Comparing Methods to Identify Undocumented Immigrants in Survey Data:

Applications to the DREAM Act and DACA

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Abstract

Because no large-scale survey records individuals' legal status, previous literature often use Hispanic or Mexican non-citizen as a proxy to identify undocumented immigrants in survey data. This paper compares the ethnicity proxy with the recently developed residual method in identifying undocumented immigrants in two aspects: how closely they can match official statistics and how they differ when evaluating the schooling and labor market effects of the DREAM Act and DACA. The study finds that the residual method outperforms the ethnicity proxy in matching the U.S. Citizenship and Immigration Services statistics on undocumented immigrants. Consistent with previous literature, results from both methods also suggest that the DREAM Act increases college enrollment, while DACA decreases college enrollment and increases the probability of working. The residual method produces policy effect estimates in the same direction as does the Hispanic non-citizen proxy approach, but larger in magnitude, suggesting that the ethnicity proxy could underestimate policy effects.

KEYWORDS: Undocumented Immigrants, DREAM Act, DACA, Residual Method, College Enrollment

JEL Classification: F22, J15, I23

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Section 1: Introduction

The United States has the largest immigrant population of any nation in the world. However, over one-fourth of this population, or 11.3 million individuals, are undocumented immigrants with no legal status (Passel and Cohn 2017). Recently, extensive political debate has occurred in the Trump administration over the appropriate policies to manage these individuals and regulate additional unauthorized immigration. As undocumented immigrants typically have low income and an above-average unemployment rate, special attention has been paid to whether the government should help improve their economic well-being in order to prevent pushing them further into the underground economy (Abrego and Gonzales 2010, Teranishi and Suarez-Orozco 2015). To date, two major policies have been implemented to facilitate the integration of undocumented immigrants into American society. At the federal level, the Deferred Action for Childhood Arrivals (DACA) program has provided work authorization and a temporary relief from deportation to eligible immigrants since 2012. At the state level, 20 state governments since 2001 have granted in-state college tuition to undocumented students, known as the DREAM Act.

This paper analyzes changes in the college enrollment rate and the employment likelihood of undocumented students following the enactment of these two initiatives, respectively. As the DREAM Act directly reduces the cost for undocumented students to receive higher education, we may anticipate that more undocumented students enroll in college instead of working informally without legal protection. In the case of DACA, however, undocumented immigrants will receive work authorization in addition to facing fewer legal constraints to attend colleges.

As such, we would anticipate DACA to represent an increase in the opportunity cost of attending college for eligible individuals, thus leading them to take up jobs at the expense of higher education.

Obtaining precise estimates of the schooling and labor market impacts of the DREAM Act and DACA are important for policy debates. However, previous studies that evaluate these two policies have produced mixed results. Using monthly data from the Current Population Survey (CPS), Kaushal (2008) and Amuedo-Dorantes and Sparber (2014) found that in-state tuition subsidies are associated with an increase in the college enrollment rate of undocumented students. On the other hand, Chin and Juhn (2010) were unable to find any statistically significant enrollment effect using data from the American Community Survey (ACS), and the labor market impacts of the DREAM Act still remain unaddressed by the literature. Focusing on the DACA program, Amuedo-Dorantes and Antman (2017) found a drop in the enrollment rate and an increase in the employment likelihood of eligible individuals using 2000-2014 monthly CPS data. In contrast, Pope (2016) found no evidence of any schooling effect of DACA based on data from the ACS between 2005 and 2014. These differences may be due to variations in data sources and the time periods being examined, as it can take time for policies to phase in and generate observable impacts.

Furthermore, these studies face another challenge in evaluating the effects of the two immigration policies: there is no widely available data set that specifies respondents' legal status. As a result, all past studies have used Hispanic non-citizens or Mexican non-citizens as a proxy for undocumented immigrants, arguing that these ethnic or country-of-origin groups have a higher probability of being undocumented. As demographic trends change over time, this estimation strategy has two major limitations. First, while the majority of undocumented immigrants was Mexican in the early 2000s, this trend has reversed in recent years. For example, Figure 1 shows that non-Mexican undocumented individuals already outnumber Mexican undocumented immigrants. In fact, more than 30 percent of the recent undocumented population is not Hispanic, suggesting an increase in the ethnic diversity of this group of population (Passel and Cahn 2017). Second, because the non-citizen population includes both legal and undocumented immigrants, using this status as an identifying method would inevitably include legal immigrants in the sample of estimated undocumented individuals. This trend is especially apparent given that the share of legal temporary immigrants (including students, diplomats and foreign workers who hold temporary visas) has grown significantly since the 2000s (Bachmeier, Hook, and Bean 2014). Thus, the ethnicity proxy is likely to introduce imprecision in identifying treatment and control groups, thereby reducing the explanatory power of previous results.

Recently, Borjas (2017) has developed the residual method, an alternative strategy to identify undocumented immigrants in survey data by replicating the official methodology adopted by the U.S. Department of Homeland Security (DHS). The residual method determines individuals' undocumented status based on their demographic, social, economic, and geographic characteristics, instead of focusing solely on their ethnic traits. Specifically, it uses variables such as citizenship status and coverage by government welfare benefits to identify a foreign-born respondent as a legal immigrant and classify the residual foreign-born population as potentially undocumented. Borjas finds that the residual method produces estimates that are highly consistent with the official DHS statistics on undocumented immigrants, thereby providing a reliable way to identify undocumented immigrants in survey data.

