key assumption of the DiD design is that the treatment and control groups would have followed parallel trends in the absence of treatment. I test this by estimating differential trends during the pre-treatment period:

$$Y_{it} = \alpha + \beta_1 \cdot \text{Treated}_i + \beta_2 \cdot \text{Year}_t + \beta_3 \cdot (\text{Treated}_i \times \text{Year}_t) + \varepsilon_{it}$$

The coefficient on the interaction term ( $\beta_3 = 0.0026$ , SE = 0.004,  $p = 0.528$ ) is small and statistically insignificant, providing no evidence of differential pre-trends. This supports the parallel trends assumption.

### 5.4.2 Placebo Test

As an additional check, I conduct a placebo test using only pre-treatment data (2006–2011) and assigning a “fake” treatment date of 2009. If the DiD design is valid, we should not observe significant effects at this placebo date.

The placebo DiD estimate is 0.006 (SE = 0.014,  $p = 0.668$ ), which is small, statistically insignificant, and close to zero. This provides further support for the identification strategy.

### 5.4.3 Alternative Outcome: Any Employment

As a robustness check, I examine any employment (rather than full-time employment) as an alternative outcome. The DiD estimate for employment is 4.0 percentage points (SE = 0.010,  $p < 0.001$ ), similar to the full-time employment result. This suggests that DACA not only increased full-time employment but also overall employment.

### 5.4.4 Heterogeneity by Gender

Table 4 presents results separately by gender. Both males and females show positive and statistically significant effects, though the point estimate is larger for females (4.9 percentage points) than for males (3.3 percentage points). However, the confidence intervals overlap, so we cannot conclude that the effect differs significantly by gender.

Table 4: Heterogeneity by Gender

	Males	Females
Treated $\times$ Post	0.033*** (0.012)	0.049*** (0.018)
<i>p</i> -value	0.007	0.007
N	24,590	18,648

Notes: \*\*\*  $p < 0.01$ . Robust standard errors in parentheses. Models include year fixed effects and controls (married, education, years in US).

## 5.5 Event Study Analysis

Figure ?? presents year-specific treatment effects from an event study specification, using 2011 as the reference year. This analysis allows us to examine (1) whether pre-treatment effects are close to zero (supporting parallel trends) and (2) how the treatment effect evolves over time after DACA implementation.

The pre-treatment coefficients (2006–2010) are all small and statistically insignificant, fluctuating around zero. This provides strong visual evidence in support of the parallel trends assumption. The post-treatment coefficients are generally positive, with the effect becoming larger and statistically significant by 2016.

Table 5: Event Study: Year-Specific Treatment Effects

Year	Coefficient	SE	95% CI	<i>p</i> -value
<i>Pre-Treatment Period</i>				
2006	0.007	0.023	[−0.038, 0.051]	0.767
2007	−0.032	0.022	[−0.076, 0.012]	0.150
2008	0.007	0.023	[−0.037, 0.052]	0.744
2009	−0.009	0.023	[−0.055, 0.037]	0.694
2010	−0.014	0.023	[−0.059, 0.032]	0.552
<i>Reference Year: 2011</i>				
<i>Post-Treatment Period</i>				
2013	0.034	0.024	[−0.014, 0.081]	0.166
2014	0.034	0.025	[−0.014, 0.083]	0.164
2015	0.019	0.025	[−0.029, 0.068]	0.432
2016	0.063**	0.025	[0.015, 0.112]	0.010

Notes: \*\*  $p < 0.05$ . Coefficients represent the differential effect for the treatment group relative to the control group in each year, compared to the reference year (2011). Model includes year fixed effects and controls.

The pattern in the event study is consistent with a causal interpretation: no effects before DACA implementation, followed by positive effects afterward that grow over time. The delayed and increasing effect may reflect the gradual uptake of DACA—applications began in August 2012, and processing took several months, so the full effects would not be immediate.

## 6 Discussion

### 6.1 Interpretation of Results

The main finding is that DACA eligibility increased full-time employment by approximately 4.3 percentage points among Hispanic-Mexican, Mexican-born non-citizens who met the other eligibility criteria. This represents a meaningful effect—a 6.9% increase relative to the pre-period baseline.

Several factors support a causal interpretation of this estimate:

1. **Parallel trends:** Pre-trend tests show no evidence of differential trends before DACA implementation.
2. **Placebo test:** The placebo analysis using a fake treatment date finds no effect, as expected under the null.
3. **Event study:** Year-specific effects are close to zero before treatment and positive afterward.
4. **Robustness:** The estimate is stable across specifications with different controls and fixed effects.

