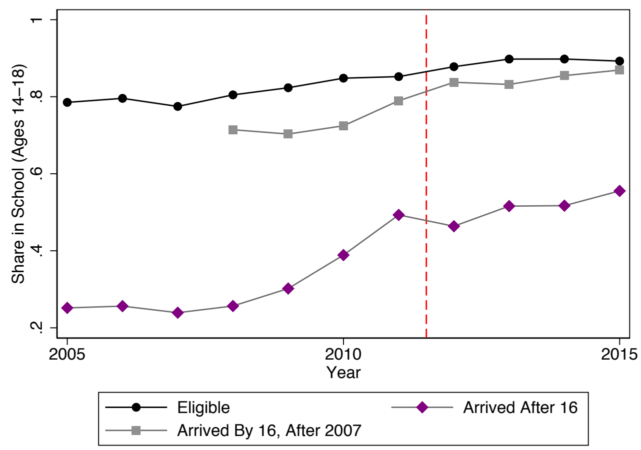
ONLINE APPENDIX:
Do Human Capital Decisions Respond to the Returns to Education? Evidence from DACA

A Appendix A: Supplementary Tables and Figures

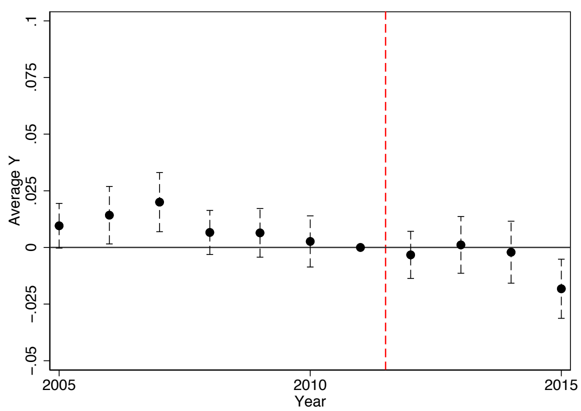
Figure A.1: Trends in School Attendance Among Non-Chosen Comparison Groups, Hispanic Immigrant Non-Citizens Ages 14-18



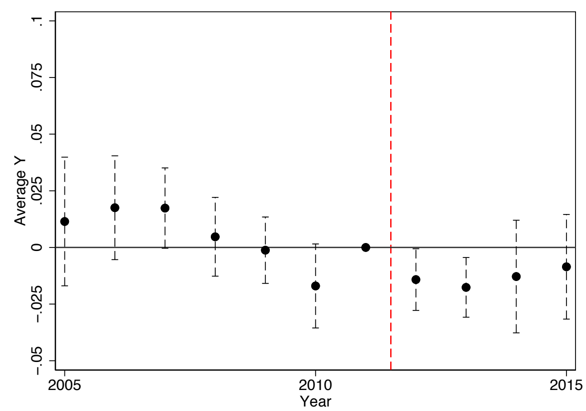
Notes: This figure shows school attendance rates for Hispanic immigrant non-citizens aged 14-18 who immigrated by age 10 and by 2007, or who immigrated after 16 or 2007, calculated from the 2005-2015 American Community Surveys. The vertical dashed line indicates the implementation of DACA.

Figure A.2: Effect of DACA on *Predicted* School Attendance and High School Completion, Hispanics

(a) School Attendance, Ages 14-18



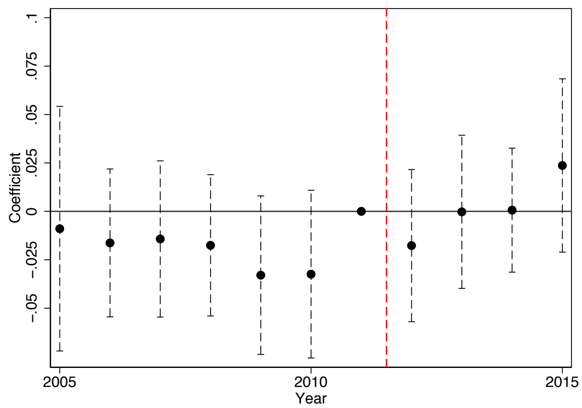
(b) High School Completion, Ages 19-22



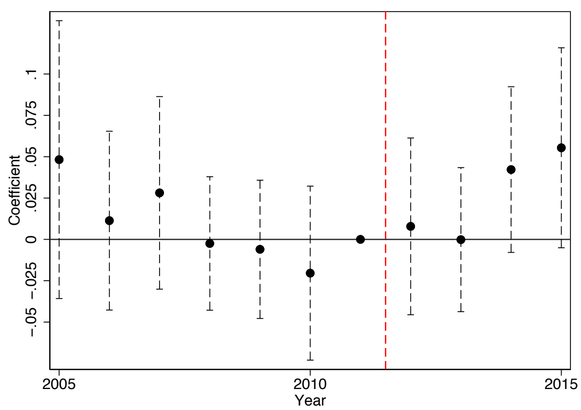
Notes: This figure shows the coefficients and 95 percent confidence intervals from event study regressions that estimate interactions between year and eligibility indicators, where the outcomes are *predicted* schooling outcomes, and year 2011 is the omitted category. The outcomes are the fitted values of likelihood of being in school (Panel A) and high school completion (Panel B), obtained from regressions of observed schooling outcomes on indicators for age, race, sex, age and year of immigration, citizenship status, birthplace, language, state, metropolitan status, health insurance coverage, presence of mother and father in the household, parental college attendance, family size, number of siblings, household poverty status, and the presence of a food stamp recipient in the household using data from 2005 to 2011. See the notes of Figure 3 for definition of eligibility, control variables, clustering, and sample weights. Data: 2005–2015 American Community Survey. Sample is composed of foreign born Hispanics who immigrated by age 10 and by 2007.

