THE EFFECTS OF DEFERRED ACTION FOR CHILDHOOD ARRIVALS ON LABOR MARKET OUTCOMES

Nhan Tran

*Binghamton University**

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 might have had limited effects for DACA-eligible immigrants, especially among an older cohort of DACA recipients.

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 earn as much as 10% less than documented immigrants (Borjas and Cassidy, 2019). This wage gap may reflect that legal status is either correlated with an individual's characteristics or directly affects labor market outcomes.

Lack of legal status may hurt immigrants' labor market outcomes in two primary ways. First, undocumented immigrants may opt for jobs with a lower risk of being caught and deported. This restriction adds constraints to their job search and may push them into less desirable jobs, or discourage them from working altogether. Second, lack of legal status may also prevent undocumented immigrants from working for employers who run E-Verify to check employment eligibility.

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 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 the 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 eligibility criterion which I do not observe is the legal status of an immigrant. In practice, about 60% of 8.3 million non-citizen young adult immigrants 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 and the other. This paper measures the local 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 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 large-scale formal employment setting, where they are more likely to provide health insurance. 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 each occupation. These findings suggest that DACA eligibility had little effects on immigrants' ability to find high-skilled jobs.

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 treatment 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 7 ppts (CI: 3-10 ppts); increases the probability of working last year by 4 ppts

[1]See Appendix A8 for details.

(CI: 0.8- 7 ppts); and increases weekly working hours by 1.8 hours (CI: 0.3-3.2 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 Pope (2016), but the region of overlap is at the low end of his 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. 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. In Section 5.3, I discuss the sample construction and the trade-off between statistical power and validity of empirical design, which may in part explain the results.

Apart from the 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 finds that DACA improves the lives of DACA participants, recent research shows mixed or null impacts on distinct groups of DACA recipients (Hamilton et al., 2021; Henderson and Sperlich, 2022). This paper departs from and contributes to 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. There is a common misconception that this group of DACA recipients has been addressed by (Pope, 2016), [3] indicating positive effects on several labor market outcomes. However, the findings in this paper show null effects, which is similar to the effects by Pope (2016) after adjusting for a coding error. Thus, it suggests that the older group of DACA recipients may not equally benefit from the program. See Section 5.3 for more details. Third, this paper im-

[2]Coefficients from Pope (2016) are also adjusted to recover treatment effects, please refer to Section 5.3 for details.

[3]Panel B Table 2 from Pope (2016

plements a regression discontinuity design to examine the effects of DACA on various outcome variables of interest, which overcomes potential parallel trend issues in 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 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."[4]

DACA was introduced by President Obama on June 15, 2012, as a substitute for Dream Act legislation. DACA provides 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 apply for work authorization to legally work in the US. In many states, DACA status additionally enables undocumented immigrants to acquire occupational licenses (Liang, 2023). However, DACA does not provide a path to permanent residency, therefore, DACA recipients have to renew their status every two years.

To be eligible for DACA, an individual has to qualify for all of the following requirements:

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

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 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 the Migration Policy Institute, there are over 1.3 million 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.[5] There were over 800,000 immigrants who had ever been DACA holders, which made up around 60% of the total DACA-eligible population. Of those who did not apply for DACA, 43% of them claimed that they couldn't afford the application fee, while 22% were missing the required paperwork and 17% were afraid that the DACA application process would expose them 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.[6]

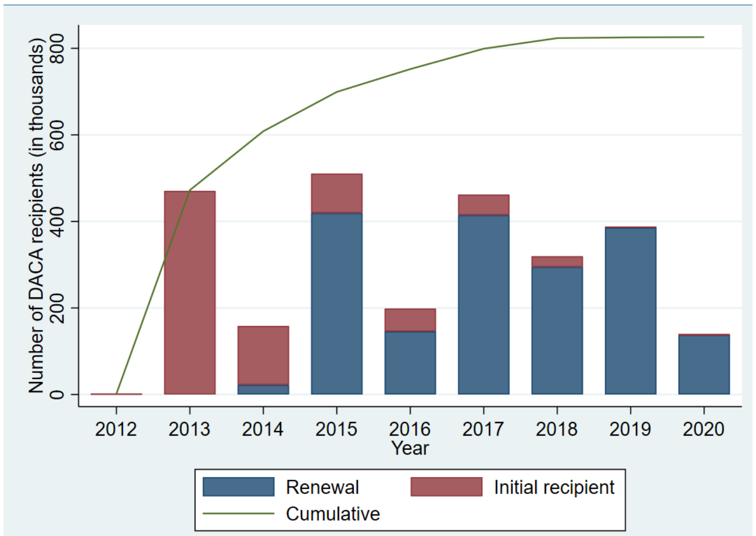
During the 2016 presidential election, DACA was one of the most controversial topics and went through several legal challenges, which significantly affected the number of new DACA applicants. Figure 1 shows the total number of DACA recipients as well as the number of initial and renewal recipients from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

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

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

has made several attempts to codify DACA into federal regulation. However, these efforts have encountered repeated challenges. Following a court ruling that deemed their actions unlawful, the administration issued a final rule on DACA, only to face another legal challenge in June 2023.

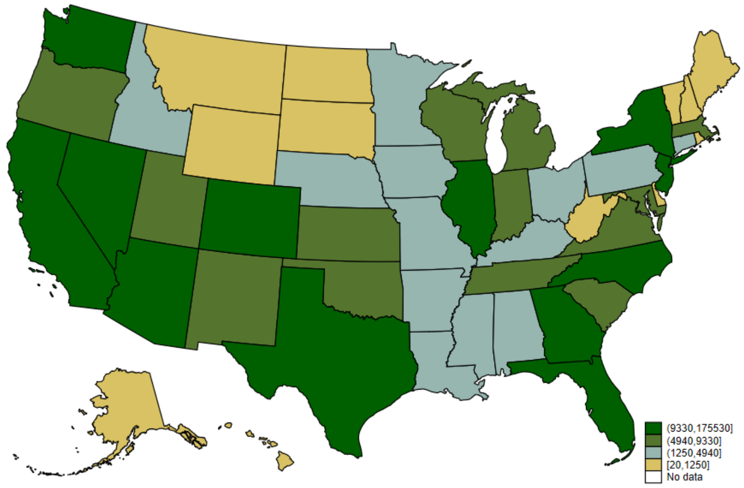
Figure 1: The number of cumulative, initial and renewal DACA recipients



Source: US Citizenship and Immigration Services

DACA recipients reside in all 50 US states and the District of Columbia. Nonetheless, nearly half of them live in California and Texas. California alone made up for almost 29% of nationwide 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). 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. The ACS selects its sample from the Master Address File and sends out mail surveys to the listed addresses at the start of each month. For individuals who do not respond to the mail survey, follow-up contact is made through phone interviews and in-person visits. From 2000 to 2019, the response rate among sampled households is around 95% on average. Importantly, the ACS interviews the resident population without regard to legal status or citizenship. It relies on a systematic sampling approach using US addresses, which means that undocumented immigrants are neither more nor less likely than documented immigrants and citizens to be included in the sample.

My ACS data is from 2013 to 2019.[7] To serve the purpose of this study, my data sample starts from 2013 because it is the first year that the effects are expected to have kicked in after the Department of Homeland Security started to accept DACA applications in late 2012. My data sample ends in 2019.

To construct my sample, I restrict my sample to only non-citizen individuals who are from 25 to 60 and satisfy all of the 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 who immigrated to the U.S. before 2007, has constantly presented in the U.S. as of June 15, 2012. Hence, I use the 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.

After restricting my sample to individuals who met all the above requirements, I evaluate an individual's age in 2012 from the survey year and the 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 the 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. However, this individual may be born in either 1981 Quarter 1 or

[7] 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.

1982 Quarter 1. In other words, it is not reliable to use the 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 the 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, and 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.[8] 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

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 the job skill assignment, I take an average of skills of 8-digit O*NET codes that 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 eligible for DACA, they tend to be younger (28.97 versus 44.35 years of age); have lived in the US for a shorter 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 US$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.[9]

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

[9] 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.

Table 1: Summary statistics

Panel A: Demographics	Likely DACA ineligible Obs	Mean	SD	Likely DACA eligible 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
Panel B: Job skills	Likely DACA ineligible Obs	Mean	SD	Likely DACA eligible 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

To identify the effects of DACA as a quasi-experiment on labor market outcomes, this paper exploits a parametric RDD. Two options that are potentially used as running variables: individuals' age in 2012 and individuals' age at arrival. Nonetheless, age at arrival is correlated with education (Evans and Fitzgerald, 2017; Gonzalez, 2003) and English proficiency (Bleakley and Chin, 2010). Therefore, it is correlated with labor market outcomes. Moreover, the RDD model based on age at arrival with a 16-year-old threshold faces limited support from the right side of the threshold due to another discontinuity at the age of 18. Specifically, individuals who immigrate at the age of 18 are more likely to have already completed high school and decided to move to the U.S. independently, whereas those who immigrate at younger ages may not have finished high school and typically relocate with their families. Consequently, in addition to the 16-year-old threshold, there exists a discontinuity at the age of 18, making it difficult to measure the limit from the right side of the 16-year-old threshold and estimate the RDD model. Thus, I leverage individuals' age in 2012 as my primary running variable.

As explained in section 3.1, I restrict 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 a treatment group. On the other hand, individuals who are 31 or older are ineligible and classified as a 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:

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

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.[10]

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 functional form would produce specification errors. In other words, the low-order polynomials are going to introduce some biases unless I use an extremely high-order polynomials. However, if I

[10] 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 differences. My results also do not change if I control for race and/or ethnicity.

