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

Replication Study #55

Independent Replication

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Abstract

This study estimates the causal effect of eligibility for the Deferred Action for Childhood Arrivals (DACA) program on full-time employment among Mexican-born Hispanic individuals in the United States. Using a difference-in-differences design that compares individuals aged 26–30 (eligible) to those aged 31–35 (ineligible due to age cutoff) before and after the 2012 policy implementation, I find that DACA eligibility is associated with a 6.4 percentage point increase in full-time employment (SE = 0.022, p = 0.004). While this effect is statistically significant, examination of pre-treatment trends reveals some instability, suggesting caution in causal interpretation. The findings contribute to the growing literature on the labor market effects of immigration policy reforms.

Keywords: DACA, immigration policy, employment, difference-in-differences, natural experiment

Contents

1 Introduction

The Deferred Action for Childhood Arrivals (DACA) program, implemented on June 15, 2012, represented a significant shift in U.S. immigration policy. The program granted temporary relief from deportation and work authorization to undocumented immigrants who arrived in the United States as children, met certain continuous residence requirements, and were under 31 years of age at the time of implementation.

This replication study examines a fundamental question about DACA's labor market effects: **Did DACA eligibility increase the probability of full-time employment among eligible individuals?**

The theoretical motivation for expecting an employment effect is straightforward. Prior to DACA, eligible individuals faced significant barriers to formal employment due to their undocumented status. Work authorization under DACA allowed these individuals to pursue legitimate employment without fear of deportation, potentially increasing both the supply of their labor to formal markets and employer demand for their services.

This analysis uses data from the American Community Survey (ACS) spanning 2008–2016 (excluding 2012) to estimate the effect of DACA eligibility on full-time employment using a difference-in-differences framework. The treatment group consists of individuals aged 26–30 at the time of policy implementation who met other eligibility criteria. The comparison group consists of individuals aged 31–35 who would have been eligible but for exceeding the age cutoff.

2 Background

2.1 The DACA Program

DACA was announced by the Obama administration on June 15, 2012, and began accepting applications on August 15, 2012. To be eligible, individuals had to:

- Have arrived in the United States before their 16th birthday
- Have been under 31 years of age as of June 15, 2012
- Have resided continuously in the United States since June 15, 2007
- Have been present in the United States on June 15, 2012
- Have not had lawful immigration status at that time

- Have either been in school, graduated from high school, obtained a GED, or been honorably discharged from the military
- 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. Recipients received two-year renewable work authorization and protection from deportation.

2.2 Expected Labor Market Effects

DACA could affect employment through several channels:

1. **Direct work authorization effect**: DACA provides legal work authorization, allowing recipients to work in jobs that require documentation.
2. **Driver's license access**: Many states allowed DACA recipients to obtain driver's licenses, expanding geographic mobility and access to employment.
3. **Reduced fear of deportation**: The security provided by DACA may have encouraged recipients to seek formal employment rather than informal work arrangements.
4. **Human capital investment**: Recipients may have increased investment in education and training, though this is more relevant for longer-term outcomes.

While we might expect overall employment to increase, the effect on full-time employment specifically is less certain. DACA could shift workers from part-time to full-time work, or it could primarily affect extensive margin employment decisions.

3 Data

3.1 Data Source

The analysis uses American Community Survey (ACS) data from 2008–2016, with 2012 excluded because it cannot be determined whether observations from that year are pre- or post-treatment. The data were obtained through IPUMS USA and have been pre-processed to include only individuals in the relevant age groups who meet basic eligibility criteria.

3.2 Sample Description

The analytical sample consists of 17,382 observations representing Mexican-born, ethnically Hispanic individuals meeting DACA eligibility criteria (other than age). The sample is divided as follows:

Table 1: Sample Composition

	N	Percent
Treatment Status		
Treatment (ELIGIBLE=1, Ages 26–30)	11,382	65.5%
Control (ELIGIBLE=0, Ages 31–35)	6,000	34.5%
Time Period		
Pre-DACA (2008–2011)	9,527	54.8%
Post-DACA (2013–2016)	7,855	45.2%
Sex		
Male	9,075	52.2%
Female	8,307	47.8%
Total	17,382	100.0%

3.3 Key Variables

Outcome Variable:

- `FT`: Binary indicator equal to 1 if the individual usually works 35 hours per week or more, 0 otherwise. Individuals not in the labor force are coded as 0 and included in the analysis per the study protocol.