Figure A.3: Effect of DACA on School Attendance, Ages 19-22

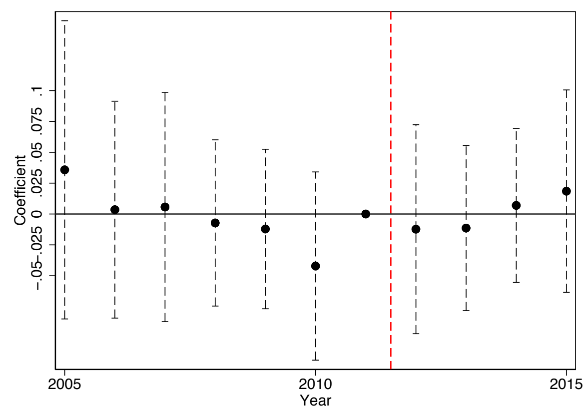
(a) All



(b) Hispanic

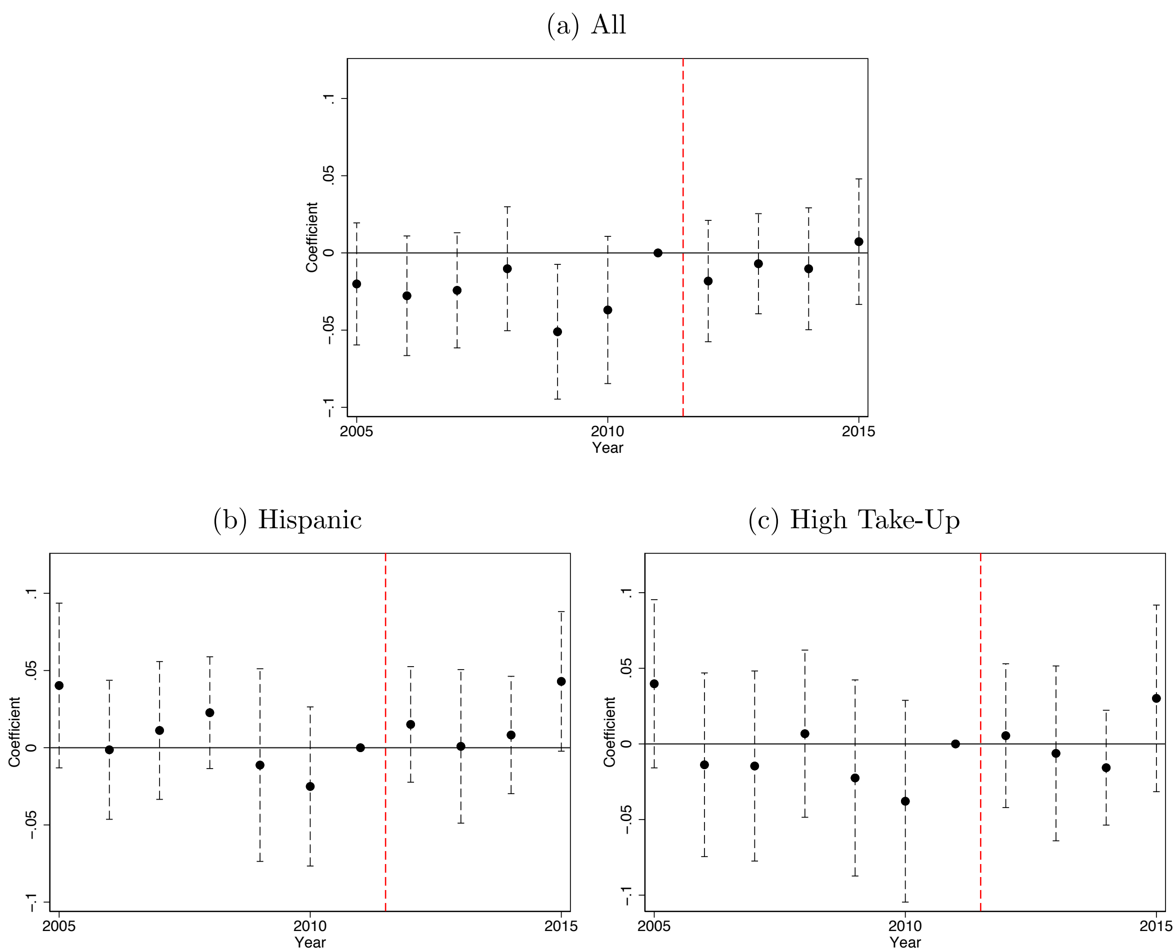


(c) High Take-Up



Notes: This figure shows the coefficients and 95 percent confidence intervals from event study regressions that estimate interactions between year and eligibility indicators, where the outcomes is school attendance during ages 19-22, and year 2011 is the omitted category. The dashed vertical line indicates the enactment of DACA. See the notes of Figure 3 for definition of eligibility, control variables, clustering, sample weights, and high take-up. Data: 2005–2015 American Community Survey. Sample is composed of foreign born Hispanics ages 19-22 who immigrated by age 10 and by 2007.

Figure A.4: Effect of DACA on College Enrollment, Ages 19-22

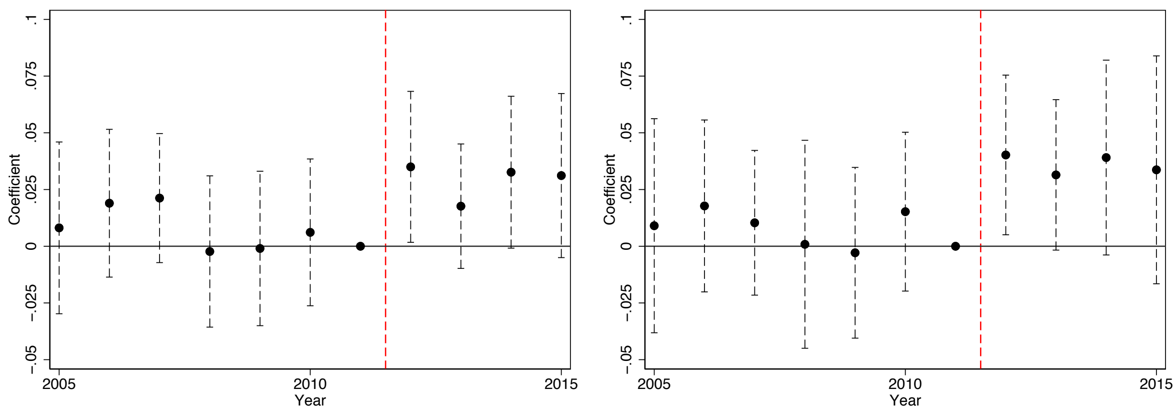


Notes: This figure shows the coefficients and 95 percent confidence intervals from event study regressions that estimate interactions between year and eligibility indicators, where the outcome is attainment of some college (more than 12 years of completed education), and year 2011 is the omitted category. The dashed vertical line indicates the enactment of DACA. See the notes of Figure 3 for definition of eligibility, control variables, clustering, sample weights, and high take-up. Data: 2005–2015 American Community Survey. Sample is composed of foreign born Hispanics ages 19-22 who immigrated by age 10 and by 2007.

Figure A.5: Impact of DACA on School Attendance, Ages 14-18 –

Controlling for Secure Communities

(a) Hispanic (b) High Take-Up



Notes: This figure shows the coefficients and 95 percent confidence intervals from event study regressions that estimate interactions between year and eligibility indicators, where the outcome is school attendance between ages 14-18, and year 2011 is the omitted category. The dashed vertical line indicates the enactment of DACA. We include controls for the presence of Secure Communities in the county in addition to the following fixed effects: sex, year of immigration, birth region, age of immigration-by-eligibility, age-by-eligibility, state-by-year, race-by-year, and age-by-year (see Equation 1). See the notes of Figure 3 for definition of eligibility, clustering, sample weights, and high take-up. Data: 2005–2015 American Community Survey. Sample is composed of foreign born ages 14-18 who immigrated by age 10 and by 2007. Data on Secure Community activation dates by county were provided by Alsan and Yang (2018).

Table A.1: Pre-DACA Characteristics of Hispanic Treatment and Comparison Groups

	Eligible	Control			
	(1)	(2)	(3)	(4)	(5)
	All	All	US Territories	US Parents	Naturalized
A: Individual Characteristics					
Female	0.47	0.49	0.48	0.50	0.50
Current Age	17.69	18.26	17.79	17.90	18.57
Age at Immigration	5.13	3.81	4.17	3.00	3.92
Year of Immigration	1995.57	1993.69	1994.62	1993.43	1993.39
Born in US Territory	0.00	0.24	1.00	0.00	0.00
Health Insurance	0.24	0.42	0.49	0.51	0.37
English Primary Language	0.03	0.16	0.11	0.36	0.12
Poor English	0.08	0.03	0.03	0.02	0.04
B: Family Characteristics					
Parent(s) in HH, Ages 14-17	0.92	0.93	0.92	0.95	0.94
Parent(s) in HH, Ages 14-17	0.92	0.93	0.92	0.95	0.94
Single Mother HH, Ages 14-17	0.18	0.26	0.41	0.21	0.20
Parent(s) College	0.07	0.19	0.14	0.24	0.19
Number of Siblings	1.54	1.17	1.19	1.08	1.20
In Poverty	0.32	0.22	0.36	0.16	0.18
Income to Poverty Ratio	1.64	2.26	1.82	2.60	2.35
Food Stamp Recipient in HH	0.18	0.19	0.37	0.12	0.13
C: Outcomes					
School Attendance, Ages 14-18	0.87	0.91	0.89	0.93	0.91
School Attendance, Ages 19-22	0.33	0.49	0.38	0.55	0.51
High School Completion, Ages 19-22	0.70	0.85	0.75	0.87	0.88
College Enrollment, Ages 19-22	0.31	0.51	0.37	0.57	0.55
Individuals	39820	18714	4206	3633	10875

Notes: This table shows summary characteristics for eligible individuals (Column 1), and the comparison group (Columns 2-5; entire (Column 2), born in US territories (Column 3), born to American parents abroad (Column 4), naturalized (Column 5)). Eligible individuals are defined as non-citizen immigrants, and the comparison group is comprised of citizen immigrants. Data: 2005–2011 American Community Survey. Sample is composed of Hispanic foreign born individuals ages 14 to 22 who immigrated by age 10 and by 2007.