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 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.

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

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:[11]

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)

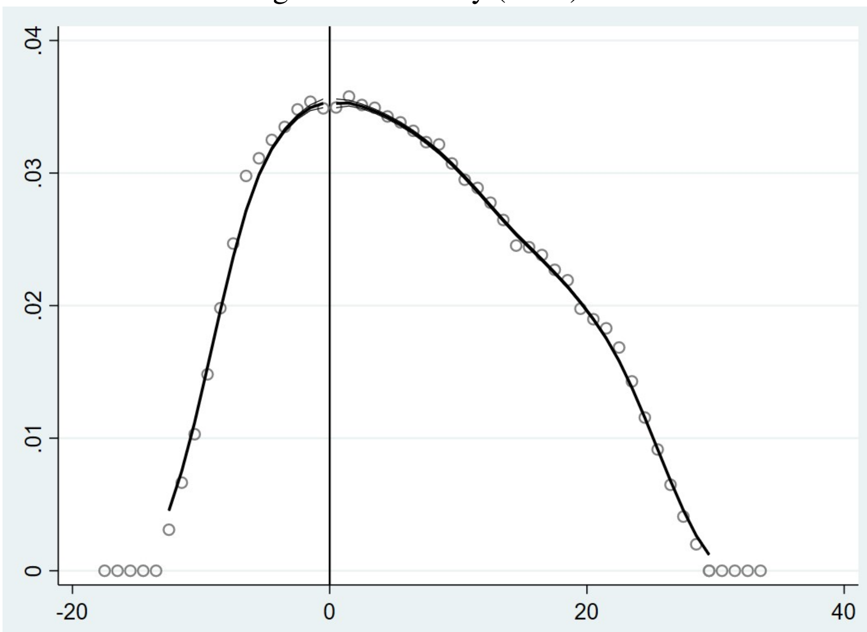
[11] My main specification is equation (1a), while I present the results for euations (1b) and (1c) in my robustness check.

The main concern for RDD is the possibility of data manipulation and discontinuity in unobservables around the threshold. In other words, the results will be misleading if people who are close to the threshold, might attempt to manipulate it and sort them into their preferred group. 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 the age of 16 at arrivals, arrivals before 2007, and high school diploma or equivalent holder. It is 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. Thus, individuals who are adjacent to the threshold are comparable.[12]

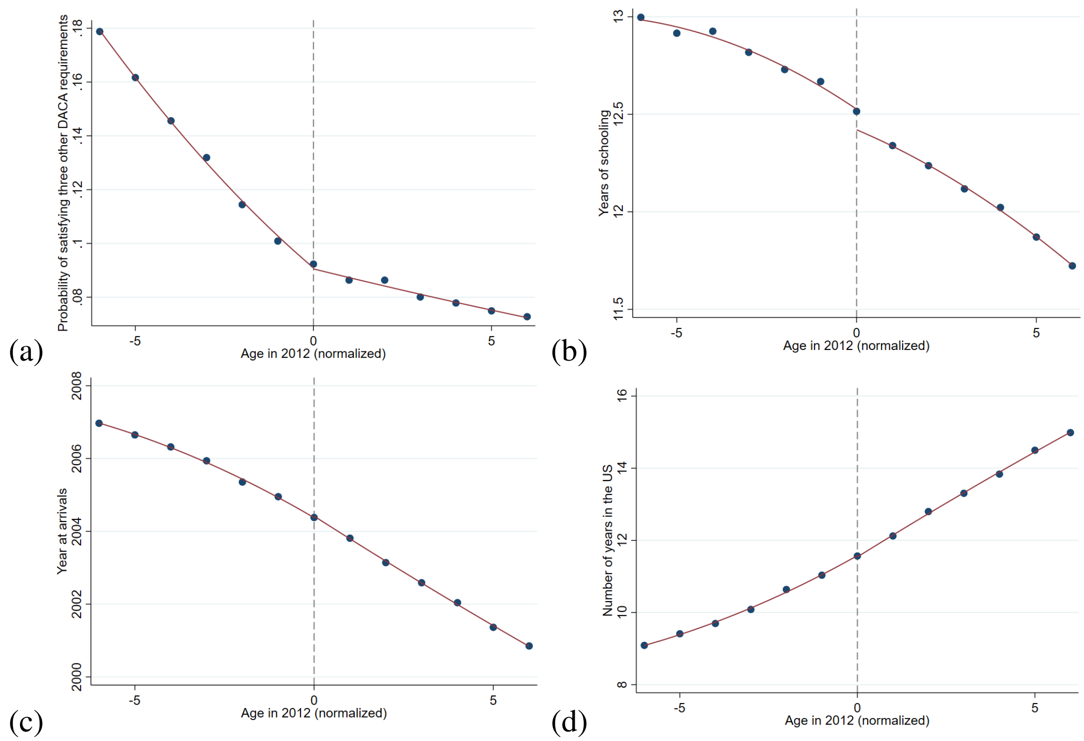
[12] I also plot outcome variables before the policy and present them in Appendix 7.

Figure 3: McCrary (2008) test



Notes: This figure shows 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. Data spans from 2013 to 2019.

5 Results

My results report β coefficients from the equation (1a) 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. 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. Finally, confidence intervals reported on the higher-order function are deceptive because they fail to include zero with a substantially high probability. So, the estimates from higher order polynomial functions are often not reliable. In this paper, my preferred specification is a linear functional form with a bandwidth of 6. However, I still report the estimates from quadratic and cubic functions in the form of specification curves in my robustness checks (Simonsohn et al., 2020). 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.

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 skills, 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 functional form with bandwidth of 6. The first row of Table 2 shows the effect of DACA eligibility on being employed. The coefficient is close to 0 and 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 is statistically insignificant. Table 2 also shows that coefficients on weekly working hours is negative and statistically insignificant. Lastly, the effect on wage income is small and statistically insignificant. In general, the results from Table 2 verify that the impacts of DACA eligibility on employment outcomes are trivial. I present my results across different functional forms and bandwidths in my robustness checks.

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

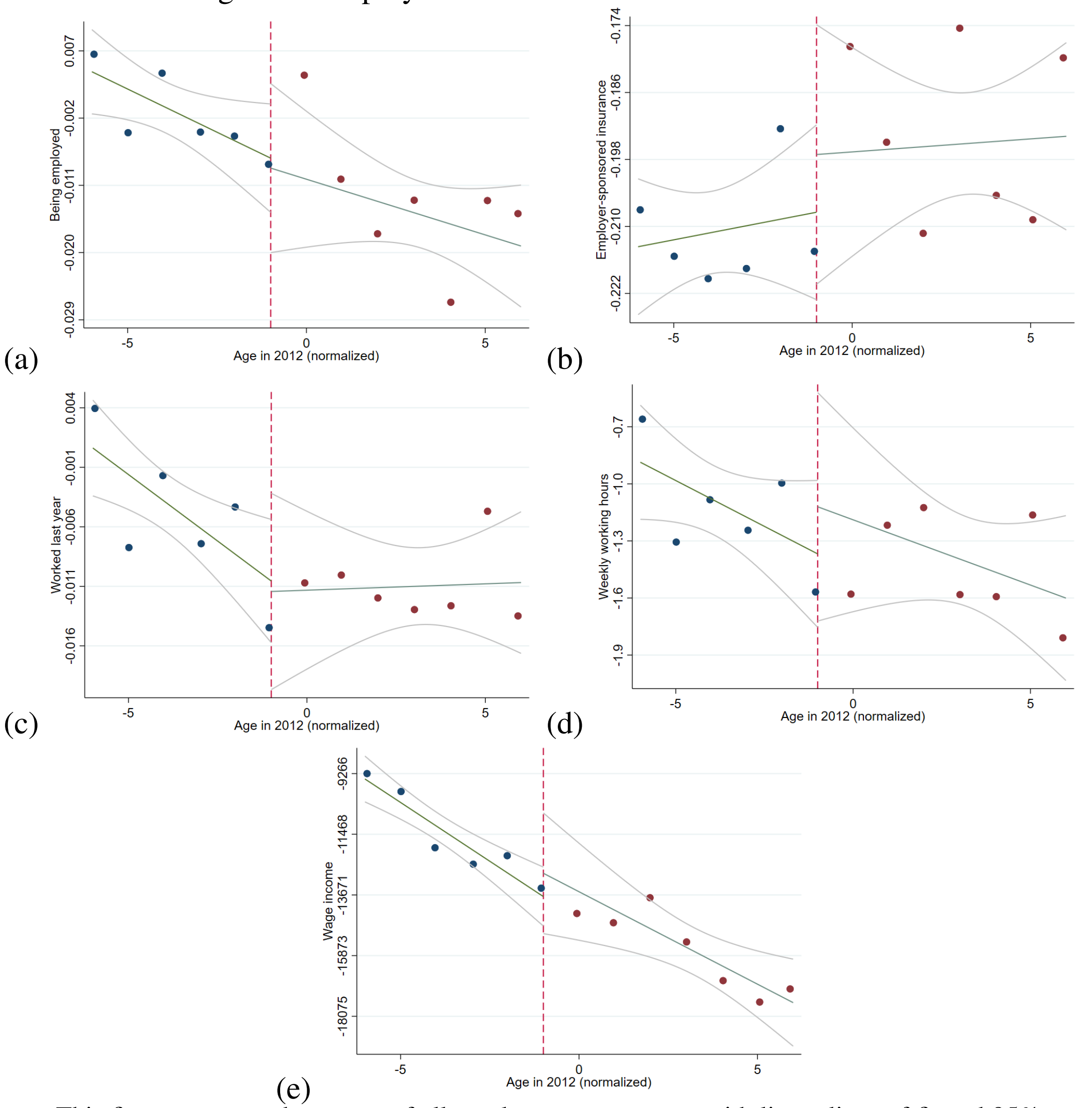
Bandwidth	Linear 6
Being employed	0.001
	(0.005)
Employer-sponsored insurance	0.002
	(0.015)
Worked last year	-0.001
	(0.004)
Weekly working hours	-0.205
	(0.326)
Wage income	-172
	(1113)
Observations	29029

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, employing the linear functional form with a bandwidth of 6. 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 fits a linear line with the bandwidth of 6 and confirms my regression results.[13] Figures 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. Figures 5b and 5d show little evidence that there are discontinuities in the probability of getting employer-sponsored insurance and weekly working hours around the threshold. However, the standard errors are large to draw any solid evidence on the effects. In general, the graphs confirm what I find in the regression that DACA eligibility has no effect on all variables of interest.

