The effects of deferred action for childhood arrivals on labor market outcomes.

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ABSTRACT. I study the effects of the Deferred Action for Childhood Arrivals program (DACA) on labor market outcomes among potentially eligible immigrants. DACA allowed undocumented immigrants to participate in the labor market without fear of deportation, which might be expected to increase the probability of working and allowing workers to move to higher-skilled occupations. However, using a regression discontinuity design, I find very little to no effects on the probability of working and the likelihood of working in high-skilled jobs among DACA-eligible immigrants. The confidence intervals permit modest effects on these variables, but rule out large ones. Overall, my results suggest that temporary legal status had limited effects for DACA-eligible individuals.

JEL classification: J08, J15, J18

Keywords: DACA; undocumented immigrants; labor market outcomes; high-skilled jobs; regression discontinuity design.

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1 Introduction

There were approximately 11.4 million undocumented immigrants residing in the US in 2017, accounting for around 30% of total immigrants (Baker, 2021). Undocumented immigrants earned as much as 10% less than documented immigrants (Borjas and Cassidy, 2019). This wage gap may reflect that legal status is either correlated with individual's characteristics or directly affects labor market outcomes.

Lack of legal status may hurt immigrants' labor market outcomes in two primary ways. First, it may make them more likely to work in low-wage and low-skilled jobs where there is a low probability of being caught and deported. Second, it also prevents them from working for large employers who are more likely to run E-Verify to check employment eligibility (Orrenius et al., 2020).

In this paper, I examine the effects of temporary legal status on labor market outcomes among undocumented immigrants using the Deferred Action for Childhood Arrivals program (hereafter DACA) as a quasi-experiment. DACA, which was introduced in 2012, granted a temporary legal status to individuals who had been brought into the US as children to reside and work without the constant threat of deportation. However, DACA does not provide a path to permanent legal status and recipients have to renew their status every two years.

I measure the effects of DACA eligibility on several labor market outcomes using a regression discontinuity design (RDD). To be eligible for DACA, an immigrant needs to have been under 31 years old on June 15, 2012. So, I compare labor market outcomes of immigrants who were just above versus below the age of 31 in 2012. I focus on non-citizen immigrants who would otherwise be eligible for DACA, and compare people on one side to people on the other side of the threshold. Nonetheless, the sole eligibility criterion which I do not observe is the legal status of an immigrant. In practice, about 60% of 8.3 million non-citizen immigrants under 35 years old in 2012 are undocumented (Acosta et al., 2014; Baker, 2021) while over 60% of DACA eligible individuals applied for DACA as described in detail in section 2. Thus, there are up to 36%

changes in DACA uptake between one side of the threshold than the other. This paper measures the average treatment effects of being on one side of the threshold versus just on the other side of the threshold, i.e., I measure an intention-to-treat type parameter rather than a treatment effect. For the remainder of the paper, I will refer to this as measuring the effect of DACA eligibility, though technically some people in the sample are not DACA eligible regardless of which side of they are on because they already have legal status. That being said, I also attempt to gauge the upper bound estimates of DACA treatment effects from my intention-to-treat estimates and discuss more in Section 5.3.

I have four primary findings. First, depending on specifications, I find DACA eligibility yields between no effect and a 2% increase in the probability of working. It is most likely driven by individuals with at least a college degree. [1] Second, I find no effect on the probability of working in the last year, on the number of weekly working hours among likely eligible immigrants, and wage income. Third, DACA eligibility does not increase the probability of receiving health insurance from employers, suggesting a limited effect on the probability of working in a formal employment setting. Fourth, I find zero effects on job skill requirements, which are math skills, critical thinking, creativity, science knowledge, and the number of years of schooling of typical people in that occupation. These findings suggest that DACA eligibility had little effects on immigrants' ability to find high-skilled jobs. My findings are robust to different types of robustness checks.

Because there is likely a priori that DACA eligibility would have improved labor market outcomes like hours, compensation, and occupational skill usage, I next consider what magnitude of positive effects can or cannot be statistically rejected. Taking the upper end of my confidence intervals (CI) and then adjusting for likely uptake rates, I find that the largest plausible effect on the probability of being employed is 3 percentage points (ppts); on the probability of working last year is 2 ppts; and on weekly working hours is 1.2 hours. For comparison, using a difference-in-differences approach, Pope (2016) finds DACA increases the probability of being employed by around 6 ppts (CI: 3-10 ppts); increases the probability of working last year by 4-5 ppts (CI: 0.8-10

[1] See Appendix A8 for details.

ppts); and increases weekly working hours by 1.9 hours on average (CI: 0.4-3.8 hours). Amuedo-Dorantes and Antman (2017) also use a difference-in-differences approach, and find that DACA increases the probability of being employed by 14 ppts (CI: 4-24 ppts), but has no effect on weekly working hours (CI: -3.7-2.1 hours).[2] However, Hamilton et al. (2021) use the California Health Interview Survey and show that DACA has no impact on labor force participation (CI: -0.09 to 0.19 ppts) or the likelihood of finding employment (CI: -0.19-0.16 ppts) using DACA-ineligible undocumented immigrants as a control group . That is, my CIs generally overlap with those estimates by Amuedo-Dorantes and Antman (2017) and Pope (2016), but the region of overlap is at the low end of their CIs. My point estimates are most consistent with those of Hamilton et al. (2021). Taking my estimates together with the previous literature, it seems likely that DACA may have improved participants' labor market outcomes, but only moderately so. However, because they are using a difference-in-differences framework while I am measuring a local average treatment effect for the oldest eligible cohorts of DACA, my estimates are not entirely comparable to theirs.

Apart from those papers discussed above, there are several studies on the effects of DACA on educational attainment (Amuedo-Dorantes and Antman, 2017; Henderson and Sperlich, 2022; Hsin and Ortega, 2018; Kuka et al., 2020), health and health insurance (Bae, 2020; Giuntella and Lonsky, 2020; Giuntella et al., 2021). Although the majority of them demonstrate that DACA improves the lives of DACA participants, recent research show mixed or null impacts on distinct groups of DACA recipients (Hamilton et al., 2021; Henderson and Sperlich, 2022). This work contributes to the debate and improves the literature by employing a different econometric technique. Specifically, this paper departs from existing literature in four primary ways. First, I construct a more comparable sample by assigning the treatment status to non-citizen individuals based on their ages in 2012. Second, this sample construction measures the effect of DACA eligibility on a group of likely older DACA individuals, which I reserve a more detailed discussion in Section 5.3. Third, this paper implements a regression discontinuity design approach to examine the effects of DACA on various outcome variables of interest, which overcomes potential parallel trend issues in

[2] Coefficients from Pope (2016) and Amuendo-Dorantes and Antman (2017) are also adjusted, please refer to Section 5.3 for details.

previous studies. Fourth, this paper expands the set of outcome variables, which includes job skills measured by O*NET data, the probability of having employer-sponsored health insurance, and the years of schooling of typical people in a specific occupation.

The remainder of this paper is divided as follows. Section 2 describes the DACA program and its eligibility criteria. Section 3 depicts my dataset. Section 4 constructs my econometric models. Section 5 presents and discusses the main results. Section 6 performs robustness checks. Section 7 concludes.

2 Undocumented immigrants and DACA program

"... Dreamers. These are young people who study in our schools, they play in our neighborhoods, they're friends with our kids, they pledge allegiance to our flag. They are Americans in their heart, in their minds, in every single way but one: on paper. They were brought to this country by their parents – sometimes even as infants – and often have no idea that they're undocumented until they apply for a job or a drivers license, or a college scholarship."[3]

DACA was introduced by President Obama on June 15, 2012 as a substitute for Dream Act legislation. DACA gives a solution to the long-term residence of millions of undocumented immigrants who had been brought to the US by their parents as a child. It allows recipients to remain in the country with temporary lawful status. DACA recipients may also apply for work authorization and must renew their status every two years.

To be eligible for DACA, an individual has to qualify for all of the following requirements: a) they must be undocumented as of June 15, 2012; b) they entered the US before their 16th birthday; c) they must be under 31 as of June 15, 2012; d) they must have constantly resided in the US since June 15, 2007; e) they must be either enrolled in school, have obtained a high school diploma, general education development, or be an honorably discharged veteran of the Coast Guard

[3]Remarks by President Obama at Rose Garden on June 15, 2012.

or Armed Forces of the United States; f) they must have no record of a felony or have significant misdemeanors.

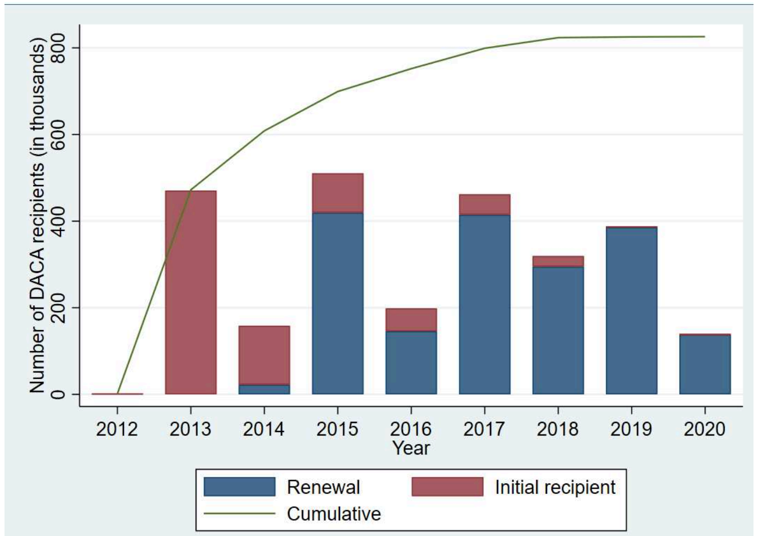
Nonetheless, the precise estimate on the number of DACA eligible population is challenging due to the shortage of administrative data. According to Migration Policy Institute, there are over 1.3 million of DACA-eligible individuals. This estimate does not account for some criteria that are unavailable to researchers, which are criminal records and continuous presence in the US. So, this estimate is on the high end of the range of DACA eligible population.[4] There were over 800,000 immigrants who had ever been DACA holders, which made up around 60% of total DACA eligible population. Of those who did not file an application for DACA, 43% of them claimed that they couldn't afford the application fee, while 22% were missing required paperwork and 17% was afraid that DACA application process would expose themselves to authorities (Watson and Thompson, 2022). As of March, 2020, around 650,000 individuals had active DACA status because a proportion of DACA holders either failed to renew their status or adjusted to long-term legal status.[5]

During the 2016 presidential election, DACA was one of the most controversial topics and went through several legal challenges, which significantly affected the number of new DACA applicants. Figure 1 shows the total number of DACA recipients as well as the number of initial and renewal recipients from 2012 to 2020. The number of initial DACA recipients peaked in 2013 and started to significantly drop in 2014 to almost 0 in 2019 and 2020. That resulted from the effort to suspend DACA from the Trump administration in 2017 when USCIS stopped accepting new applications, but they still allowed for renewal.

[4] https://www.migrationpolicy.org/sites/default/files/datahub/State%20Estimates%20of%20DACA-Eligible%20Population_Dec%202020.xlsx

[5] https://www.uscis.gov/sites/default/files/document/data/Approximate%20Active%20DACA%20Receipts%20-%20March%2031%2C%202020.pdf

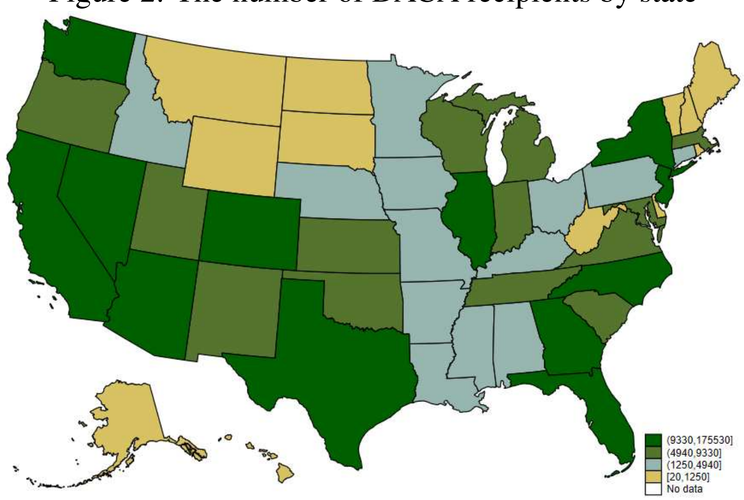
Figure 1: The number of cumulative, initial and renewal DACA recipients



Source: US Citizenship and Immigration Services

DACA recipients reside in all 50 US states and District of Columbia. Nonetheless, nearly half of them live in California and Texas. California alone made up for almost 29% of nation-wide DACA recipients, while 17% of them name Texas as their home state. Figure 2 illustrates the map of DACA recipient distribution by state as of March, 2021.

Figure 2: The number of DACA recipients by state



Source: US Citizenship and Immigration Services

3 Data and descriptive statistics

3.1 American Community Survey

In this paper, I use micro-level data drawn from the American Community Survey (ACS) from 2013 to 2019.[6] American Community Survey is an annual survey conducted by the U.S Census Bureau, which surveys both US and non-US citizens on citizenship, educational attainment, income, language proficiency, employment, and housing characteristics. To serve the purpose for this study, my data sample starts from 2013 because it is the first year that the effects are expected to have kicked in after Department of Homeland Security started to accept DACA applications in late 2012. My data sample ends in 2019.

To construct the data sample, I restrict my sample to only non-citizen individuals who are from 25 to 60 and satisfy all of following requirements: a) they entered the US before their 16th birthday; b) they must have constantly resided in the US since June 15, 2007; c) they must have obtained a high school diploma or equivalent. Then, I leverage the age in 2012 requirement to define likely DACA eligibility and likely DACA ineligibility.

ACS does not ask directly about the legal status of immigrants, so I assume all non-citizens are undocumented, following Pope (2016). This measure is contaminated by individuals who are permanent residents or on temporary visas.

I can directly observe non-citizen immigrants based on their places of birth and citizenship status. I use their age, year of immigration and survey year to verify if they arrived in the US before their 16th birthday. I also assume that an individual immigrant to the US before 2007 as a proxy that they have constantly presented in the US since 2007 as of June 15, 2012. Hence, I use year of immigration to identify if an individual entered the US before 2007 in ACS. In addition, I can also observe if an individual has completed high school or equivalent and received their diploma.

[6] I use the ACS data from 2005 to 2019 for a difference-in-differences framework in Section 5.3 and a difference-in-discontinuities framework in Section 6.4.

After restricting my sample to individuals who met all above requirements, I compute an individual's age in 2012 from survey year and age when they were surveyed, which determines DACA eligibility (i.e: under 31 as of June 15, 2012). One complication in ACS data is that respondents are not asked directly about their year of birth. Data on year of birth is inferred based on age and survey year. Moreover, ACS is surveyed year-round, which adds another layer of complication. For example, a person who was 30 in 2012 and was born in Quarter 1, was recorded as being born in 1982. In fact, this individual may be born in either 1981 Quarter 1 or 1982 Quarter 1. In other words, it is not reliable to use year of birth to construct my running variable. Instead, I rely on age and quarter of birth to construct my sample and drop observations where the classification is ambiguous. I present my detailed approach on how to deal with this issue in Appendix 1.

I examine several outcome variables using ACS data: probability of being employed, employer-sponsored health insurance, probability of working last year, and weekly working hours. I also construct a number of years of schooling required, which is average of years of schooling across all individuals for each job.