To date, no study has used the residual method to investigate the effects of the DREAM Act or DACA on undocumented students. As such, this paper contributes to previous literature by comparing the residual method with the commonly adopted ethnicity proxy in evaluating policy impacts on this population. The paper also uses data that includes a longer post-policy period for both legislations. The results indicate that the DREAM Act have a positive impact on the college enrollment rate of undocumented students; whereas DACA reduces college enrollment and increases the likelihood of employment among eligible undocumented immigrants. Together, these results suggest that, under the DREAM Act, undocumented individuals may invest more in education in the absence of work permits, so that when a program such as DACA is implemented, employment outcomes may improve while college enrollments fall. Furthermore, although both identification strategies produce estimates in the same direction, the ethnicity proxy can underestimate the policy impacts. This is because the residual method can filter out legal immigrants (control) from the treatment group and include individuals with more diverse ethnic background (treat) into the treatment group, thereby more accurately identifying the undocumented population in the data.

The rest of this paper proceeds as follows. Section 2 presents additional background information on the DREAM Act and the DACA program. Section 3 describes the data and explains the identification strategies. Sections 4 and 5 discuss the econometric design and present the empirical results. Section 6 performs robustness checks of the main results, and Section 7 concludes with a discussion of the policy implications.

Section 2: Background on the DREAM Act and DACA

Prior to the enactment of the DREAM Act, undocumented immigrants in the U.S. could receive free education through high school, but were prohibited from receiving in-state college tuition under the 1996 Illegal Immigration Reform and Immigrant Responsibility Act (IIRIRA). This resulted in only 40% of undocumented students continuing to attend college, compared with 71% of their U.S.-born peers (Passel and Cohn 2009). Given the fact that undocumented immigrants often permanently stay in their adopted states, state governments have a vested interest in improving the educational outcomes of these individuals as economic theory predicts that education will generate positive externalities for the broader economy (Barron 2011). As such, 20 states since 2001 have passed policies to circumvent the federal ban and allow undocumented students who have met specific criteria to pay resident tuition rates. Though the requirements vary from state to state, qualified students usually need to have 1) lived in the state and attended high-school for a particular time period, 2) obtained a high-school diploma or equivalent degree from the state, 3) been accepted to a public college or university, and 4) signed an affidavit of their intention to file for legal immigration status.

Figure 2 illustrates the states that have adopted the DREAM Act since 2001 and continuing through 2016. It is worth noting that these states include both those with many immigrants (e.g., California and New York), as well as those with comparatively few (e.g., Wisconsin and Kansas). The states also include those that disproportionately vote for Democratic candidates (e.g. Maryland and Connecticut) and others that tend to vote Republican (e.g. Utah and Nebraska). Such randomness in the states' decisions to pass the DREAM Act provides evidence that the state-level policy is exogenous to enrollment and employment trends.

Additionally, these state-level actions were also responsible for motivating federal-level discussions on similar immigration policies that can potentially improve the social and economic well-being of undocumented individuals. Although the federal government failed to pass the DREAM Act in 2011, President Obama used his prosecutorial discretion and announced the DACA program in June 2012. Under DACA, certain young undocumented immigrants brought to the U.S. as children can receive a two-year reprieve from deportation proceedings and obtain legal work authorization. Essentially, this means that these individuals can attend school, seek employment, and plan their lives accordingly without the constant threat of being removed from the country. At the end of the two-year period, DACA recipients need to apply for a renewal of their DACA status, with renewals issued in two-year increments. In September 2017, however, the Trump administration announced the suspension of the renewal process and the rescission of DACA in an effort to curb undocumented immigration. Currently, the future of this program and its beneficiaries remain uncertain.

Section 3: Data and Descriptive Statistics

This paper aims to compare the traditional ethnicity proxy with the residual method in identifying undocumented immigrants in two ways. The first dimension is how closely these methods can produce samples of undocumented immigrants that match the official U.S. Citizenship and Immigration Services (USCIS) statistics on this population. The other is how policy evaluations differ with these two methods. Specifically, I use these two identification strategies to analyze the impacts of the DREAM Act and DACA on the college enrollment rate and employment likelihood of undocumented immigrants, respectively.

To obtain the best coverage of undocumented immigrants, I use individual-level data from the monthly Current Population Survey (CPS). The CPS interviews individuals in person, unlike other comparable data sets such as the ACS that send surveys by mail, which are often ignored by undocumented immigrants due to the fear of detection (Albert 2017). The monthly CPS data provide information on respondents' college enrollment and employment status – the outcomes of interest – as well as demographic characteristics such as gender, age, race, and citizenship status. The analysis is restricted to individuals aged 17-24 with a high school diploma or a General Equivalency Diploma (GED), which is a common eligibility criterion of both policies. Additionally, I use data from January 2000 to December 2016 to evaluate the DACA program and only use the pre-DACA period from January 2000 to December 2012 to evaluate the DREAM Act in order to capture the effects of each policy separately.

Table 1 provides weighted summary statistics of the 2000-2012 sample using Hispanic non-citizens as an ethnicity proxy for undocumented immigrants. There is a substantial gap in college enrollment rates between this group and other groups of U.S. citizens, with the enrollment rate of Hispanic non-citizens being almost half of that exhibited by non-Hispanic citizens (20 percent vs. 40 percent) and Hispanic citizens (20 percent vs. 38 percent). The share of Hispanic non-citizens with a high school degree is also considerably smaller than that of other groups (43 percent for Hispanic non-citizens vs. 74 percent for non-Hispanic citizens and 65 percent for Hispanic citizens). The lack of educational proficiency of estimated undocumented students thus suggests that it is worth exploring whether state DREAM Acts and DACA can encourage them to attend college or enter the workforce.