Treatment Variables:

- `ELIGIBLE`: Binary indicator equal to 1 for individuals aged 26–30 at the time of DACA implementation (treatment group), 0 for individuals aged 31–35 (control group).
- `AFTER`: Binary indicator equal to 1 for years 2013–2016 (post-treatment), 0 for years 2008–2011 (pre-treatment).

Control Variables:

- `SEX`: Sex of respondent (1=Male, 2=Female)
- `MARST`: Marital status

- `FAMSIZE`: Number of family members in household
- `NCHILD`: Number of own children in household
- `STATEFIP`: State FIPS code (used for fixed effects and clustering)

Survey Weight:

- `PERWT`: Person weight for generating population-representative estimates

3.4 Year-by-Year Sample Sizes

Table 2: Observations by Year

Year	N	Period
2008	2,354	Pre-DACA
2009	2,379	Pre-DACA
2010	2,444	Pre-DACA
2011	2,350	Pre-DACA
2013	2,124	Post-DACA
2014	2,056	Post-DACA
2015	1,850	Post-DACA
2016	1,825	Post-DACA

4 Methodology

4.1 Identification Strategy

I employ a difference-in-differences (DiD) design to estimate the causal effect of DACA eligibility on full-time employment. The key identifying assumption is that, in the absence of DACA, the treatment group (ages 26–30) would have experienced the same trend in full-time employment as the control group (ages 31–35).

The treatment and control groups are defined by the age cutoff in DACA eligibility: individuals had to be under 31 years of age as of June 15, 2012 to be eligible. This creates a natural comparison between those just below the cutoff (who became eligible) and those just above it (who did not), who are otherwise similar in their characteristics and would have been eligible but for their age.

4.2 Empirical Specification

The basic difference-in-differences model is:

$$FT_{it} = \beta_0 + \beta_1 ELIGIBLE_i + \beta_2 AFTER_t + \beta_3 (ELIGIBLE_i \times AFTER_t) + \epsilon_{it} \quad (1)$$

where FT_{it} is an indicator for full-time employment, $ELIGIBLE_i$ indicates treatment group membership, $AFTER_t$ indicates the post-treatment period, and β_3 is the difference-in-differences estimate of the treatment effect.

The extended specification includes demographic controls:

$$FT_{it} = \beta_0 + \beta_3 (ELIGIBLE_i \times AFTER_t) + \mathbf{X}_i' \gamma + \alpha_s + \delta_t + \epsilon_{it} \quad (2)$$

where $\mathbf{X}_i$ is a vector of individual-level controls (sex, marital status, family size, number of children), α_s represents state fixed effects, and δ_t represents year fixed effects.

4.3 Estimation

All models are estimated using weighted least squares (WLS) with person weights (`PERWT`) to generate population-representative estimates. Standard errors are clustered at the state level to account for within-state correlation in the error terms, following standard practice in the literature.

The DiD estimate $\hat{\beta}_3$ can be interpreted as the average treatment effect of DACA eligibility on full-time employment, measured as a change in probability (percentage points).

4.4 Identification Assumptions

The validity of the difference-in-differences design relies on several key assumptions:

1. **Parallel trends**: In the absence of treatment, the treatment and control groups would have followed parallel trends in full-time employment.

2. **No anticipation**: Individuals did not change their behavior in anticipation of DACA before its implementation.

3. **SUTVA**: The treatment status of one individual does not affect the outcomes of others, and treatment is well-defined.

4. **No compositional changes**: The composition of the treatment and control groups does not change differentially over time in ways that affect the outcome.

I examine the parallel trends assumption empirically by analyzing pre-treatment trends in Section 5.

5 Results

5.1 Descriptive Statistics

Table 3 presents the full-time employment rates by treatment status and time period, using person weights.

Table 3: Full-Time Employment Rates by Group and Period (Weighted)

	Treatment (Ages 26–30)		**Control (Ages 31–35)**	
	FT Rate	N	FT Rate	N
Pre-DACA (2008–2011)	63.69%	6,233	68.86%	3,294
Post-DACA (2013–2016)	68.60%	5,149	66.29%	2,706
Change	+4.91 pp		−2.57 pp	

The simple difference-in-differences calculation yields:

$$\begin{aligned} \text{DiD} &= (68.60\% - 63.69\%) - (66.29\% - 68.86\%) \\ &= 4.91\% - (-2.57\%) \\ &= \textbf{7.48 percentage points} \end{aligned}$$

This raw estimate suggests a substantial positive effect of DACA eligibility on full-time employment.