Table A.2: Effect of DACA on Main Outcomes, Hispanics – Accounting for Time Trends

	No Trend	Linear Trend	De-Trend
A: School Attendance, Ages 14-18			
Eligible*Post	0.022***	0.033*	0.035***
	(0.008)	(0.017)	(0.009)
Mean Y	0.891	0.891	0.891
Individuals	54015	54015	54015
B: High School Completion, Ages 19-22			
Eligible*Post	0.059***	0.053***	0.063***
	(0.010)	(0.019)	(0.010)
Mean Y	0.781	0.781	0.781
Individuals	38704	38704	38704
C: College Enrollment, Ages 19-22			
Eligible*Post	0.013	0.033*	0.045**
	(0.010)	(0.018)	(0.018)
Mean Y	0.407	0.407	0.407
Individuals	38704	38704	38704

Notes: This table shows the sensitivity of the difference-in-difference estimates of the impact of DACA on schooling outcomes of eligible youth, when using different methods to account for differential linear trends by eligibility. Column (1) shows our baseline results when we do not control for trends, Column (2) shows the estimates when we include an indicator for eligibility interacted with year, and Column (3) shows the estimates when we perform a two-step procedure, in which we first estimate a regression of each outcome and covariate on an indicator for eligibility interacted with year using the years 2005-2011, and then estimate the difference-in-difference on the residuals. See the notes of Table 1 for the definition of eligibility, high take-up, control variables, clustering, and sample weights. * p<0.10, ** p<0.05, *** p<0.01. Data: 2005–2015 American Community Survey. Sample is composed of Hispanic foreign born individuals ages 14-18 (Panel A) or 19 to 22 (Panels B and C) who immigrated by age 10 and by 2007.

Table A.3: Effect of DACA on Main Outcomes, Hispanics –
Inverse Propensity Score Weighting

	All	Hispanic	High Take-Up
A: School Attendance, Ages 14-18			
Eligible*Post	0.012**	0.021**	0.030***
	(0.005)	(0.008)	(0.008)
Individuals	109170	51727	46234
B: High School Completion, Ages 19-22			
Eligible*Post	0.037***	0.062***	0.069***
	(0.006)	(0.008)	(0.008)
Individuals	78199	36994	33178
C: College Enrollment, Ages 19-22			
Eligible*Post	0.016*	0.012	0.013
	(0.009)	(0.010)	(0.011)
Individuals	78199	36994	33178

Notes: This table shows the difference-in-difference estimates of the impact of DACA on schooling outcomes of eligible youth, when using inverse propensity score weighting. We predict the propensity to be eligible using the demographics in Equation 1, as well as household poverty, and dummies for whether the individual primarily speaks English, primarily speaks Spanish, is fluent in English, and lives in a metropolitan area. For regressions of schooling attendance between ages 14 to 18, we also include additional controls for family composition. See the notes of Table 1 for the definition of eligibility, high take-up, control variables, clustering, and sample weights. * p<0.10, ** p<0.05, *** p<0.01. Data: 2005–2015 American Community Survey. Sample is composed of foreign born individuals who immigrated by age 10 and by 2007.

Table A.4: Effect of DACA on School Attendance, California County Data

		Test Takers	
	Enrollment	Math	ELA
High Share DACA Eligible * Post	0.042	0.024***	0.013*
	(0.026)	(0.009)	(0.007)
Mean Y	0.762	0.316	0.321
Observations	374	340	340

Notes: This table shows the difference-in-difference estimates of the impact of DACA on various measures of school attendance using county-level variation from California. Treated counties are those with an above-median share of Hispanics that are DACA-eligible. The outcomes are high school enrollment (column 1), the number students taking the Math CAHSEE exam (column 2) and the number of students taking the ELA CAHSEE exam (column 3). All of these attendance measures are expressed as a share of the average Hispanic population aged 14-18 in the county between 2005 and 2011. Post is an indicator for 2012 or after. Regressions include county fixed effects, year fixed effects, and control for the county unemployment rate (See Equation 2). Regressions are weighted by the average number of Hispanics aged 14 to 18 in the county in the 2005-2011 ACS, and standard errors are clustered by county. * p<0.10, ** p<0.05, *** p<0.01. Data: Enrollment data for academic years 2005/06 to 2015/16 and CAHSEE data for 2005/06 to 2014/15, provided by the California Department of Education.

Table A.5: Effect of DACA on California High School Exit Exam Performance

	Math			ELA		
	Tested	Pass	Score	Tested	Pass	Score
A: Grade 10						
High Share DACA Eligible * Post	0.011*	-0.023***	-2.963***	0.010*	-0.011***	-1.597***
	(0.006)	(0.006)	(0.751)	(0.005)	(0.003)	(0.448)
Mean Y	0.18	0.74	374.20	0.18	0.74	370.63
Observations	340	340	340	340	340	340
B: Grade 11						
High Share DACA Eligible * Post	0.008***	-0.011	-0.586	0.004**	0.009	0.427
	(0.002)	(0.009)	(0.595)	(0.002)	(0.008)	(0.733)
Mean Y	0.07	0.33	340.77	0.07	0.34	338.03
Observations	340	340	340	340	340	340
C: Grade 12						
High Share DACA Eligible * Post	0.005***	0.006	0.697	-0.001	0.017**	1.647**
	(0.002)	(0.006)	(0.504)	(0.002)	(0.007)	(0.623)
Mean Y	0.06	0.27	337.29	0.06	0.24	332.41
Observations	340	340	340	340	340	340

Notes: This table shows the difference-in-difference estimates of the impact of DACA on California High School Exit Exam (CAHSEE) performance in counties with an above-median share of Hispanics that are DACA-eligible. The outcomes are the share of Hispanics taking the math or ELA exam (Columns 1 and 3), the share of test takers passing the exam (Columns 2 and 4), and the average test score in the county (Columns 3 and 6). The denominator for the shares is the average number of Hispanics ages 14 to 18 in the county between 2005-2011. Post is an indicator for 2012 or after. Regressions include county fixed effects, year fixed effects, and control for the county unemployment rate (See Equation 2). Regressions are weighted by the average number of Hispanics aged 14 to 18 in the county in the 2005-2011 ACS, and standard errors are clustered by county. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Data: Enrollment data for academic years 2005/06 to 2015/16 and CAHSEE data for 2005/06 to 2014/15, provided by the California Department of Education.

Table A.6: Effect of DACA on Schooling and Work, By Gender and Age

	In School		Not In School	
	Any	Sec.	Working Only	Idle
A: Males 14–18				
Eligible*Post	0.021**	0.024**	-0.013	-0.012
	(0.010)	(0.011)	(0.010)	(0.018)
Mean Y	0.885	0.837	0.083	0.081
Individuals	28214	28214	17315	17315
B: Males 16–18				
Eligible*Post	0.025	0.032**	-0.013	-0.012
	(0.017)	(0.015)	(0.010)	(0.018)
Mean Y	0.836	0.759	0.083	0.081
Individuals	17315	17315	17315	17315
C: Females 14–18				
Eligible*Post	0.025**	0.010	-0.001	-0.026**
	(0.012)	(0.012)	(0.011)	(0.011)
Mean Y	0.897	0.831	0.047	0.102
Individuals	25801	25801	15573	15573
D: Females 16–18				
Eligible*Post	0.028*	-0.001	-0.001	-0.026**
	(0.016)	(0.017)	(0.011)	(0.011)
Mean Y	0.851	0.741	0.047	0.102
Individuals	15573	15573	15573	15573

Notes: Table shows difference-in-differences estimates of the effect of DACA on school attendance (Column 1), attending a secondary school (i.e junior or senior high school, Column 2), working only (Column 3), and being idle (Column 4). See the notes of Table 1 for the definition of eligibility, high take-up, control variables, clustering, and sample weights. * p<0.10, ** p<0.05, *** p<0.01. Data: 2005–2015 American Community Survey. Sample is composed of foreign born individuals who immigrated by age 10 and by 2007.