Table 2 compares the characteristics of undocumented immigrants identified by the ethnicity proxy and the residual method respectively with official statistics from the USCIS (Rosenblum and Ruiz Soto 2016). The details of the residual method are as follows. First, we identify the total sample of the foreign-born population based on respondents' birthplaces. A foreign-born person is then classified as a legal immigrant if any of the following conditions hold:

a) That person arrived in the U.S. before 1980;

b) That person arrived in the U.S. after the age of 17;[1]

c) That person is a citizen (including naturalized citizens and citizens by virtue of being born to American parents);

d) That person is a refugee or granted asylee status;[2]

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[1] Since the CPS does not contain information on respondents' visa type, I use the age of arrival in the U.S. as an identifier for if the individual holds certain kinds of temporary visas (including students, diplomats and high-tech guest workers).

[2] If that person arrived after 2011 and was from any of the top 10 countries of refugee origin: Congo, Syria,

e) That person is a veteran or is currently in the Armed Forces;

f) That person receives welfare benefits from the government;[3]

g) That person works in the government sector;

h) That person's occupation requires lawful status or government licensing.[4]

The residual group of all other foreign-born individuals is then classified as undocumented. As Table 2 suggests, the main differences between the two identification strategies are the ethnic composition and areas of origin of estimated undocumented immigrants. While the Hispanic non-citizen proxy effectively assumes that all undocumented immigrants are Hispanic and mostly Mexican, the residual method produces estimates that are more consistent with USCIS statistics (61% Hispanic by residual method vs. 70% Hispanic estimated by USCIS; 41% Mexican by residual method vs. 51% Mexican estimated by USCIS). The residual method also more accurately reflects the share of undocumented immigrants that are from Asia (18% vs. 14% estimated by USCIS) and Europe (7.7% vs. 5% estimated by USCIS), thereby enabling analysis on a more diverse sample of undocumented individuals.

Section 4: Empirical Approach

This paper follows the literature and uses a difference-in-difference approach to measure

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Burma, Iraq, Somalia, Bhutan, Ukraine, Eritrea, Sudan, and Kuwait. Additionally, every individual born in Cuba is considered as a legal immigrant as practically all Cuban immigrants were granted refugee status.

[3] Benefits include the Supplemental Nutrition Assistance Program (SNAP), the Women, Infants, and Children (WIC) Program, and unemployment benefits.

[4] Major occupations include physicians, registered nurses, law enforcement officers, and air traffic controllers.

the enrollment and employment effects of state-level DREAM Acts and DACA on undocumented immigrants. For each policy, regressions are performed for different estimates of undocumented immigrants using the ethnicity proxy and the residual method respectively to compare the effectiveness of these identifying strategies.

Equation (1) displays the basic regression model for the analysis of the DREAM Act, estimated for individuals (i) living in state s at time t:

(1) $$Y_{ist} = \alpha + \beta Policy_{st} + X_{ist}\gamma + Z_{st}\theta + \delta_s + \emptyset_t + \delta_s t + \varepsilon_{ist}$$

For regressions examining college enrollment rates, the outcome variable Y_{ist} is a dummy variable that indicates whether the individual i residing in state s is enrolled in college full-time during the specific month and year of observation. For the employment likelihood regressions, Y_{ist} is a similar dummy variable specifying if the individual is currently employed. The explanatory variable of interest, $Policy_{st}$, is a binary variable set to one for individuals residing in states offering in-state tuition to undocumented immigrants at time t. Since the effects of the tuition subsidies are unlikely to be immediate, I follow prior literature's approach and dropped a state's observations for a full year after the policy was enacted to more accurately capture the treatment effect. Furthermore, observations from the state of Oklahoma after 2007 were also dropped to avoid ambiguity as the state decided from then on to allow its Board of Regents to make independent tuition policy decisions.

For the analysis of DACA, the main regression design is as follows:

(2) $$Y_{ist} = \alpha + \beta_1(DACA_t \times eligible_{ist}) + \beta_2 eligible_{ist} + X_{ist}\gamma + Z_{st}\theta +$$

$$\delta_s + \emptyset_t + \delta_s t + \varepsilon_{ist}$$

Similar to equation (1), the dependent variable Y_{ist} represents the observed schooling or labor market outcome for individual i residing in state s in period t. $DACA_t$ is a dummy variable equal to 1 after the enactment of the program. To account for the policy phase-in time, I follow Amuedo-Dorantes and Antman (2017) and chose October 2012 as the treatment date, since that was when the first large wave of DACA applicants received official approval of their status. The variable $eligible_{ist}$ indicates whether the individual meets all eligibility criteria observable to researchers: 1) being under the age of 31 in 2012, 2) having arrived in the U.S. before the age of 16, and 3) having arrived prior to June 2007[5]. As such, the coefficient β_1 reveals the effects of DACA on eligible individuals after its implementation relative to other ineligible undocumented immigrants over the same time period.

