

# The Effect of DACA Eligibility on Full-Time Employment Among Hispanic-Mexican Immigrants: 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 non-citizens in the United States. Using American Community Survey (ACS) data from 2006-2016 and a difference-in-differences design, I compare individuals aged 26-30 at DACA's implementation (treatment group) to those aged 31-35 (control group, ineligible due to age). The preferred specification with state and year fixed effects yields a point estimate of 1.70 percentage points, though this effect is not statistically significant at conventional levels ( $SE = 0.0157$ ,  $p = 0.278$ ). Models without year fixed effects show larger, statistically significant effects (approximately 6.5 percentage points). The event study analysis provides some support for the parallel trends assumption, though pre-treatment coefficients are imprecise. These findings suggest DACA may have had a modest positive effect on full-time employment, though estimates are sensitive to model specification.

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# 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 allowed a selected group of undocumented immigrants who arrived in the United States as children to apply for temporary protection from deportation and authorization to work legally. Given that DACA provides legal work authorization and enables recipients to obtain identification documents such as driver’s licenses in some states, the program could plausibly affect labor market outcomes for eligible individuals.

This study investigates the causal effect of DACA eligibility on full-time employment among 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 on the probability of full-time employment?*

Full-time employment is defined as usually working 35 hours per week or more. I employ a difference-in-differences (DiD) research design that compares individuals who were ages 26-30 at the time DACA was implemented (treatment group) to those who were ages 31-35 (control group). The control group would have been eligible for DACA except that they exceeded the age cutoff—applicants needed to be under 31 years of age as of June 15, 2012.

The analysis uses data from the American Community Survey (ACS), a large nationally representative survey conducted by the U.S. Census Bureau. The ACS provides detailed information on demographics, immigration status, and employment outcomes necessary for identifying DACA-eligible individuals and measuring labor market outcomes.

## 2 Background

### 2.1 The DACA Program

DACA was announced by the Obama administration on June 15, 2012, and applications began being accepted on August 15, 2012. The program offered qualifying individuals a two-year period of deferred action (protection from deportation) and eligibility for work authorization. Recipients could reapply for an additional two years after the initial period.

To be eligible for DACA, an individual must have:

1. Arrived in the United States before their 16th birthday
2. Not yet reached their 31st birthday as of June 15, 2012
3. Lived continuously in the United States since June 15, 2007
4. Been present in the United States on June 15, 2012
5. Not had lawful immigration status (citizenship or legal permanent residency) at that time

In the first four years of the program, nearly 900,000 initial applications were received, with approximately 90% approved. While DACA was not specific to any country of origin, the great majority of eligible individuals were from Mexico due to the structure of undocumented immigration to the United States.

### 2.2 Theoretical Mechanisms

There are several mechanisms through which DACA could affect employment outcomes:

**Legal work authorization:** The most direct mechanism is that DACA provides legal authorization to work. Prior to DACA, undocumented individuals could only work in the informal sector or with fraudulent documents. Legal work authorization opens access to formal employment in sectors that require documentation.

**Reduced fear of deportation:** The temporary protection from deportation may encourage individuals to seek more visible formal employment rather than informal work where they might be less exposed to immigration enforcement.

**Access to identification:** DACA enables recipients to obtain state-issued identification such as driver’s licenses in many states. This can facilitate employment in jobs requiring identification or commuting by car.

**Human capital investment:** The temporary security provided by DACA may encourage investments in job training or education that improve employment prospects.

## 2.3 Prior Literature

Several studies have examined the effects of DACA on various outcomes. Research has found positive effects on educational attainment, labor force participation, and wages among DACA-eligible individuals. However, findings on employment outcomes have been mixed, with some studies finding positive effects while others find null or modest effects. The variation in findings may result from differences in research designs, sample definitions, outcome measures, and time periods examined.

# 3 Data

## 3.1 Data Source

The analysis uses data from the American Community Survey (ACS) as provided by IPUMS USA. The ACS is an annual survey conducted by the U.S. Census Bureau that collects detailed demographic, social, economic, and housing information from approximately 3 million households each year.

I use the one-year ACS samples from 2006 through 2016, excluding 2012. The year 2012 is excluded because DACA was implemented midway through the year (June 15), and the

ACS does not indicate the month of data collection, making it impossible to distinguish pre- and post-DACA observations within that year.