5.2 Main Regression Results

Table 4 presents the difference-in-differences estimates from several model specifications.

Table 4: Difference-in-Differences Regression Results

	(1) OLS	(2) WLS	(3) Controls	(4) State FE	(5) Preferred
ELIGIBLE × AFTER	0.064***	0.075***	0.064***	0.074***	0.064***
	(0.015)	(0.015)	(0.014)	(0.015)	(0.022)
ELIGIBLE	−0.043***	−0.052***	−0.025***	−0.051***	−0.031***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.014)
AFTER	−0.025**	−0.026**	−0.019	−0.024**	−0.019
	(0.012)	(0.012)	(0.012)	(0.012)	(0.016)
Constant	0.670***	0.689***	0.558***	0.655***	0.571***
	(0.008)	(0.008)	(0.028)	(0.014)	(0.038)
Person Weights	No	Yes	Yes	Yes	Yes
Demographics	No	No	Yes	No	Yes
State FE	No	No	No	Yes	Yes
Clustered SE	No	No	No	No	Yes
Observations	17,382	17,382	17,382	17,382	17,382

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.
Column (5) clusters standard errors at the state level.
Demographics include sex, marital status, family size, and number of children.

5.3 Preferred Estimate

The preferred specification (Column 5) includes person weights, demographic controls, state fixed effects, and state-clustered standard errors. The results indicate:

Preferred Estimate

Effect Size: **6.4 percentage points** (0.064)
Standard Error: 0.022 (clustered by state)
95% Confidence Interval: [0.021, 0.107]
p-value: 0.004
Sample Size: 17,382

This estimate suggests that DACA eligibility increased the probability of full-time employment by approximately 6.4 percentage points, an effect that is statistically significant at the 1% level.

5.4 Interpretation

Relative to the pre-treatment full-time employment rate of 63.69% among the treatment group, a 6.4 percentage point increase represents a relative increase of approximately 10%. This is a meaningful effect size that aligns with expectations about the impact of legal work authorization on employment outcomes.

The coefficient on `ELIGIBLE` alone is negative, indicating that the treatment group had lower baseline full-time employment rates than the control group. This is consistent with the treatment group being younger and therefore less likely to have settled into stable full-time employment.

6 Robustness and Validity

6.1 Parallel Trends Analysis

The validity of the difference-in-differences design depends crucially on the parallel trends assumption. Table 5 shows the year-by-year full-time employment rates for each group.

Table 5: Year-by-Year Full-Time Employment Rates (Weighted)

Year	Treatment	Control	Gap
Pre-Treatment Period			
2008	67.99%	74.69%	−6.70 pp
2009	63.66%	68.54%	−4.88 pp
2010	60.92%	69.02%	−8.10 pp
2011	62.49%	62.38%	+0.11 pp
Post-Treatment Period			
2013	67.39%	65.71%	+1.69 pp
2014	64.30%	64.19%	+0.11 pp
2015	69.26%	69.01%	+0.25 pp
2016	74.14%	66.62%	+7.51 pp

The pre-treatment trends raise some concerns. The gap between treatment and control groups is not constant during the pre-period:

- 2008: Treatment group 6.7 pp below control
- 2009: Treatment group 4.9 pp below control
- 2010: Treatment group 8.1 pp below control

- 2011: Treatment group 0.1 pp above control (essentially equal)

This variability suggests the parallel trends assumption may not hold perfectly.

6.2 Event Study

To formally test pre-trends, I estimate an event study regression with year-specific treatment effects, using 2011 as the reference year.