3.2 O*NET

My second source of data is O*NET, which is developed under U.S. Department of Labor/Employment and Training Administration. O*NET is a source of occupational information, which measures skills, knowledge, abilities, etc. on almost 1,000 occupations. To construct indices to measure job skills, I follow the paper by Mansfield and Slichter (2021). For example, I construct the math index by taking an average of all measures from Mathematics (Skills), Mathematical Reasoning (Abilities), and Number Facility (Abilities). The details for all indices are as follows:

- **Math:** Mathematics (Skills), Mathematical Reasoning (Abilities), and Number Facility (Abilities).

- **Creativity:** Originality (Abilities) and Fluency of Ideas (Abilities).
- **Critical thinking**: Critical Thinking (Skills), Judgment and Decision Making (Skills), Operations Analysis (Skills), Systems Analysis (Skills), Deductive Reasoning (Abilities), and Inductive Reasoning (Abilities).
- **Science**: Science (Skills), Biology (Knowledge), Chemistry (Knowledge), and Physics (Knowledge).

In O*NET data, most skills are measured by both the importance of skills and level of skills on a scale ranging from 0 to 100.[7] They are highly correlated, so I use the importance of skills as a measurement in this paper.

3.3 Crosswalks between ACS and O*NET

In order to assign job skill indices for each occupation, I use the occupation code as an identifier to merge O*NET data into ACS. While ACS uses Standard Occupational Code (SOC), O*NET data uses O*NET-SOC. O*NET-SOC has two levels of occupation codes: 6-digit code and 8-digit code. The 6-digit code might be divided into several 8-digit codes, depending on how specialized those occupations are. To serve the purpose of job skill assignment, I take an average of skills of 8-digit O*NET codes which share the same first 6 digits. Then, I crosswalk between ACS and O*NET data using the 6-digit O*NET code.

3.4 Descriptive statistics

Table 1 displays the summary statistics for people who are non-citizen immigrants under 16 years old upon arrival in the US, entered the US before 2007 and have obtained a high school diploma. I report the summary in two groups, one is DACA eligibles if individuals are under 31 years old in 2012 and ineligibles otherwise. Panel A represents people who are potentially

[7]In my results, these indices have been standardized.

eligible for DACA, they tend to be younger (28.97 versus 44.35 years of age); have lived in the US for a shorter period of time (19.94 versus 35.26 years); are less likely to be self-employed (0.07 versus 0.13) and have lower wage income (US$31,200 versus 42,600) than people who are potentially ineligible for DACA . Panel B shows that in general, people who are potentially eligible for DACA, work in jobs that require lower job skills than people who are not.[8]

Table 1: Summary statistics

	Likely DACA ineligible			Likely DACA eligible		
Panel A: Demographics	Obs	Mean	SD	Obs	Mean	SD
Age	27881	44.35	6.99	33347	28.97	2.92
Male	27881	0.58	0.49	33347	0.57	0.50
Years of schooling	27881	13.34	2.01	33347	13.28	1.89
Years in the US	27881	35.26	9.07	33347	19.94	5.61
Year of immigration	27881	1980	8.93	33347	1996	5.49
Employed	27881	0.94	0.24	33347	0.95	0.23
Self-employed	27881	0.13	0.33	33347	0.07	0.26
Wage income	27881	42580	50412	33347	31156	30815
Weekly working hours	27881	39.25	13.02	33347	38.42	12.16
Employer-sponsored insurance	27881	0.59	0.49	33347	0.48	0.50
	Likely DACA ineligible			Likely DACA eligible		
Panel B: Job skills	Obs	Mean	SD	Obs	Mean	SD
Math skills	24757	40.71	12.65	32046	40.66	12.52
Critical thinking	24757	47.40	10.87	32046	46.16	10.54
Creativity	24757	42.47	12.82	32046	41.29	12.57
Science knowledge	24757	16.46	12.26	32046	16.09	12.35
Years of schooling required	24757	13.15	1.74	32046	13.00	1.70

Notes: Sample in Panel A includes people who arrived in the US before their 16 years old, before 2007, and have obtained high-school diploma. Sample in Panel B is conditional on being employed.

4 Econometric strategies

In order to identify the effects of DACA as a quasi-experiment on labor market outcomes, this paper exploits a parametric RDD. There are 2 options that are potentially used as a running variables: individuals' age in 2012 and individuals' age at arrivals. Nonetheless, age at arrivals are correlated with education (Evans and Fitzgerald, 2017; Gonzalez, 2003), and therefore, it is correlated with labor market outcomes. Moreover, people who emigrate at age of 18 may be

[8] I am reporting the raw O-NET indices with a scale ranging from 0 to 100 here. However, in my results, they have been standardized to be easily interpreted

discontinuously different from people who emigrate as minors. So, it is difficult to do the extrapolation from the right side of the threshold. Thus, I leverage individuals' age in 2012 as my primary running variable.

As explained in section 3.1, I restricted my sample to only non-citizen immigrants who meet three out of four observable DACA criteria and then define a treatment group and a control group based on my running variable. Specifically, individuals who are under 31 as of June 15, 2012 are eligible and identified as treatment group. On the other hand, individuals who are 31 or older are ineligible and classified as control group in my setting. To simplify my notation and computation, I normalize individuals' age in 2012. Let R_{it} = individual's age in 2012 - 31. Then, $\mathrm{D}_{it} = \begin{cases} 0 & \text{if } R_{it} \geq 0 \\ 1 & \text{if } R_{it} < 0 \end{cases}$ is defined as a binary treatment variable.

The main empirical specification has the following form:

$$Y_{it} = \alpha + \beta \mathrm{D}_{it} + \sum_{1}^{n} \gamma_n \mathrm{R}_{it}^n + \sum_{1}^{n} \delta_n \mathrm{R}_{it}^n * \mathrm{D}_{it} + \mathrm{X}_{it} + \epsilon_{it} \tag{1}$$

in which Y_{it} refers to the outcome variables of interest of individual *i* at time *t*. In this parametric regression discontinuity, n indicates the order of the polynomial function, where $n = 1, 2, 3$ are linear, quadratic and cubic functions respectively. The coefficient of interest β measures my RDD intention-to-treat effects.

This model also includes a vector of control variables X_{it} which controls for sex, years of education and number of years in the US.[9]

In this paper, non-parametric RDD is not appropriate because my running variable is discrete. Thus, I have to rely more on choosing a functional form to correctly identify the effect of treatment on outcome variables (Lee and Card, 2008). That being said, the uncertainty in the selection of

[9] I do not include state and year fixed effects because it will result in a small number of observations in one bin and may potentially lead to noisy results. However, I note that the results do not change if I include them to control for time and location difference. My results also do not change if I control for race and/or ethnicity.

functional form would produce specification errors. In other words, the low-order polynomial are going to introduce some bias unless I use an extremely high-order polynomial. However, if I keep increasing polynomial order, estimates will rely heavily on observations far away from the threshold. One piece of evidence that specification choices might introduce bias is that, among natives –for whom I have a larger sample size and can therefore estimate a conditional expectation function precisely –polynomial fits do not seem to exactly fit the data. To minimize the possible bias arising from specification errors, I instead use the conditional expectation function (CEF) among natives as an approximation for the CEF among immigrants, then add an additional polynomial adjustment to account for any remaining differences in the CEF between natives and immigrants. Specifically, I follow a 2-step method as described below:

Step 1:

I regress all outcome variables on dummy variables of individuals' age in 2012 for natives only.

$$Y_i = \kappa + \sum_{m=-14}^{m=28} \nu_n * 1(\mathrm{R}_i = m) + \tau_i \quad (2)$$

in which, Y_i is the original outcome for native individual *i* and m is individuals' normalized age in 2012.

Step 2:

Then, I use the estimate of Y_i ($\widehat{Y_i}$) in Equation (2) to adjust for my original outcome variables as follows:

$$\tilde{Y}_{it} \equiv \mathrm{Y}_{it} - \widehat{Y_i}.$$

Specifically, my three models using the parametric regression discontinuity approach are:

1. $\tilde{Y}_{it} = \alpha_0 + \beta \mathrm{D}_{it} + \gamma_1 \mathrm{R}_{it} + \delta_1 \mathrm{R}_{it}\mathrm{D}_{it} + \lambda \mathrm{X}_{it} + \epsilon_{it}$ (1a)

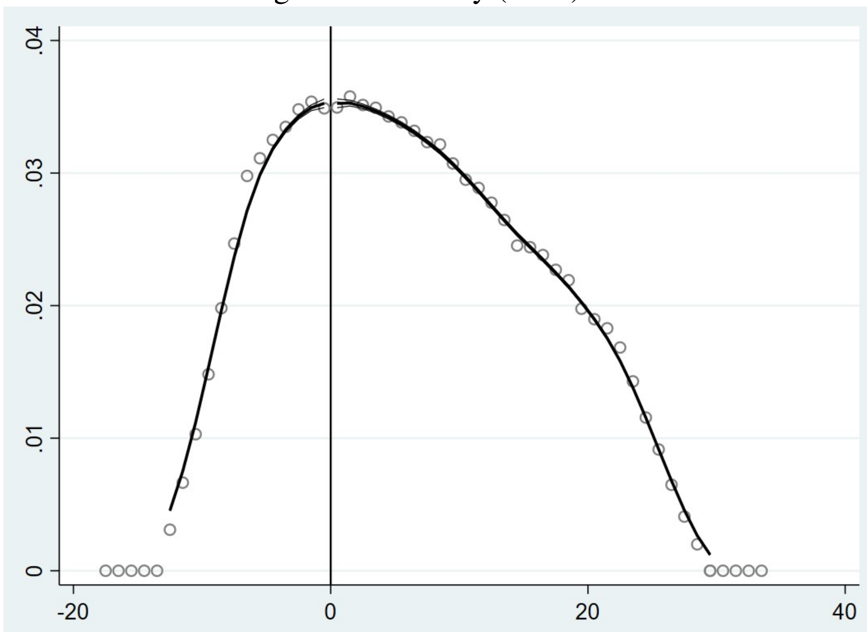
2. $\tilde{Y}_{it} = \alpha_0 + \beta \mathrm{D}_{it} + \gamma_1 \mathrm{R}_{it} + \gamma_2 \mathrm{R}_{it}^2 + \delta_1 \mathrm{R}_{it}\mathrm{D}_{it} + \delta_2 \mathrm{R}_{it}^2 \mathrm{D}_{it} + \lambda \mathrm{X}_{it} + \epsilon_{it}$ (1b)

3. $\tilde{Y}_{it} = \alpha_0 + \beta \mathrm{D}_{it} + \gamma_1 \mathrm{R}_{it} + \gamma_2 * \mathrm{R}_{it}^2 + \gamma_3 \mathrm{R}_{it}^3 + \delta_1 \mathrm{R}_{it}\mathrm{D}_{it} + \delta_2 \mathrm{R}_{it}^2 \mathrm{D}_{it} + \delta_3 \mathrm{R}_{it}^3 \mathrm{D}_{it} + \lambda \mathrm{X}_{it} + \epsilon_{it}$ (1c)

The main concern for RDD is the possibility of data manipulation and discontinuity in unobservables around the threshold. In other words, the result will be misleading if people who are close to the threshold, might attempt to manipulate it and sort them in their preferred group. In order to address that, I perform the density test based on the non-parametric local polynomial density estimator developed by McCrary (2008). The test statistic is -0.004 with s.e 0.009, which fails to reject the null hypothesis of continuity. I plot the density of the running variable in Figure 3, following McCrary (2008), which visually confirms the smoothness of the density function of my running variable.

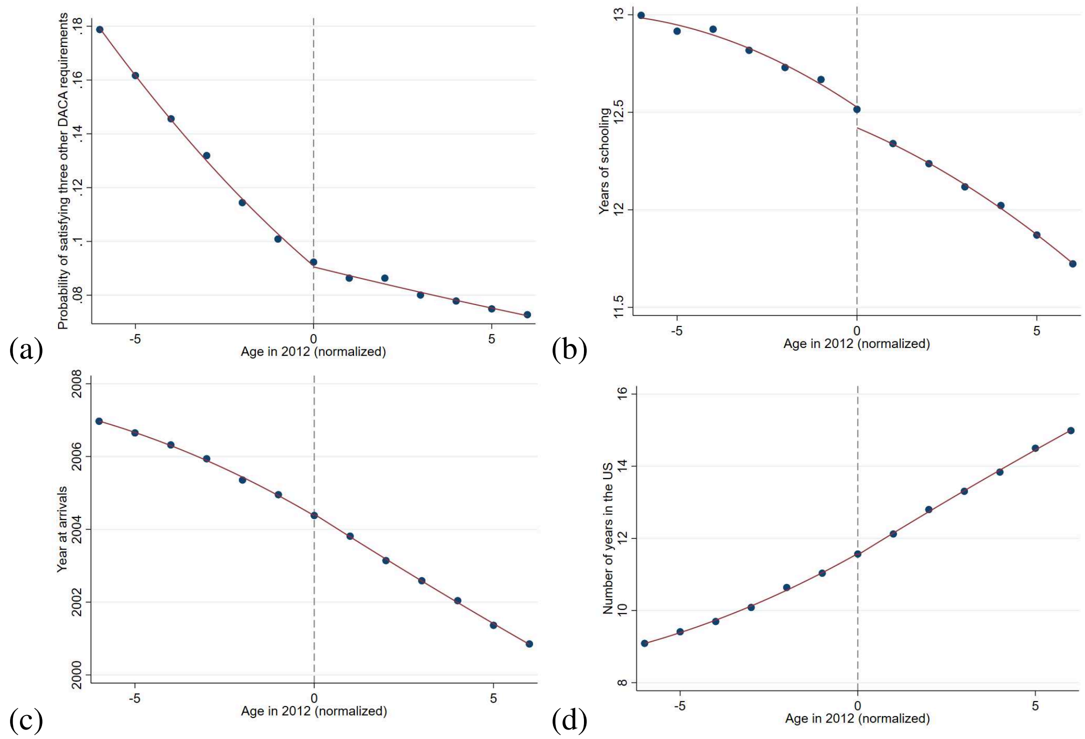
I also demonstrate in Figure 4 the graphical version of balance tests, plotting the means of variables in different brackets of age in 2012. Figure 4a shows the probability of qualifying for the other three DACA requirements, which are under age of 16 at arrivals, arrivals before 2007 and high school diploma or equivalent holder. It is clearly evident that there is no bunching around the threshold. Similarly, Figure 4b, 4c, and 4d illustrate that all plots have smooth transitions at the threshold. In other words, individuals who are adjacent to the threshold are comparable.

Figure 3: McCrary (2008) test



Notes: This figure show the formal manipulation test based on a methodology proposed by McCrary (2008). This supports the reliability of the RDD method that observations near the threshold are comparable and free from manipulation.

Figure 4: Balance check of covariates



Notes: This figure shows the means of four variables to verify the continuities of those variables across the threshold.

5 Results

In a parametric regression model, the results report β coefficients from three equations (1a), (1b) and (1c) described in section 4. I also run my models within a restricted window, so it requires a bandwidth selection. In my model setting, I choose the bandwidth of 6 to start off. However, I also run the model with bandwidths of 5 and 7 to ensure robustness. There is an additional concern that estimates from cubic functional form usually yield different estimates from linear and quadratic functions. However, Gelman and Imbens (2019) argue the global higher order polynomial causes some major concerns. First, the weights implied by higher-order can take on extreme values relative to the weights based on local linear or quadratic regressions. Additionally, the higher the order of polynomial function is, the more sensitive the causal effects are. Last but not least, confidence intervals reported on the higher order function are deceptive. So, the estimates from higher order polynomial function are often not reliable. In this paper, my preferred specification is linear functional from with the bandwidth of 6. However, I still report the estimates from quadratic and cubic function as a reference. Standard errors in my parametric model are conventional heteroskedasticity-robust standard errors at the state-year level, which is suggested by Kolesár and Rothe (2018). They concluded that standard errors, which are clustered by the running variable (Lee and Card, 2008), do not resolve specification bias and may have poor coverage properties.