## 3.2 Sample Selection

The analysis sample is constructed through several filtering steps designed to identify individuals who would have been eligible for DACA (treatment group) or would have been eligible except for age (control group).

**Step 1: Hispanic-Mexican ethnicity.** I restrict to individuals who report Hispanic origin of Mexican type ( $HISPAN = 1$  in the IPUMS coding). This captures individuals who identify as ethnically Mexican.

**Step 2: Born in Mexico.** I further restrict to individuals born in Mexico ( $BPL = 200$ ). This ensures the sample consists of Mexican-born immigrants rather than U.S.-born individuals of Mexican descent.

**Step 3: Non-citizen status.** I limit to individuals who are not U.S. citizens ( $CITIZEN = 3$ ). While the ACS cannot distinguish between documented and undocumented non-citizens, I follow the instructions to assume that non-citizens who have not received immigration papers are undocumented for DACA purposes.

**Step 4: Arrived before age 16.** DACA requires arrival in the U.S. before one's 16th birthday. I calculate age at immigration as the year of immigration ( $YRIMMIG$ ) minus birth year ( $BIRTHYR$ ) and restrict to those where this value is less than 16.

**Step 5: Continuous residence since 2007.** DACA requires continuous residence in the U.S. since June 15, 2007. I approximate this by requiring that the year of immigration is 2007 or earlier.

**Step 6: Age eligibility.** For the treatment group, I include individuals born 1982-1986, who would have been ages 26-30 as of June 15, 2012. For the control group, I include individuals born 1977-1981, who would have been ages 31-35—ineligible due to exceeding the age cutoff but otherwise similar to the treatment group.

The final analysis sample contains 44,725 observations across the 10 years of data.

### 3.3 Variables

**Outcome variable:** Full-time employment is defined as usually working 35 or more hours per week, based on the UHRSWORK variable. This is coded as a binary indicator equal to 1 if UHRSWORK  $\geq 35$  and 0 otherwise.

**Treatment indicator:** The treatment variable equals 1 for individuals born 1982-1986 (treatment group) and 0 for those born 1977-1981 (control group).

**Post-treatment indicator:** The post variable equals 1 for years 2013-2016 (after DACA implementation) and 0 for years 2006-2011 (before DACA).

**Covariates:** I include several demographic and socioeconomic covariates:

- Sex (male indicator)
- Age and age squared (to capture nonlinear age effects)
- Marital status (married indicator)
- Education level (indicators for high school graduate, some college, and college or more, with less than high school as the reference)
- Years in the United States (survey year minus immigration year)

**Sample weights:** All analyses use PERWT, the person-level sampling weight provided by the ACS, to generate nationally representative estimates.

## 4 Methodology

### 4.1 Difference-in-Differences Design

The identification strategy relies on a difference-in-differences (DiD) design that compares changes in full-time employment between the treatment group (DACA-eligible, ages 26-30 in



2012) and control group (DACA-ineligible due to age, ages 31-35 in 2012) from the pre-DACA period to the post-DACA period.

The basic DiD estimating equation is:

$$Y_{it} = \beta_0 + \beta_1 \text{Treated}_i + \beta_2 \text{Post}_t + \beta_3 (\text{Treated}_i \times \text{Post}_t) + \varepsilon_{it} \quad (1)$$

where  $Y_{it}$  is an indicator for full-time employment for individual  $i$  in year  $t$ ,  $\text{Treated}_i$  indicates membership in the treatment group,  $\text{Post}_t$  indicates the post-DACA period, and the coefficient  $\beta_3$  on the interaction term captures the DiD effect of interest.

The key identifying assumption is the **parallel trends assumption**: in the absence of DACA, the treatment and control groups would have experienced the same trends in full-time employment. This assumption cannot be directly tested but can be assessed by examining pre-treatment trends.

## 4.2 Model Specifications

I estimate five specifications with progressively more controls:

**Model 1 (Basic DiD):** No covariates beyond the treatment, post, and interaction terms.

**Model 2 (Demographic controls):** Adds male, married, age, and age squared.

**Model 3 (Full covariates):** Adds education indicators and years in the U.S.

**Model 4 (Year fixed effects):** Replaces the single post indicator with year fixed effects to control for common shocks affecting all groups in each year.

**Model 5 (State and year fixed effects):** Adds state fixed effects to control for time-invariant state-level factors.

All models use weighted least squares with person-level sampling weights and heteroskedasticity-robust (HC1) standard errors.

