Estimating the Effect of Deferred Action for Childhood Arrivals (DACA) on DREAMers

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Abstract

Deferred Action for Childhood Arrivals (DACA) was an immigration policy which allowed approximately 1.5–2 million undocumented immigrants brought to the United States as children (also known as DREAMers) who met specific eligibility criteria to apply for and receive temporary deportation relief and work authorization. This paper seeks to quantify the effect that DACA had on the labor market outcomes of DREAMers, as well as its effects on schooling and healthcare. I utilize a two-stage difference-in-differences design using data from the American Community Survey and the Survey of Income and Program Participation, and find that DACA significantly increased the likelihood of working, moving about 10 percent of the DREAMer population into the labor force and employment, and decreasing unemployment by 3.8 percentage points. I also report that DACA increased incomes among DREAMers, as well as health insurance coverage, but had no effect on school attendance. Furthermore, I find that the effects of DACA are unequal, with DREAMers lower in the income distribution gaining the most from it.

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1. Introduction

"This is not amnesty, this is not immunity. This is not a path to citizenship. It's not a permanent fix. This is a temporary stopgap measure that lets us focus our resources wisely while giving a degree of relief and hope to talented, driven, patriotic young people. It is the right thing to do."

— President Obama on the announcement of DACA, June 15, 2012.[1]

On June 15, 2012 in the Rose Garden in the White House, President Barack Obama announced that his administration was utilizing its prosecutorial discretion to implement a policy of Deferred Action for Childhood Arrivals (DACA). DACA was introduced two years after the failure of the DREAM ("Development, Relief and Education for Alien Minors") Act of 2010 in the Senate[2] which would have granted unauthorized immigrants brought to the U.S. as children (commonly known as DREAMers) who met certain eligibility criteria conditional resident status, followed by permanent residency after six years. DACA granted these DREAMers a two-year, renewable period of deferred action from deportation, as well as temporary work authorization.

Following the Republican victory in the 2016 presidential election, Attorney General Jeff Sessions announced the repeal of DACA on September 5, 2017, with the first permits expiring from March 5, 2018, and President Trump urged Congress to introduce a legislative replacement for the program. The congressional disputes over a possible replacement for DACA led to a three-day shutdown of the federal government, from January 20 to 22, 2018, which ended without any resolution over what to do with the DREAMers. In the courts, following a legal challenge by the

[1] https://obamawhitehouse.archives.gov/the-press-office/2012/06/15/remarks-president-immigration/

[2] The (Democratic-controlled) House of Representatives passed the DREAM Act 216–198 on December 10, 2010, but the bill only received 55 votes in the Senate, insufficient to overcome a Republican filibuster.

University of California system and UC President Janet Napolitano (who as Secretary of Homeland Security oversaw the introduction and implementation of DACA), the U.S. District Court for the Northern District of California temporarily blocked part of the Trump administration's repeal of DACA on January 9, 2018, ordering the government to continue to renew deferred action for existing DACA recipients; in a separate case the U.S. District Court for the Eastern District of New York granted an injunction on February 13, 2018 requiring the government to restore the full DACA program. These decisions have been appealed to higher courts, and at the time of writing of this essay the fate of the DREAMers still remains in limbo.

It is thus perhaps unsurprising that the issue of immigration, both legal and unauthorized, looms large in American society and political discourse today, especially after the 2016 election. It is estimated that there are over 12 million unauthorized immigrants living in the United States, i.e. approximately 3.5% of the total population of the country (Baker, 2014). Even though they live under the constant threat of deportation and are unable to legally work, unauthorized immigrants still play a significant role in the American economy; studies have found that unauthorized immigrants contribute approximately 3% to the nation's GDP (Edwards and Ortega, 2017). There is therefore no easy answer to the question of what to do about the unauthorized population already in the country — mass deportation is both practically and politically impossible, yet given the current political climate legalization is also out of the question.

The unauthorized immigrant population in the U.S. skews young: approximately 72%, or about 8 million, is between the ages of 18 and 44, compared to 36% of the U.S. population as a whole (Capps et al., 2013; U.S. Census Bureau, 2010). Of these young adults, it is estimated that approximately 1.5 to 2 million of them qualify as DREAMers, i.e. are eligible for DACA (Batalova et al., 2014). These DREAMers are perhaps the most politically sympathetic group of immigrants

— most were brought to the U.S. as children and therefore (arguably) not responsible for their undocumented status; most have been raised as Americans and have never returned to their birthplaces; in President Obama's words when he announced DACA "they are Americans in their heart, in their minds, in every single way but one: on paper."[3] In fact, recent polling has shown that almost 9 in 10 Americans support a path to permanent residency or citizenship for DREAMers.[4] The moral case for DACA is therefore an easy one to make; the economic argument, on the other hand, is more interesting.