In order to comprehensively understand the labor market outcomes of DACA eligibility, I examine two sets of variables. First, to measure employment outcomes, I use 5 dependent variables from ACS data: probability of being employed, probability of getting health insurance from employers, probability of working last year, weekly working hours, and wage income. Second, to measure job movement conditional on being employed, I use math skill, creativity, critical thinking, and science as described in section 3.2 as well as the number of years of schooling of typical people for each job.

5.1 Employment outcomes

Table 2 presents the effects of DACA eligibility on employment outcomes under linear, quadratic and cubic functional forms with bandwidth ranging from 5 to 7. The first row of Table 2 shows the effect of DACA eligibility on being employed. The coefficients are close to 0 and all of them are statistically insignificant. Similarly, the probability of getting health insurance from employers is almost 0 and statistically insignificant. The probability of working in the last year centers at zero and statistically insignificant. Table 2 also shows that coefficients on weekly working hours is dependent on specifications. Lastly, the effect on wage income is small and statistically insignificant. In general, those results from Table 2 verify that the impacts of DACA eligibility on employment outcomes are trivial and sensitive to the specifications.

Table 2: Effects of DACA eligibility on employment outcomes from 2013-2019

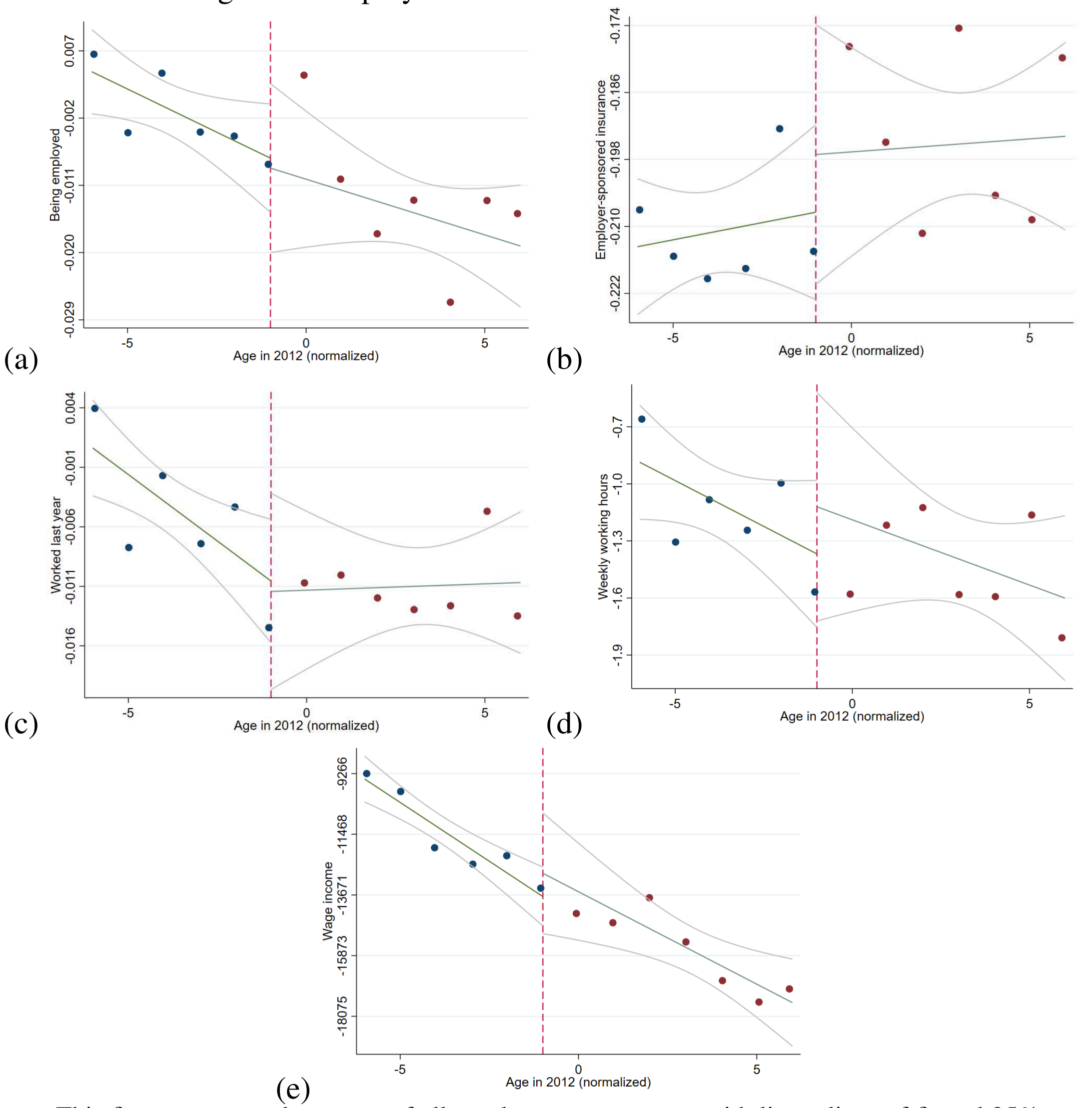
	Linear			Quadratic			Cubic		
Bandwidth	5	6	7	5	6	7	5	6	7
Being employed	0.002	0.001	0.003	-0.020	-0.008	-0.007	0.005	-0.024	-0.014
	(0.007)	(0.005)	(0.005)	(0.013)	(0.013)	(0.011)	(0.027)	(0.020)	(0.017)
Employer-sponsored insurance	0.000	0.002	-0.006	-0.013	-0.005	0.009	-0.107**	-0.062	-0.044
	(0.015)	(0.015)	(0.014)	(0.029)	(0.023)	(0.021)	(0.049)	(0.046)	(0.036)
Worked last year	0.004	-0.001	-0.001	-0.015	0.002	-0.001	-0.010	-0.029*	-0.009
	(0.005)	(0.004)	(0.004)	(0.010)	(0.008)	(0.007)	(0.023)	(0.017)	(0.014)
Weekly working hours	0.191	-0.205	-0.147	-0.460	0.390	0.040	-0.490	-1.249	0.059
	(0.362)	(0.326)	(0.284)	(0.741)	(0.620)	(0.591)	(1.504)	(1.195)	(0.864)
Wage income	-267	-172	-259	1932	809	639	-2256	1527	1254
	(1263)	(1113)	(936)	(2533)	(2098)	(1905)	(4548)	(3782)	(3179)
Observations	23645	29029	34608	23645	29029	34608	23645	29029	34608

Standard errors in parentheses are clustered at the state-year level.
Notes. This table shows the effects of DACA on labor market outcomes among non-citizen immigrants across different bandwidth and order of polynomial function. Sample includes those who have obtained high-school diploma, have entered the US before their 16th birthday and have immigrated to the US before 2007.
* $p < .10$, ** $p < .05$, *** $p < .01$

Figure 5 visualizes the mean of each employment outcome without any control variables and fit a linear line with the bandwidth of 6 and confirms my regression results.[10] Figure 5a, 5c and 5e confirm no discontinuity in the probability of being employed, the probability of working in the last year or wage income around the threshold. Figure 5b and 5d show very little evidence that there are discontinuities in the probability of getting employer-sponsored insurance and weekly working hours around the threshold. In general, the graphs confirm what I find in the regression that DACA eligibility has no effect on all variables of interest.

[10]Refer to Appendix 2 for quadratic lines of fit.

Figure 5: Employment outcomes with linear lines of fit



Notes: This figure presents the means of all employment outcomes with linear lines of fit and 95% confidence intervals. Observations are on the left side of the threshold are treated and observations are on the right side of the threshold are untreated.

5.2 Occupational skill usage

Table 3 estimates the effects of DACA eligibility on working in high skilled jobs under linear, quadratic and cubic functional forms with bandwidth ranging from 5 to 7. Table 3 shows that there is no evidence that likely DACA eligible people move to jobs that require higher math skills, creativity thinking, creativity, science, and years of schooling. The coefficients on science shows a mix of negative and positive coefficients. However, all of those coefficients are close to 0. Most of coefficients on math skills, critical thinking, and years of schooling are trivial and indifferent from 0.

Table 3: Effects of DACA eligibility on occupational skill usage

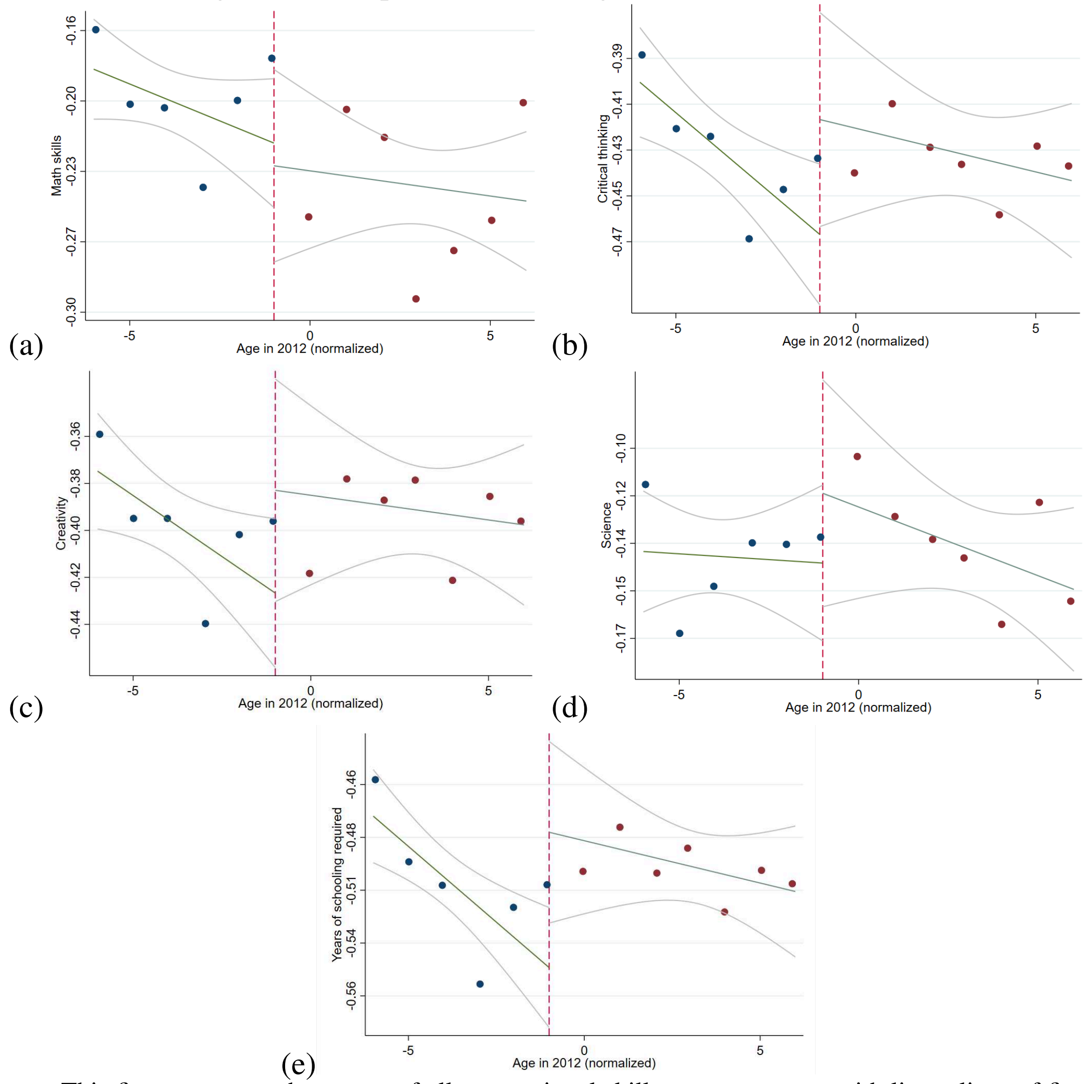
	Linear			Quadratic			Cubic		
Bandwidth	5	6	7	5	6	7	5	6	7
Math skills	0.018	0.022	0.012	0.050	0.036	0.036	0.149	0.104	0.087
	(0.028)	(0.026)	(0.024)	(0.061)	(0.050)	(0.043)	(0.100)	(0.087)	(0.072)
Critical thinking	-0.029	-0.034	-0.033	-0.033	-0.025	-0.033	0.063	-0.001	-0.001
	(0.029)	(0.023)	(0.024)	(0.046)	(0.046)	(0.039)	(0.095)	(0.071)	(0.058)
Creativity	-0.016	-0.028	-0.021	-0.008	0.004	-0.019	0.061	0.010	0.036
	(0.032)	(0.023)	(0.023)	(0.052)	(0.051)	(0.044)	(0.107)	(0.085)	(0.064)
Science	0.013	-0.019	-0.017	-0.042	0.029	0.003	-0.029	-0.107	0.001
	(0.027)	(0.025)	(0.022)	(0.066)	(0.049)	(0.044)	(0.100)	(0.093)	(0.078)
Years of schooling required	-0.033	-0.043**	-0.042**	-0.036	-0.021	-0.033	0.011	-0.029	-0.009
	(0.024)	(0.019)	(0.019)	(0.038)	(0.039)	(0.032)	(0.089)	(0.059)	(0.051)
Observations	21861	26877	32022	21861	26877	32022	21861	26877	32022

Standard errors in parentheses are clustered at the state-year level. Coefficients are measured in standard deviation.
Notes. This table shows the effects of DACA on the probability of choosing high-skilled jobs among immigrants across different bandwidth and order of polynomial function. Sample includes those who have obtained high-school diploma, have entered the US before their 16th birthday and have immigrated to the US before 2007.
* $p < .10$, ** $p < .05$, *** $p < .01$

Figure 6 illustrates the mean of each occupational skill usage variable with a linear line of fit.[11] It is shown that there are no discontinuities around the threshold for all variables of interest.

[11] Refer to Appendix 2 for the plot with quadratic lines of fit.

Figure 6: Occupational skill usage with linear lines of fit



Notes: This figure presents the means of all occupational skill usage outcomes with linear lines of fit and 95% confidence intervals. Observations are on the left side of the threshold are treated and observations are on the right side of the threshold are untreated.

5.3 Result discussion

DACA is a large immigration policy, which was expected to have a significant impact on eligible individuals. While several studies show the positive effects of DACA on labor market outcomes (Amuedo-Dorantes and Antman, 2017; Pope, 2016) or educational attainment (Kuka et al., 2020), my results are surprising. There are two possible explanations for this divergence.

First, the sample in this paper encompasses a period during which DACA encountered various legal challenges, which may dampen the effects of DACA on labor market outcomes. Second, this paper constructs a different sample, which measures a different group of DACA individuals. To understand if the sample period or the econometric model cause the difference, I restrict my post-DACA period to 2013 and 2014, which was prior to any legal dispute. Then, I perform my main analysis again and also use the same difference-in-differences framework as Pope (2016).