[13]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 the linear functional form with a bandwidth of 6. 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 show 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. I present my results across different functional forms and bandwidths in my robustness checks.

Table 3: Effects of DACA eligibility on occupational skill usage

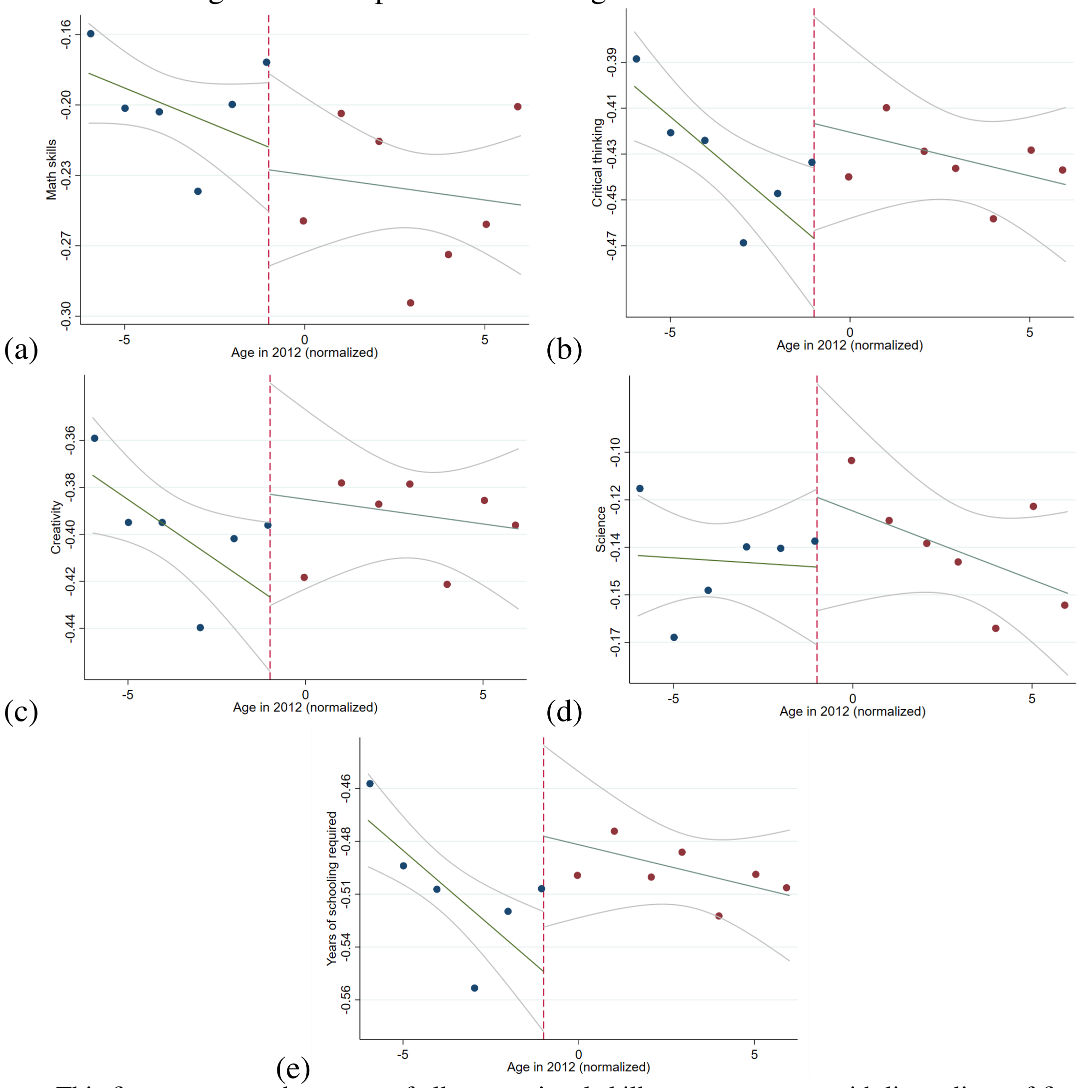
	Linear
Bandwidth	6
Math skills	0.022
	(0.026)
Critical thinking	-0.034
	(0.023)
Creativity	-0.028
	(0.023)
Science	-0.019
	(0.025)
Years of schooling required	-0.043**
	(0.019)
Observations	26877

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, employing the linear functional form with a bandwidth of 6. 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.[14] It is shown that there are no discontinuities around the threshold for all variables of interest.

[14]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 three 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 use a regression discontinuity design, which may yield a different result than a difference-in-differences design. Third, this paper constructs a different sample, which measures a different group of DACA individuals.

Sub-period To examine whether my findings differ from the existing literature as a result of employing a longer period, I maintain consistency in my econometric model (i.e., RDD) and sample construction. I specifically truncate the sample period to 2013 and 2014, aligning with the timeframe examined in prior literature. Table 4 illustrates the effects of DACA eligibility on employment outcomes from 2013 to 2014. The coefficient on the probability of being employed is 0.1 percentage point and statistically insignificant. Similarly, 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

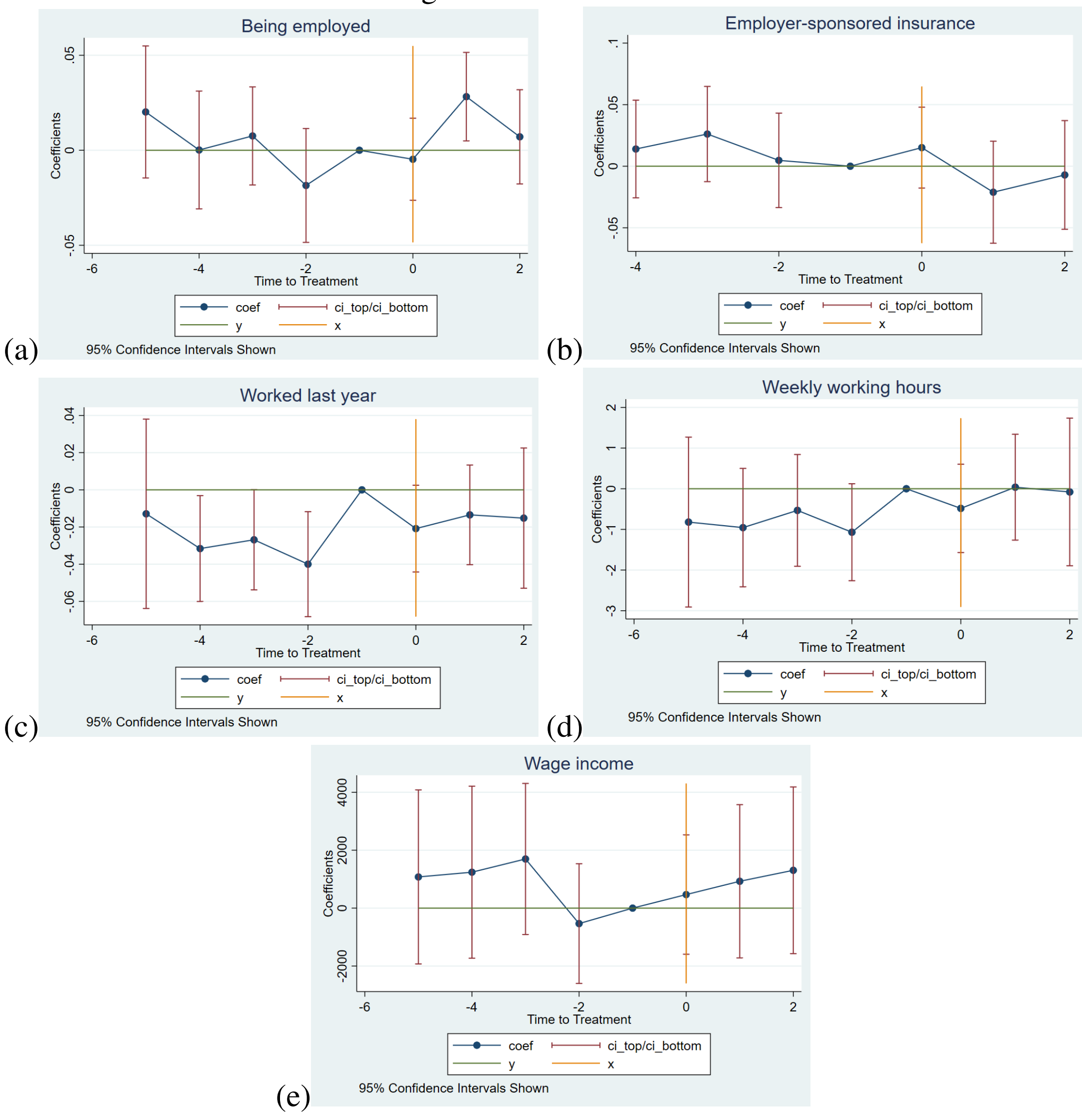
	Linear
Bandwidth	6
Being employed	0.001
	(0.011)
Employer-sponsored insurance	-0.02
	(0.024)
Worked last year	-0.003
	(0.008)
Weekly working hours	-0.087
	(0.595)
Wage income	-1575
	(1723)
Observations	9595

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, employing the linear functional form with a bandwidth of 6 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 investigate whether the divergence in my results is attributable to my RDD approach, I now utilize a difference-in-differences framework. I use the ACS data from 2005 to 2014.[15] I construct the sample as same as my main econometric strategy. See Appendix 5 for details on how I design my difference-in-difference design. 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. However, Figure 7c suggests a violation of the parallel trends assumption. This casts doubt on the suitability of a difference-in-differences framework for assessing the impact of DACA eligibility on labor market outcomes in some cases. Consequently, when evaluating existing literature, we should not prioritize studies that employ a difference-in-differences approach for reliable conclusions.