DREAMers and other unauthorized immigrants encounter significant labor market frictions — without work authorization, they are often restricted to informal jobs at the periphery of the labor market where employers are willing to ignore their legal status; they also work under constant threat of arrest and deportation. Furthermore, unauthorized immigrants are unable to receive driver's licenses or other forms of identification, which further restricts labor mobility. For example, Hall et al. (2010) find a 17 percent disparity in wages of unauthorized and legal Mexican immigrants. By reducing or even eliminating these frictions, DACA can potentially improve the labor market outcomes of DREAMers, raising their incomes and reducing unemployment and underemployment. DACA can therefore also be beneficial for the larger economy, by increasing the supply of educated labor, reducing unemployment and raising wages and output.

This paper therefore aims to examine and quantify the impacts of DACA on the labor market outcomes of DREAMers, specifically labor force participation and employment, hours worked, and income, building on the work by Pope (2016). I draw upon his identification strategy, utilizing data from the 2005 – 2016 American Community Survey (ACS) and a difference-in-

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[3] See note 1.
[4] http://thehill.com/blogs/blog-briefing-room/news/369487-poll-nearly-nine-in-10-favor-allowing-daca-recipients-to-stay/

differences approach with some regression discontinuity design elements based on the eligibility criteria for DACA to estimate the effects of the program on the population identified as potentially DACA-eligible. However, the ACS does not include questions directly relating to immigration status, which can result in issues in identifying undocumented individuals and DREAMers, such as legal immigrants being incorrectly classified as DREAMers. This in turn would bias the DID estimates toward zero, which may lead to a serious understatement of the effects of DACA — Pope states in his work that due to this issue his estimates may be up to 1.6 times lower than the actual effect of the program. Therefore, I remedy this problem by using data from the 2008 Survey of Income and Program Participation (SIPP) to predict a two-stage model for determining whether an individual is an unauthorized immigrant, in order to improve upon the identification strategy used in the difference-in-differences model.

In addition, I also examine the effects of DACA on schooling and health insurance coverage for DREAMers. Education and work are close substitutes; hence it is possible that DACA might have shifted DREAMers out of schooling and into the labor force. However, by expanding the labor opportunities available to DREAMers, DACA might also encourage them to pursue higher education or additional qualifications.[5] Healthcare is also an important issue to consider, given how the U.S. has the largest proportion of uninsured in the developed world, as well as some of the highest healthcare costs. Even though DACA recipients do not qualify for the Medicaid expansion, are not subject to the individual mandate to purchase health insurance and are not eligible to participate in the insurance exchanges established under the Affordable Care Act,[6] they are able to receive health insurance through their employers, hence DACA can improve health

[5] Of course, DACA might also push unauthorized immigrants who do not possess the necessary educational qualifications for DACA back into education in order to become eligible for DACA; however, this is beyond the scope of this paper.
[6] https://ccf.georgetown.edu/2014/04/11/for-daca-youth-health-insurance-is-only-a-dream/

insurance coverage and health outcomes among DREAMers by allowing them access to jobs that provide them insurance. Also, states may elect to allow low-income DACA recipients to participate in state-based and -funded Medicaid programs, and several, such as California and New York, home to 27 and five percent of DACA recipients, respectively, have done so, thereby potentially increasing health insurance coverage among the DREAMer population.

I find that DACA has had large and significant effects on the labor market outcomes of DREAMers. In my preferred specification, DACA has increased the likelihood of a DREAMer working by 12.7 percentage points. This effect arises through two pathways: I estimate that DACA has shifted about 10 percent of the total estimated DREAMer population, or approximately 160,000 individuals, into the labor force and employment, while also decreasing unemployment among DREAMers by about 3.8 percentage points, from a pre-DACA level of 11.6 percent.

I also find that DACA has raised incomes among the DREAMer population, with the greatest increases, of about 33% relative to the pre-DACA subsample mean, for DREAMers in the bottom half of the income distribution. My estimates for these labor market outcomes are about 2.5 to 3.5 times larger than Pope's (2016), which I attribute to downward bias in his results due to measurement error in determining DACA eligibility associated with immigration status. I examine the effect of DACA on hourly wage rates, but do not find any significant effect; however, this may be explained by the presence of a strong, negative differential pre-trend in the data. Also, I report that DACA has also increased the rate of health insurance coverage among DREAMers, by 8.5 percentage points from a pre-DACA level of 48 percent; however, I do not find any significant effects on school attendance.