Regression Discontinuity Table 4 illustrates the effects of DACA eligibility on employment outcomes from 2013 to 2014. The coefficients on the probability of being employed range from 1.2% to 1.8% for linear functional form. However, the coefficients' signs flip and become negative for the quadratic functional form. Most of those coefficients are statistically insignificant. I do not see any effect on employer-sponsored health insurance. The effects of DACA eligibility on the probability of working in the last year, weekly working hours, and wage income also show the same pattern, which presents no solid evidence of the effects of DACA eligibility. This suggests that even in the early days of DACA, the effects of DACA eligibility on labor market outcomes are also limited, which are not caused by legal challenges in later years.

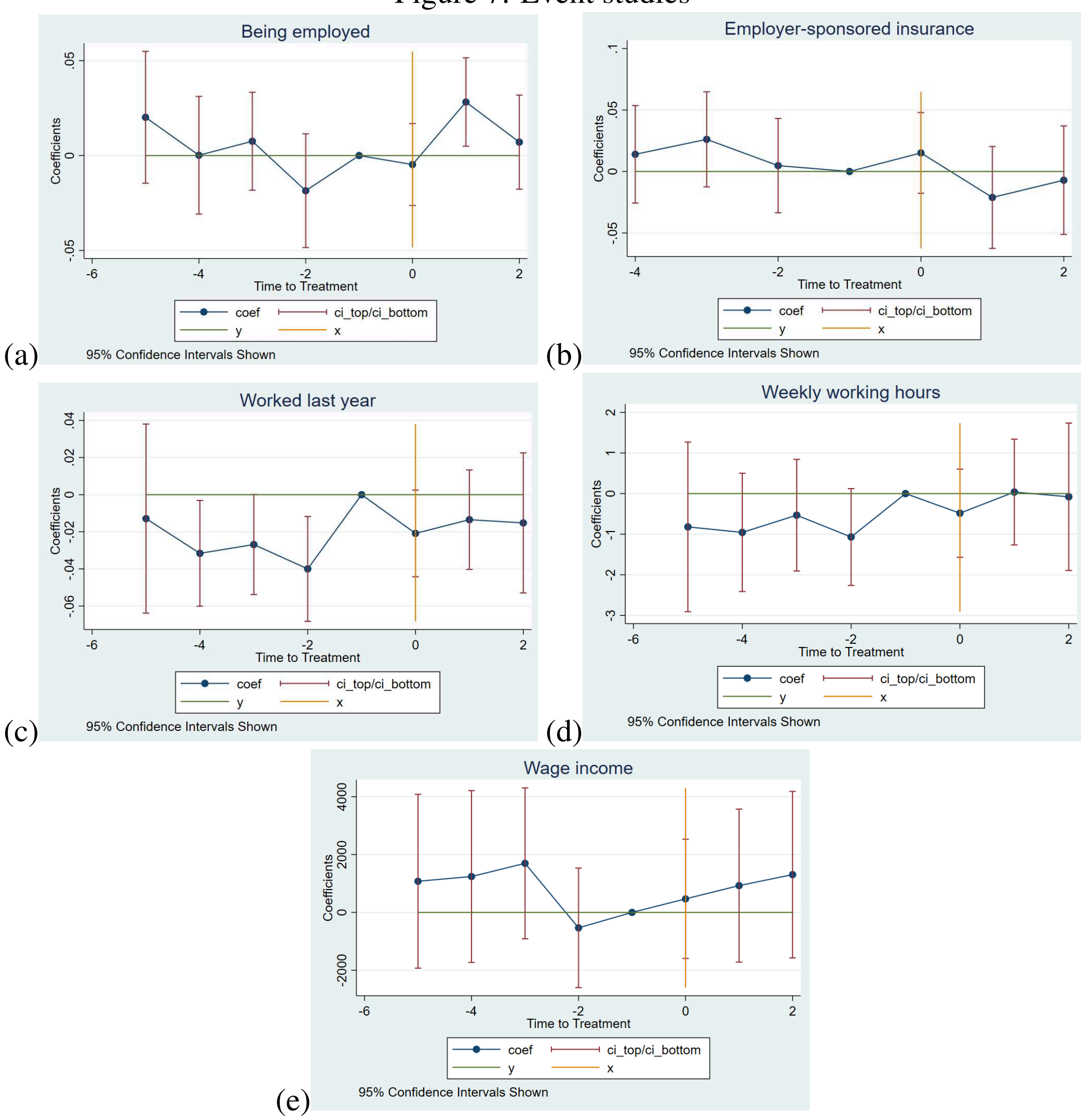
Table 4: Effects of DACA eligibility on employment outcomes from 2013-2014

	Linear			Quadratic			Cubic		
Bandwidth	5	6	7	5	6	7	5	6	7
Being employed	0.010	0.010	0.018*	-0.016	-0.003	-0.009	0.002	-0.025	-0.005
	(0.016)	(0.011)	(0.010)	(0.032)	(0.032)	(0.024)	(0.044)	(0.036)	(0.040)
Employer-sponsored insurance	-0.013	-0.020	-0.034	0.008	0.014	0.017	-0.006	-0.016	0.006
	(0.023)	(0.024)	(0.021)	(0.040)	(0.029)	(0.030)	(0.075)	(0.072)	(0.042)
Worked last year	0.004	-0.003	-0.001	-0.011	0.006	-0.000	-0.022	-0.032	-0.005
	(0.008)	(0.008)	(0.008)	(0.024)	(0.020)	(0.013)	(0.045)	(0.036)	(0.036)
Weekly working hours	0.240	-0.087	0.120	-1.238	-0.086	-0.411	-0.041	-2.053	-0.669
	(0.656)	(0.595)	(0.502)	(1.343)	(1.052)	(1.060)	(2.671)	(2.201)	(1.465)
Wage income	-853	-1575	-401	1752	1445	-1139	3323	2394	4174
	(1894)	(1723)	(1502)	(3856)	(3129)	(2830)	(6347)	(5458)	(4325)
Observations	7812	9595	11393	7812	9595	11393	7812	9595	11393

Standard errors in parentheses are clustered at the state-year level.
Notes. This table shows the effects of DACA on labor market outcomes among non-citizen immigrants across different bandwidth and order of polynomial function from 2013-2014. Sample includes those who have obtained high-school diploma, have entered the US before their 16th birthday and have immigrated to the US before 2007.
* $p < .10$, ** $p < .05$, *** $p < .01$

Difference-in-Differences To employ a difference-in-difference framework, I use the ACS data from 2005 to 2014.[12] I construct the sample as described in Section 3.1. Then, I follow the difference-in-difference econometric strategies by Pope (2016).[13] My results consistently confirm null effects. In Figure 7, I present event studies to show parallel trends and the effects of DACA eligibility. Most of the coefficients during the post-DACA period are indifferent from zero, which confirms the null effects of DACA eligibility.

Figure 7: Event studies



Notes: This figure presents the event studies for employment outcomes with 95% confidence intervals. Data is collected from the ACS, spanning from 2005 to 2014.

[12]For employer-sponsored insurance, the data is from 2008 because ACS has not asked about insurance until 2008.
[13]Please refer to Appendix 5 for details.

Regardless of sample period and econometric models, my results still corroborate null effects, thus reinforcing the hypothesis that the difference in my sample construction are the primary explanatory factor. My sample measures a different group of people who are likely to be older DACA individuals. In my sample, I assign treatment status based on whether an individual is under 31 in 2012 among a sample of non-citizens who have obtained a high-school degree, arrived in the US before their 16th birthday, and arrived before 2007. Pope (2016) constructed a sample of people who are non-citizens who are from 18 to 40 and defined a treatment group as those who have met all observable DACA requirements.[14] This would leave all individuals who do not satisfy one, two, three, or all of DACA requirements in the control group. Nonetheless, one possible issue is that the control group is not homogeneous because individuals who failed one DACA requirements are generally different from those who failed all of them. This may make the treatment and control groups less likely to be comparable.

One important aspect of this paper is that I cannot definitively rule out positive effects. To evaluate the largest possible effects of DACA eligibility, I adjust the CIs from my baseline RDD estimates by uptake rates. It is estimated that about 60% of non-citizens under 35 were undocumented in 2012 and just over 60% of DACA-eligible individuals actually applied for DACA.[15] So, I will approximate the uptake rate on one side of the threshold to be 36%. I will assume that it is 0% on the other side. In other words, the uptake-adjusted estimates should be 1 divided by 0.36 equals 2.7 times larger than the baseline RDD estimates. This is consistent with the finding by Mira (2022), which documents the average treatment-on-the-treated effects of DACA is at least twice as large as the intention-to-treat estimates. In Appendix 9, I present my uptake-adjusted point estimates and CIs along with estimates from Pope (2016) and Amuedo-Dorantes and Antman (2017). Using my preferred specification, DACA eligibility likely increases the probability of being employed at most 3 ppts, increase the probability of working last year at most 2 ppts, and increase

[14] Pope (2016) also examined several sub-samples. He restricted to individuals who entered the US between ages 12 and 19; ages 18 and 35 with a high-school degree; ages 27 to 34 in the current data year. Even though Panel B in Table 2 in his paper said that he restricted to people aged 27 to 34 in 2012, I obtained his codes and it restricted to people aged 27 to 34 in the current data year. This is different from my sample.

[15] As I discussed in Section 1

weekly working hours by 1.2 hours. These upper ends of my CIs generally overlap with the lower end of the CIs of previous papers, though my point estimates are smaller.

In short, the upper bounds of my CIs fail to reject small positive effects, which overlap with the lower end of CIs in the previous literature. However, I can comfortably rule out the top end of CIs by Pope (2016) and Amuedo-Dorantes and Antman (2017). Lastly, obviously my estimates are more consistent with smaller parameter values than with larger ones.

6 Robustness checks

In this section, I present a set of multiple robustness checks on my main results.

6.1 Mexican population

Mexican immigrants I run the main model only for Mexican immigrants. Mexican immigrants made up approximately 50% of total undocumented population in the US in 2018 (Baker, 2021). According to Pew Research Center (2019), approximately one in every two Mexicans is undocumented. In terms of DACA participation, Mexicans made up for almost 80% of all ever DACA holders. Therefore, restricting the sample to immigrants from Mexico focuses the estimates on a population with a larger anticipated effect.

Table 5 shows the impacts of DACA eligibility on employment outcomes for Mexican immigrants. The results show that there is no evidence that DACA moves Mexican immigrants into employment across specifications. In terms of getting health insurance from the employers, the coefficients are mixed and statistically insignificant. In other words, there is no empirical evidence that DACA eligibility has a causal effect on the probability of working in formal employment among eligible Mexican immigrants. Similarly, I see almost no effects for Mexican immigrants in terms of the probability of working in the last year, weekly working hours, and wage income.

In general, the effects of DACA eligibility on Mexican population on the probability of working, employer-sponsored insurance, and wage income are consistent with what I find for the whole sample.[16]

Table 5: Effects of DACA eligibility on employment outcomes: Mexican

	Linear			Quadratic			Cubic		
Bandwidth	5	6	7	5	6	7	5	6	7
Being employed	-0.003	-0.009	-0.006	-0.018	-0.001	-0.009	-0.050	-0.047**	-0.013
	(0.008)	(0.007)	(0.007)	(0.013)	(0.014)	(0.012)	(0.040)	(0.022)	(0.017)
Employer-sponsored insurance	0.002	0.002	-0.007	-0.022	-0.004	0.011	-0.202***	-0.122*	-0.073
	(0.025)	(0.023)	(0.020)	(0.038)	(0.034)	(0.034)	(0.074)	(0.066)	(0.049)
Worked last year	0.003	-0.008	-0.006	-0.015	0.007	-0.001	-0.035	-0.042*	-0.007
	(0.007)	(0.006)	(0.005)	(0.012)	(0.011)	(0.009)	(0.032)	(0.022)	(0.018)
Weekly working hours	-0.187	-0.770*	-0.476	-0.814	0.278	-0.524	-2.473	-2.468	-0.183
	(0.508)	(0.416)	(0.392)	(0.967)	(0.854)	(0.783)	(1.978)	(1.509)	(1.145)
Wage income	112	7	-52	-99	220	377	-9694**	-4243	-2161
	(1222)	(1020)	(934)	(2537)	(2257)	(1878)	(4151)	(3186)	(3195)
Observations	11649	14430	17414	11649	14430	17414	11649	14430	17414

Standard errors in parentheses are clustered at the state-year level.
Notes. This table shows the effects of DACA on labor market outcomes among non-citizen Mexican immigrants across different bandwidth and order of polynomial function. Sample includes those who have obtained high-school diploma, have entered the US before their 16th birthday and have immigrated to the US before 2007.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 6 presents the effects of DACA eligibility on moving to work in high-skilled jobs. Some of the coefficients are positive, which may suggest a positive effect on moving up to high-skilled jobs. However, they are small in magnitude, statistically insignificant and sensitive to specifications. Thus, I cannot differentiate them from 0. These results also re-confirm that there is no empirical evidence on working in high-skilled jobs among likely eligible individuals.

[16] I also run the main regression for non-Mexican, and present the results in Appendix 3.

Table 6: Effects of DACA eligibility on occupational skill usage: Mexican

	Linear			Quadratic			Cubic		
Bandwidth	5	6	7	5	6	7	5	6	7
Math skills	-0.004	0.012	0.001	0.009	-0.010	0.007	0.134	0.070	0.033
	(0.043)	(0.037)	(0.032)	(0.089)	(0.076)	(0.067)	(0.163)	(0.128)	(0.107)
Critical thinking	-0.022	-0.025	-0.020	-0.009	-0.008	-0.022	-0.005	-0.016	0.010
	(0.037)	(0.030)	(0.026)	(0.075)	(0.072)	(0.061)	(0.126)	(0.093)	(0.094)
Creativity	-0.000	-0.012	0.003	0.009	0.023	-0.013	-0.050	-0.025	0.045
	(0.040)	(0.031)	(0.026)	(0.079)	(0.073)	(0.062)	(0.127)	(0.102)	(0.099)
Science	0.015	-0.010	-0.018	-0.034	0.028	0.020	0.063	-0.063	0.003
	(0.037)	(0.034)	(0.028)	(0.074)	(0.058)	(0.058)	(0.122)	(0.104)	(0.085)
Years of schooling required	-0.048	-0.059***	-0.041*	-0.023	-0.015	-0.057	-0.123	-0.071	0.008
	(0.030)	(0.022)	(0.021)	(0.064)	(0.064)	(0.048)	(0.112)	(0.078)	(0.087)
Observations	10823	13438	16225	10823	13438	16225	10823	13438	16225

Standard errors in parentheses are clustered at the state-year level. Coefficients are measured in standard deviation. Notes. This table shows the effects of DACA eligibility on job-related skill indices among non-citizen Mexican immigrants across different bandwidth and order of polynomial function. Sample includes those who have obtained high-school diploma, have entered the US before their 16th birthday and have immigrated to the US before 2007.
* $p < .10$, ** $p < .05$, *** $p < .01$

Mexican in California and Texas California and Texas are homes to approximately 36% of undocumented population in the US. According to Pew Research Center, 69% and 73% of undocumented population in California and Texas respectively are Mexican. In contrast, Massachusetts has less than 4% of undocumented population and only 2% of them are Mexican.[17] So, suppose I compare a Mexican who lives in Massachusetts and a Mexican who lives in Texas, a Mexican in Texas is much more likely to be undocumented. So, I run my main analysis again on the sample of Mexicans who reside in California and Texas only. Appendix 3 clearly shows that there is no empirical evidence that Mexicans in California and Texas, who are more likely to be undocumented, with DACA eligibility are more likely to move into employment or work in high-skilled jobs.