[15]For employer-sponsored insurance, the data is from 2008 because ACS has not asked about insurance until 2008.

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.

Sample construction Regardless of the sample period and econometric models, my results still corroborate null effects, thus suggesting that the difference in my sample construction is 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) defines a treatment group as non-citizens aged from 18 to 40 who meet all observable DACA requirements. This would leave all individuals who do not satisfy one, two, three, or all DACA requirements in the control group. Nonetheless, one possible issue is that the control group is not homogeneous because individuals who failed one DACA requirement are generally different from those who failed all of them. Another concern is that my sample is looking at people around 31 years old in 2012, which is similar to the sample in Panel B in Table 2 from Pope (2016). However, I obtained his codes and it actually restricted to people aged 27 to 34 in the current data year. I replicate his results, but I use age in 2012 instead of age in the current year while holding everything else constant. I report these results and compare with my results in Table 5. While again his sample construction is not entirely similar to mine, the results corrected for age in 2012 suggest that people around 31 years old are less beneficial from the DACA program, which is similar to my findings. Specifically, the probability of being employed and weekly working hours in the third column are positive but they are only statistically significant at the 10% level, while the other variable is statistically insignificant.

Table 5: Estimates by Pope (2016) and this paper

	Pope (2016)	Pope (2016) adjusted for age	RDD full sample	RDD sub-sample
Working	0.044**	0.039*	0.001	0.001
	(0.013)	(0.022)	(0.005)	(0.011)
Hours per week	1.184**	0.779*	-0.205	-0.087
	(0.486)	(0.745)	(0.326)	(0.595)
Work last year	0.027**	0.017	-0.001	(-0.003)
	(0.011)	(0.018)	(0.004)	(0.008)
Sample	ACS 2005-2014	ACS 2005-2014	ACS 2013-2019	ACS 2013-2014

Notes. This table presents the impact of DACA on various intersecting labor market outcomes as analyzed by Pope (2016) and the findings of this study. The first column displays the results extracted from Panel B in Table 2 by Pope (2016). The second column presents the estimates after rectify a coding error by using the age in 2012 instead of the current data year, while keeping all other things constant as per Pope's (2016) code. The third and fourth columns are estimates taken from Table 2 and Table 4 in this paper, respectively.
* $p < .10$, ** $p < .05$, *** $p < .01$

Next, I will discuss three potential concerns related to my results.

First, one important aspect of this paper is that I cannot definitively rule out positive effects. To evaluate the largest possible treatment effects of DACA eligibility from the intention-to-treat effects, 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.[16] 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 that the average treatment-on-the-treated effect of DACA is at least twice as large as the intention-to-treat estimates. In Appendix 11, I present my uptake-adjusted point estimates and CIs along with estimates from Pope (2016). Using my preferred specification, DACA eligibility likely increases the probability of being employed at most 3 ppts, increases the probability of working last year at most 2 ppts, and increases weekly working hours by 1.2 hours. These upper ends of my CIs generally overlap with the lower end of the CIs of Pope (2016), 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). Lastly, obviously my estimates are more consistent with smaller parameter values than with larger ones.

Second, the small and insignificant effects in my RDD design may be due to the low takeup rate around the threshold. First, it is important to acknowledge that that is the trade-off between statistical power and empirical design. While my econometric model addresses the potential issue of parallel trends, the local average treatment effect may not be representative. However, the argument about the low participation of older DACA recipients reflects the limited impact of DACA on this demographic group of recipients. Older undocumented immigrants may be generally less likely to face deportation due to their lengthy tenure and strong ties in the US. Consequently, their incentive to apply for DACA is typically lower compared to the other group of DACA recipients. Around 25% of first-time applicants were 24 to 31 in 2013.[17]

[16] As discussed in Section 1

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

The third concern is the differential willingness to respond to ACS data among undocumented immigrants and DACA recipients. Specifically, the risk of deportation varies among undocumented immigrants, which could impact their inclination to participate in the ACS data collection. So, undocumented immigrants who respond to the ACS may be discontinuously different from those who opt not to participate, partly due to the perception of the deportation risk. However, this scenario is highly unlikely as it would trigger a violation of the continuity assumption in my McCrary test in Section 4. Similarly, Pope (2016) finds that there is minimal to no evidence of selection bias in willingness to complete the ACS data, and there is no indication that individuals' willingness to fill out ACS data changes after receiving DACA status.

6 Robustness checks

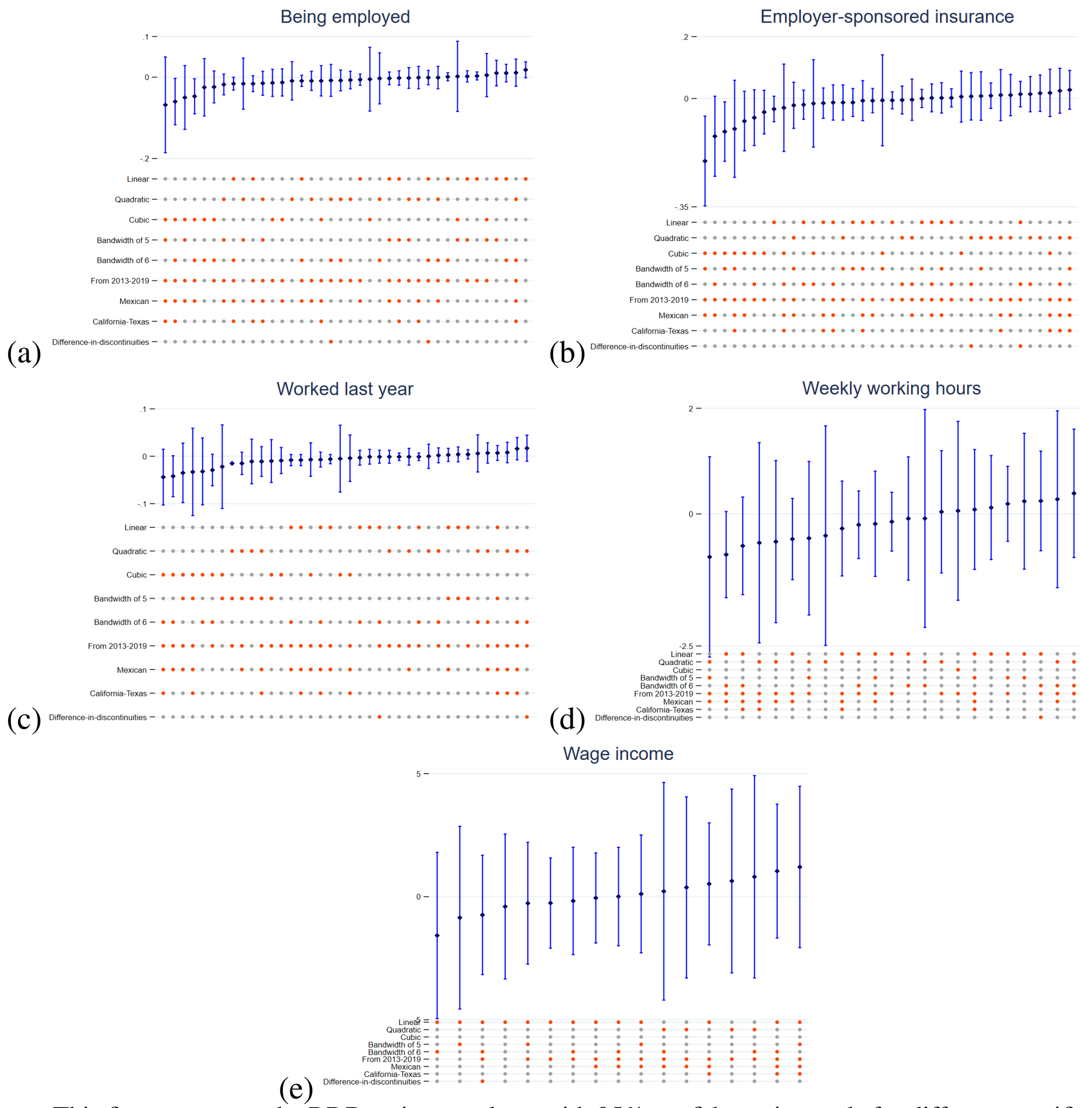
6.1 Specification curves

In my preferred specification, I utilize a sample comprising non-citizens, employing the linear functional form with a bandwidth of 6. Nonetheless, to enhance the robustness of my analysis, I explore various specifications to evaluate my RDD estimates. I present all RDD estimates in a form of specification curves (Simonsohn et al., 2020).