B Appendix B: Converting Difference-in-Difference to ITT

B.1 ACS ITT

In order to convert our difference-in-difference estimates in the ACS to ITT estimates, we need to understand the frequency with which youth non-citizens are undocumented. We perform this calculation for the overall population and for the Hispanic population, and for context, we also calculate the share of non-citizens with legal status and the share of the undocumented that are Hispanic.

Estimating the share of all non-citizen youth are undocumented is straightforward. Baker and Rytina (2013) estimate that there were 1.4 million undocumented youth between the ages of 18 and 24 in 2012, and Acosta, Larsen and Grieco (2014) estimate there to be 2.55 million non-citizens of the same ages in the 2012 ACS. Thus, we calculate that 55 percent of all non-citizens between the ages of 18 and 24 are undocumented in 2012.

Estimating the share of Hispanic non-citizen youth that are undocumented is more complex, since data are not always available at the level of aggregation that we need for these calculations. Therefore we make the following approximations to get close to these statistics:

1. We use the number of non-citizen Hispanics from the fourteen most common countries of origin to approximate the total number of Hispanic non-citizens. Immigrants from these countries account for 95 percent of all Hispanics in the US (Flores, 2017; Passel and Cohn, 2014).

2. We use the share of undocumented among non-citizens from Latin America (LA) (Central America, South America, and the Caribbean) to approximate the share of undocumented among Hispanic non-citizens. We estimate that Latin American immigrants account for at least 94 percent of all Hispanic immigrants (Flores, 2017; Passel and Cohn, 2014).[36]

Using these estimates, we calculate:

∘ 72 percent of Hispanic non-citizens are undocumented, as: $\frac{\text{8.75M undocumented from LA}}{\text{12.2M non-citizens from LA}} = 0.72$. Source: Hispanic Origin Profiles table of Flores (2017) and Table 2.1 of Passel and Cohn (2014).

∘ 55 percent of non-citizens have legal status, as $1 - \frac{\text{11.2M undocumented}}{\text{(42.5M foreign born} - \text{17.8M citizens)}} = 0.55$. Source: Figure 5.8 of Lopez, Passel and Rohal (2015).
∘ 78 percent of the undocumented population are Hispanic, as $\frac{\text{8.75M undocumented from LA}}{\text{11.2M undocumented}} = 0.78$. Source: Table 2.1 of Passel and Cohn (2014).

[36] We use data from the fourteen most common countries of origin for Hispanic immigrants to calculate this. Among this group, 99 percent of Hispanic immigrants are from Latin America.

B.2 California ITT

We perform two adjustments to obtain the ITT for the California analysis. First, we rescale our estimates to take account of the difference in the underlying treatment across above- and below-median undocumented counties. Since these counties have 17.6 percent and 10.4 percent share non-citizens among Hispanics, respectively, we divide our estimates by the 7.2 p.p difference in this treatment measure.

Second, we need to account for the fact that not all non-citizens are undocumented, as we did above. We obtain estimates of the undocumented working-age population in California counties in year 2008 from Hill and Johnson (2011) and counts of working non-citizens ages 18-65 by county from the 2008 ACS. We estimate that 85 percent of non-citizens in California are undocumented, which yields an adjusted difference of 6.1 p.p. Together, this implies that the ITT is 16.3 ($\frac{1}{0.061}$) times as large as the difference-in-difference estimate. This may be an over-estimate, however, if non-citizens are more likely to be undocumented in areas with a larger share of Hispanic non-citizens. If we assume that the probability of being undocumented is instead 100 percent and 70 percent (averaging to 85 percent) across above- and below-median counties, the scaling factor becomes 9.7 ($\frac{1}{0.176-0.7\times0.104}$).

Using this rescaling, our 4.2 p.p. difference-in-difference estimate thus implies an ITT for high school enrollment between 41 p.p. and 68 p.p., and between 12.6 and 21.3 p.p. for ELA test-taking, although the 95 percent confidence interval does not allow us to reject zero effect for these outcomes and includes the ACS estimate. When we rescale the lower bound of the 95 percent confidence interval for math test-taking, we obtain an ITT between 5.8 and 9.8 p.p.. We speculate that the discrepancy between the ITT in the ACS and CA is caused by possible under-reporting of non-citizens in California, which could inflate the scaling factors we estimate, and spillover effects to native-born Hispanics, which we do not measure in the ACS.

C Appendix C: Extended Conceptual Framework and Elasticity Estimation

In this section, we formalize the framework described briefly in Section 2 and derive implications of the framework for education decisions. Schooling levels are denoted by s and include high school drop-out (D), high school diploma (HS), and some college (C), respectively. O represents the country of origin, and in the US n indicates undocumented status, and ℓ indicates legal status.

C.1 Set-Up

Consider the decisions of an undocumented youth in his final year of high school: (i) drop out immediately; (ii) stay in school for one additional year to obtain a diploma; or (iii) commit to enrolling in college after high school. He anticipates that after he has completed schooling, he will work either in the US or, if deported, in his country of origin. For simplicity, we assume that he cannot return to the US once deported, such that the deportation risk is equivalent to the deportation risk net of the probability of return.

His expected lifetime earnings are the weighted sum of yearly wages in the US and yearly wages in their country of origin, where the weights are given by the expected years of work in the US versus expected years of work in the country of origin.[37] If an individual drops out of high school, he works the maximum number of years, equal to the difference between retirement age and his current age, T; otherwise, his working years are equal to $T - \alpha$, where α is the number of years spent in additional schooling. When we empirically estimate lifetime earnings, we assume $T = 43$, the difference between age 18 and 60, $\alpha = 1$ if an individual chooses to complete high school, and $\alpha = 2$ if an individual chooses to attend some college.[38]

Given a deportation risk, d, the expected number of years spent working in the US is the cumulative probability that they are not deported, given by $Y_\tau^{US} = \sum_{t=\alpha}^{T}(1 - d_\tau)^t$. The number of years spent working in one's country of origin is then $T - \alpha - Y_\tau^{US}$. For simplicity, we assume yearly wages are static and can hence describe expected lifetime earnings for different each status and schooling combination. We abstract from discounting in the notation to have a more parsimonious model, but account for a 5 percent discount factor in our empirical estimates.[39] The expected lifetime earnings before ($\tau = 0$) and after ($\tau = 1$) DACA are:

$$\omega_0^s = w^{O,s} \cdot Y_0^O + w^{n,s} \cdot Y_0^{US}$$

[37] It is worth mentioning that we have not explicitly included the nontrivial tuition costs of college in this framework, but to the extent college tuition remains unchanged after DACA, introducing a fixed college tuition cost would lead to the same result.

[38] We assign the wage associated with some college after one year of college to match our empirical work, where we will measure college attendance as having attended at least one year of college.

[39] For example, to incorporate a discount rate r for wages prior to DACA we set $\omega_0^s = \sum_{t=\alpha}^{T} \frac{w^{O,s}}{(1+r)^t} \cdot [1 - (1 - d_\tau)^t] + \frac{w^{n,s}}{(1+r)^t} \cdot (1 - d_\tau)^t$.

$$\omega_1^s = w^{O,s} \cdot Y_1^O + w^{\ell,s} \cdot Y_1^{US}$$

We assume that the policy affected the anticipated years of work in the US and in the origin country by lowering the deportation risk ($Y_1^{US} > Y_0^{US}$), and also allowing individuals to earn higher wages associated with legal status in the US ($w^{\ell,s} > w^{n,s}$). We ignore any general equilibrium changes in market wages for any education level in either the US or abroad. Additionally, we assume high school dropouts do not see any change in deportation risk and cannot access legal wages since choosing to they are ineligible for DACA. Hence, the expected lifetime wages of a high school dropout are equivalent before and after DACA,

$$\omega_1^D = \omega_0^D = w^{O,D} \cdot Y_0^O + w^{n,D} \cdot Y_0^{US}$$

The youth arrives at his decision by comparing expected lifetime earnings under each schooling decision and status, and choosing the option that yields the highest net benefit. Specifically, he decides to finish high school if $\omega_\tau^{HS} - \omega_\tau^D > 0$. He then enrolls in college if $\omega_\tau^C - \omega_\tau^{HS} > 0$.