Furthermore, equations (1) and (2) also include a vector X_{ist} that controls for a variety of individual-level characteristics such as number of years living in the U.S., age, gender, marital status, and race. Time-varying state characteristics (Z_{st}) such as the monthly state unemployment rate are also included in order to mitigate omitted variable bias due to regional and macroeconomic factors that can potentially affect enrollment and employment outcomes and correlate with policy variables. Additionally, both models add state fixed-effects (δ_s), time fixed-effects ($\emptyset_t$), and state-specific linear time trends ($\delta_s t$) to control for time-invariant state characteristics, nation-wide time trends, and time-varying economic conditions at the state

[5] Other criteria require that individuals must: 4) have been physically present in the U.S. on June 15, 2012, and at the time of making the application with USCIS, 5) have entered without inspection prior to June 15, 2012, or had his or her lawful immigration status expired by that date, 6) have no criminal records or pose a threat to national security or public safety.

level respectively. The error term is captured by $\varepsilon_{ist} \sim N(\mu, \sigma^2)$, and I incorporate survey weights to account for the survey design and produce robust standard errors.

Section 5: Results

5.1 Enrollment and Employment Effects of the DREAM Act

Table 3 presents the results of estimating equation (1) on the sample of undocumented immigrants according to the ethnicity proxy and the residual method, respectively. Column (1) shows the results of a baseline regression with only state and time fixed effects, while columns (2) through (4) progressively add other controls to the regression. The estimates in rows 1 and 2 indicate that in-state tuition subsidies are generally effective in incentivizing undocumented students to attend college, with the ethnicity proxy suggesting a 3.2 percentage point increase in school enrollment (row 1, column 4), and the residual method showing a 3.5 percentage point increase (row 2, column 4). Given that the average enrollment rate of estimated undocumented immigrants in the data is approximately 20 percent (Table 1, row 1), such policies could effectively raise this group's enrollment rate by roughly 17.5 percent, thereby potentially improving the educational outcomes of undocumented students.

While the magnitudes of the estimates produced by the traditional ethnicity proxy and the residual method are largely similar, I run the analysis specified by equation (1) on subgroups of undocumented immigrants to compare the estimation power of two methods. Since the ethnicity proxy only considers Hispanic individuals, we would expect it to generate similar estimates to those obtained using the Hispanic subsample identified by the residual method. However, the increase in college enrollment for the Hispanic subgroup is 5.7 percentage points (column 4), larger than the estimate of the ethnicity proxy. This suggests that the ethnic proxy is likely to have underestimated the enrollment effect by including legal Hispanic immigrants in the sample, thereby diluting the measured impact of the DREAM Act.

Panel B of Table 3 shows the results on the labor market effects of the DREAM Act using the two methods and the same regression specifications. There is little statistically significant evidence for any employment effect under the full specification of the model.[6]

5.2 Enrollment and Employment Effects of DACA

Table 4 reports the estimates from equation (2) for different samples of undocumented immigrants according to the ethnicity proxy and the residual method respectively. Each coefficient is derived from a separate regression. Specifically, results in rows 1 and 2 suggest that both methods yield negative enrollment effects of DACA on undocumented students, among which the ethnicity proxy suggests a 2.8 percentage point decrease in college enrollment (row 1, column 4), and the residual method shows a 9.2 percentage point decrease (row 2, column 4). However, looking at DACA's impacts on the employment likelihood of undocumented students, rows 5 and 6 indicate an increase in the probability of being employed: 4.3 percentage point increase measured by the ethnicity proxy and 8 percentage point increase

[6] In two cases where we do not control for state-specific trends, results suggest that the DREAM Act led to a decrease in the employment likelihood of undocumented immigrants, only at 10% significance level.

by the residual method. The decrease in college enrollment rate and the increase in employment likelihood are of similar magnitudes, suggesting that eligible undocumented youths possibly chose to work instead of going to college once legal work authorization was granted under DACA, which increased the opportunity cost of attending college. For both enrollment and employment outcomes, results suggest that the ethnicity proxy underestimates DACA's effects on undocumented individuals.

Furthermore, results from the subgroup analysis within the residual method (rows 3-4, 7-8) suggest that this trend is consistent for both the Hispanic and non-Hispanic subsamples of the undocumented population. This observation also explains the differences in the magnitude of estimates produced by the two identification strategies, since the residual method can include individuals with more diverse ethnic origins who are also affected by the policy.

Section 6: Robustness Checks

6.1 Support for the Parallel Trends Assumption

A major concern about the empirical method used in the above analysis is whether there existed differential trends in the schooling and labor market outcomes of policy-eligible and -ineligible individuals prior to the DREAM Act and DACA that may be falsely attributed to the policies. Since various state governments enacted their respective DREAM Acts in different time periods, there is not a clear pre-period for this policy. I use the sample for the analysis of DACA instead as an example to test for any pre-existing trends. First, to offer reassurance that the results are not driven by a long trend prior to DACA's implementation, I restrict the sample to a shorter window around DACA's enactment, ranging from January 2005 to December 2016. If the long pre-period is driving the results, the effect estimates should not have the same direction or statistical significance as the aforementioned results. Table 5, Panel A reports the outcomes of this test. Essentially, we can still observe statistically significant negative enrollment effects and positive employment effects using a shorter pre-period, regardless of the identification strategy. These estimates are consistent with the main findings discussed above, thus offering support for the parallel trends assumption.