6.2 Sample selection

As the results from Table 4, there is suggestive evidence that DACA may move up to 2% of people into employment in early years followed the introduction of DACA. So, if DACA moved people at lowest percentile of the job skill distribution into employment, this sample selection would bias the estimated downwards. To determine the maximum extent that sample selection of

[17] https://www.pewresearch.org/hispanic/interactives/u-s-unauthorized-immigrants-by-state/

this kind migh affect my results, I eliminate all individuals in the bottom 2% for each job skill distribution by each age in 2012 and year bracket. For instance, when the outcome is math skills, I rerun my main analysis, dropping 2% of observations to the left of the discontinuity with the lowest usage of math skills.

Table 7 presents the effects of DACA eligibility on working in high skilled jobs under linear, quadratic and cubic functional forms with bandwidth ranging from 5 to 7 after 2% removal.[18] The coefficients for math skills range from 0.08 to 0.13 S.D across specifications and are all statistically significant at either 5% or 1%. All other estimates on critical thinking, creativity and science also become positive. However, they are mostly statistically insignificant, so I cannot differentiate them from 0. The results provide the evidence that my main results could be consistent with effects on skill usage if DACA moves people into employment in the lowest part of the job skill distribution who would have otherwise not been employed. In other words, Table 7 shows the maximum extent of the impact of DACA eligibility on the probability of working in high-skilled jobs.

Table 7: Effects of DACA eligibility on occupational skill usage, remove lowest 2%

	Linear			Quadratic			Cubic		
Bandwidth	5	6	7	5	6	7	5	6	7
Math skills	0.081***	0.085***	0.076***	0.129**	0.105**	0.103**	0.230**	0.196**	0.168**
	(0.029)	(0.026)	(0.024)	(0.061)	(0.049)	(0.045)	(0.095)	(0.083)	(0.068)
Critical thinking	0.008	0.002	0.004	0.008	0.016	0.004	0.125	0.049	0.049
	(0.028)	(0.023)	(0.023)	(0.047)	(0.046)	(0.039)	(0.099)	(0.074)	(0.059)
Creativity	0.051	0.035	0.031	0.073	0.086*	0.069	0.086	0.071	0.100
	(0.032)	(0.024)	(0.024)	(0.056)	(0.051)	(0.045)	(0.127)	(0.097)	(0.067)
Science	0.043	0.009	0.013	-0.001	0.069	0.033	0.026	-0.060	0.056
	(0.026)	(0.025)	(0.021)	(0.066)	(0.049)	(0.044)	(0.102)	(0.094)	(0.077)
Years of schooling required	-0.006	-0.016	-0.015	-0.005	0.009	-0.005	0.043	0.004	0.024
	(0.023)	(0.019)	(0.018)	(0.040)	(0.041)	(0.032)	(0.085)	(0.059)	(0.054)
Observations	21547	26471	31529	21547	26471	31529	21547	26471	31529

Standard errors in parentheses are clustered at the state-year level. Coefficients are measured in standard deviation. Notes. This table shows the effects of DACA eligibility on job-related skill indices among non-citizen immigrants across different bandwidth and order of polynomial function. Sample includes those who have obtained high-school diploma, have entered the US before their 16th birthday and have immigrated to the US before 2007. This table presents the results after I remove observations in lowest 2 percentile of each skill distribution.

* $p < .10$, ** $p < .05$, *** $p < .01$

However, the results shown in Table 7 probably substantially overstate the actual amount of bias from sample selection, since my main estimates imply that the true effect in employment is

[18] I only present results for occupational skill usage because most of employment outcomes are just binary variables. However, I include results for weekly working hours and wage income in Appendix 4

likely closer to 0% than to 2%, and since workers drawn into employment by DACA will probably have a mix of skill levels.

6.3 Placebo tests

If the only reason for DACA eligibility affecting labor market outcomes is a temporary legal status, then those effects should be null in samples where DACA eligibility is not relevant. In order to confirm that, I run the main specification on naturalized citizens. [19]

However, one of the concerns on naturalized citizens is that individuals who had been DACA recipients and then were naturalized later on, which would contaminate my estimates. To deal with that issue, I restricted my immigrant citizens to only individuals who were naturalized before 2012. Table 8 presents the results of DACA eligibility on employment outcomes. It is evident that most of coefficients are negative, but nearly 0. Table 9 presents the results of DACA eligibility on the probability of working in high-skilled jobs among immigrant citizens. Like what I find in Table 8 most of coefficients are statistically insignificant and trivial. In general, I find no evidence that DACA eligibility has impacts on employment and working in high skilled jobs among naturalized citizens upon the launch of DACA.

Table 8: Effects of DACA eligibility on employment outcomes: Naturalized citizens

	Linear			Quadratic			Cubic		
Bandwidth	5	6	7	5	6	7	5	6	7
Being employed	-0.003	-0.001	0.001	-0.010	-0.010	-0.009	-0.025*	-0.014	-0.013
	(0.004)	(0.003)	(0.003)	(0.007)	(0.007)	(0.006)	(0.013)	(0.011)	(0.010)
Employer-based insurance	-0.019**	-0.018**	-0.009	-0.008	-0.015	-0.029**	-0.042	-0.011	0.002
	(0.009)	(0.008)	(0.007)	(0.017)	(0.015)	(0.014)	(0.035)	(0.027)	(0.023)
Worked last year	-0.004	-0.002	-0.001	-0.006	-0.008*	-0.007*	-0.020*	-0.007	-0.009
	(0.003)	(0.002)	(0.003)	(0.005)	(0.005)	(0.004)	(0.010)	(0.008)	(0.007)
Weekly working hours	-0.212	-0.120	-0.130	-0.986**	-0.727*	-0.450	-2.615***	-1.830***	-1.527***
	(0.240)	(0.233)	(0.233)	(0.439)	(0.371)	(0.336)	(0.821)	(0.679)	(0.578)
Wage income	-1401	-1424	-1464	-1059	-1147	-955	-3648	-1753	-1821
	(1079)	(897)	(906)	(2274)	(1901)	(1592)	(4266)	(3354)	(2957)
Observations	61796	74005	86135	61796	74005	86135	61796	74005	86135

Standard errors in parentheses are clustered at the state-year level.
Notes. This table shows the placebo tests effects of DACA eligibility on labor market outcomes among naturalized citizens across different bandwidth and order of polynomial function. Sample includes those who have obtained high-school diploma, have entered the US before their 16th birthday and have immigrated to the US before 2007.
* $p < .10$, ** $p < .05$, *** $p < .01$

[19] I also run my analysis on US citizens born outside of the US and present them in Appendix 6

Table 9: Effects of DACA eligibility on occupational skill usage: Naturalized citizens

	Linear			Quadratic			Cubic		
Bandwidth	5	6	7	5	6	7	5	6	7
Math skills	0.018	0.001	0.006	0.022	0.043	0.020	0.168**	0.056	0.075*
	(0.018)	(0.017)	(0.016)	(0.032)	(0.028)	(0.025)	(0.072)	(0.051)	(0.044)
Critical thinking	-0.015	-0.019	-0.022	-0.034	-0.017	-0.014	0.016	-0.038	-0.027
	(0.016)	(0.015)	(0.014)	(0.029)	(0.026)	(0.023)	(0.063)	(0.047)	(0.040)
Creativity	-0.003	-0.012	-0.012	-0.037	-0.006	-0.007	-0.069	-0.086	-0.041
	(0.018)	(0.016)	(0.014)	(0.035)	(0.028)	(0.027)	(0.073)	(0.058)	(0.044)
Science	-0.014	-0.002	0.012	-0.072	-0.063*	-0.057*	0.016	-0.048	-0.061
	(0.020)	(0.019)	(0.017)	(0.045)	(0.037)	(0.031)	(0.080)	(0.064)	(0.057)
Years of schooling required	-0.020	-0.024*	-0.027**	-0.004	-0.003	-0.007	0.000	-0.004	0.002
	(0.015)	(0.013)	(0.013)	(0.034)	(0.027)	(0.022)	(0.055)	(0.049)	(0.043)
Observations	57967	69458	80813	57967	69458	80813	57967	69458	80813

Standard errors in parentheses are clustered at the state-year level. Coefficients are measured in standard deviation.
Notes. This table shows the placebo tests effects of DACA eligibility on job-related skill indices among naturalized citizens across different bandwidth and order of polynomial function. Sample includes those who have obtained high-school diploma, have entered the US before their 16th birthday and have immigrated to the US before 2007.
* $p < .10$, ** $p < .05$, *** $p < .01$

In general, I find no evidence that DACA eligibility has the effects on labor market outcomes among people who are not justified by the policy.

6.4 Difference in discontinuities

In this section, I modify my econometric strategy in two ways. First, I use the raw data without adjusting for the CEF of natives as described in Section 4. Second, I adopt a difference-in-discontinuity framework and examine the effects of DACA eligibility on labor market outcomes over the period from 2005 to 2019. These adjustments serve to possibly solve two potential problems: 1) Instead of using CEF of natives in my main analysis to adjust for the functional form in a regression discontinuity design, this method incorporates the population of non-immigrants before the DACA policy started, which is comparable to my post-DACA sample; 2) This will also allow having a larger sample and I could examine how characteristics of the sample composition change from pre-DACA to post-DACA. The idea of a difference in discontinuity framework is to examine the difference around the threshold in the pre-policy period and post-policy period. In other words, I compare two separate regression discontinuities, which are the effects of DACA eligibility. Specifically, the econometric model is as follows:

$$Y_{ist} = \alpha + \beta_1 \boldsymbol{D}_{ist} + \beta_2 \boldsymbol{D}_{ist} * \boldsymbol{Post}_t + \boldsymbol{f(RVF)}_i + \lambda X_{ist} + \omega_s + \theta_t + \epsilon_{ist} \tag{2}$$

in which: D_{ist} was defined in Section 4. $Post_t$ is equal to 1 if year is 2013 onward, 0 otherwise. $f(RVF)_i$ is a function of running variable R_{ist}, it may take a linear form or a quadratic form. X_{ist} is a vector of control variables. To make it precise with my main analysis, I control for sex, year of education, year in the US. I also add state (ω_t) and year (θ_t) fixed effects because my data sample ranges over a period of 14 years and includes the Great Recession period.

The results of DACA eligibility on employment outcomes and occupational skill usage are presented in Table 10 and Table 11, respectively. It is evident that there are no effects on any measurement of labor market outcomes. This is in line with my main analysis. I present the regression discontinuity graphs for the pre-period and the post-period in Appendix 7.

Table 10: Effects of DACA on employment using Difference-in-Discontinuities

	Linear	Quadratic
Being employed	-0.001	-0.008
	(0.009)	(0.020)
Employer-sponsored insurance	0.014	0.007
	(0.021)	(0.039)
Worked last year	-0.001	0.017
	(0.007)	(0.014)
Weekly working hours	0.246	1.453
	(0.481)	(0.888)
Wage income	-741	-442
	(1237)	(2403)
Observations	58833	58833

Standard errors are clustered at the state-year level.
Notes. This table shows the effects of DACA eligibility on employment outcomes among non-citizen immigrants who have obtained high-school diploma, have entered the US before their 16th birthday and have immigrated to the US before 2007. This results are represented with linear and quadratic functional forms with the bandwidth of 6. For employer-sponsored insurance, the number of observations is smaller because ACS has only reported insurance since 2008.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 11: Effects of DACA eligibility on occupational skill usage using Difference-in-Discontinuities

	Linear	Quadratic
Math skills	0.045	0.160***
	(0.031)	(0.058)
Critical thinking	-0.009	0.033
	(0.032)	(0.053)
Creativity	-0.020	-0.007
	(0.029)	(0.050)
Science	0.003	0.052
	(0.034)	(0.065)
Year of schooling required	-0.046**	-0.031
	(0.021)	(0.038)
Observations	53611	53611

Standard errors are clustered at the state-year level.
Notes. This table shows the effects of DACA eligibility on occupational skill usage among non-citizen immigrants who have obtained high-school diploma, have entered the US before their 16th birthday and have immigrated to the US before 2007. This results are reported with linear and quadratic functional form with the bandwidth of 6.
* $p < .10$, ** $p < .05$, *** $p < .01$

In short, regardless of econometric models, I find consistently null effects of DACA eligibility on labor market outcomes among likely DACA eligible individuals.

7 Conclusion

This paper examines the labor market outcomes of DACA-eligible immigrants. Unlike previous research, the econometric model allows me to examine an older set of DACA eligible individuals, namely those who were about 31 years old in 2012. I find that DACA eligibility has very little effect on the probability of employment, the likelihood of working last year, weekly working hours, and wage income. This study also suggests that there is no empirical evidence that likely DACA-eligible immigrants advance to higher-skilled employment. However, my estimates fail to reject small positive effects and the higher ends of my CIs are comparable with the lower end of CIs observed in earlier literature.

DACA has removed the constant danger of deportation and opened up many previously unavailable options for persons with DACA status. Nonetheless, even accounting for 25% of all DACA recipients in 2013,[20] older DACA individuals (i.e: who are around 31 years old in 2012) are among the least advantageous group of DACA recipients. Broadly speaking, my paper contends that not all DACA recipients gain equally from the program, be able to advance economically, and overcome their daily insecurity. As a result, they would be on the same trajectories as other who are not protected by DACA. These may also cause some intergenerational effects for their US-born children, who do not have the same opportunity to advance up the economic ladder as US-born children to younger DACA parents. The findings of this paper are also crucial for legislators and DACA activists as they work to pave the way for a possible path to becoming permanent legal residents.