This setup allows us to conveniently analyze the expected impacts of DACA. First, DACA should increase the number of high school graduates if it increases the return to high school. In this simple framework, the return to high school is simply the difference between the dropout wage and the high school wage ($\omega_\tau^{HS} - \omega_\tau^D$). The *change* in the return to high school after DACA is,

$$\begin{aligned}
&(\omega_1^{HS} - \omega_1^D) - (\omega_0^{HS} - \omega_0^D) \\
&= (\omega_1^{HS} - \omega_0^D) - (\omega_0^{HS} - \omega_0^D), \textit{ following from equation C.1} \\
&= \omega_1^{HS} - \omega_0^{HS} \\
&= (w^{O,HS} \cdot Y_1^O + w^{\ell,HS} \cdot Y_1^{US}) - (w^{O,HS} \cdot Y_0^O + w^{n,HS} \cdot Y_0^{US})
\end{aligned}$$

To further simplify the expression we add and subtract $Y_1^{US} \cdot w^{n,HS}$,

$$= w^{O,HS} \cdot (Y_1^O - Y_0^O) + w^{n,HS} \cdot (Y_1^{US} - Y_0^{US}) + (w^{\ell,HS} - w^{n,HS}) \cdot Y_1^{US}$$

$$= \underbrace{(w^{n,HS} - w^{O,HS}) \cdot (Y_0^O - Y_1^O)}_{\text{US premium, if non-legal } \times \Delta \text{ deportation risk}} + \underbrace{(w^{\ell,HS} - w^{n,HS}) \cdot Y_1^{US}}_{\text{legal premium}} \tag{3}$$

The resulting expression elucidates two potential ways in which DACA may incentivize individuals to attain a high school diploma:

1. By changing the deportation risk, DACA affects the number of anticipated work years spent in the country of birth, and hence the number of expected years that undocumented individuals can earn US wages rather than home country wages. DACA will thus incentivize high school graduation if $(Y_0^O - Y_1^O) > 0$ and $(w^{n,HS} - w^{O,HS}) > 0$ – i.e. that individuals actually perceived a decline in deportation risk and decrease in expected work years abroad, and that the wages paid to undocumented high school

graduates in the US are greater than the wages they could earn as high school graduates abroad (i.e. there is a "US premium").

2. By providing work authorization, DACA allows individuals to earn the high school wages paid to those with legal status. This is a benefit that encourages high school graduation if $(w^{\ell,HS} - w^{n,HS}) > 0$ (i.e. there is a "legal premium").

Using the same framework, we can assess how DACA affects the decision to enroll in college. Specifically, we compare the returns to college – defined here as the difference between expected lifetime earnings associated with some college and a high school diploma – before and after DACA:

$$\begin{aligned}(\omega_1^C - \omega_1^{HS}) - (\omega_0^C - \omega_0^{HS}) &= (w^{O,C} \cdot Y_1^O + w^{\ell,C} \cdot Y_1^{US}) - (w^{O,HS} \cdot Y_1^O + w^{\ell,HS} \cdot Y_1^{US}) \\ &\quad - (w^{O,C} \cdot Y_0^O + w^{n,C} \cdot Y_0^{US}) + (w^{O,HS} \cdot Y_0^O + w^{n,HS} \cdot Y_0^{US}) \\ \\ &= (w^{O,C} - w^{O,HS}) \cdot Y_1^O + (w^{n,C} - w^{n,HS}) \cdot Y_1^{US} \\ &\quad - [(w^{O,C} - w^{O,HS}) \cdot Y_0^O + (w^{n,C} - w^{n,HS}) \cdot Y_0^{US}]\end{aligned}$$

Similar to before, we can further simplify the expression by adding and subtracting $(w^{n,C} - w^{n,HS}) \cdot Y_1^{US}$,

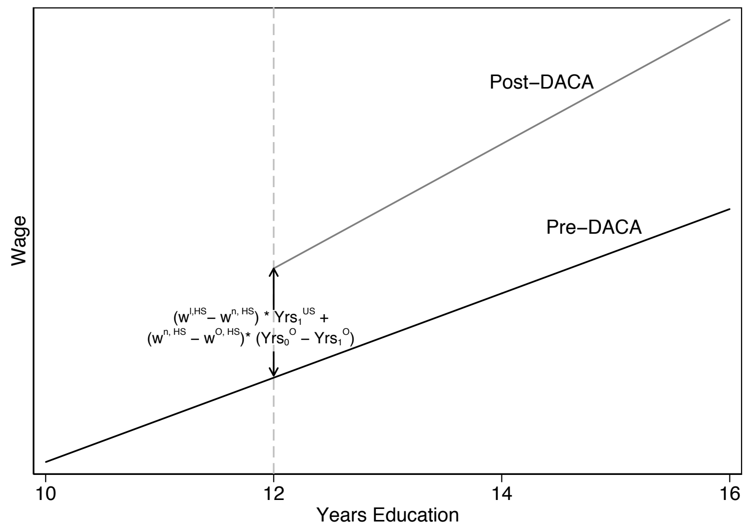
$$\begin{aligned}&= (w^{O,C} - w^{O,HS}) \cdot (Y_1^O - Y_0^O) + (w^{n,C} - w^{n,HS}) \cdot (Y_1^{US} - Y_0^{US}) \\ &+ [(w^{\ell,C} - w^{\ell,HS}) - (w^{n,C} - w^{n,HS})] \cdot Y_1^{US} \\ \\ &= \underbrace{[(w^{n,C} - w^{n,HS}) - (w^{O,C} - w^{O,HS})] \cdot (Y_0^O - Y_1^O)}_{\text{add'l college return in US vs. O, if non-legal } \times \Delta \text{ deportation risk}} \\ &+ \underbrace{[(w^{\ell,C} - w^{\ell,HS}) - (w^{n,C} - w^{n,HS})] \cdot Y_1^{US}}_{\text{add'l college returns for } \textit{legals} \text{ in US}}\end{aligned} \tag{4}$$

Hence, simplification gives us a similar expression as before, where the last line follows from the fact that $Y_1^{US} - Y_0^{US} = Y_0^O - Y_1^O$.

We expect DACA to incentivize college enrollment in two distinct ways:

1. Similarly to above, DACA affects the number of expected years that undocumented individuals can earn the US college wage premium. This will incentivize high school graduation if $Y_0^O - Y_1^O > 0$ and $(w^{n,C} - w^{n,HS}) - (w^{O,C} - w^{O,HS}) > 0$ – i.e. that individuals actually perceived a decline in deportation risk and decrease in expected work years abroad, and that the college wage premium paid to undocumented in the US is greater than the college wage premium they could earn abroad.
2. By providing work authorization, DACA allows individuals to earn the college wage premium associated with legal status $(w^{\ell,C} - w^{\ell,HS})$, rather than the college wage premium associated with undocumented status $(w^{n,C} - w^{n,HS})$. This is a benefit that encourages college enrollment if $(w^{\ell,C} - w^{\ell,HS}) - (w^{n,C} - w^{n,HS}) > 0$.

Figure C.1: Returns to Education, Before and After DACA



Notes: This figure shows the hypothetical changes in returns to education due to DACA. The vertical axis measures wages, while the horizontal axis measures years of education.

To solidify this intuition, we illustrate the earnings-schooling profile before and after DACA in Figure C.1. This figure illustrates the discrete increase in the return to high school after DACA and assumes that the returns to college also increase.

C.2 Estimating the Elasticity of Schooling

In our estimation of the elasticity, we estimate life time earnings using this model with a few adjustments. First, we allow d to vary by age (18 to 24, 25 to 34, 35 to 44, 45 to 54, and 55 to 60) and sex based on the tabulations of deportations. Second, we calculate $w^{n,s}$, $w^{\ell,s}$ and $w^{s,O}$ as the expected annual earnings by multiplying annual earnings for each country, schooling, and legal status by the probability of working for that group. Table C.1 shows the inputs into the expected wages before and after DACA by sex. We pair these inputs with the implied ITT estimates of DACA for Hispanics that we calculate in Section 7 divided by the mean rate of schooling of Hispanics in our sample to obtain the percent increase in schooling. The resulting elasticity of schooling estimates are in Table 5.