- **Functional forms:** In my specification curves, I present the estimates for the linear, quadratic, and cubic functional forms.
- **Bandwidths:** In addition to a bandwidth of 6, I also use two other bandwidths of 5 and 7.
- **Methods to impute legal status:** To focus on potential DACA recipients, I expand the analysis to include Mexican non-citizen immigrants residing in the entire US and those in California and Texas. See Appendix 6 for details."
- **Quasi-experimental method:** In addition to my primary econometric model, I implement a regression-discontinuity design following Bae (2020). See Appendix 6 for details.

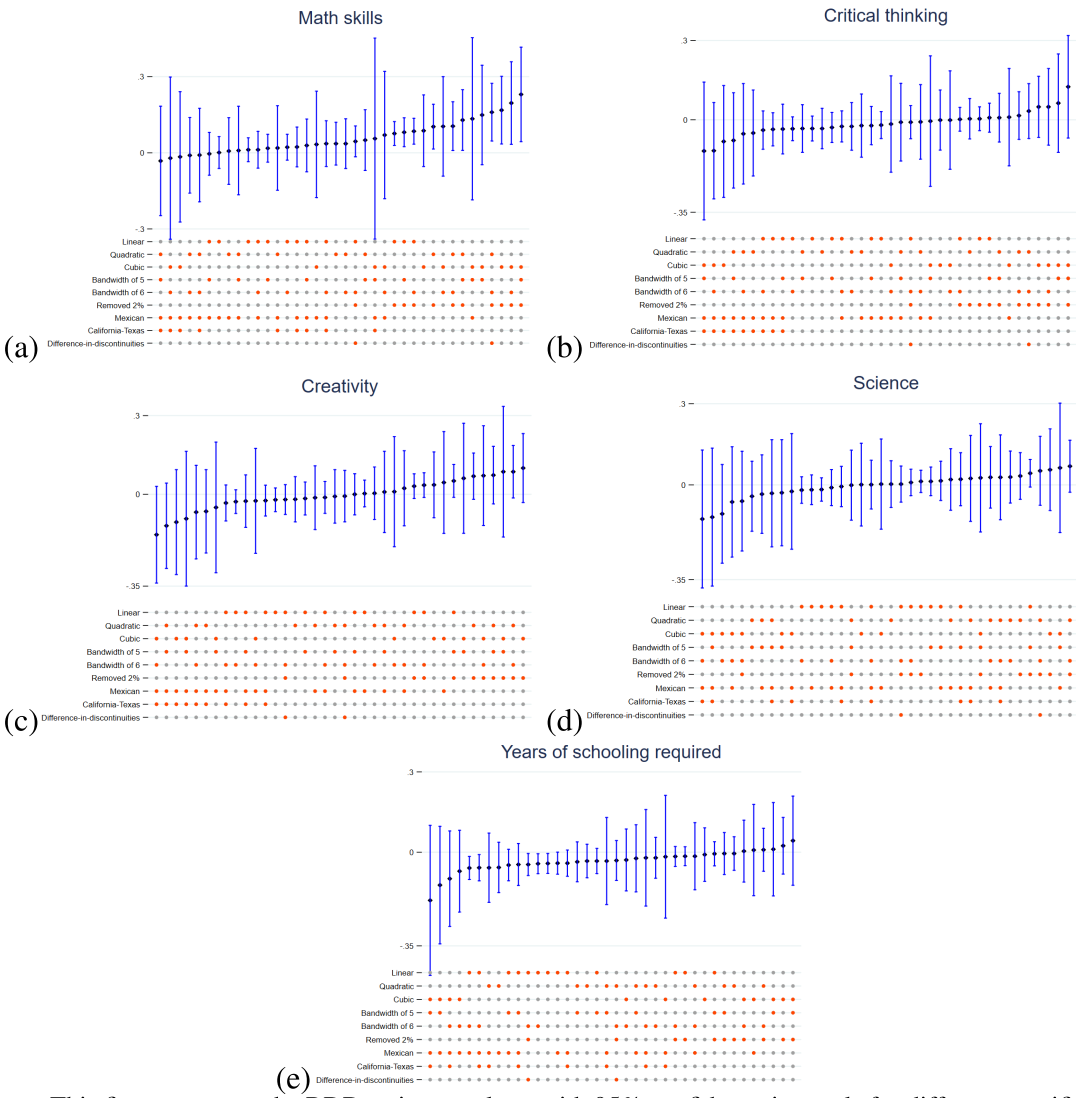
- **Sample** I also present the shorter sample of 2013 to 2014 in Figure 8 as I describe in Section 5.3. For the specification curves for occupational skill usage, I include the sample after I remove 2% of observations with lowest job skills. See sample selection in Appendix 6 for details.

Figure 8: Specification curves on employment outcomes



Notes: This figure presents the RDD estimates along with 95% confidence intervals for different specification choices (functional forms, bandwidths, samples, and econometric models. The lower panel shows the choices made in each specification (e.g. if the dot in the linear is red, that specific specification uses the linear functional form). The upper panel shows the RDD estimates and confidence intervals. In sub-figures e) and d), I remove several specification curves with extreme value to enhance the visibility.

Figure 9: Specification curves on occupational skill usage



Notes: This figure presents the RDD estimates along with 95% confidence intervals for different specification choices (functional forms, bandwidths, samples, and econometric models. The lower panel shows the choices made in each specification (e.g. if the dot in the linear is red, that specific specification uses the linear functional form). The upper panel shows the RDD estimates and confidence intervals

The results from the specification curves show two key points. First, DACA eligibility has minimal and statistically insignificant effects on most labor market outcomes. Second, the few extreme values are associated with the cubic functional form, which are not reliable as discussed in Section 5. In general, my main results are robust to a variety of specification choices.

6.2 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. [18]

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 restrict 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.

[18] I also run my analysis on US citizens born outside of the US and present them in Appendix 7

Table 6: DACA eligibility and employment outcomes: Naturalized citizens

	Linear
Bandwidth	6
Being employed	-0.001
	(0.003)
Employer-sponsored insurance	-0.018**
	(0.008)
Worked last year	-0.002
	(0.002)
Weekly working hours	-0.12
	(0.233)
Wage income	-1424
	(897)
Observations	74005

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, employing the linear functional form with a bandwidth of 6. 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 7: DACA eligibility and occupational skill usage: Naturalized citizens

	Linear
Bandwidth	6
Math skills	0.001
	(0.017)
Critical thinking	-0.019
	(0.015)
Creativity	-0.012
	(0.016)
Science	-0.002
	(0.019)
Years of schooling required	-0.024*
	(0.013)
Observations	69458

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, employing the linear functional form with a bandwidth of 6. 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.

7 Conclusion

This paper examines the labor market outcomes of DACA-eligible immigrants. There have been mixed evidence on the effects of DACA on labor market outcomes. This paper differs from the existing literature in econometric model and sample construction. Firstly, this study pioneers the use of the regression discontinuity design, providing independent evidence that does not hinge on the parallel trend assumption found in previous research. Secondly, it conducts a comparative analysis of labor market outcomes between highly comparable treatment and control groups, differing solely in their age as of 2012. This sample construction enhances the precision of the study's findings.

This paper finds that DACA eligibility has very little effects 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 DACA-eligible immigrants advance to higher-skilled employment. Second, 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. The effects identified in this paper are likely localized among individuals around the age of 31 in 2012 (i.e.: and older group of DACA recipients), reflecting the specific setup of my econometric model. Even though the samples are not entirely comparable, this study addresses a coding error in Pope (2016) and arrives at quite similar findings for the older cohort of DACA recipients.

My paper suggests 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 trajectory as people 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.

Declarations

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The author has no competing interests to declare that are relevant to the content of this article.