### 4.3 Event Study Analysis

To assess the parallel trends assumption, I estimate an event study specification that allows for year-specific treatment effects:

$$Y_{it} = \alpha + \gamma_i + \lambda_t + \sum_{k \neq 2011} \delta_k (\text{Treated}_i \times \mathbf{1}[t = k]) + X_{it}\beta + \varepsilon_{it} \quad (2)$$

where 2011 is the reference year. The coefficients  $\delta_k$  for pre-treatment years (2006-2010) should be close to zero if the parallel trends assumption holds. The coefficients for post-treatment years (2013-2016) capture the dynamic treatment effects.

### 4.4 Robustness Checks

I conduct several robustness checks:

1. **Subgroup analysis by gender:** Separate estimates for males and females.
2. **Alternative outcome:** Employment (any hours worked) instead of full-time employment.
3. **Narrower age bands:** Restricting to individuals closer to the age cutoff (ages 28-30 vs. 31-33) to improve comparability.

## 5 Results

### 5.1 Summary Statistics

Table 1 presents summary statistics for the analysis sample by treatment status. The sample consists of 26,591 treatment group observations and 18,134 control group observations.

Table 1: Summary Statistics by Treatment Status

Variable	Control (Ages 31-35)	Treatment (Ages 26-30)
Full-time employment rate	0.632	0.619
Employment rate (any)	0.685	0.676
Male	0.561	0.560
Age	31.40	26.29
Married	0.547	0.419
Years in U.S.	21.51	16.97
Less than high school	0.457	0.378
High school graduate	0.512	0.589
Some college	0.031	0.033
College or more	0.000	0.000
N	18,134	26,591

The groups are reasonably similar on observable characteristics. The treatment group is younger by construction (26.3 years vs. 31.4 years) and has been in the U.S. for fewer years (17.0 vs. 21.5 years). The treatment group has a lower marriage rate (42% vs. 55%), which is expected given their younger age. Education levels are similar, with the majority having a high school degree or less.

## 5.2 Raw Difference-in-Differences

Table 2 presents the raw (unadjusted) difference-in-differences calculation.

Table 2: Raw Difference-in-Differences

Group	Pre-DACA	Post-DACA	Change
Treatment (26-30)	0.611	0.634	+0.023
Control (31-35)	0.643	0.611	-0.032
Difference-in-Differences			<b>0.055</b>

The raw DiD estimate suggests that DACA increased full-time employment among the treatment group by 5.5 percentage points. The treatment group's full-time employment rate increased from 61.1% to 63.4% after DACA, while the control group's rate decreased from 64.3% to 61.1%. This raw calculation does not account for covariates or secular trends.

## 5.3 Main Regression Results

Table 3 presents the DiD regression results across specifications.

Table 3: Difference-in-Differences Regression Results

	(1) Basic	(2) Demographics	(3) Full	(4) Year FE	(5) State+Year FE
DiD Coefficient	0.0620*** (0.0116)	0.0657*** (0.0148)	0.0654*** (0.0148)	0.0187 (0.0157)	0.0170 (0.0157)
Demographic controls	No	Yes	Yes	Yes	Yes
Education controls	No	No	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes
State FE	No	No	No	No	Yes
N	44,725	44,725	44,725	44,725	44,725
R-squared	0.002	0.148	0.152	0.156	0.160

*Notes: Heteroskedasticity-robust standard errors in parentheses. All regressions weighted by person-level sampling weights (PERWT). \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .*

The results reveal substantial sensitivity to the inclusion of year fixed effects. Models 1-3, which include only a single post-treatment indicator, estimate effects ranging from 6.2 to 6.6 percentage points, all statistically significant at the 1% level. However, when year fixed effects are included (Models 4-5), the estimated effect drops to approximately 1.7-1.9 percentage points and becomes statistically insignificant ( $p \approx 0.28$ ).

The preferred specification is Model 5, which includes both state and year fixed effects along with the full set of covariates. This model yields a point estimate of 1.70 percentage points with a standard error of 0.0157. The 95% confidence interval is  $[-0.0137, 0.0478]$ , which includes zero but also includes economically meaningful positive effects.

## 5.4 Event Study Results

Table 4 presents the event study results, which show year-by-year treatment effects relative to 2011 (the year before DACA).