I also observe that the effects and benefits of DACA are unequally distributed, and vary both by gender and across the income distribution. I find that DACA reduced unemployment among male DREAMers by 4.9 percentage points, but had no effect on female DREAMers; on the other hand, DACA increased the labor force participation of female DREAMers by 13.8 percentage points, compared to 7.7 percentage points for male DREAMers. Also, I report that individuals with lower incomes benefit the most from DACA, with larger increases in the likelihood of working, labor force participation, health insurance coverage and income as a result of DACA.

The remainder of this paper proceeds as follows. Section 2 provides a brief overview of DACA, the eligibility criteria for the program and some statistics regarding DACA applications. Section 3 discusses prior studies on DREAMers and how they have benefited from DACA. Section 4 provides a simple conceptual framework for understanding the results. Section 5 outlines the difference-in-differences and identification strategies used with the data sources for this paper, which are described in Section 6. Section 7 presents the results of the analysis and Section 8 concludes.

2. Deferred Action for Childhood Arrivals

As discussed in the introduction of this paper, DACA was introduced by the Obama administration in June 2012, and allowed unauthorized immigrants who met specific eligibility criteria (also known as DREAMers) to apply for two-year, renewable periods of deferred action from deportation and work authorization. Following the announcement, the Department of Homeland Security began taking applications from DREAMers in August 2012. The application comprised two forms and a worksheet, as well as a $465 processing fee, and applicants had to provide substantial documentation to U.S. Customs and Immigration Services (USCIS) showing that they met the various criteria for DACA. Despite the onerous application process, over 90% of applications were approved by USCIS. Applications for renewal of DACA follow a similar process.

In order to be eligible for DACA, unauthorized immigrants have to meet the following seven criteria: they have to (1) have had no lawful status (i.e. be unauthorized) on June 15, 2012; (2) had come to the U.S. before their 16th birthday; (3) be under the age of 31 as of June 15, 2012; (4) have continuously resided in the U.S. since June 15, 2007 (i.e. for at least 5 years up to the time of application); (5) had been physically present in the U.S. on June 15, 2012 and at time of filing their application for DACA; (6) be currently in school, or graduated from high school, or obtained a General Education Development (GED) certificate, or be an honorably discharged Armed Forces or Coast Guard veteran; and (7) not have been convicted of a felony, significant misdemeanor or three or more other misdemeanors and "not otherwise pose a threat to national security or public safety".[7] Also, unauthorized immigrants have to be at least 15 years old to apply for DACA.

Figure 1 shows the number of DACA applications approved each year since the program began in 2012, split into new approvals and renewals (dark grey and light grey bars, respectively). We can see that the bulk of new applications were approved in late 2012 and 2013, suggesting that most DACA-eligible individuals applied soon after the program was announced. Figure 1 also shows the cumulative number of new DACA approvals (black line, on right axis) from 2012 to 2018; as of January 2018, there have been over 900,000 DACA applications approved, out of an estimated DREAMer population of 1.5–2 million (Batalova et al., 2014).

The Migration Policy Institute, a Washington D.C.-based think tank, estimated using data from the ACS that in 2014 there were over 2.1 million unauthorized immigrants who met the age and residency requirements of DACA (i.e. requirements (1) to (4) above), and hence were

[7] https://www.uscis.gov/archive/consideration-deferred-action-childhood-arrivals-daca