Table C.1: Wages and Returns from DACA - Inputs into Elasticity Calculation

	All	Female	Male
A: Inputs for Calculation of Returns			
Dropout Wages - Mexico	1733	821	2751
HS Wages - Mexico	2631	1566	3677
Some College Wages - Mexico	5143	3616	6844
Dropout Wages - U.S. Noncitizens	4469	2280	6005
HS Wages - U.S. Noncitizens	5471	3667	6864
Some College Wages - U.S. Noncitizens	7143	5778	8536
Dropout Wages - U.S. Citizens	5270	3518	6874
HS Wages - U.S. Citizens	8355	6480	10180
Some College Wages - U.S. Citizens	15397	12057	19552
Deportation Risk, Ages 16-18 - Prior to DACA	0.035	0.008	0.058
B: Expected Years			
Years illegal in U.S. - Prior to DACA	16.467	33.472	11.168
Years in Mexico - Prior to DACA	26.533	9.528	31.832
Years legal in U.S. - Prior to DACA	0.000	0.000	0.000
Years in Mexico - 4 Year DACA	21.187	7.580	26.580
Years illegal in U.S. - 4 Year DACA	17.862	31.470	12.470
Years legal in U.S. - 4 Year DACA	3.950	3.950	3.950
Years in Mexico - 6 Year DACA	17.996	6.565	23.246
Years illegal in U.S. - 6 Year DACA	19.108	30.539	13.858
Years legal in U.S. - 6 Year DACA	5.896	5.896	5.896
Years in Mexico - Permanent DACA	4.415	4.415	4.415
Years illegal in U.S. - Permanent DACA	0.000	0.000	0.000
Years legal in U.S. - Permanent DACA	38.585	38.585	38.585
C: Returns to Schooling			
Return to HS - Prior to DACA	28554	46345	23541
Return to College - Prior to DACA	71193	72750	89736
Change in Return to HS - 6 Year DACA	55349	33846	66405
Change in Return to College - 6 Year DACA	26490	20555	35572
Change in Return to HS - Permanent DACA	162064	115248	200205
Change in Return to College - Permanent DACA	167412	116709	229327

Notes: This table shows the inputs to the calculation of the benefits of DACA for all, male, and female DACA-eligible youth under various assumptions of the duration of DACA; 4 years, 6 years, and permanent. Wages in Panel A are expected annual earnings are calculated for each country and education as the probability of being employed times the average annual earnings. Wage and employment data for Mexico are from the 2010 Census. Wages for the US are calculated for adults between the ages of 18 and 60 year old individuals who arrived in the US by age 10 and year 2007 using the 2009 to 2011 ACS. Expected years in Mexico and the US in Panel B are calculated using the equations for Y^{US} and Y^{O} in Section C. In Panel C, the return to HS is the difference between the expected lifetime earnings for a high school graduate and a high school dropout, and the return to college is the difference between the expected lifetime earnings for an individual with some college and a high school graduate.

Table C.2: Implied Elasticity of College Enrollment to Wages

	Expected Duration of DACA:		
	4 Years	6 Years	Permanent
Elasticity - All	0.282	0.104	0.017
Elasticity - Males	0.384	0.145	0.022
Elasticity - Females	0.254	0.097	0.017

Notes: Estimates of the elasticity of college enrollment for all, males, and female DACA-eligible youth, under various expectations of the duration of DACA (4 years, 6 years, and permanent). Elasticity calculated using (1) the implied ITT effects of DACA for Hispanics (see Section 7) and (2) estimates of the wage benefits of DACA using inputs from Table C.1 together with the framework for expected wages in Section C.

Table C.3: Implied Semi-Elasticity of High School Enrollment to Wages

	Actual Dep. Risk,	Perceived Dep. Risk:	
	Age-Based	0%	30%
A: 4 Years Exp. Duration			
Semi-Elasticity - All	0.395	1.101	0.244
Semi-Elasticity - Males	0.581	1.739	0.444
Semi-Elasticity - Females	0.242	0.328	0.079
B: 6 Years Exp. Duration			
Semi-Elasticity - All	0.250	0.692	0.160
Semi-Elasticity - Males	0.364	1.094	0.292
Semi-Elasticity - Females	0.154	0.207	0.052
C: Permanent Exp. Duration			
Semi-Elasticity - All	0.085	0.172	0.045
Semi-Elasticity - Males	0.121	0.272	0.081
Semi-Elasticity - Females	0.045	0.051	0.014

Notes: Estimates of the semi-elasticity of college enrollment for all, males, and female DACA-eligible youth, under various expectations of the duration of DACA (4 years, 6 years, and permanent). Semi-elasticity calculated using (1) the implied ITT effects of DACA for Hispanics (see Section 7) and (2) estimates of the wage benefits of DACA using inputs from Table C.1 together with the framework for expected wages in Section C.

D Appendix D: High School Graduation by Month in the NLSY97

The NLSY97 is a longitudinal survey of a nationally representative sample of roughly 9,000 youth that were between the ages of 12 and 16 by December 31, 1996. Respondents are surveyed on an annual basis on a range of topics, including educational progress. We use the NLSY97 to estimate the proportion of youth that receive a high school diploma in each month for individuals that graduate in 4, 5, or 6 years. We calculate the years of high school attended at the time of diploma as the ceiling of the difference between the year and month of diploma and the year and month that high school began. For simplicity, we assume the school year begins in September. Hence, graduating in September at the beginning of one's 4^{th} year is considered as graduating in four years. The statistics below are unweighted, and are unchanged when weighted.

Table D.1: Graduation by Month and Year

	Graduated in:		
	4 yrs	5 yrs.	6+ yrs.
Jan. to Jun.	0.975	0.757	0.824
Jul. to Aug.	0.019	0.025	0.049
Sep. to Dec.	0.006	0.218	0.127
Observations	6091	325	102

Notes: Data include individuals surveyed in the NLSY97. Statistics in each column represent the share of individuals that graduate in each set of months among those that graduate in a given number of years.

E Appendix E: Deportation Risk Analysis

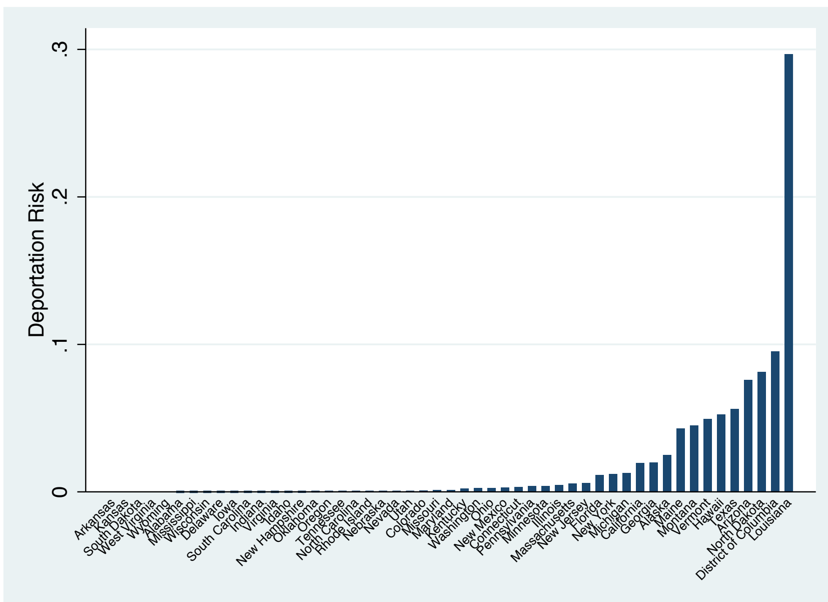
To measure the risk of deportation in each state, we obtained publicly available Immigration and Customs Enforcement data on aggregate deportations maintained by the Transactional Records Access Clearinghouse.[40] We obtain the annual deportation rate as the number of interior deportations by state of departure in each fiscal year from 2005-2011 divided by the noncitizen population aged 10-30 in each state, calculated from the ACS. We then take the average of the deportation rate over the 2005-2011 period to create a single pre-DACA measure of deportation risk that we assign to each individual in the ACS based on their current state of residence. Since 55 percent of all deportations are in the 10-30 age range, we scale our deportation risk measures by 0.55.