[20] https://www.brookings.edu/research/immigration-facts-deferred-action-for-childhood-arrivals-daca/

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Appendices

Appendix 1

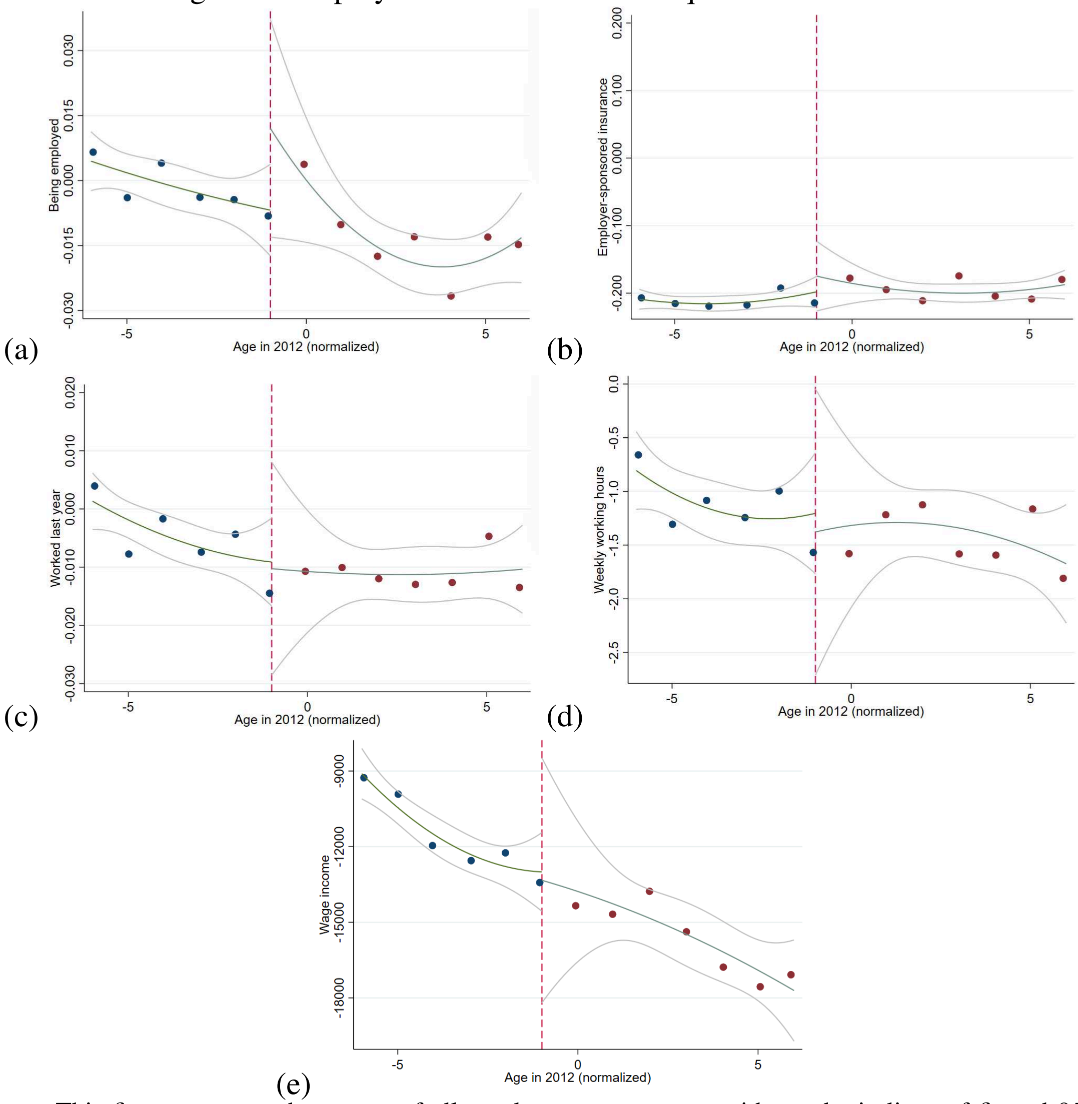
Table A1: Classification of observations around the threshold

Age in 2012	Quarter of birth	Possible year of birth	DACA eligibility	Conclusion
31	1	1981 or 1980	No	Control group
31	2 or 3 or 4	1981 or 1980	Ambiguous	Exclude from sample
30	1 or 2	1981 or 1982	Ambiguous	Exclude from sample
30	3 or 4	1981 or 1982	Yes	Treatment group

Appendix 2

Employment outcomes with a quadratic line of fit

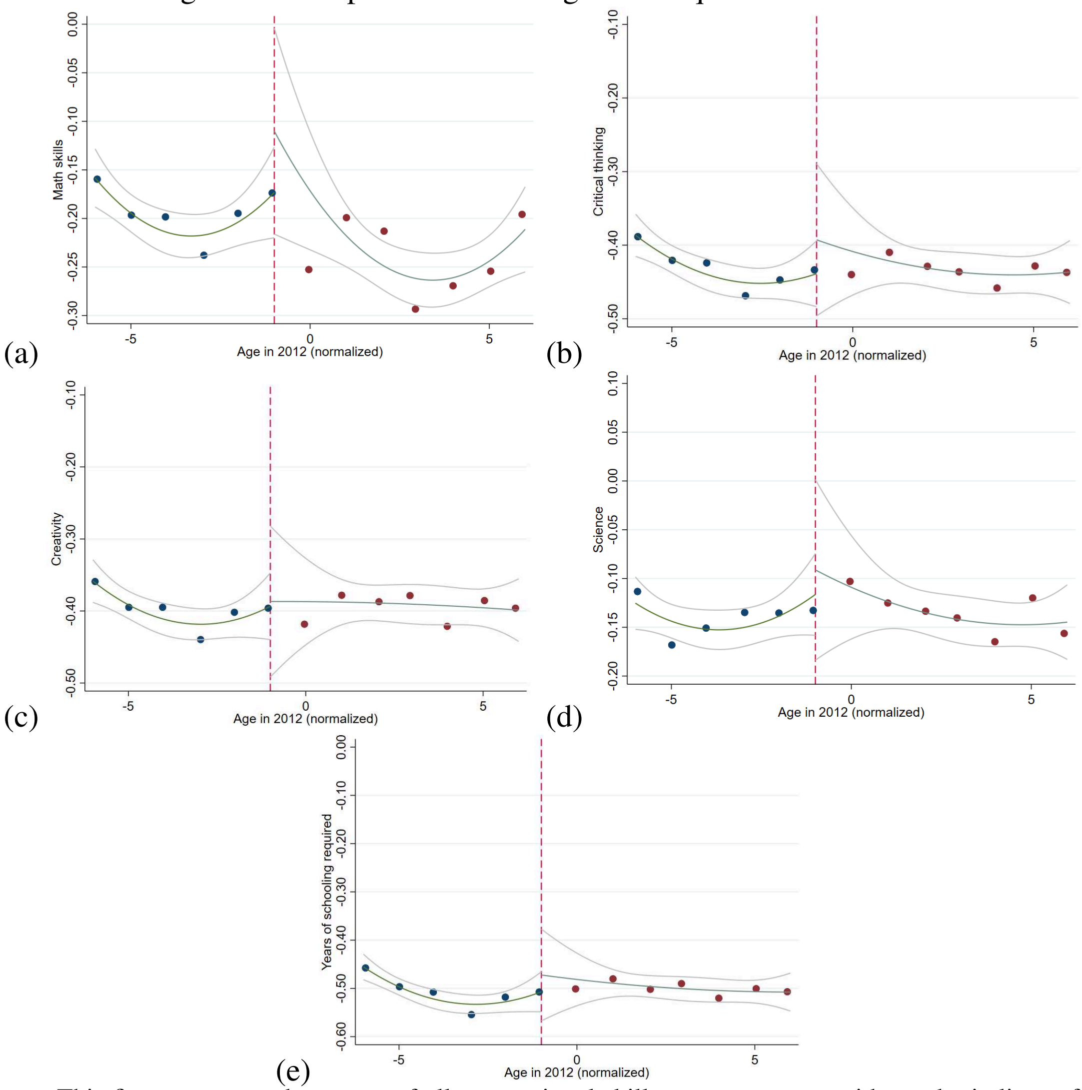
Figure 8: Employment outcomes with a quadratic line of fit



Notes: This figure presents the means of all employment outcomes with quadratic lines of fit and 95% confidence intervals. Observations are on the left side of the threshold are treated and observations are on the right side of the threshold are untreated.

Occupational skill usage with a quadratic line of fit

Figure 9: Occupational skill usage with a quadratic line of fit



Notes: This figure presents the means of all occupational skill usage outcomes with quadratic lines of fit and 95% confidence intervals. Observations are on the left side of the threshold are treated and observations are on the right side of the threshold are untreated.

Appendix 3

Table A2: Effects of DACA eligibility on labor market outcomes: Mexican in CA and TX

	Linear			Quadratic			Cubic		
Bandwidth	5	6	7	5	6	7	5	6	7
Being employed	-0.002	-0.016*	-0.016	-0.015	0.011	-0.001	-0.068	-0.060*	-0.009
	(0.009)	(0.008)	(0.010)	(0.015)	(0.017)	(0.014)	(0.060)	(0.029)	(0.019)
Employer-sponsored insurance	-0.007	-0.013	-0.015	0.028	0.025	0.011	-0.098	-0.030	0.018
	(0.033)	(0.029)	(0.025)	(0.032)	(0.037)	(0.042)	(0.080)	(0.072)	(0.039)
Worked last year	0.007	-0.007	-0.008	-0.011	0.016	0.008	-0.033	-0.044	-0.004
	(0.008)	(0.008)	(0.006)	(0.016)	(0.012)	(0.011)	(0.047)	(0.030)	(0.025)
Weekly working hours	0.084	-0.604	-0.276	-1.376	0.167	-0.546	-3.725	-3.566*	-1.005
	(0.579)	(0.471)	(0.458)	(1.131)	(0.981)	(0.967)	(2.519)	(1.921)	(1.287)
Wage income	1206	1040	520	-705	317	1545	-8164	-4501	-3670
	(1672)	(1387)	(1266)	(3776)	(3317)	(2746)	(5971)	(4632)	(4672)
Observations	7297	9024	10887	7297	9024	10887	7297	9024	10887

Standard errors in parentheses are clustered at the state-year level.
Notes. This table shows the effects of DACA eligibility on labor market outcomes among non-citizen Mexican immigrants in California anD Texas across different bandwidth and order of polynomial function. Sample includes those who have obtained high-school diploma, have entered the US before their 16th birthday and have immigrated to the US before 2007.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table A3: Effects of DACA eligibility on occupational skill usage: Mexican in CA and TX

	Linear			Quadratic			Cubic		
Bandwidth	5	6	7	5	6	7	5	6	7
Math skills	0.029	0.036	0.023	-0.032	-0.009	0.019	0.056	-0.021	-0.016
	(0.053)	(0.046)	(0.040)	(0.110)	(0.094)	(0.085)	(0.202)	(0.163)	(0.131)
Critical thinking	-0.035	-0.039	-0.036	-0.078	-0.053	-0.050	-0.118	-0.117	-0.082
	(0.048)	(0.037)	(0.032)	(0.092)	(0.097)	(0.083)	(0.133)	(0.093)	(0.108)
Creativity	-0.026	-0.033	-0.024	-0.120	-0.068	-0.065	-0.093	-0.154	-0.106
	(0.051)	(0.035)	(0.030)	(0.083)	(0.091)	(0.081)	(0.131)	(0.094)	(0.102)
Science	0.021	0.001	-0.006	-0.031	0.028	0.024	-0.119	-0.126	-0.024
	(0.050)	(0.046)	(0.038)	(0.101)	(0.080)	(0.081)	(0.130)	(0.130)	(0.109)
Years of schooling required	-0.046	-0.058**	-0.041	-0.033	-0.021	-0.058	-0.180	-0.099	-0.017
	(0.040)	(0.025)	(0.025)	(0.083)	(0.092)	(0.066)	(0.143)	(0.091)	(0.117)
Observations	6742	8353	10093	6742	8353	10093	6742	8353	10093

Standard errors in parentheses are clustered at the state-year level.
Notes. This table shows the effects of DACA eligibility on choosing high-skilled jobs among non-citizen Mexican immigrants in California and Texas across different bandwidth and order of polynomial function. Sample includes those who have obtained high-school diploma, have entered the US before their 16th birthday and have immigrated to the US before 2007.
* $p < .10$, ** $p < .05$, *** $p < .01$

Employment outcomes for non-Mexican

Table A4: Effects of DACA eligibility on labor market outcomes: Non-Mexican

	Linear			Quadratic			Cubic		
Bandwidth	5	6	7	5	6	7	5	6	7
Being employed	0.004	0.009	0.009	-0.022	-0.015	-0.008	0.060	0.001	-0.014
	(0.011)	(0.010)	(0.009)	(0.022)	(0.018)	(0.016)	(0.038)	(0.032)	(0.025)
Employer-sponsored insurance	0.005	0.010	0.003	-0.001	-0.002	0.012	-0.012	-0.005	-0.014
	(0.021)	(0.020)	(0.019)	(0.048)	(0.037)	(0.032)	(0.080)	(0.071)	(0.056)
Worked last year	0.004	0.004	0.003	-0.014	-0.004	-0.001	0.016	-0.015	-0.010
	(0.007)	(0.007)	(0.006)	(0.013)	(0.011)	(0.010)	(0.033)	(0.023)	(0.017)
Weekly working hours	0.469	0.254	0.080	-0.001	0.532	0.584	1.408	0.071	0.427
	(0.575)	(0.494)	(0.436)	(1.016)	(0.929)	(0.878)	(2.216)	(1.623)	(1.318)
Wage income	216	506	588	4790	2280	1530	4076	7148	5442
	(2117)	(1910)	(1676)	(4196)	(3405)	(3040)	(7533)	(6429)	(5207)
Observations	11996	14599	17194	11996	14599	17194	11996	14599	17194

Standard errors in parentheses are clustered at the state-year level.
Notes. This table shows the effects of DACA eligibility on labor market outcome among non-citizen non-Mexican immigrants across different bandwidth and order of polynomial function. Sample includes those who have obtained high-school diploma, have entered the US before their 16th birthday and have immigrated to the US before 2007.
* $p < .10$, ** $p < .05$, *** $p < .01$

Occupational skill usage for non-Mexican

Table A5: Effects of DACA eligibility on occupational skill usage: Non-Mexican

	Linear			Quadratic			Cubic		
Bandwidth	5	6	7	5	6	7	5	6	7
Math skills	0.046	0.038	0.031	0.092	0.084	0.068	0.154	0.131	0.140
	(0.045)	(0.039)	(0.036)	(0.084)	(0.073)	(0.066)	(0.160)	(0.121)	(0.104)
Critical thinking	-0.019	-0.025	-0.026	-0.047	-0.030	-0.030	0.133	0.015	-0.005
	(0.043)	(0.036)	(0.034)	(0.078)	(0.062)	(0.060)	(0.152)	(0.129)	(0.089)
Creativity	-0.014	-0.025	-0.024	-0.019	-0.003	-0.013	0.181	0.041	0.027
	(0.043)	(0.036)	(0.034)	(0.078)	(0.064)	(0.061)	(0.173)	(0.142)	(0.093)
Science	0.001	-0.034	-0.021	-0.054	0.018	-0.025	-0.133	-0.152	-0.010
	(0.040)	(0.035)	(0.033)	(0.097)	(0.073)	(0.061)	(0.169)	(0.150)	(0.125)
Years of schooling required	-0.001	-0.009	-0.020	-0.041	-0.014	0.003	0.146	0.010	-0.020
	(0.035)	(0.031)	(0.027)	(0.066)	(0.054)	(0.050)	(0.138)	(0.109)	(0.082)
Observations	11038	13439	15797	11038	13439	15797	11038	13439	15797

Standard errors in parentheses are clustered at the state-year level.
Notes. This table shows the effects of DACA eligibility on choosing high-skilled jobs among non-citizen non-Mexican immigrants across different bandwidth and order of polynomial function. Sample includes those who have obtained high-school diploma, have entered the US before their 16th birthday and have immigrated to the US before 2007.
* $p < .10$, ** $p < .05$, *** $p < .01$

Appendix 4

Table A6: Effects of DACA eligibility on employment outcomes, remove lowest 2%

	Linear			Quadratic			Cubic		
Bandwidth	5	6	7	5	6	7	5	6	7
Weekly working hours	0.639**	0.340	0.384*	0.604	1.032*	0.677	0.840	0.348	1.143
	(0.291)	(0.230)	(0.220)	(0.653)	(0.533)	(0.450)	(1.167)	(1.041)	(0.834)
Wage income	1848	1895*	1827*	4939*	3501	3043	1193	4938	4640
	(1294)	(1145)	(972)	(2614)	(2140)	(1933)	(4843)	(4035)	(3331)
Observations	21500	26383	31447	21500	26383	31447	21500	26383	31447

Standard errors in parentheses are clustered at the state-year level.

Notes. This table shows the effects of DACA eligibility on weekly working hours and wage income indices among non-citizen immigrants across different bandwidth and order of polynomial function. Sample includes those who have obtained high-school diploma, have entered the US before their 16th birthday and have immigrated to the US before 2007. This table presents the results after I restrict to individuals who are employed and remove observations in lowest 2 percentile of each outcome variable.