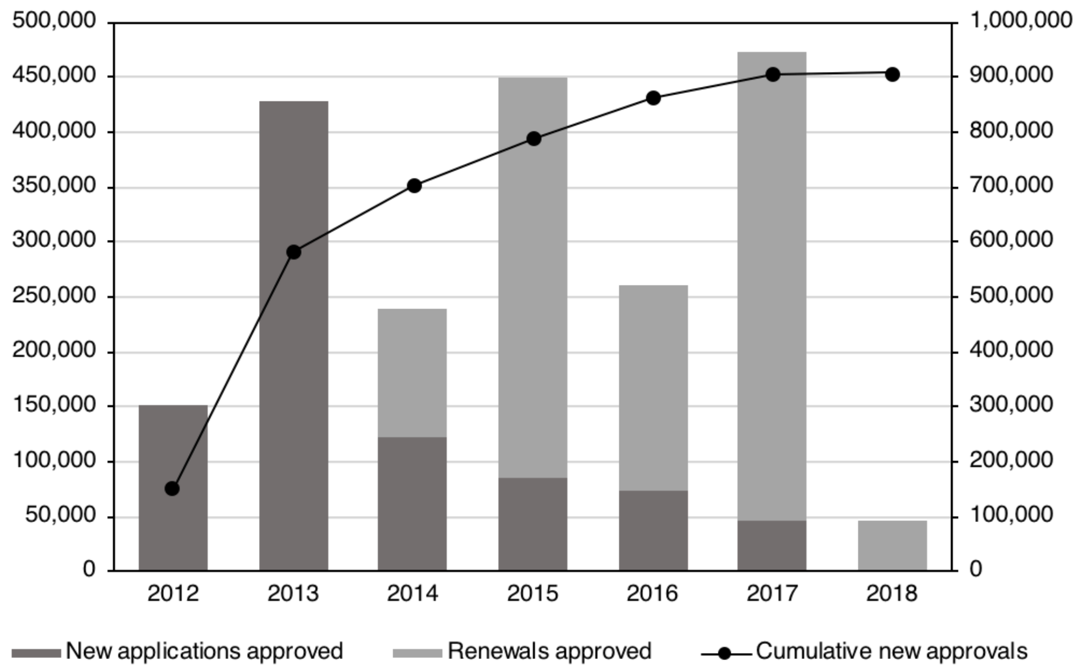

Figure 1. DACA approvals by year, as of January 31, 2018, split by new applications and renewals (dark and light grey bars on left axis, respectively); and cumulative new DACA approvals (black line, right axis). Data from U.S. Citizenship and Immigration Services.

potentially DACA-eligible. Of these 2.1 million, approximately 1.2 million were considered *immediately* eligible for DACA in 2012 since they met the education requirement (6) as well (the ACS does not collect data on criminal activity or veteran status). The remaining 900,000 are *potentially* eligible: about half meet all the DACA requirements except the education requirement (6), while the other half were children under 15 who could qualify and apply for DACA after they turned 15; the authors of the study estimate that in this latter group 80,000–90,000 individuals will "age into" DACA eligibility every year (Batalova et al., 2014). From these numbers we can see that about half of all immediately eligible DREAMers applied for DACA when it was first introduced, which is a considerable fraction of the population, especially considering the relatively high application fee and the numerous documentation requirements for the application. This perhaps suggests the high expected or perceived value of DACA status for these DREAMers.

Also, USCIS provides some information about the demographics of DACA recipients: 78 percent of all DACA recipients were born in Mexico and a further 16 percent in Central or South America,[8] which lines up somewhat broadly with the demographics of the undocumented population of the United States as a whole. The Department of Homeland Security's Office of Immigration Statistics estimates that 55 percent of all undocumented immigrants were born in Mexico, and 27 percent in Central or South America (Baker, 2014). Twenty-seven percent of DACA recipients reside in California, 16 percent in Texas and 5 percent each in New York and Florida, which is also similar to the distribution of unauthorized immigrants in the country as a whole.

3. Literature Review

There have been several studies on the effects of DACA on DREAMers and unauthorized immigrants; however, they are all limited by the relatively short time period for which DACA has been in effect, as well as the availability of data, especially pertaining to immigration status and identifying DACA recipients. Most surveys (understandably) do not ask for immigration status, and those that do are limited by small sample sizes that make any analysis difficult.

Gonzales and co-workers (2014) surveyed 2,381 DACA recipients recruited through immigrant service agencies, schools, churches, law offices and community organizations, and found that 45 percent of survey respondents reported increased earnings after receiving DACA status. They also report that 57 percent of respondents have obtained driver's licenses, 49 percent have opened bank accounts, and 21 percent have obtained health insurance coverage post-DACA (Gonzales and Bautista-Chavez, 2014; Gonzales et al., 2014). In a similar vein, Wong and

[8] https://www.uscis.gov/sites/default/files/USCIS/Resources/Reports%20and%20Studies/Immigration%20Forms%20Data/All%20Form%20Types/DACA/DACA_FY18_Q1_Data_plus_Jan_18.pdf

co-workers (2017) conducted an online survey of 3,063 DACA recipients and found that 69 percent of respondents moved to a higher-paying job, and the average hourly wage of respondents aged 25 and older increased by 84 percent since receiving DACA (Wong et al., 2017). However, these two surveys are largely descriptive, suffer from small sample sizes, lack control groups and do not demonstrate causal inference.