Figure E.1 ranks states according to this measure of deportation risk. A select few states have very large deportation rates; Louisiana (30 percent) being the highest, followed by Washington DC, North Dakota, Arizona and Texas (5.6 percent to 9.5 percent). The remaining states have deportation rates deportation rates that fall between 0 percent and 5 percent. Because the variation in deportation risk is concentrated in a handful of states, we use a flexible estimation strategy in which we impose no parametric relationship between deportation risk and the impact of DACA, instead visually inspecting for such a relationship.

Our difference-in-difference estimator extends our baseline regression model to allow the coefficient on PostxEligible to vary for each. We also include the two-way interactions of state and eligibility indicators. We then plot state-specific treatment effects in order of the state deportation risk, along with 95 percent confidence intervals in Figure E.2. Marker size is proportional to the size of the state's non-citizen population.

[40]Data retrieved from http://trac.syr.edu/phptools/immigration/removehistory/.

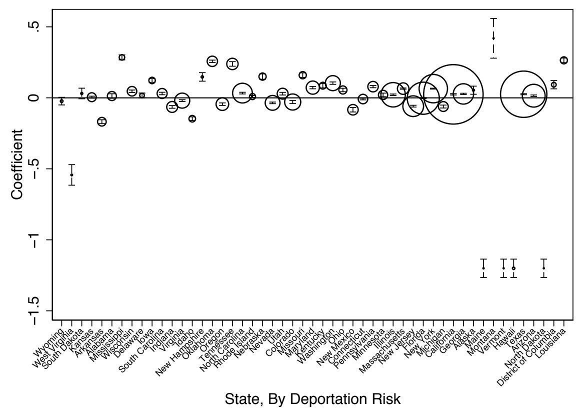
Figure E.1: Deportation Rate by State Prior to DACA



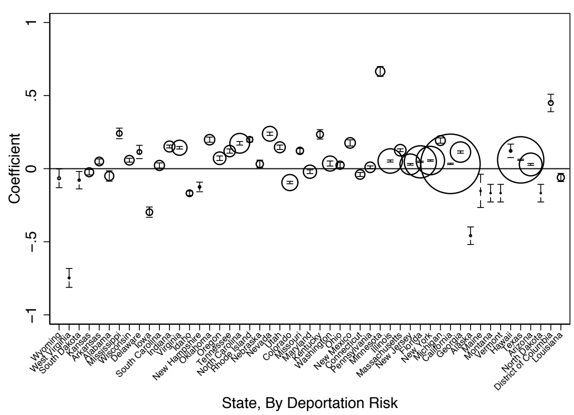
Notes: This figure shows the deportation rate within each state prior to DACA. We define the deportation rate as the number of interior deportations by state of departure in each fiscal year from 2005-2011, obtained from the Transactional Records Access Clearinghouse, divided by the Hispanic non-citizen population aged 10-30 in each state, calculated from the ACS. We adjust these by scaling factor of 0.55, as 55 percent of deportations are of individuals aged 10-30.

Figure E.2: Effect of DACA on Main Outcomes, Hispanics – Heterogeneity By Deportation Risk

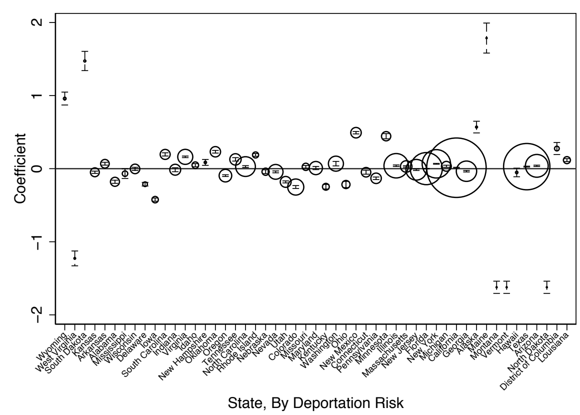
(a) School Attendance, Ages 14-18



(b) High School Completion, Ages 19-22



(c) College Enrollment, Ages 19-22



Notes: This figure shows difference-in-differences estimates of the impact of DACA on school attendance, separately by state, with state's ordered according to their deportation risk. Each point represents coefficients from difference-in-difference regressions that estimate the coefficient on the interaction between eligibility, post, and state of residence. States are placed in ascending ordered according to their baseline deportation risk, which is calculated as the number of interior deportations by state of departure in each fiscal year from 2005-2011, obtained from the Transactional Records Access Clearinghouse, divided by the Hispanic non-citizen population aged 10-30 in each state, calculated from the ACS. We adjust these by scaling factor of 0.55, as 55 percent of deportations are of individuals aged 10-30. All regressions control for the following fixed effects: sex, year of immigration, birth region, age of immigration-by-eligibility, age-by-eligibility, state-by-year, race-by-year, and age-by-year (see Equation 1). Standard errors, shown in parentheses, are clustered by state, and regressions are weighted by the survey sampling weights. * p<0.10, ** p<0.05, *** p<0.01. Data: 2005–2015 American Community Survey sample composed of foreign born individuals who immigrated by age 10 and by 2007.

F Appendix F: Reconciliation of Post-Secondary Results

In this section, we review the prior work on the impact of DACA on education. Our goals are to (i) place our estimates in context of the broader literature; (ii) highlight differences in methodologies across these works, and (iii) and propose ways to reconcile our findings. As discussed in the introduction, these earlier studies focus on educational choices post-high school, and do not analyze high school completion or the school attendance of high-school-aged youth. Therefore, the most comparable estimates in our study are the positive coefficients we find on school attendance for ages 19 to 22 in Panel B of Table 1 and on college attendance for individuals 19 to 30 in Panels B and C of Table 2.

Hsin and Ortega (2017). Hsin and Ortega (2017) study college dropping out in 4-year and 2-year colleges using administrative data from an urban college system. They use a difference-in-difference strategy comparing self-identified undocumented students to all documented students. They find that DACA leads to a 3.7 (s.e.: 0.7 p.p) increase in dropping out of any college. There are seven main differences from our work: Hsin and Ortega (2017) use a sample where (i) the minority of the undocumented are Hispanic as defined by country of birth,[41] (ii) the comparison group is primarily (75 percent) US-born individuals, (iii) individuals are from one metropolitan area; (iv) are unable to distinguish between students that transfer to another system and those that dropout; (v) can track individuals over time; (vi) do not measure effects of DACA on entry into college; (vii) do not have information on age or year of arrival.

Amuedo-Dorantes and Antman (2017). Amuedo-Dorantes and Antman (2017) study school attendance of non-citizen high school graduates ages 18 to 24 using data from the 2000 to 2014 monthly CPS surveys. They use a difference-in-difference approach comparing eligible to non-eligible individuals, before and after October 2012. They find that DACA led to a 11.7 p.p. (s.e.: 3 p.p.) decline in school attendance. There are four main differences from our work: Amuedo-Dorantes and Antman (2017) use a sample that is (i) limited to individuals with a high school degree and (ii) non-citizens, and (iii) is not limited to individuals who immigrated by age 10 or by 2007; and (iv) use the CPS.

Pope (2016). Pope (2016) studies school attendance in multiple samples in the 2005-2014 ACS surveys, with each sample choice showing the sensitivity of the results to different treatment and comparison groups. The difference-in-difference strategy is the same as Amuedo-Dorantes and Antman (2017). In his preferred sample, focusing on non-citizen high school graduates ages 18 to 30 who entered the US between ages 12 and 19, Pope (2016) finds that DACA led to a 2.1 p.p. (s.e.: 0.09 p.p.) decline in school attendance. There are five main differences from our work: Pope (2016) uses a sample that (i) limits to non-citizens that arrived between 12 and 19 and (ii) have a high school degree and (iii) is not limited to individuals who immigrated by age 10 or by 2007; and defines eligible as (iv) having been in the US for 5 years (not since 2007), and (v) currently under 31 (not under 31 as of 2012).[42]

In Table F.1 below we examine the impact of each of the latter four specification choices,

[41] 48 percent of 2-year and 35 percent of 4-year undocumented in the sample are from Latin America.