Table 6: Event Study Estimates (Reference Year: 2011)

Year	**Coefficient**	**Std. Error**	**95% CI**
Pre-Treatment			
ELIGIBLE × 2008	−0.068**	(0.029)	[−0.126, −0.011]
ELIGIBLE × 2009	−0.050	(0.037)	[−0.123, 0.024]
ELIGIBLE × 2010	−0.082***	(0.030)	[−0.140, −0.024]
Post-Treatment			
ELIGIBLE × 2013	0.016	(0.041)	[−0.064, 0.095]
ELIGIBLE × 2014	0.000	(0.028)	[−0.055, 0.055]
ELIGIBLE × 2015	0.001	(0.038)	[−0.074, 0.077]
ELIGIBLE × 2016	0.074**	(0.030)	[0.016, 0.133]

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered SE at state level.

The event study reveals:

- **Pre-treatment coefficients** (2008, 2010) are statistically significant and negative, indicating differential pre-trends. This is concerning for the parallel trends assumption.
- **Post-treatment coefficients** show the effect building over time, with the largest effect in 2016 (0.074, p=0.013).

6.3 Placebo Test

As an additional check, I conduct a placebo test using only pre-treatment data (2008–2011) with a fake treatment date of 2010.

Placebo Test Results

Fake treatment (2010): 0.018 (SE = 0.026)

p-value: 0.486

Result: Not significant, partially supporting parallel trends

The placebo coefficient is small and not statistically significant, providing some support for the parallel trends assumption.

6.4 Subgroup Analysis

I examine whether the treatment effect varies by sex:

Table 7: Heterogeneous Effects by Sex

Subgroup	**DiD Estimate**	**Std. Error**	**p-value**
Male	0.072***	(0.020)	0.000
Female	0.053*	(0.029)	0.070

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered SE at state level.

Both males and females show positive effects, but the effect is larger and more precisely estimated for males. This could reflect gender differences in labor market attachment or in the types of jobs affected by DACA eligibility.

7 Discussion

7.1 Summary of Findings

This replication study finds that DACA eligibility is associated with a 6.4 percentage point increase in full-time employment among Mexican-born Hispanic individuals who were aged 26–30 at the time of policy implementation. This effect is statistically significant at conventional levels (p = 0.004) and robust to the inclusion of demographic controls and state fixed effects.

7.2 Threats to Validity

Several factors warrant caution in interpreting these results as causal:

1. **Pre-treatment trend variation**: The event study analysis reveals that the gap between treatment and control groups varied substantially in the pre-period. The treatment group performed relatively worse in 2008 and 2010 compared to 2011. This raises concerns about whether the parallel trends assumption holds.

2. **Age-related confounders**: The treatment and control groups differ by age (26–30 vs. 31–35). While the DiD design is intended to difference out level differences, any age-specific trends could confound the estimate. For example, the Great Recession may have affected different age groups differently.

3. **Timing of effects**: The largest treatment effect appears in 2016, four years after DACA implementation. This delay is somewhat puzzling if the main mechanism is work authorization, which was immediate.

4. **Measurement of treatment**: The `ELIGIBLE` variable captures potential eligibility based on age and other criteria, but not actual DACA receipt. Not all eligible individuals applied for or received DACA, which could attenuate the estimated effect.

7.3 Comparison to Literature

The estimated effect of 6.4 percentage points is within the range of effects found in the prior literature on DACA and employment outcomes. Studies using similar methodologies have found effects ranging from near zero to 10+ percentage points, depending on the specific outcome, sample, and methodology.

The finding that effects are larger for males than females is consistent with prior research suggesting that DACA had differential effects by gender, potentially due to differences in labor market attachment and the types of industries affected.

7.4 Policy Implications

If interpreted causally, these findings suggest that providing work authorization to undocumented immigrants can substantially increase their formal labor market participation. This has implications for debates about comprehensive immigration reform and the economic integration of unauthorized immigrants.

However, the robustness concerns noted above suggest caution in drawing strong policy conclusions from this single analysis.

8 Conclusion

This replication study estimates the effect of DACA eligibility on full-time employment using a difference-in-differences design. The preferred estimate indicates a 6.4 percentage point increase in full-time employment (SE = 0.022, 95% CI: [0.021, 0.107]), which is statistically significant at the 1% level.

However, examination of pre-treatment trends reveals instability in the gap between treatment and control groups, raising concerns about the parallel trends assumption. The placebo test provides some reassurance, but the event study shows significant pre-treatment differences.

Given these findings, I conclude that there is suggestive evidence that DACA eligibility increased full-time employment, but the causal interpretation should be treated with some caution. Future research using alternative identification strategies (such as regression discontinuity at the age cutoff) could help strengthen causal inference.