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Appendices

Appendix 1

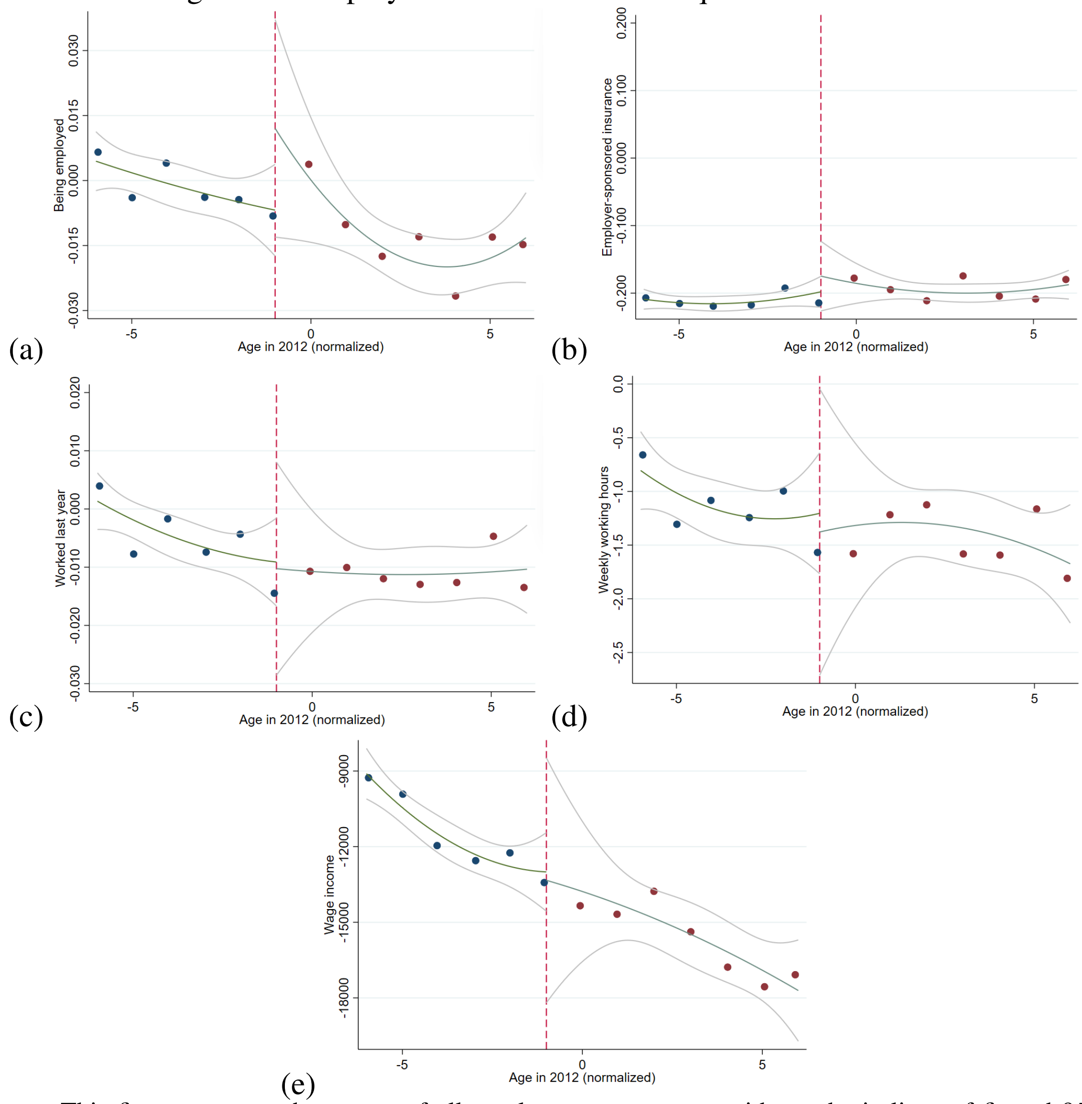
Table A1: Classification of observations around the threshold

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

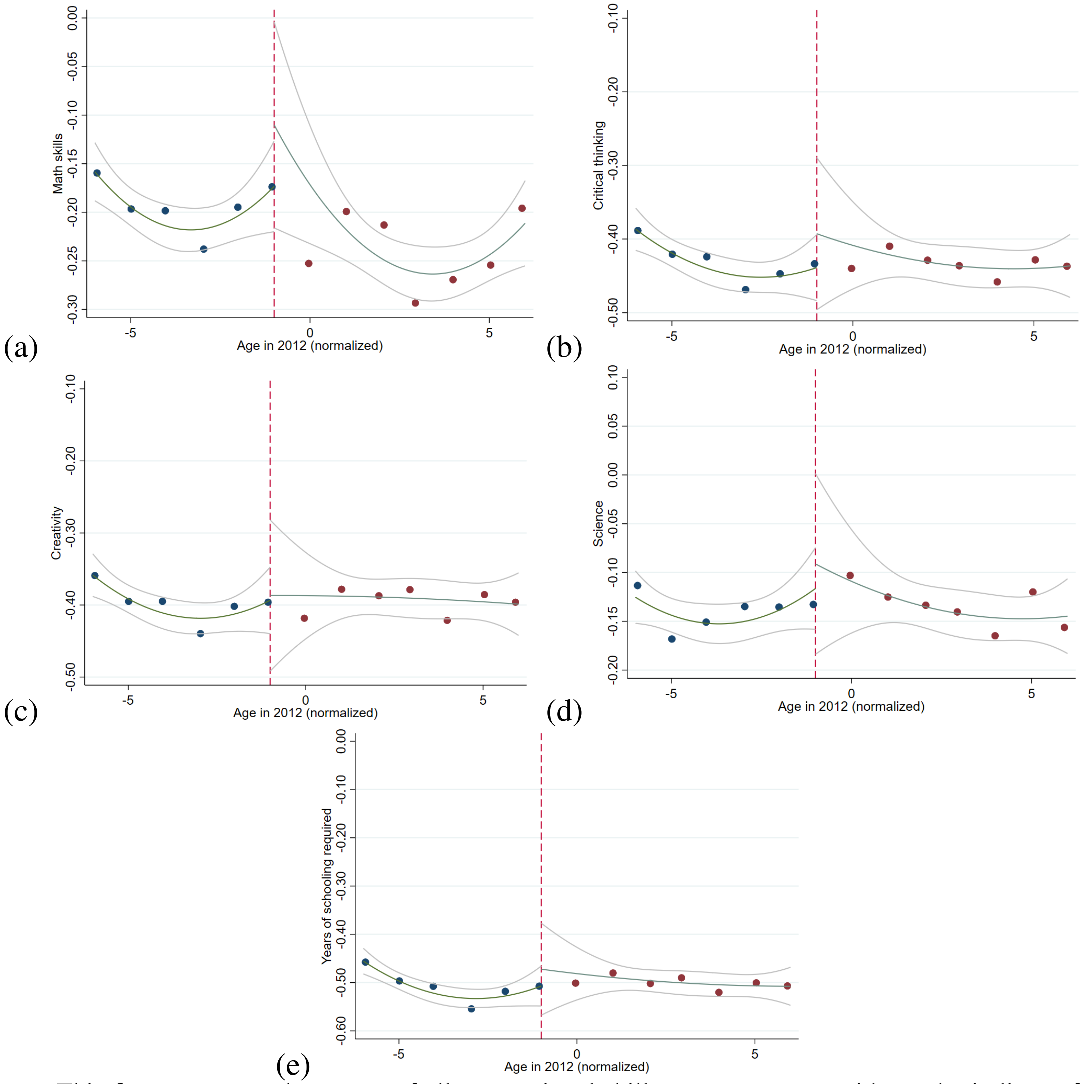
Figure 10: Employment outcomes with a quadratic line of fit



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 11: 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: DACA eligibility and employment outcomes: Mexican in CA and TX

	Linear
Bandwidth	6
Being employed	0.016*
	(0.008)
Employer-sponsored insurance	-0.013
	(0.029)
Worked last year	-0.007
	(0.008)
Weekly working hours	-0.604
	(0.471)
Wage income	1040
	(1387)
Observations	9024

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, employing the linear functional form with a bandwidth of 6. 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: DACA eligibility and occupational skill usage: Mexican in CA and TX

	Linear
Bandwidth	6
Math skills	0.036
	(0.046)
Critical thinking	-0.039
	(0.037)
Creativity	-0.033
	(0.0035)
Science	0.001
	(0.046)
Years of schooling required	-0.058**
	(0.025)
Observations	8353

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, employing the linear functional form with a bandwidth of 6. 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
Bandwidth	6
Being employed	0.009
	(0.010)
Employer-sponsored insurance	0.010
	(0.020)
Worked last year	0.004
	(0.007)
Weekly working hours	0.254
	(0.494)
Wage income	506
	(1910)
Observations	14599

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, employing the linear functional form with a bandwidth of 6. 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: DACA eligibility and occupational skill usage: Non-Mexican

	Linear
Bandwidth	6
Math skills	0.038
	(0.039)
Critical thinking	-0.025
	(0.036)
Creativity	-0.025
	(0.036)
Science	-0.034
	(0.035)
Years of schooling required	-0.009
	(0.031)
Observations	13439

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, employing the linear functional form with a bandwidth of 6. 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: DACA eligibility and employment outcomes, remove lowest 2%

	Linear
Bandwidth	6
Weekly working hours	0.340
	(0.230)
Wage income	1895*
	(1145)
Observations	26383

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, employing the linear functional form with a bandwidth of 6. 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:

$$Y_{it} = \alpha + \beta_1 D_{it} * Post_{it} + \beta_2 D_{it} + \beta_3 Post_{it} + \beta_4 X_{it} + \beta_5 W_{it} + \theta_t + \gamma_s + \epsilon_{it} \quad (2)$$

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

Mexican immigrants I run the main model only for Mexican immigrants. Mexican immigrants made up approximately 50% of the 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 almost 80% of all DACA holders. Therefore, restricting the sample to non-citizen immigrants from Mexico focuses the estimates on a population with a larger anticipated effect.

Mexican in California and Texas California and Texas are home to approximately 36% of the undocumented population in the US. According to the Pew Research Center, 69% and 73% of the undocumented population in California and Texas respectively are Mexican. In contrast, Massachusetts has less than 4% of the undocumented population and only 2% of them are Mexican.[19] Suppose I compare a Mexican who lives in Massachusetts and a Mexican who lives in Texas, a Mexican in Texas is more likely to be undocumented. So, I run my main analysis again on the sample of Mexicans who reside in California and Texas only.

Sample selection There is suggestive evidence that DACA may move up to 2% of people into employment in the early years following the introduction of DACA. So, if DACA moved people at the lowest percentile of the job skill distribution into employment, this sample selection would bias the estimates downwards. To determine the maximum extent that sample selection of this kind might 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.[20]

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-discontinuities 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-discontinuities framework is to examine the difference around the threshold in the pre-policy period and post-policy period. Specifically, I compare two separate regression discontinuities, which are the effects of DACA eligibility. The econometric model is as follows:

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

[20] 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

$$Y_{ist} = \alpha + \beta_1 \boldsymbol{D}_{ist} + \beta_2 \boldsymbol{D}_{ist} * \textbf{\textit{Post}}_t + \textbf{\textit{f(RVF)}}_i + \lambda \boldsymbol{X}_{ist} + \omega_s + \theta_t + \epsilon_{ist} \tag{3}$$

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, and 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.