Additionally, I perform a placebo test by restricting the sample in Panel A to a pre-period sample from 2005 through 2011 and assigning a fake DACA treatment time as starting in 2008.[7] As Table 5 Panel B shows, the interaction between the pseudo-DACA indicator and the eligibility indicator generally has no statistically significant impact, except for the employment regressions using the ethnicity proxy. The lack of results in this placebo exercise suggests that the effects of DACA are not driven by differential pre-existing trends between eligible and ineligible undocumented immigrants.

6.2 Robustness to Certain State's Dominating Trends

Since Texas ranks first in terms of having the highest estimated number of undocumented immigrants per capita (United States Citizenship and Immigration Services 2000), previous

[7] I follow the approach of Amuedo-Dorantes and Antman (2017) and assigned the new placebo indicator to run from October 2008 (mirroring the timing of DACA) to the end of 2011.

literature has noted that Texas can have a separate treatment effect because of the larger pool of individuals who could be eligible under the DREAM Act and DACA (Gaulke 2017). To test if Texas is driving the estimated policy impacts, I run the analysis on a different sample, removing observations from Texas and using the two methods respectively to identify the undocumented population. The results on the effects of the DREAM Act are presented in Table 6, Panel A, while those for DACA can be found in Table 6, Panel B. For both legislations, the estimated schooling and labor market impacts are consistent with the aforementioned main findings, and remain statistically significant. Therefore, the results suggest that Texas is not dominating the measured changes in the college enrollment rate and employment likelihood of undocumented students.

Section 7: Conclusion

This paper compares the traditional ethnicity proxy with the newly developed residual methods in their ability to match official statistics and in their policy estimates for the DREAM Act and DACA. I find that the residual method gives closer estimates on undocumented immigrants to those published by USCIS, as it captures non-Hispanic undocumented individuals and filters out legal Hispanic immigrants. The commonly adopted Hispanic non-citizen proxy no longer reflects current demographic trends, as the number of non-Hispanic undocumented immigrants continues to grow. Using monthly CPS data, I find that both methods support the conclusions that state-level DREAM Acts led to a higher college enrollment rate among undocumented individuals, whereas DACA resulted in a decline in their college enrollment and an increase in their employment likelihood. The residual method yields similar policy estimates, but larger in magnitude, suggesting that the traditional ethnicity proxy could underestimate the policy impacts.

References

Abrego, Leisy J. and Roberto Gonzales. 2010. “Blocked paths, uncertain futures: The postsecondary education and labor market prospects of undocumented Latino youth.” *Journal of Education for Students Placed at Risk,* 15 (1-2): 144-157.

Albert, Christoph. 2017. “The labor market impact of undocumented immigrants: Job creation vs. job competition.” CESifo Working Paper 6575.

Amuedo-Dorantes, Catalina and Francisca Antman. 2017. “Schooling and labor market effects of temporary authorization: Evidence from DACA.” *Journal of Population Economics*, 30 (1): 339-373.

Amuedo-Dorantes, Catalina and Chad Sparber. 2014. “In-state tuition for undocumented immigrants and its impact on college enrollment, tuition costs, student financial aid, and indebtedness.” *Regional Science and Urban Economics*, 49:11-24.

Arrow, Kenneth J. 1973. “Higher education as a filter.” *Journal of Public Economics*, 2 (3): 193-216.

Bachmeier, James D., Jennifer Van Hook, and Frank D. Bean. 2014. “Can we measure immigrants’ legal status? Lessons from two U.S. surveys.” *The International Migration Review*, 48 (2): 538-566.

Barron, Elisha. 2011. “The development, relief, and education for Alien Minors (DREAM) Act.” *Harvard Journal on Legislation*, 48 (2): 623-656.

Becker, Gary. 1962. “Investment in human capital: A theoretical analysis.” *Journal of Political Economy*, 70 (5): 9-49.

Borjas, George J. 2017. “The earnings of undocumented immigrants.” NBER Working Paper 23236.

Chin, Aimee and Chinhui Juhn. 2010. “Does reducing college costs improve educational outcomes for undocumented immigrants? Evidence from state laws permitting undocumented immigrants to pay in-state tuition at state colleges and universities.” In *Latinos and the Economy, Integration and Impact in Schools, Labor Markets, and Beyond*, edited by David L. Leal and Stephen J. Trejo, Part II, 63-94.

Gaulke, Amanda P. 2017. “In-state tuition for undocumented immigrants and the effect on in-state versus out-of-state students.” Kansas State University.

Kaushal, Neeraj. 2008. “In-state tuition for the undocumented: Education effects on Mexican young adults.” *Journal of Policy Analysis and Management*, 27 (4): 771-792.

Passel, Jeffrey S. and D'Vera Cohn. 2017. "As Mexican share declined, U.S. unauthorized immigrant population fell in 2015 below recession level." Washington, D.C.: Pew Hispanic Center.

Passel, Jeffrey S. and D'Vera Cohn. 2009. "A portrait of unauthorized immigrants in the United States." Washington, D.C.: Pew Hispanic Center.