Table 4: Event Study Coefficients (Reference Year: 2011)

Year	Coefficient	SE	95% CI
2006	0.029	0.025	[-0.019, 0.078]
2007	0.007	0.024	[-0.039, 0.053]
2008	0.031	0.023	[-0.014, 0.077]
2009	0.020	0.024	[-0.026, 0.066]
2010	0.022	0.023	[-0.023, 0.067]
2011	0.000	—	[Reference]
2013	0.033	0.024	[-0.015, 0.081]
2014	0.038	0.025	[-0.012, 0.087]
2015	0.008	0.026	[-0.043, 0.059]
2016	0.052	0.027	[-0.001, 0.104]

The pre-treatment coefficients (2006-2010) are generally small and statistically indistinguishable from zero, providing some support for the parallel trends assumption. However, several coefficients are positive (e.g., 0.029 in 2006, 0.031 in 2008), suggesting the treatment group may have experienced slightly higher full-time employment growth relative to the control group even before DACA. The imprecision of these estimates (wide confidence intervals) limits our ability to definitively assess parallel trends.

The post-treatment coefficients show a pattern of positive effects that are larger than the pre-treatment coefficients, though only 2016 approaches statistical significance. The largest effect is observed in 2016 (0.052, SE = 0.027), the final year in the sample, which may indicate gradual accumulation of benefits as more eligible individuals obtained DACA status and adjusted their labor market behavior.

## 5.5 Robustness Checks

Table 5 presents results from several robustness checks.

Table 5: Robustness Checks

Specification	DiD Coefficient	SE
<i>Subgroups:</i>		
Males only	0.0674***	0.0178
Females only	0.0528**	0.0244
<i>Alternative outcome:</i>		
Employment (any hours)	0.0573***	0.0141
<i>Alternative sample:</i>		
Narrow age bands (28-30 vs 31-33)	0.0866***	0.0185

*Notes: These models include demographic covariates but not year or state fixed effects. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .*

**By gender:** The estimated effect is larger for males (6.7 pp) than females (5.3 pp), though both are positive and statistically significant. This may reflect differential labor market effects by gender, with males more likely to be in industries where work authorization matters.

**Alternative outcome:** When using any employment (rather than full-time employment) as the outcome, the estimated effect is 5.7 percentage points, similar in magnitude to the full-time employment effect. This suggests DACA increased both the likelihood of working and the intensity of work.

**Narrower age bands:** Restricting to individuals closer to the age cutoff (ages 28-30 vs. 31-33) yields a larger estimated effect of 8.7 percentage points. These individuals are more comparable in age and may be more similar on unobservables, though the trade-off is reduced sample size and precision.

## 5.6 Trends in Full-Time Employment

Table 6 shows the time series of full-time employment rates for the treatment and control groups.

Table 6: Full-Time Employment Rates by Year and Group

Year	Control (31-35)	Treatment (26-30)
2006	0.693	0.638
2007	0.723	0.660
2008	0.692	0.660
2009	0.645	0.612
2010	0.629	0.599
2011	0.630	0.580
2013	0.632	0.642
2014	0.617	0.637
2015	0.666	0.659
2016	0.654	0.699

Both groups show declining full-time employment rates from 2006-2011, consistent with the effects of the Great Recession (2008-2009). After 2012, the treatment group shows improvement relative to the control group. By 2016, the treatment group’s full-time employment rate (69.9%) exceeds the control group’s rate (65.4%), representing a reversal of the pre-DACA pattern.

## 6 Discussion

### 6.1 Interpretation of Results

The analysis produces mixed evidence on the effect of DACA eligibility on full-time employment. The key findings can be summarized as follows:

**Magnitude:** Point estimates range from 1.7 to 8.7 percentage points depending on the specification. The preferred model (with state and year fixed effects) yields an estimate of 1.7 percentage points.

**Statistical significance:** Models without year fixed effects find statistically significant positive effects. However, the preferred model with year fixed effects yields an estimate that is not statistically significant at conventional levels ( $p = 0.28$ ).

**Pattern over time:** The event study shows a pattern consistent with a positive treatment effect emerging after DACA, with the largest effects in later years (especially 2016). Pre-treatment coefficients are close to zero on average, providing some support for the parallel trends assumption.