Appendix A: Data Dictionary

The following variables from the ACS data were used in this analysis:

Variable	Description
YEAR	Survey year (2008–2011, 2013–2016)
STATEFIP	State FIPS code
PERWT	Person weight for population estimates
ELIGIBLE	Treatment indicator (1 = ages 26–30, 0 = ages 31–35)
AFTER	Post-treatment indicator (1 = 2013–2016, 0 = 2008–2011)
FT	Full-time employment (1 = 35+ hours/week)
SEX	Sex (1 = Male, 2 = Female)
MARST	Marital status
FAMSIZE	Number of family members in household
NCHILD	Number of own children in household
AGE_IN_JUNE_2012	Age of respondent on June 15, 2012

Appendix B: Full Regression Output

B.1 Basic DiD Model (OLS)

	coef	std err	t	P>|t|	[95% CI]
Intercept	0.6697	0.008	80.591	0.000	[0.653, 0.686]
ELIGIBLE	-0.0434	0.010	-4.220	0.000	[-0.063, -0.023]
AFTER	-0.0248	0.012	-2.007	0.045	[-0.049, -0.001]
ELIGIBLE_AFTER	0.0643	0.015	4.202	0.000	[0.034, 0.094]

Observations: 17,382

R-squared: 0.003

B.2 Preferred Model (WLS with Controls and Clustered SE)

	coef	std err	t	P>|t|	[95% CI]
ELIGIBLE_AFTER	0.0640	0.022	3.015	0.004	[0.021, 0.107]

Controls: Sex, Marital Status, Family Size, Number of Children

Fixed Effects: State

Standard Errors: Clustered by State

Weights: Person Weights (PERWT)

Observations: 17,382

Appendix C: Stata/Python Code

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

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

Key model specification:

```
# Preferred model with clustered standard errors
model = smf.wls(
    'FT ~ ELIGIBLE + AFTER + ELIGIBLE_AFTER + C(SEX) +
     C(MARST) + FAMSIZE + NCHILD + C(STATEFIP)',
    data=df,
    weights=df['PERWT']
).fit(cov_type='cluster', cov_kwds={'groups': df['STATEFIP']})
```

Full analysis code is available in `analysis.py`.

Appendix D: Additional Robustness Checks

D.1 Sensitivity to Model Specification

Table 9: Robustness to Different Specifications

Specification	**DiD Estimate**	**SE**
No controls, no weights	0.064	(0.015)
With weights, no controls	0.075	(0.015)
With controls, no FE	0.064	(0.014)
State FE only	0.074	(0.015)
Year FE only	0.061	(0.014)
State + Year FE	0.061	(0.014)
State + Year FE + Controls	0.064	(0.022)

The DiD estimate ranges from 0.061 to 0.075 across specifications, demonstrating reasonable robustness to model choice.

D.2 Heterogeneity by Education

Table 10: Effects by Education Level

Education	**DiD Estimate**	**N**
High School Degree	0.061	12,444
Some College	0.067	2,877
Two-Year Degree	0.182	991
BA+	0.162	1,058

Interestingly, the effects appear larger among those with higher education levels, though sample sizes for these groups are smaller.

Appendix E: Geographic Distribution

The sample is geographically concentrated in states with large Mexican-born populations:

Table 11: Sample Distribution by State (Top 10)

FIPS	**State**	**N**	**Percent**
6	California	7,796	44.9%
48	Texas	3,572	20.6%
17	Illinois	995	5.7%
4	Arizona	860	4.9%
32	Nevada	383	2.2%
53	Washington	366	2.1%
12	Florida	318	1.8%
36	New York	292	1.7%
13	Georgia	292	1.7%
8	Colorado	268	1.5%
	Other states	2,240	12.9%
	Total	**17,382**	**100.0%**

This geographic concentration reflects the settlement patterns of Mexican immigrants in the United States. California and Texas together account for nearly two-thirds of the sample. This concentration has implications for external validity and for the choice to cluster standard errors at the state level.

Appendix F: Covariate Balance

F.1 Pre-Treatment Balance

An important consideration in difference-in-differences analysis is whether the treatment and control groups are comparable on observable characteristics. Table F.1 shows the mean values of key covariates for the treatment and control groups in the pre-treatment period.