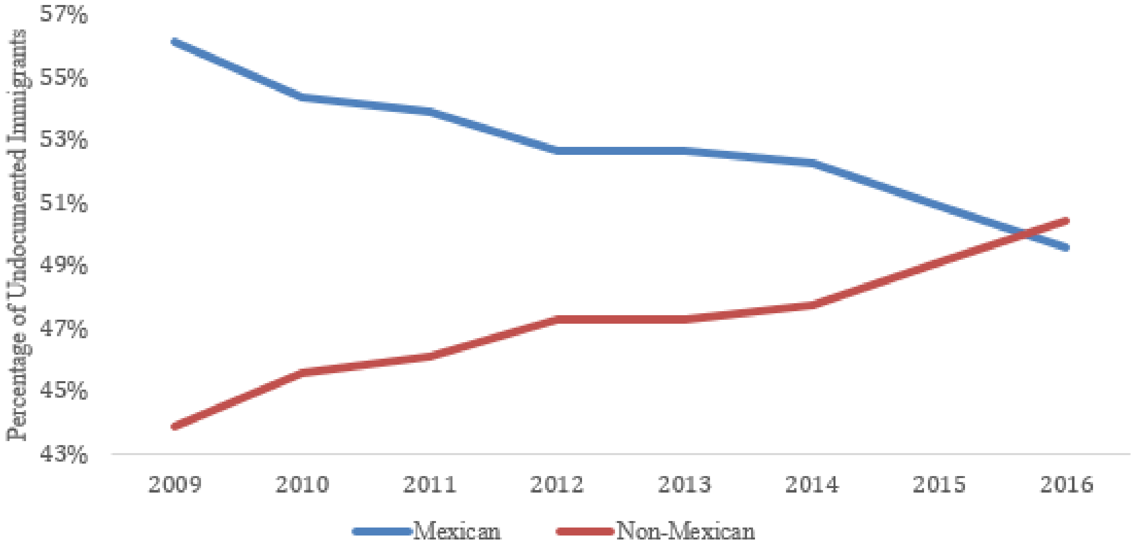
Pope, Nolan G. 2016. "The effects of DACAmentation: The impact of Deferred Action for Childhood Arrivals on unauthorized immigrants." *Journal of Public Economics*, 143 (C): 98-114.

Rosenblum, Marc and Ariel G. Ruiz Soto. 2016. "An analysis of unauthorized immigrants in the united states by country and region of birth." Washington, D.C.: Department of Homeland Security.

Teranishi, Robert and Carola Suarez-Orozco. 2015. "In the shadows of the ivory tower: Undocumented undergraduates and the liminal state of immigration reform." *The UndocuScholar Project. Institute for Immigration, Globalization & Education*, UCLA. UCLA: 852096.

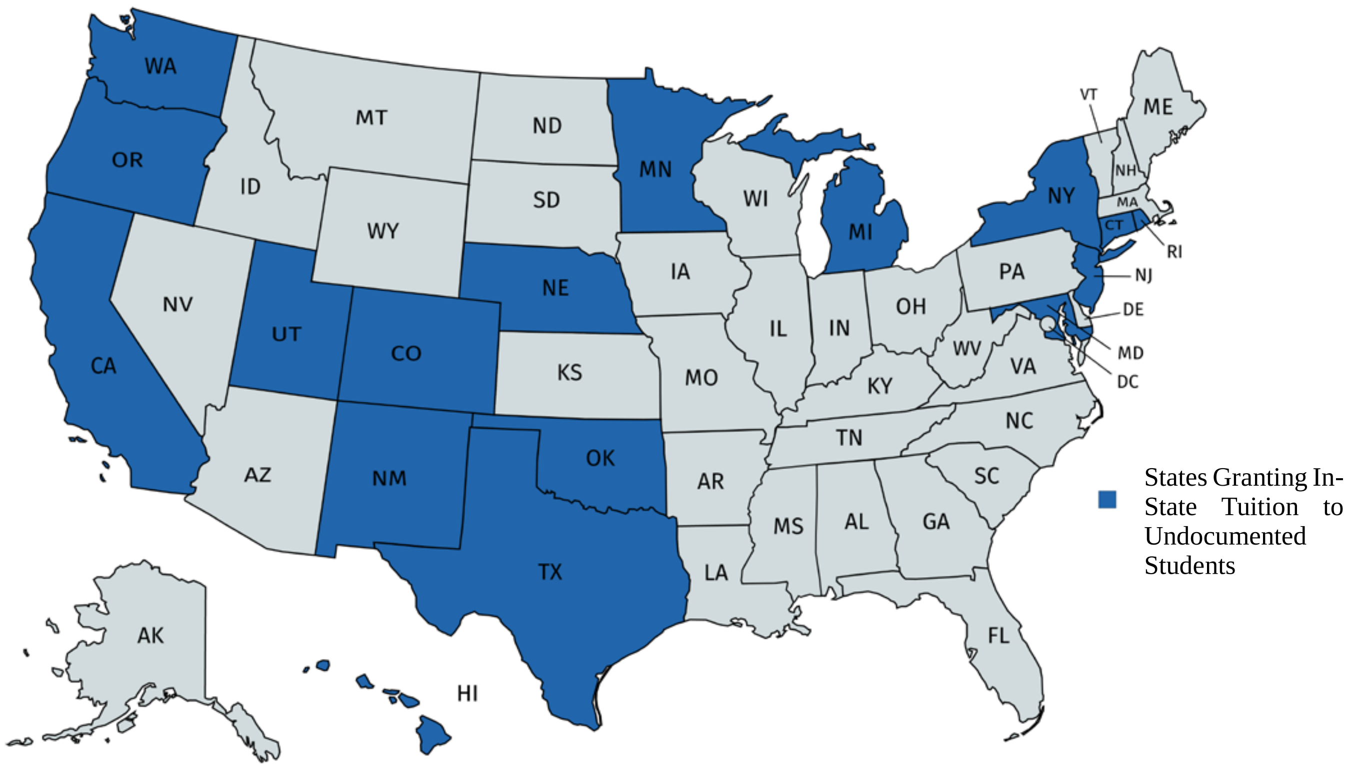
United States Citizenship and Immigration Services (2000). "Estimated number of illegal immigrants (per capita) by state." Field Report 2000.