[42] While the text of Pope (2016) lists the correct policy requirements for DACA eligibility, the code implements the less stringent eligibility requirements listed here.

as well a few more minor discrepancies in our specifications, on our estimates for the Hispanic sample ages 19 to 22.[43] The first column shows our main estimate of the effect of DACA on school attendance for ages 19 to 22, a 2.0 p.p. (s.e.: 1.4 p.p.) increase. The next five columns of the table show the estimates when we alter our estimation to converge more closely with Pope, relaxing the age/year of arrival sample criteria (Columns 2-3), the span of our data (Column 4), the length of the post period (Column 5), and removing some control variables (Column 6). The estimate is attenuated when we alter our age of arrival criteria, and remains close to zero and statistically insignificant in the remainder of the columns. Thus, altering our sample choices would reduce the point estimate, but not reverse our conclusion.

In the final four columns of the table, we continue to converge with the Pope estimation strategy, by using his maximum age and year of arrival criteria (Columns 7-8), adding controls for education (Column 9), and restricting to the high school sample (Column 10). The coefficients are now always negative, and statistically significant in two out of the four columns. Qualitatively, changing the eligibility criteria to require only 5 years in the US and restricting to high school graduates make the largest difference. This exercise indicates that the negative or zero effects in Pope (2016) could be in part due to a less stringent application of the policy criteria to determine eligibility as well as selection on high school graduates.

[43]We find very similar patterns when we examine a broader set of individuals, ages 18 to 35, although the effects tend to be more positive across the board.

Table F.1: Sensitivity of School Attendance Estimates to Alternative Assumptions, Hispanics Ages 19-22

	Our	Relax our Spec.					Less-Stringent-Policy Defn./Cond'n Educ.			
	Estimate	No AgeImm	No YearImm	2005-2014	Post = 2013+	Pope Controls	Age 31	5 yrs US	Ed Controls	HS Only
Eligible*Post	0.020	0.002	0.002	-0.003	-0.007	-0.007	-0.015*	-0.027**	-0.014	-0.024**
	(0.014)	(0.009)	(0.009)	(0.009)	(0.010)	(0.008)	(0.008)	(0.011)	(0.009)	(0.012)
Mean Y	0.405	0.297	0.291	0.283	0.283	0.283	0.283	0.283	0.283	0.382
Individuals	38704	76235	87132	80419	80419	80419	80419	80419	80419	51828

Notes: Table shows how our estimated impact of DACA on school attendance for ages 19 to 22 (shown in column 1) changes when we relax our sample restrictions (columns 2 to 6) or when we adopt the sample restrictions or less stringent policy definitions in Pope (2016) (columns 7 to 10). The changes are cumulative, such that column (3) includes the changes from column (2), column (4) includes the changes in columns (2) and (3), etc. In column (2) we include individuals who arrived to the US at all ages; (3) we include individuals who arrived to the US in all years; (4) we drop 2015; (5) we define post to begin in 2013; (6) substitute controls with those in Pope (2016), excluding education controls; (7) change eligibility to require individuals to be under 31 at interview, instead of in 2012 (8) change eligibility to require individuals to have lived in the US for 5 years at interview, instead of in 2012; (9) include controls for attending some college or college (10) restrict to high-school graduates. All regressions control (detailed further in Equation 1) for indicators for sex, year of immigration, birth region (which includes a separate indicator for being born in Mexico), and age of immigration-by-eligibility and age-by-eligibility fixed effects. Also included are state-by-year fixed effect, race-by-year fixed effects, and age-by-year dummies. Standard errors are clustered at the state level. Data: 2005–2015 American Community Survey sample composed of foreign born individuals between the ages of 19 and 22 who immigrated by age 10 and by 2007.

G Appendix G: Data Appendix

This section describes our data, sample selection criteria, and the construction of our variables in greater detail.

G.1 ACS data

G.1.1 Sample construction

The data for the individual level analysis on schooling outcomes come from the IPUMS American Community Surveys 2005-2015 (Ruggles et al., 2017). The main analysis sample consists of immigrants to the US who arrived in the US by age 10 and year 2007 and currently reside in the US. We define immigrants as individuals born outside of the 50 states, which includes individuals born in US territories, such as Puerto Rico. We calculate age of arrival as the difference between current age and the number of years since the reported year of arrival. We focus on youth, hence our primary sample is comprised of individuals ages 14-22, but we also examine the high school completion and college attendance of individuals ages 23-30.

G.1.2 ACS treatment, outcomes, and control variables

- Eligible: We assign a binary indicator for eligibility that is equal to one for individuals in the sample who arrived in the US by age 10 and by year 2007, and who are currently not citizens.
- High Take-up: We assign a binary indicator for being in the high take-up sample that is equal to 1 if birth place is: El Salvador, Mexico, Uruguay, Honduras, Bolivia, Brazil, Peru, Ecuador, Jamaica, Guatemala, Venezuela, Dominican Republic, and Colombia. Each of these countries has a DACA participation rate above 30 percent according to the Migration Policy Institute's (MPI) estimates: http://www.migrationpolicy.org/programs/data-hub/deferred-action-childhood-arrivals-daca-profiles.
- Hispanic: We assign a binary indicator for being hispanic that is equal to one if IPUMS variable *hispan* is not equal to 0.
- High school completion: We assign a binary indicator for having completed high school that is equal to 1 if an individual has a high school diploma or GED (IPUMS variable *educd* is equal to 62, 63 or 64), or if they have completed some college (*educd* is equal to 65 or above and is not missing)
- Some college attainment: We assign a binary indicator for having completed some college that is equal to 1 if an individual has attended any college (IPUMS variable *educd* is equal to 65 or above and is not missing)
- Birth region: We control for indicators for the following 5 birth regions constructed from the IPUMS *bpl* variable: Mexico (bpl=200), United Kingdom/Europe ($410 \leq bpl \leq 419$, $700 \leq bpl \leq 701$, $450 \leq bpl \leq 499$), Asia ($500 \leq bpl \leq 600$), Other Latin and South/Central America ($210 \leq bpl \leq 300$), and Rest of the world.

G.2 California DOE Data

G.2.1 Data construction

For our secondary identification strategy, we use data from academic years 2005/06 through 2015/16 provided by the California Department of Education. Data on high school enrollment come from school-grade-level enrollment files covering K-12, available for download at https://www.cde.ca.gov/ds/sd/sd/filesenr.asp. We collapse this data to the county level to match our aggregate measure of undocumented students, totaling the enrollment over all schools in the county. We then add up the enrollment of Hispanics across grades 9, 10, 11, and 12 to obtain total high school enrollment for each county.

We also obtain data on county-level CAHSEE performance test performance from the California Department of Education, available for download at https://cahsee.cde.ca.gov/datafiles.asp. We use information on the number of test takers, the share of test takers that pass the exam, and the average test score. These are separately provided by grade, for grades 10, 11, and 12, and also in aggregate for grades 10-12.

Once we have constructed these county aggregates, we then keep only the 34 counties that are identified in the ACS, since those are the counties for which we will be able to assign eligibility.

G.2.2 County treatment assignment and control variables

- Above-median-undocumented: We assign a binary indicator for having a high share of undocumented (our measure of treatment for this analysis) that is equal to 1 if the county has an above-median share of Hispanics that are DACA-eligible. To create this variable, we calculate the share of the Hispanic population aged 14-18 in each county that are DACA-eligible using our ACS sample using the years from 2005 to 2011. We then rank counties by this share, and assign counties to be above median if the share is above the median of the sample.

- Unemployment rate: We obtain annual unemployment rates for each county from 2005 to 2015 from the Bureau of Labor Statistics (see https://www.bls.gov/lau/).