Table 12: Covariate Balance (Pre-Treatment Period)

Variable	**Treatment**	**Control**	**Difference**
SEX (1=M, 2=F)	1.481	1.456	0.025
FAMSIZE	4.458	4.487	−0.029
NCHILD	0.937	1.539	−0.603***
MARST	3.850	3.171	0.679***

Note: *** indicates statistically significant at the 1% level.

The groups are well-balanced on sex and family size, but differ significantly on number of children and marital status. This is expected given the age difference between groups: older individuals (control group) are more likely to be married and have more children. These differences motivate the inclusion of these variables as controls in the regression analysis.

F.2 Education Distribution

Table 13: Education Distribution by Treatment Status (Pre-Treatment)

Education Level	**Treatment**	**Control**
Less than High School	0.03%	0.06%
High School Degree	70.9%	73.5%
Some College	18.3%	15.7%
Two-Year Degree	5.2%	5.2%
BA+	5.5%	5.6%
Total	100.0%	100.0%

Education distributions are similar across groups, with the majority having a high school degree. The treatment group has slightly more individuals with “Some College,” which is consistent with younger individuals being more likely to be enrolled in or have recently completed post-secondary education.

Appendix G: Sensitivity Analysis

G.1 Alternative Control Variables

To assess the sensitivity of results to the choice of control variables, I estimate several alternative specifications:

Table 14: Sensitivity to Control Variables

Controls Included	**DiD Estimate**	**SE**
None	0.075	(0.015)
Sex only	0.072	(0.015)
Sex + Marital Status	0.066	(0.014)
Sex + NCHILD	0.070	(0.015)
Sex + FAMSIZE	0.073	(0.015)
All demographics	0.064	(0.022)

The estimate is most sensitive to the inclusion of marital status, which makes sense given the significant difference in marital status between groups. However, all specifications yield positive and statistically significant estimates, suggesting the main finding is robust to control variable selection.

G.2 Alternative Standard Error Specifications

Table 15: Sensitivity to Standard Error Specification

SE Specification	**SE**	**p-value**
Homoskedastic (OLS)	0.015	<0.001
Heteroskedasticity-robust	0.015	<0.001
Clustered by state	0.022	0.004
Clustered by year	0.018	0.001

Clustering standard errors at the state level (the preferred specification) produces the most conservative inference. However, the estimate remains statistically significant at conventional levels regardless of the standard error specification.

G.3 Linear Probability Model vs. Probit/Logit

As a robustness check, I compared the linear probability model (LPM) to nonlinear specifications:

- **Linear Probability Model**: DiD = 0.064 (SE = 0.022)
- **Probit (marginal effect)**: DiD = 0.063 (SE = 0.021)
- **Logit (marginal effect)**: DiD = 0.063 (SE = 0.021)

The results are nearly identical across specifications, supporting the use of the linear probability model for ease of interpretation.

Appendix H: Summary Statistics

Table 16: Summary Statistics for Key Variables

Variable	**N**	**Mean**	**Std Dev**	**Min**	**Max**
FT	17,382	0.649	0.477	0	1
ELIGIBLE	17,382	0.655	0.475	0	1
AFTER	17,382	0.452	0.498	0	1
PERWT	17,382	98.2	62.3	3	694
SEX	17,382	1.478	0.500	1	2
FAMSIZE	17,382	4.457	1.728	1	15
NCHILD	17,382	1.148	1.234	0	8
MARST	17,382	3.610	2.174	1	6
AGE_IN_JUNE_2012	17,382	29.6	2.6	26	35

Table 17: Cross-Tabulation: Treatment Status by Time Period

	Pre-DACA	**Post-DACA**	**Total**
Control (ELIGIBLE=0)	3,294	2,706	6,000
Treatment (ELIGIBLE=1)	6,233	5,149	11,382
Total	**9,527**	**7,855**	**17,382**

Table 18: Full-Time Employment by Cell

	Pre-DACA	Post-DACA
Control (ELIGIBLE=0)		
N	3,294	2,706
FT Rate (Unweighted)	67.0%	64.5%
FT Rate (Weighted)	68.9%	66.3%
Treatment (ELIGIBLE=1)		
N	6,233	5,149
FT Rate (Unweighted)	62.6%	66.6%
FT Rate (Weighted)	63.7%	68.6%