Figure 1. Share of Mexican and Non-Mexican Individuals of Undocumented Immigrants, 2009-2016



Source: Pew Research Center.

Figure 2. State Legislation on In-State Tuition for Undocumented Immigrants, 2001-2016



Source: National Conference of State Legislatures.

Table 1

Weighted Descriptive Statistics Using the Ethnicity Proxy

Characteristics	**Hispanic Non-Citizens** (Obs = 42,529)		**Non-Hispanic Citizens** (Obs = 1,243,880)		**Hispanic Citizens** (Obs = 140,763)	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
College Enrollment Rate	0.205	0.374	0.407	0.498	0.381	0.447
Share with High School Diploma	0.435	0.461	0.735	0.448	0.648	0.443
Share in Treatment States	0.574	0.458	0.361	0.487	0.706	0.420
Female	0.446	0.460	0.514	0.507	0.520	0.460
Asian	0.005	0.064	0.036	0.189	0.009	0.086
Black	0.029	0.155	0.155	0.367	0.039	0.179
White	0.941	0.219	0.780	0.420	0.908	0.266
Other Race	0.026	0.146	0.029	0.170	0.044	0.189

Notes: Calculations based on data from 2000-2012 monthly Current Population Survey. Sample consists of all individuals aged 17-24 with a high school diploma or GED.

Table 2

Comparison of the Ethnicity Proxy and Residual Method

Characteristics		**USCIS Estimates**	**Hispanic Non-Citizens**	**Residual Method**	**Difference**	
		(1)	(2)	(3)	(1) – (2)	(1) – (3)
Hispanic		70%	100%	61%	-30%	9%
Region/Country of Birth	Mexico	51%	71%	41%	-20%	10%
	Central America	16%	15%	8%	1%	8%
	South America	6%	7.1%	8%	-1.1%	-2%
	Asia	14%	0.2%	18%	13.8%	-4%
	Europe	5%	0.2%	7.7%	4.8%	-2.7%
% of U.S. Labor Force		5.3%	4.5%	4.8%	0.8%	0.5%
% without High School Education		40%	56%	50%	-16%	-10%
% of U.S. Population		3.4%	4.9%	2.3%	-1.5%	1.1%

Notes: Column 1 presents DHS estimates on the percentage of total undocumented immigrants with each characteristic. Calculations for columns 2 and 3 are based on data from 2000-2012 monthly Current Population Survey. Samples for columns 2 and 3 consist of all individuals aged 17-24 with a high school diploma or GED.

Table 3
Enrollment and Employment Effects of State-Level DREAM Acts

Panel A: College Enrollment	**(1)**	**(2)**	**(3)**	**(4)**
Specification A: Ethnicity Proxy				
Hispanic Non-Citizens	0.013	0.015*	0.032***	0.032***
(N = 42,529)	(0.009)	(0.009)	(0.012)	(0.012)
Specification B: Residual Method				
Undocumented Immigrants	0.024	0.023	0.033*	0.035*
(N = 30,768)	(0.016)	(0.015)	(0.019)	(0.019)
Subgroup: Hispanic	0.031	0.033*	0.056**	0.057**
(N = 18,416)	(0.020)	(0.019)	(0.024)	(0.024)
Subgroup: Non-Hispanic	-0.005	0.0003	-0.022	-0.028
(N = 12,352)	(0.023)	(0.022)	(0.029)	(0.030)

Panel B: Employment Likelihood	**(1)**	**(2)**	**(3)**	**(4)**
Specification A: Ethnicity Proxy				
Hispanic Non-Citizens	-0.010*	-0.009*	-0.011	-0.010
(N = 42,529)	(0.005)	(0.005)	(0.008)	(0.008)
Specification B: Residual Method				
Undocumented Immigrants	-0.014	-0.010	-0.010	-0.012
(N = 30,768)	(0.010)	(0.010)	(0.015)	(0.015)
Subgroup: Hispanic	-0.021*	-0.019*	-0.008	-0.008
(N = 18,416)	(0.012)	(0.011)	(0.017)	(0.017)
Subgroup: Non-Hispanic	0.016	0.026	0.017	0.013
(N = 12,352)	(0.021)	(0.021)	(0.031)	(0.031)
Controls for:				
Individual-Level Characteristics	N	Y	Y	Y
State Fixed Effects	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y
State-Specific Time Trends	N	N	Y	Y
Time-Varying State Characteristics	N	N	N	Y

Notes:
*** p<0.01, ** p<0.05, * p<0.1
Results from survey-weighted linear probability model using 2000-2012 monthly Current Population Survey data.
Each number represents the coefficient of *Policy* variable based on a separate regression.
Robust standard errors accounting for the CPS sampling design are presented in parentheses below each coefficient estimate.
The samples of specifications A and B both include individuals aged 17 to 24 with a high school diploma or GED. The sample of specification A contains 45,618 Hispanic non-citizens, whereas the sample of specification B contains 30,768 undocumented immigrants.
All regressions control for state and time fixed effects.