* $p < .10$, ** $p < .05$, *** $p < .01$

Appendix 5

Difference-in-differences framework

The difference-in-differences equation is presented below, following Pope (2016).

$$Y_{it} = \alpha + \beta_1 D_{it} * Post_{it} + \beta_2 D_{it} + \beta_3 Post_{it} + \beta_4 X_{it} + \beta_5 W_{it} + \theta_t + \gamma_s + \epsilon_{it} \tag{3}$$

in which, D_{it} is the treatment status. $Post_{it}$ if year is 2013 onwards. X_{it} is a vector of control variables, including sex, year of education, race, hispanic ethnicity. The vector W_{it} includes fixed effects for individual i. I also include year and state fixed effects.

In this analysis, to be consistent with sample construction in my main analysis, I restrict to people age 25 to 60 and further look at people who age $\pm$ 6 in 2012. People in that age range from 2005 to 2006 are never in treatment group. So, event studies only have 5 pre-periods for most outcomes. ACS has started to ask about insurance since 2008, so employer-sponsored insurance has 4 pre-periods.

Appendix 6

Table A7: Effects of DACA eligibility on employment outcomes among US citizens born outside of the US

	Linear			Quadratic			Cubic		
Bandwidth	5	6	7	5	6	7	5	6	7
Being employed	-0.009	-0.007	-0.001	-0.003	-0.010	-0.016	0.034	0.019	0.006
	(0.008)	(0.007)	(0.006)	(0.015)	(0.012)	(0.011)	(0.030)	(0.023)	(0.019)
Employer-based insurance	0.024	0.009	0.004	0.046	0.054*	0.041	0.000	0.019	0.049
	(0.017)	(0.016)	(0.014)	(0.039)	(0.030)	(0.026)	(0.067)	(0.060)	(0.050)
Worked last year	0.001	-0.002	0.001	-0.001	0.002	-0.002	-0.015	-0.008	-0.001
	(0.005)	(0.005)	(0.004)	(0.010)	(0.009)	(0.008)	(0.021)	(0.016)	(0.013)
Weekly working hours	-0.527	-0.613	-0.246	0.423	0.017	-0.748	-1.409	0.327	0.933
	(0.436)	(0.383)	(0.343)	(0.791)	(0.699)	(0.617)	(1.612)	(1.235)	(1.045)
Wage income	-1278	-1684	-2333	-1380	-447	42	2816	-1734	-1759
	(1843)	(1583)	(1518)	(3950)	(3328)	(2700)	(6925)	(5462)	(5026)
Observations	17005	20820	24798	17005	20820	24798	17005	20820	24798

Standard errors in parentheses are clustered at the state-year level.
Notes. This table shows the placebo tests of effects of DACA eligibility on labor market outcomes among US citizens born outside of the US across different bandwidth and order of polynomial function. Sample includes those who have obtained high-school diploma, have entered the US before their 16th birthday and have immigrated to the US before 2007.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table A8: Effects of DACA eligibility on occupational skill usage among US citizens born outside of the US

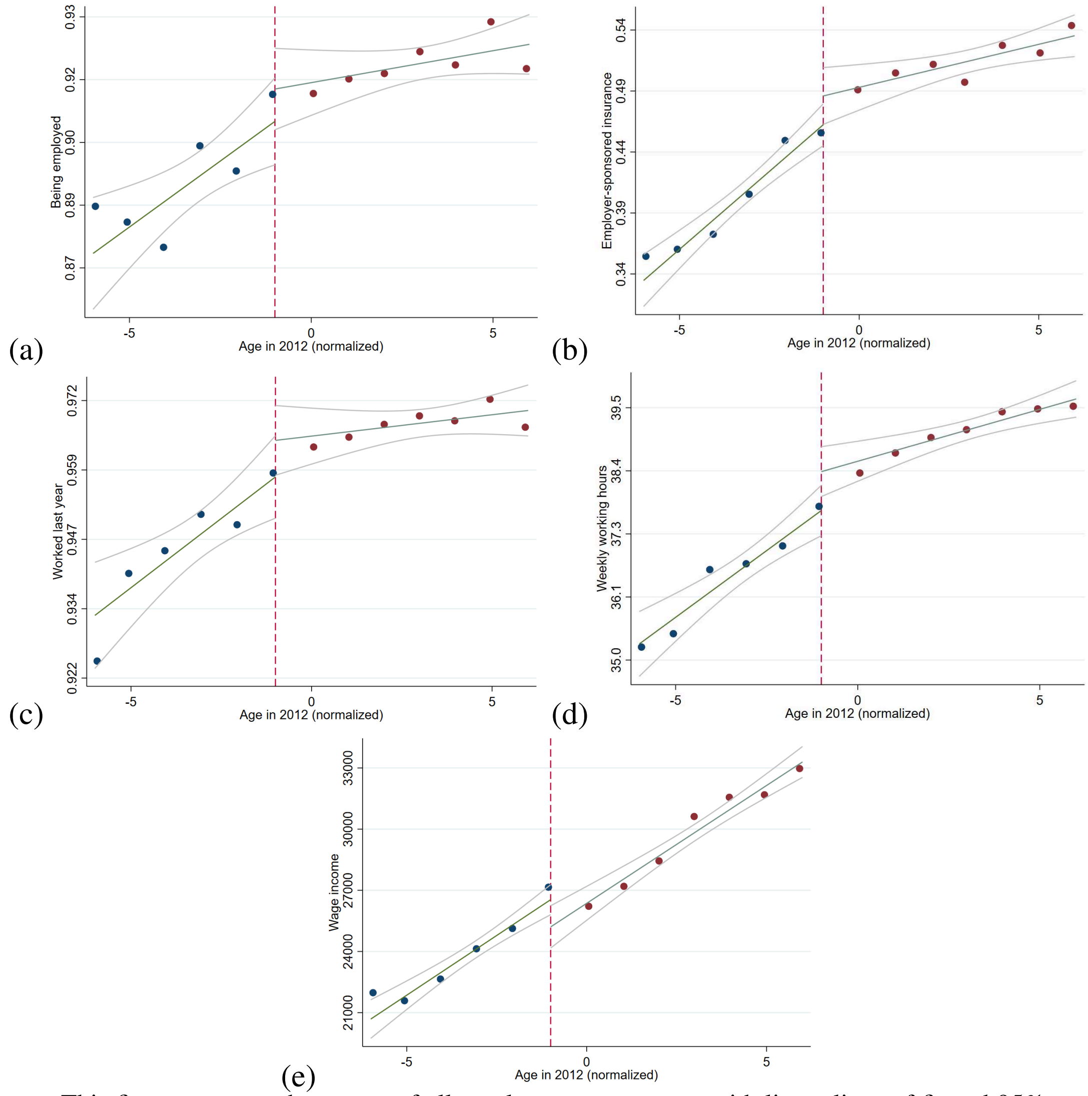
	Linear			Quadratic			Cubic		
Bandwidth	5	6	7	5	6	7	5	6	7
Math skills	0.046	0.032	0.031	0.027	0.060	0.047	-0.038	-0.035	0.030
	(0.038)	(0.033)	(0.030)	(0.065)	(0.060)	(0.054)	(0.132)	(0.093)	(0.083)
Critical thinking	0.013	0.004	-0.008	0.057	0.046	0.044	0.065	0.079	0.062
	(0.034)	(0.030)	(0.027)	(0.068)	(0.057)	(0.051)	(0.114)	(0.097)	(0.083)
Creativity	-0.023	-0.021	-0.017	0.038	0.004	-0.014	0.054	0.085	0.061
	(0.033)	(0.029)	(0.025)	(0.070)	(0.057)	(0.051)	(0.123)	(0.103)	(0.086)
Science	0.012	0.016	0.016	-0.057	-0.034	-0.012	-0.210	-0.130	-0.106
	(0.044)	(0.038)	(0.034)	(0.085)	(0.071)	(0.061)	(0.134)	(0.119)	(0.106)
Years of schooling required	-0.054*	-0.037	-0.045**	-0.063	-0.087**	-0.056	0.007	0.002	-0.076
	(0.028)	(0.025)	(0.022)	(0.056)	(0.044)	(0.040)	(0.101)	(0.087)	(0.068)
Observations	15801	19297	22942	15801	19297	22942	15801	19297	22942

Standard errors in parentheses are clustered at the state-year level. Coefficients are measured in standard deviation.
Notes. This table shows the placebo tests of effects of DACA eligibility on choosing high-skilled jobs among US citizens born outside of the US across different bandwidth and order of polynomial function. Sample includes those who have obtained high-school diploma, have entered the US before their 16th birthday and have immigrated to the US before 2007.
* $p < .10$, ** $p < .05$, *** $p < .01$

Appendix 7

Pre-DACA employment outcomes

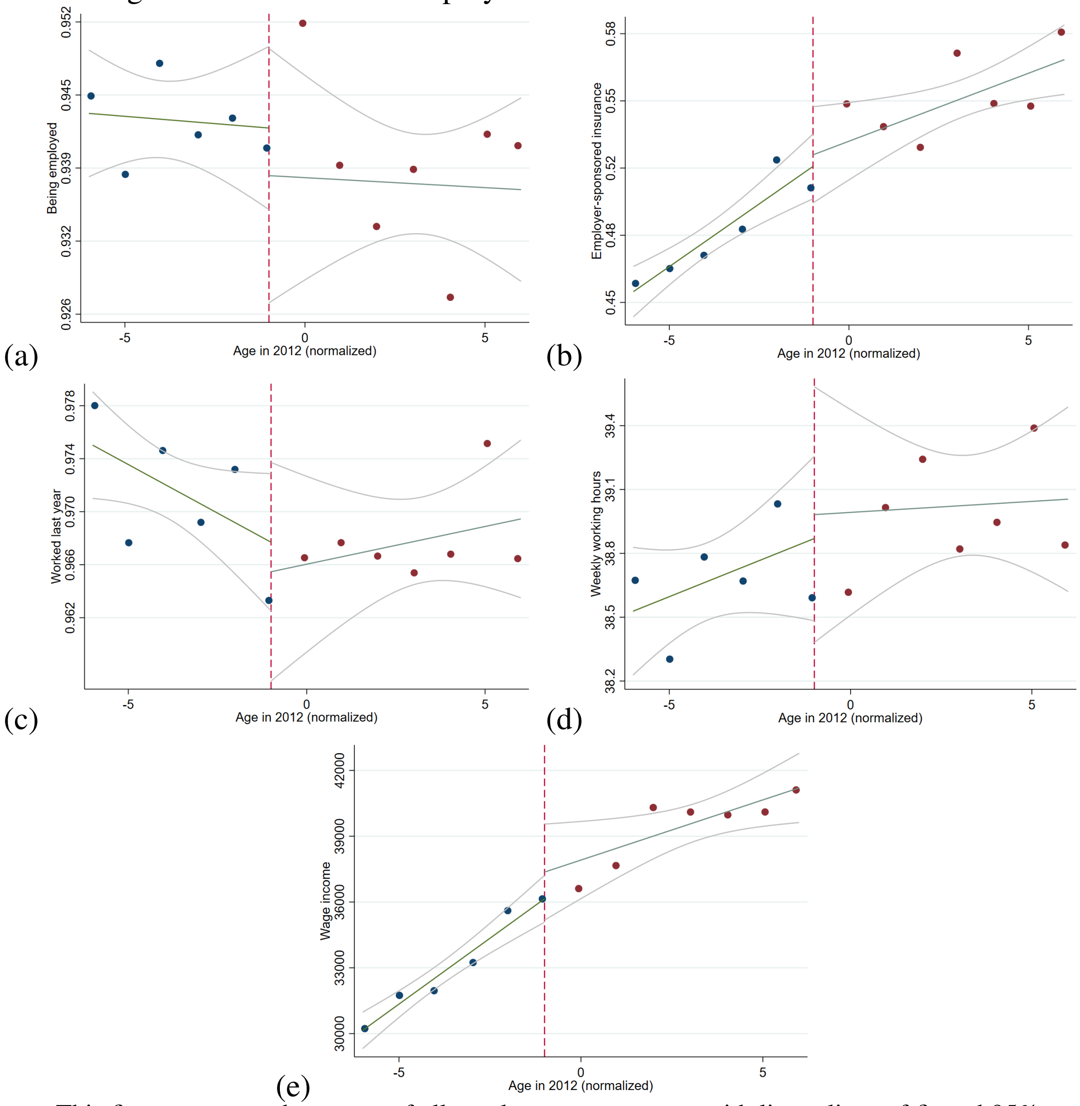
Figure 10: Pre-DACA employment outcomes with a linear line of fit



Notes: This figure presents the means of all employment outcomes with linear lines of fit and 95% confidence intervals during pre-DACA period. Observations are on the left side of the threshold are treated and observations are on the right side of the threshold are untreated.

Post-DACA employment outcomes

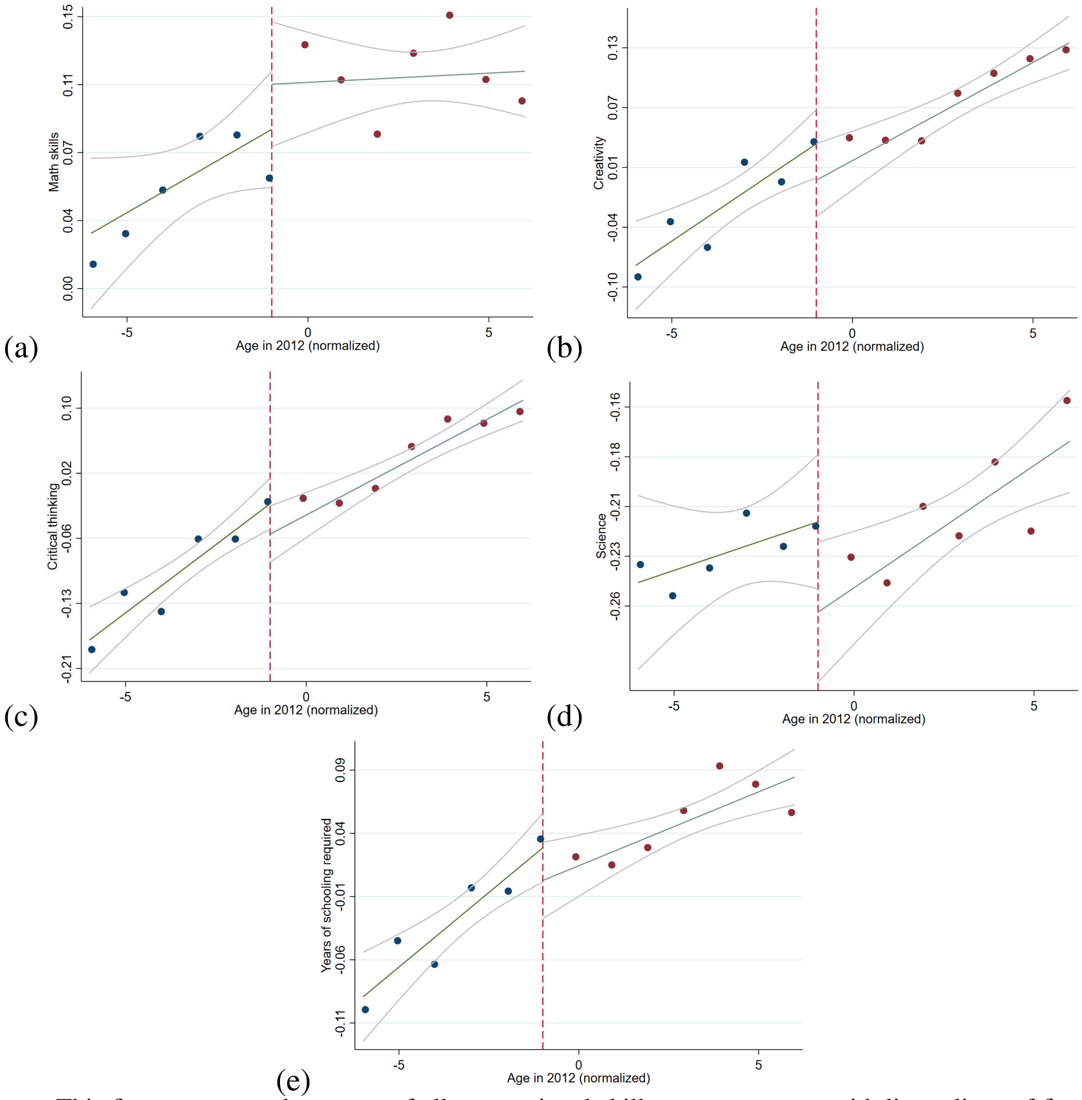
Figure 11: Post-DACA employment outcomes with a linear line of fit



Notes: This figure presents the means of all employment outcomes with linear lines of fit and 95% confidence intervals during post-DACA period. Observations are on the left side of the threshold are treated and observations are on the right side of the threshold are untreated.