Appendix 7

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

	Linear
Bandwidth	6
Being employed	-0.007
	(0.007)
Employer-sponsored insurance	0.009
	(0.016)
Worked last year	-0.002
	(0.005)
Weekly working hours	-0.613
	(0.383)
Wage income	-1684
	(1583)
Observations	20820

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, employing the linear functional form with a bandwidth of 6. 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: DACA eligibility on occupational skill usage among US citizens born outside of the US

	Linear
Bandwidth	6
Math skills	0.032
	(0.033)
Critical thinking	0.004
	(0.030)
Creativity	-0.021
	(0.029)
Science	0.016
	(0.038)
Years of schooling required	-0.037
	(0.025)
Observations	19297

Standard errors in parentheses are clustered at the state-year level. Coefficients are measured in standard deviation.

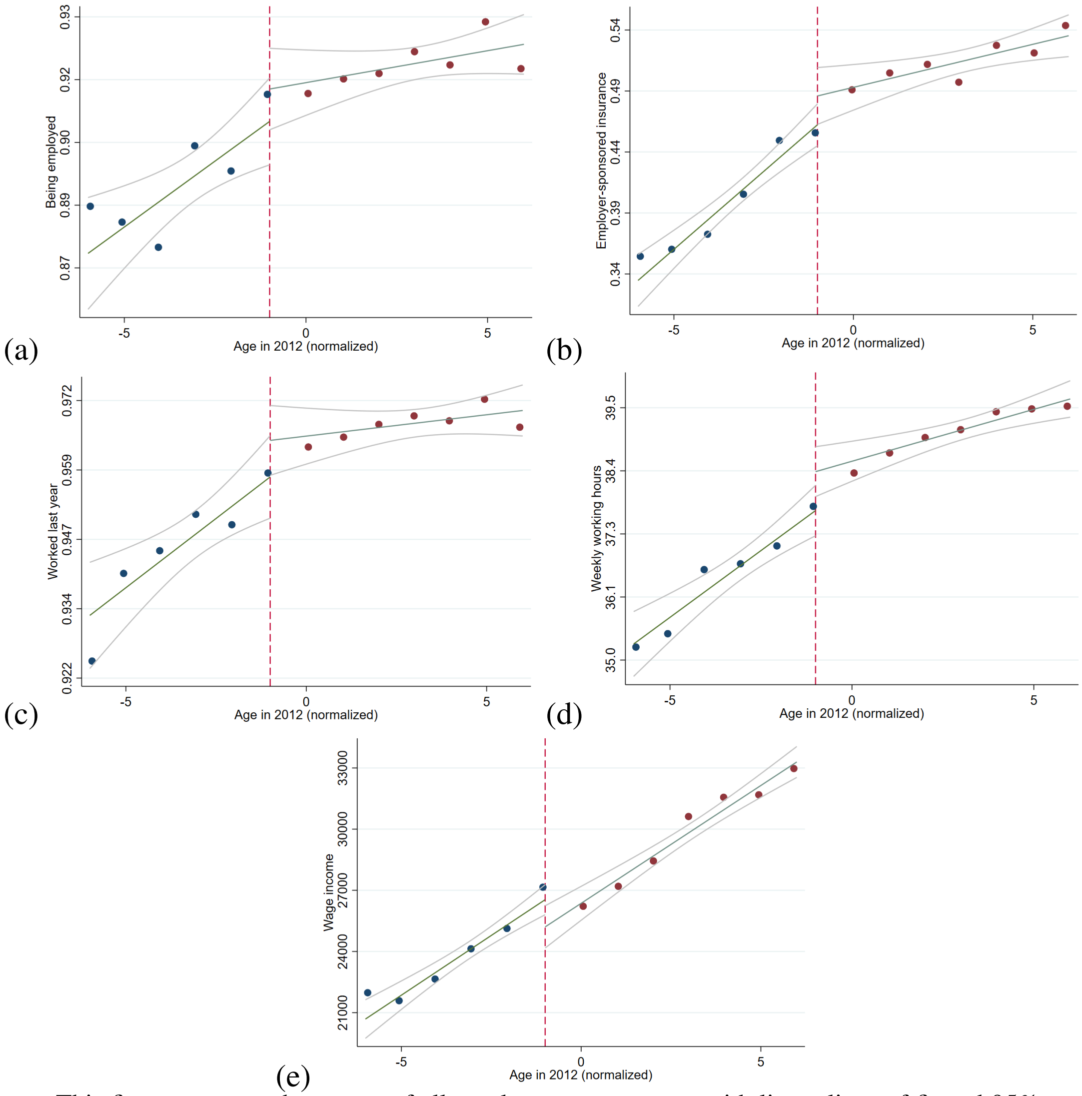
Notes. This table shows the placebo tests of effects of DACA eligibility on choosing high-skilled jobs among US citizens born outside of the US, employing the linear functional form with a bandwidth of 6. Sample includes those who have obtained high-school diploma, have entered the US before their 16th birthday and have immigrated to the US before 2007.

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

Appendix 8

Pre-DACA employment outcomes

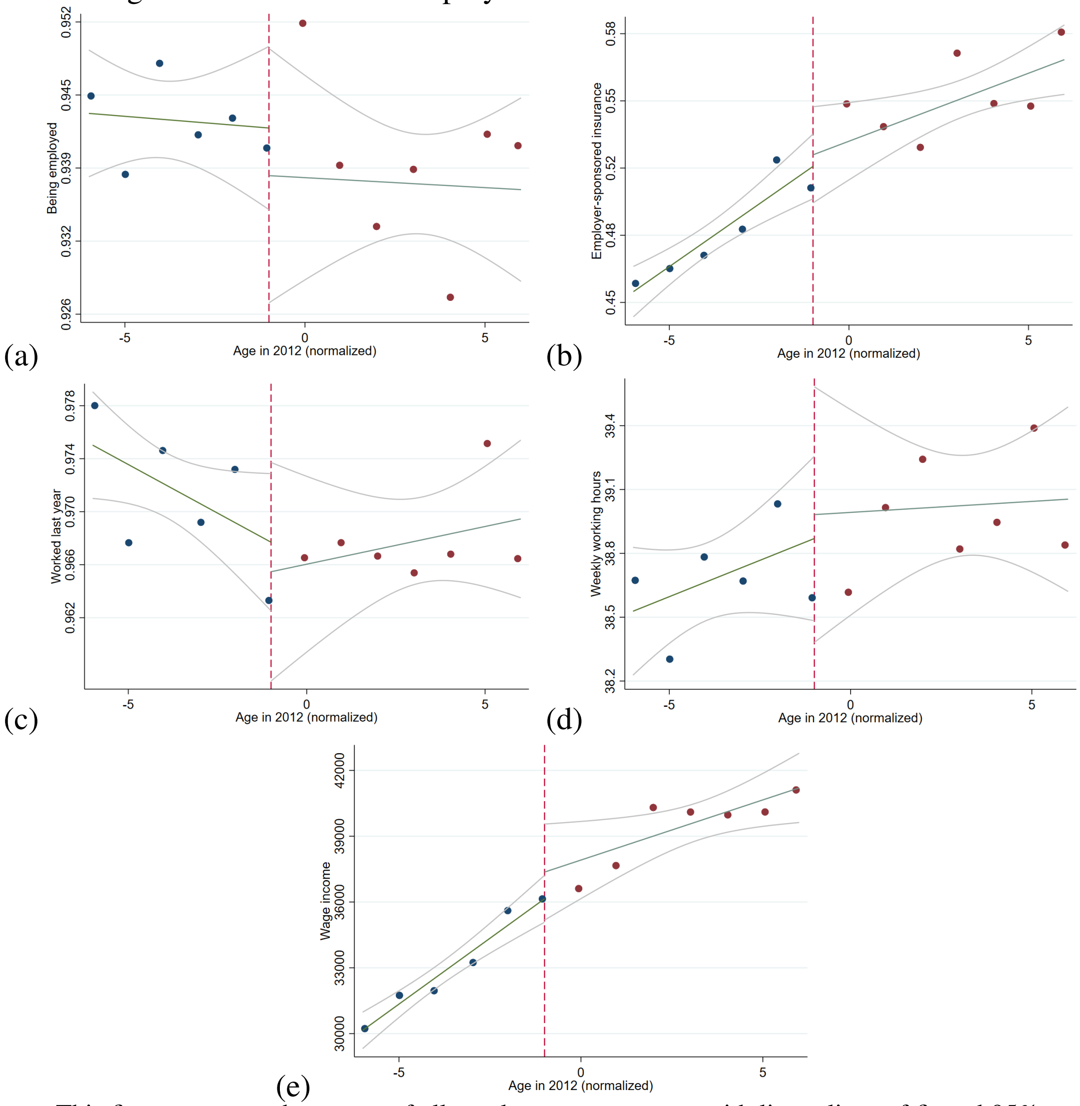
Figure 12: Pre-DACA employment outcomes with a linear line of fit