## 6.2 Why Do Year Fixed Effects Matter?

The sensitivity of results to year fixed effects is noteworthy and deserves explanation. The large difference between Models 3 and 4 suggests that the simple pre/post comparison may be confounded by differential secular trends across the treatment and control groups that coincide with but are not caused by DACA.

Several factors could explain this:

1. **Age-specific recovery from the recession:** Younger workers may have experienced different labor market recovery patterns from the Great Recession.
2. **Cohort effects:** Individuals born in different years may have different labor market outcomes for reasons unrelated to DACA.
3. **Life-cycle transitions:** The 5-year age difference means treatment and control groups are at different life stages, with potentially different employment trajectories.

## 6.3 Limitations

Several limitations should be noted:

**Cannot observe DACA receipt:** The ACS does not indicate whether individuals actually received DACA. The analysis identifies the intent-to-treat effect among those eligible based on observable characteristics. Actual take-up was less than 100%, so effects on those who actually received DACA may be larger.

**Cannot distinguish documented from undocumented:** The data cannot distinguish between documented and undocumented non-citizens. Some individuals coded as



“non-citizens” may have legal status (e.g., visa holders) and would not be affected by DACA.

**Parallel trends uncertainty:** While the event study provides some support for parallel trends, the pre-treatment coefficients are imprecisely estimated and show some positive values, suggesting potential violations.

**Selection into treatment group:** The age-based assignment is not truly random. Individuals who were 26-30 in 2012 differ from those 31-35 in ways that may affect employment outcomes beyond their DACA eligibility.

## 6.4 Comparison to Prior Research

The findings are broadly consistent with prior research finding positive but modest effects of DACA on employment outcomes. The sensitivity to specification is also consistent with the mixed findings in the literature. The range of estimates (1.7 to 8.7 percentage points) spans estimates found in prior studies, suggesting that methodological choices play an important role in determining findings.

## 7 Conclusion

This study examined the effect of DACA eligibility on full-time employment among Hispanic-Mexican, Mexican-born immigrants using a difference-in-differences design. The preferred specification with state and year fixed effects yields a point estimate of 1.70 percentage points, suggesting a modest positive effect of DACA eligibility on full-time employment. However, this effect is not statistically significant at conventional levels ( $p = 0.28$ , 95% CI:  $[-0.014, 0.048]$ ).

Alternative specifications without year fixed effects yield larger and statistically significant estimates (approximately 6.5 percentage points), but these may be confounded by differential trends across age groups. Robustness checks show consistent positive effects across genders, alternative outcomes, and alternative sample definitions.

The event study analysis provides some support for the parallel trends assumption, with pre-treatment coefficients generally close to zero. Post-treatment effects appear to grow over time, with the largest estimated effect in 2016, suggesting gradual accumulation of benefits as the program matured.

Overall, the evidence suggests DACA may have had a positive effect on full-time employment among eligible individuals, though the magnitude is uncertain and depends on modeling assumptions. The finding that effects may be larger in later years points to potential avenues for future research examining the dynamic effects of immigration policy changes.

## 8 Appendix: Data and Code

### 8.1 IPUMS Variable Definitions

Table 7: Key Variable Definitions from IPUMS

Variable	Definition
YEAR	Survey year
PERWT	Person-level sampling 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
UHRSWORK	Usual hours worked per week
EMPSTAT	Employment status (1 = Employed)
SEX	Sex (1 = Male, 2 = Female)
MARST	Marital status
EDUC	Educational attainment
STATEFIP	State FIPS code

### 8.2 Sample Construction

The sample was constructed as follows:

1. Started with ACS 1-year samples 2006-2011 and 2013-2016

2. Restricted to Hispanic-Mexican (HISPAN = 1)
3. Restricted to born in Mexico (BPL = 200)
4. Restricted to non-citizens (CITIZEN = 3)
5. Restricted to those who arrived before age 16
6. Restricted to those who immigrated by 2007
7. Restricted to those born 1977-1986
8. Excluded 2012 observations

### 8.3 Preferred Estimate Summary

**Effect Size:** 0.0170 (1.70 percentage points)

**Standard Error:** 0.0157

**95% Confidence Interval:** [-0.0137, 0.0478]

**P-value:** 0.278

**Sample Size:** 44,725

## 9 References

- IPUMS USA, University of Minnesota, [www.ipums.org](http://www.ipums.org)
- U.S. Citizenship and Immigration Services, DACA Program Information
- American Community Survey Technical Documentation, U.S. Census Bureau