Pre-DACA occupational skill usage outcomes

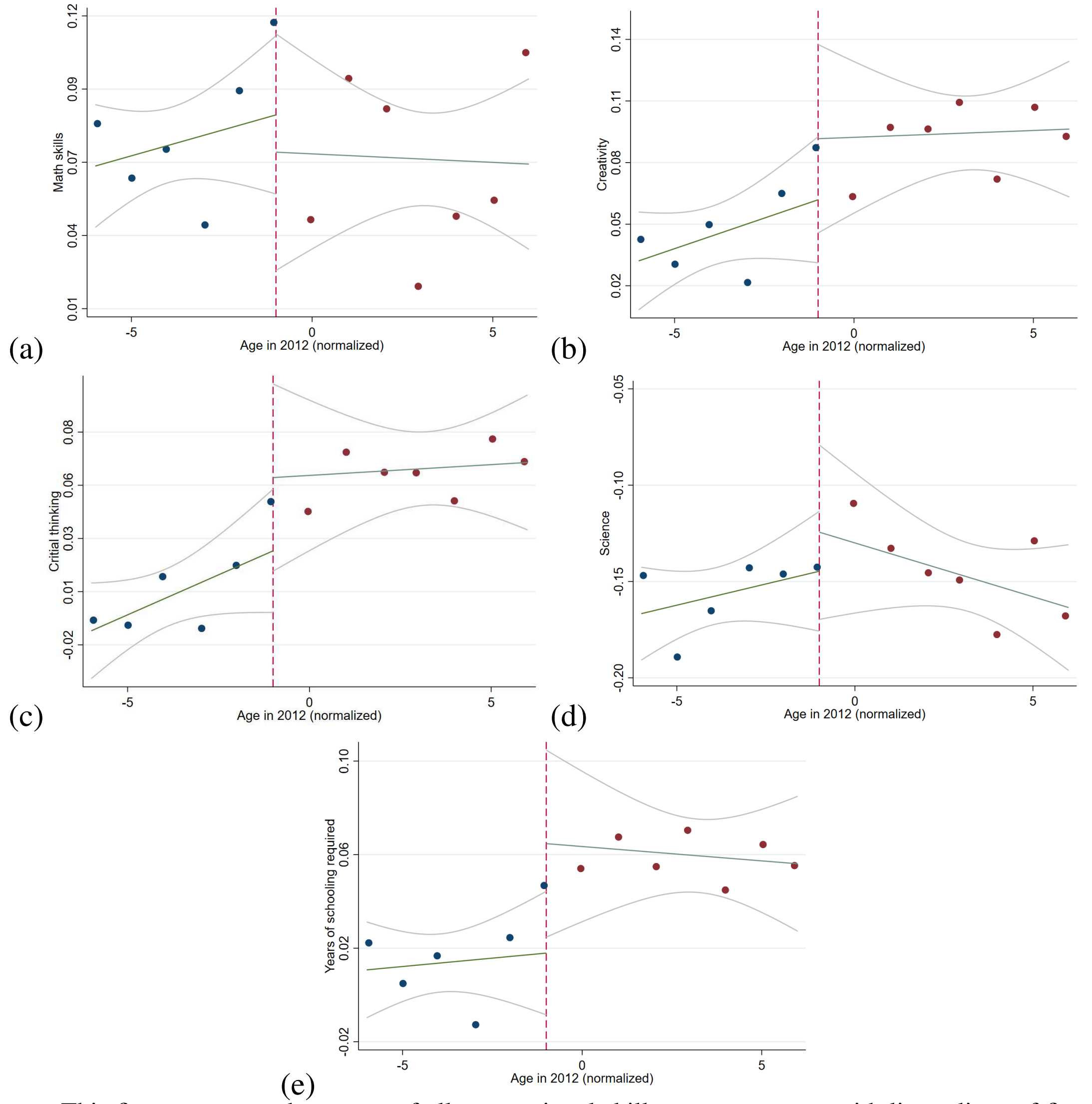
Figure 12: Pre-DACA occupational skill usage outcomes with a linear line of fit



Notes: This figure presents the means of all occupational skill usage outcomes with linear lines of fit and 95% confidence intervals during pre-DACA period. Observations are on the left side of the threshold are treated and observations are on the right side of the threshold are untreated.

Post-DACA occupational skill usage outcomes

Figure 13: Post-DACA occupational skill usage outcomes with a linear line of fit



Notes: This figure presents the means of all occupational skill usage outcomes with linear lines of fit and 95% confidence intervals during post-DACA period. Observations are on the left side of the threshold are treated and observations are on the right side of the threshold are untreated.

Appendix 8: Heterogeneous effects

Even I have found no evidence of DACA eligibility on labor market outcomes, the results may be divergent among different groups of education. This section estimates the effects of DACA eligibility on individuals who have either only high school degree or at least a college degree.[21]

[21]I also do with males and females, however, there is no appreciable effects for both.

In Panel A of Table A9, it is shown that DACA eligibility among individuals who have at least a college degree are around 2 to 4 percentage points more likely to be employed. However, statistical significance is sensitive to specifications. There is no evidence in employer-sponsored insurance, the probability of working last year, weekly working hours, or wage income. Panel B shows that it is unlikely that there is an increase in the probability of working among individuals with less than a college degree.

Table A9: Effects of DACA eligibility on employment outcomes: College and non-college educated individuals

Panel A: College or higher		Linear			Quadratic			Cubic	
Bandwidth	5	6	7	5	6	7	5	6	7
Being employed	0.023**	0.022**	0.010	0.016	0.022	0.039**	0.055	0.021	0.001
	(0.011)	(0.010)	(0.010)	(0.025)	(0.021)	(0.016)	(0.040)	(0.035)	(0.033)
Employer-sponsored insurance	0.039	0.029	0.005	0.085	0.087	0.097**	0.041	0.051	0.070
	(0.031)	(0.026)	(0.024)	(0.061)	(0.055)	(0.049)	(0.110)	(0.091)	(0.074)
Worked last year	0.015	0.007	0.003	0.010	0.024	0.021*	0.024	-0.003	0.013
	(0.009)	(0.008)	(0.008)	(0.017)	(0.015)	(0.013)	(0.035)	(0.027)	(0.023)
Weekly working hours	0.634	0.074	-0.001	-0.676	0.790	0.605	3.110	-0.705	0.457
	(0.834)	(0.736)	(0.684)	(1.710)	(1.473)	(1.266)	(2.954)	(2.622)	(2.067)
Wage income	-784	-348	-407	7125	3442	2553	9000	10258	7600
	(4350)	(3914)	(3321)	(9414)	(7679)	(6799)	(16887)	(14178)	(11766)
Observations	4631	5702	6773	4631	5702	6773	4631	5702	6773

Panel B: Less than college		Linear			Quadratic			Cubic	
Bandwidth	5	6	7	5	6	7	5	6	7
Being employed	-0.003	-0.004	0.001	-0.029*	-0.015	-0.019	-0.009	-0.036	-0.019
	(0.008)	(0.005)	(0.005)	(0.016)	(0.015)	(0.012)	(0.032)	(0.023)	(0.019)
Employer-sponsored insurance	-0.008	-0.004	-0.008	-0.033	-0.025	-0.011	-0.145**	-0.087*	-0.068*
	(0.015)	(0.015)	(0.015)	(0.031)	(0.023)	(0.020)	(0.057)	(0.052)	(0.039)
Worked last year	0.002	-0.003	-0.002	-0.021*	-0.004	-0.006	-0.020	-0.036*	-0.015
	(0.005)	(0.005)	(0.004)	(0.012)	(0.010)	(0.008)	(0.025)	(0.020)	(0.016)
Weekly working hours	0.072	-0.276	-0.188	-0.453	0.262	-0.101	-1.479	-1.483	-0.128
	(0.413)	(0.366)	(0.322)	(0.769)	(0.665)	(0.638)	(1.652)	(1.249)	(0.923)
Wage income	-117	-74	-125	381	7	55	-5248	-1028	-569
	(957)	(835)	(763)	(1817)	(1539)	(1294)	(3657)	(2672)	(2342)
Observations	19011	23324	27832	19011	23324	27832	19011	23324	27832

Standard errors are clustered at the state-year level.

Notes. This table shows the effects of DACA on labor market outcomes among non-citizen immigrants who have obtained at least college degree and less than college across different bandwidth and order of polynomial function. Sample includes those who have obtained high-school diploma, have entered the US before their 16th birthday and have immigrated to the US before 2007.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table A10 shows that both individuals with at least a college degree and less than a college degree do not move to work in high-skilled jobs.

Table A10: Effects of DACA eligibility on occupational skill usage: College and non-college educated individuals

Panel A: College or higher		Linear			Quadratic			Cubic	
Bandwidth	5	6	7	5	6	7	5	6	7
Math skills	0.067	0.045	0.035	0.111	0.128	0.097	0.297	0.162	0.217
	(0.073)	(0.059)	(0.055)	(0.145)	(0.130)	(0.106)	(0.284)	(0.219)	(0.196)
Critical thinking	-0.019	-0.024	-0.047	0.151	0.082	0.062	0.328	0.290*	0.220
	(0.074)	(0.060)	(0.055)	(0.123)	(0.118)	(0.102)	(0.234)	(0.175)	(0.158)
Creativity	-0.024	-0.032	-0.037	0.179*	0.094	0.049	0.047	0.227	0.215
	(0.066)	(0.050)	(0.048)	(0.107)	(0.112)	(0.088)	(0.219)	(0.144)	(0.137)
Science	-0.001	-0.036	-0.065	0.006	0.054	0.054	-0.123	-0.107	-0.015
	(0.094)	(0.076)	(0.067)	(0.162)	(0.151)	(0.130)	(0.318)	(0.237)	(0.206)
Years of schooling required	-0.027	-0.058	-0.073	0.004	0.036	0.017	-0.012	-0.028	0.037
	(0.071)	(0.061)	(0.052)	(0.117)	(0.110)	(0.101)	(0.255)	(0.186)	(0.154)
Observations	4385	5388	6388	4385	5388	6388	4385	5388	6388

Panel B: Less than college		Linear			Quadratic			Cubic	
Bandwidth	5	6	7	5	6	7	5	6	7
Math skills	0.009	0.017	0.009	0.045	0.020	0.023	0.111	0.098	0.068
	(0.032)	(0.030)	(0.028)	(0.067)	(0.052)	(0.046)	(0.129)	(0.107)	(0.079)
Critical thinking	-0.030	-0.036	-0.028	-0.071	-0.046	-0.054	-0.004	-0.067	-0.046
	(0.029)	(0.024)	(0.024)	(0.052)	(0.047)	(0.041)	(0.112)	(0.085)	(0.068)
Creativity	-0.011	-0.026	-0.015	-0.043	-0.007	-0.031	0.075	-0.031	0.009
	(0.034)	(0.027)	(0.025)	(0.061)	(0.056)	(0.048)	(0.117)	(0.094)	(0.075)
Science	0.013	-0.017	-0.008	-0.065	0.013	-0.013	-0.015	-0.122	-0.016
	(0.030)	(0.026)	(0.022)	(0.071)	(0.054)	(0.047)	(0.088)	(0.096)	(0.081)
Years of schooling required	-0.033	-0.038**	-0.032*	-0.044	-0.034	-0.045	0.010	-0.029	-0.020
	(0.022)	(0.018)	(0.017)	(0.040)	(0.038)	(0.030)	(0.089)	(0.062)	(0.053)
Observations	17476	21489	25634	17476	21489	25634	17476	21489	25634

Standard errors are clustered at the state-year level.
Notes. This table shows the effects of DACA on occupational skill usage among non-citizen immigrants who have obtained at least college degree and less than college across different bandwidth and order of polynomial function. Sample includes those who have obtained high-school diploma, have entered the US before their 16th birthday and have immigrated to the US before 2007.
* $p < .10$, ** $p < .05$, *** $p < .01$

Amuedo-Dorantes and Antman (2017) find that DACA program reduced the probability of school enrollment of eligible higher-educated individuals because the opportunity cost of pursuing higher education is higher when they are given a legal status. While restricting to individuals who are most likely to finish their education (i.e: who are at least 25 years old), my results complements their findings by showing that even when the opportunity cost may be higher, there are some improvement in employment for college-educated individuals.

Appendix 9: Effects of DACA on employment outcomes from different studies

Table A11: Estimates on employment outcomes from three different papers

Pope (2016)				Amuendo-Dorantes Antman (2017)				This paper			
Non-citizens from 18-30 with high-school degree and enter US 12-19				**Non-citizens from 18-24 years old with high-school degree**				**Non-citizens with high-school degree enter the US before 16 and before 2007**			
	Point estimates	95% conf. interval			Point estimates	95% conf. interval			Point estimates	95% conf. interval	
Being employed	0.072	0.042	0.072	Being employed	0.143	0.039	0.246	Being employed	0.003	-0.024	0.030
Weekly working hours	2.573	1.338	3.807	Weekly working hours	-0.804	-3.729	2.121	Weekly working hours	-0.569	-2.344	1.205
Worked last year	0.059	0.026	0.090					Worked last year	-0.003	-0.025	0.019
Income	-1.500	-1371	1368					Wage income	-742	-6537	5582
Non-citizens age 27 to 34, with high-school degree, and enter before 16											
	Point estimates	95% conf. interval									
Being employed	0.066	0.028	0.104								
Weekly working hours	1.776	0.347	3.205								
Worked last year	0.041	0.008	0.073								
Income	2096	-563	4754								
Non-citizens age 18 to 35 with at least high-school											
	Point estimates	95% conf. interval									
Being employed	0.056	0.038	0.073								
Weekly working hours	1.397	0.465	2.328								
Worked last year	0.045	0.027	0.063								
Income	-1568	-3543	408								

Notes. This table compares the effects of DACA on employment outcomes between this paper and two other papers: Pope (2016) and Amuendo-Dorantes and Antman (2017). To be comparable with my uptake-adjusted estimates, estimates from Pope (2016) are adjusted by multiplying by 1.5 as discussed in his paper. Although, Amuendo-Dorantes and Antman (2017) do not discuss the treatment-on-the-treated effects, their samples are similar to Pope (2016), I adjust their estimates similarly. This table presents all estimates along with confidence intervals.