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

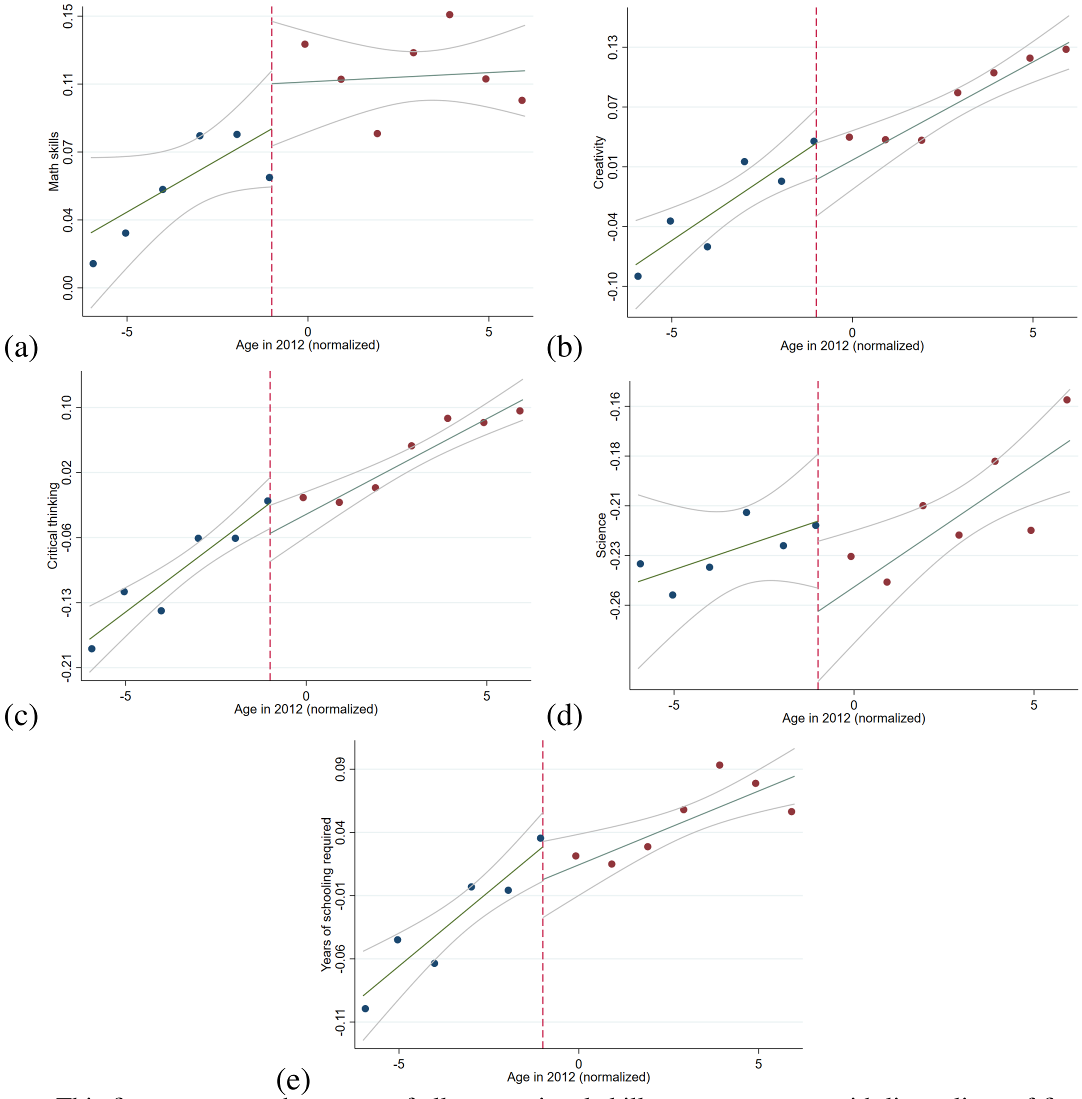
Figure 13: Post-DACA employment outcomes with a linear line of fit



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

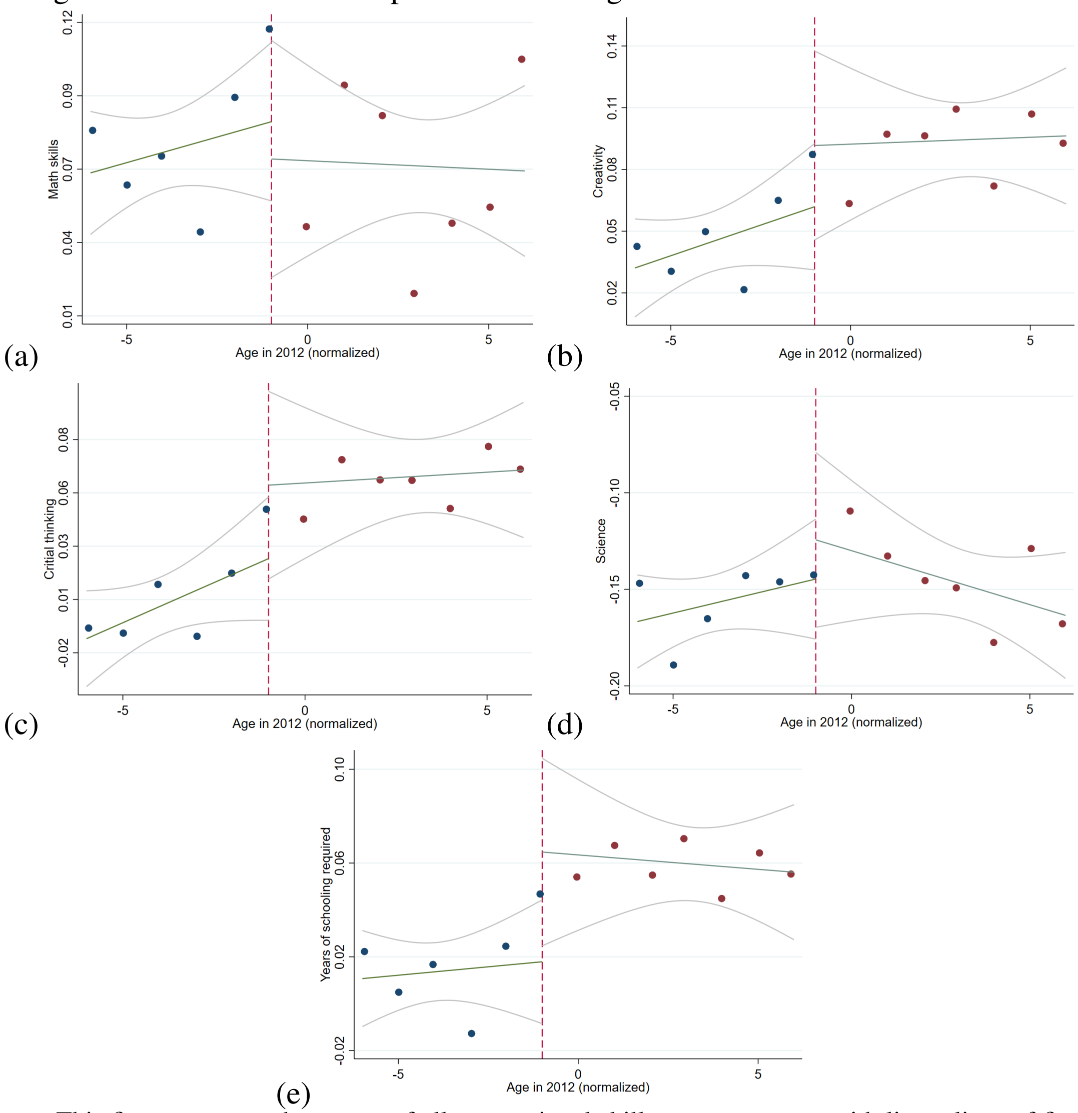
Figure 14: Pre-DACA occupational skill usage outcomes with a linear line of fit



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 15: 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 9: 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

	College or higher	Less than college
Being employed	0.022**	-0.004
	(0.010)	(0.005)
Employer-sponsored insurance	0.029	-0.004
	(0.026)	(0.015)
Worked last year	0.007	-0.003
	(0.008)	(0.005)
Weekly working hours	0.074	-0.276
	(0.736)	(0.923)
Wage income	-407	-74
	(3914)	(835)
Observations	5702	23324

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, employing the linear functional form with a bandwidth of 6. 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

	College or higher	Less than college
Math skills	0.045	0.017
	(0.059)	(0.030)
Critical thinking	-0.024	-0.036
	(0.060)	(0.024)
Creativity	-0.032	-0.026
	(0.050)	(0.027)
Science	-0.036	-0.017
	(0.076)	(0.026)
Years of schooling required	-0.058	-0.038**
	(0.061)	(0.018)
Observations	5388	21489

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, employing the linear functional form with a bandwidth of 6. 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 11 Comparison of treatment effects of DACA

Table A11: Estimates on employment outcomes from Pope (2016) and this paper

Pope (2016)				This paper			
NCs age 27 to 34, with high-school degree, and enter before 16				**NCs with high-school degree, enter the US before 16, before 2007**			
	Point estimates	95% conf. interval			Point estimates	95% conf. interval	
Being employed	0.066	0.028	0.104	Being employed	0.003	-0.024	0.030
Weekly working hours	1.776	0.347	3.205	Weekly working hours	-0.569	-2.344	1.205
Worked last year	0.041	0.008	0.073	Worked last year	-0.003	-0.025	0.019
Income	2096	-563	4754	Wage income	-742	-6537	5582

Notes. This table compares the effects of DACA on employment outcomes between this paper and Pope (2016). To be comparable with my uptake-adjusted estimates, estimates from Pope (2016) are adjusted by multiplying by 1.5 as discussed in his paper. This table presents all estimates along with confidence intervals.