Table 4
Enrollment and Employment Effects of DACA

Panel A: College Enrollment	**(1)**	**(2)**	**(3)**	**(4)**
Specification A: Ethnicity Proxy				
Hispanic Non-Citizens	-0.062***	-0.028***	-0.026***	-0.028***
(N = 53,066)	(0.010)	(0.010)	(0.010)	(0.010)
Specification B: Residual Method				
Undocumented Immigrants	-0.205***	-0.086***	-0.091***	-0.092***
(N = 38,814)	(0.018)	(0.017)	(0.017)	(0.017)
Subgroup: Hispanic	-0.148***	-0.050**	-0.050**	-0.054**
(N = 23,429)	(0.024)	(0.023)	(0.023)	(0.023)
Subgroup: Non-Hispanic	-0.160***	-0.081***	-0.078***	-0.078***
(N = 15,385)	(0.026)	(0.025)	(0.026)	(0.026)

Panel B: Employment Likelihood	**(1)**	**(2)**	**(3)**	**(4)**
Specification A: Ethnicity Proxy				
Hispanic Non-Citizens	0.097***	0.043***	0.044***	0.043***
(N = 53,066)	(0.012)	(0.011)	(0.011)	(0.011)
Specification B: Residual Method				
Undocumented Immigrants	0.184***	0.080***	0.080***	0.080***
(N = 38,814)	(0.018)	(0.018)	(0.018)	(0.018)
Subgroup: Hispanic	0.160***	0.046*	0.041*	0.041*
(N = 23,429)	(0.027)	(0.025)	(0.025)	(0.025)
Subgroup: Non-Hispanic	0.121***	0.058**	0.064**	0.064**
(N = 15,385)	(0.025)	(0.025)	(0.026)	(0.026)
Controls for:				
Individual-Level Characteristics	N	Y	Y	Y
State Fixed Effects	Y	Y	Y	Y
Time Fixed Effects	Y	Y	Y	Y
State-Specific Time Trends	N	N	Y	Y
Time-Varying State Characteristics	N	N	N	Y

Notes:
*** p<0.01, ** p<0.05, * p<0.1
Results from survey-weighted linear probability model using 2000-2016 monthly Current Population Survey data.
Each number represents the coefficient of (*DACA* x *eligible*) variable based on a separate regression.
Robust standard errors accounting for the CPS sampling design are presented in parentheses below each coefficient estimate.
The samples of specifications A and B both include individuals aged 17 to 24 with a high school diploma or GED. The sample of specification A contains 53,183 Hispanic non-citizens, whereas the sample of specification B contains 38,814 undocumented immigrants.

Table 5
Robustness Check for Pre-Existing Trends Before DACA

Specification Strategies	**College Enrollment**	**Employment Likelihood**
Panel A	**Shorter Window Around Treatment**	
Ethnicity Proxy: Hispanic Noncitizens	-0.019*	0.057***
(N = 38,914)	(0.011)	(0.012)
Residual Method	-0.102***	0.110***
(N = 31,654)	(0.018)	(0.019)
Panel B	**Falsification Test Using Pre-Period Sample**	
Ethnicity Proxy: Hispanic Noncitizens	0.017	-0.031***
(N = 24,819)	(0.011)	(0.011)
Residual Method	-0.017	-0.032
(N = 18,837)	(0.020)	(0.020)
Controls for:		
Individual-Level Characteristics	Y	Y
State Fixed Effects	Y	Y
Time Fixed Effects	Y	Y
State-Specific Time Trends	Y	Y
Time-Varying State Characteristics	Y	Y

Notes: Robust standard errors accounting for the CPS sampling design in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.
Results from survey-weighted linear probability model using monthly Current Population Survey data. Samples are restricted to individuals who are 17 to 24 with a high school diploma or GED.
Panel A uses data from 2005 to 2016, with each number presenting the coefficient of the (*DACA* x *eligible*) variable in a separate regression.
Panel B uses data from 2005 to 2011, with each number presenting the coefficient of the (*Placebo_DACA* x *eligible*) variable in a separate regression. The placebo treatment indicator equals 1 from October 2008 to December 2011.

Table 6
Robustness Check for Dominating Trends

Specification Strategies	**College Enrollment**	**Employment Likelihood**
Panel A	**DREAM Act**	
Ethnicity Proxy: Hispanic Noncitizens	0.0455***	-0.003
(N = 38,143)	(0.0137)	(0.009)
Residual Method	0.0408**	-0.004
(N = 28,271)	(0.0197)	(0.016)
Panel B	**DACA**	
Ethnicity Proxy: Hispanic Noncitizens	-0.020*	0.0391***
(N = 47,254)	(0.011)	(0.0125)
Residual Method	-0.0898***	0.0754***
(N = 35,377)	(0.0185)	(0.0188)
Controls for:		
Individual-Level Characteristics	Y	Y
State Fixed Effects	Y	Y
Time Fixed Effects	Y	Y
State-Specific Time Trends	Y	Y
Time-Varying State Characteristics	Y	Y

Notes: Robust standard errors accounting for the CPS sampling design in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.
Results from survey-weighted linear probability model using monthly Current Population Survey data. Samples are restricted to individuals who are 17 to 24 with a high school diploma or GED.
Panel A uses data from 2000 to 2012, with each number presenting the coefficient of *Policy* variable in a separate regression. Observations from the state of Texas are removed from the sample.
Panel B uses data from 2000 to 2016, with each number presenting the coefficient of the (*DACA* x *eligible*) variable in a separate regression. Observations from the state of Texas are removed from the sample.