The mechanisms behind this effect likely include:

- **Work authorization:** DACA provides legal authorization to work, allowing recipients to take formal sector jobs that were previously inaccessible.
- **Documentation:** Access to state IDs and driver's licenses facilitates job search and expands employment opportunities.
- **Reduced deportation risk:** Protection from deportation may encourage greater labor force participation.

## 6.2 Comparison with Prior Literature

The estimated effect size of 4.3 percentage points is within the range of estimates found in prior studies of DACA's labor market effects. The literature generally finds positive effects of DACA on employment, labor force participation, and earnings, though effect sizes vary depending on the sample, outcome, and identification strategy.

## 6.3 Limitations

Several limitations should be noted:

1. **Proxy for undocumented status:** The ACS does not directly identify documentation status. The sample is restricted to non-citizens, which includes some legal residents who have not yet naturalized. This measurement error may attenuate the estimated effect.
2. **Sample selection:** The control group (ages 31–35) differs from the treatment group in systematic ways, including being older and having spent more time in the US. While controls account for observable differences, unobserved differences may remain.
3. **Age effects:** Both groups are aging over the study period. If employment trajectories differ by age in ways not captured by the parallel trends assumption, this could bias estimates.
4. **Eligibility vs. receipt:** The analysis estimates the effect of eligibility, not actual DACA receipt. Since not all eligible individuals applied for or received DACA, the effect of actually receiving DACA would be larger than the estimated intent-to-treat effect.

## 7 Conclusion

This study examines the effect of DACA eligibility on full-time employment using a difference-in-differences design. The main finding is that DACA eligibility increased the probability of full-time employment by approximately 4.3 percentage points (95% CI: [0.022, 0.064]) among Hispanic-Mexican, Mexican-born non-citizens who arrived in the US before age 16.

The results are robust to various specification checks and support a causal interpretation. Pre-trend tests, placebo analyses, and event study evidence all support the validity of the parallel trends assumption. The effects are present for both men and women.

These findings have important policy implications. DACA appears to have achieved one of its primary goals—increasing formal labor market attachment among the eligible population. The positive employment effects suggest that providing work authorization and protection from deportation can meaningfully improve economic outcomes for undocumented immigrants.

Future research could examine longer-term effects of DACA, effects on other outcomes (wages, occupation, industry), and heterogeneity across subgroups. Understanding the mechanisms behind employment gains—whether through work authorization, documentation, or reduced deportation risk—remains an important area for investigation.

## 8 Technical Appendix

### 8.1 Variable Codes from IPUMS

Table 6: IPUMS Variable Codes Used in Analysis

Variable	Code	Description
YEAR	—	Survey year
PERWT	—	Person weight
BIRTHYR	—	Year of birth
BIRTHQTR	1–4	Quarter of birth
HISPAN	1	Mexican
BPL	200	Mexico
CITIZEN	3	Not a citizen
YRIMMIG	—	Year of immigration
UHRSWORK	—	Usual hours worked per week
EMPSTAT	1	Employed
SEX	2	Female
MARST	1–2	Married
EDUC	0–11	Educational attainment
STATEFIP	—	State FIPS code
METRO	2–4	Metropolitan area

### 8.2 Age Calculation

Age on June 15, 2012 is calculated as:

$$\text{Age} = 2012 - \text{BIRTHYR} - \mathbf{1}[\text{BIRTHQTR} \geq 3]$$

where the indicator function subtracts one for individuals born in Q3 or Q4, whose birthday had not yet occurred by mid-June.

### 8.3 Sample Restrictions Summary

1. HISPAN = 1 (Hispanic-Mexican)
2. BPL = 200 (Born in Mexico)
3. CITIZEN = 3 (Non-citizen)
4. YRIMMIG > 0 and YRIMMIG  $\leq$  YEAR (Valid immigration year)
5. YRIMMIG – BIRTHYR < 16 (Arrived before age 16)
6. YRIMMIG  $\leq$  2007 (Present since 2007)
7. Age on June 15, 2012  $\in$  [26, 35] (Treatment or control age range)
8. YEAR  $\neq$  2012 (Exclude implementation year)

### 8.4 Software and Replication

The analysis was conducted using Python 3.14 with the following packages:

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

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

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