Amuedo-Dorantes and Antman (2017) use data from the Current Population Survey (CPS) to estimate the effects of DACA on schooling and labor market decisions of DREAMers. They utilize a difference-in-differences strategy based on the eligibility cutoffs for DACA in order to identify their control and treatment groups, and they find that DACA reduced the probability of school enrollment for eligible individuals and increased the probability of working; i.e. DACA has shifted DREAMers from education into labor. However, their study is limited by the small sample size of the CPS; their DACA-eligible treatment group contains only 461 observations. Furthermore, the CPS does not include questions about immigration status; instead, the authors restrict the CPS sample to only noncitizens between the ages of 18 and 24 with a high school diploma or GED.

In a related work, Ameudo-Dorantes and Antman (2016) use the 2009–11 and 2013–14 ACS to examine the effect of DACA on poverty among unauthorized immigrants. Again, they use a difference-in-differences approach based on the eligibility criteria for DACA, and they find that DACA has reduced the likelihood of living in poverty by 38 percent. The sample sizes for the ACS are significantly larger, hence the authors are able to obtain about 3,500 observations, including 1,490 who are potentially DACA-eligible. As discussed above, the ACS also does not ask about immigration status, hence to get around this issue the authors restrict their sample to noncitizens aged 27–34 who were born in Mexico, since Mexicans make up the largest subset of DACA recipients. Furthermore, the authors claim ethnicity and citizenship are good predictors of the legal status of migrants (Amuedo-Dorantes and Antman, 2016).

Hsin and Ortega (2017) also investigate the effect of DACA on the education–labor choice of undocumented immigrants, using a data set of students in a large university system that contains information about the legal status of its students, which the university collects as it allows undocumented immigrants to qualify for in-state tuition if they provide a notarized affidavit attesting to their unauthorized status. This therefore addresses one of the main challenges other studies have faced in trying to identify DACA-eligible individuals. Hsin and Ortega use a difference-in-differences strategy, placing citizens and legal immigrants in the control group and all unauthorized immigrants in the intent-to-treat group, and find that DACA increased the dropout rates of undocumented students enrolled in 4-year colleges by 7.3 percentage points, but did not have an effect on dropout rates of undocumented students enrolled in 2-year community colleges. Instead, DACA decreased the probability of full-time attendance in community colleges by 5.5 percentage points. Their results therefore show that DACA may have shifted DREAMers from schooling into employment, suggesting that some unauthorized immigrants might have chosen education over the precarious nature of working without proper authorization, and that DACA has eliminated some of the labor market frictions faced by DREAMers, leading them to enter the workforce.

This paper is closest to work by Pope (2016), which uses data from the 2005 to 2014 waves of the ACS to investigate the effects of DACA on the employment and education of DACA-eligible individuals. Pope utilizes a difference-in-differences strategy based on the eligibility criteria for DACA and finds that DACA increased the probability of working by 3.7–4.8 percentage points and the average number of hours worked per week by 0.9–1.7 hours among the DACA-eligible population. He also finds an increase in labor force participation and decrease in unemployment, as well as an increase in income among DACA-eligible individuals in the bottom half of the income distribution of the sample. However, Pope finds no effect on the likelihood of attending school, which stands in contrast to the results from Amuedo-Dorantes and Antman and Hsin and Ortega. Pope's study is significant since it takes advantage of the size of the ACS to construct a much larger sample (N = 400,000, of which about 100,000 are identified as DACA-eligible) than other studies.

However, there are some issues associated with the design of his paper. Most importantly, the ACS does not collect information regarding immigration status, only asking whether respondents are citizens or noncitizens. Pope includes all noncitizens aged 18 to 35 who meet the educational requirements for DACA in his sample, hence the sample is contaminated with legal immigrants and noncitizens, such as F-1 and H-1B visa holders, and green card holders.[9] Pope acknowledges this issue in his work and asserts that this merely would bias the difference-in-differences estimate downward. But this necessarily assumes that the legal immigrants are roughly equally distributed between the control and the intent-to-treat groups. Also, if this were not the case, which is highly likely given that foreign students and work permit holders tend to come to the U.S. later and have remained in the country for a shorter period than DREAMers, making them less likely to meet the eligibility criteria for DACA, then the parallel trend assumption between the two groups required for the validity of the difference-in-differences estimates might not hold as well. Furthermore, Pope only has two years of post-DACA data, and thus might not be able to capture the full effects on DACA on employment or various labor market outcomes.

[9] For example, about 11% of his sample is born in India and 7% is born in China — two countries which make up 0.4% and 0.1%, respectively, of the population of DACA recipients, but 51% and 9.7% of H-1B recipients. (http://www.pewresearch.org/fact-tank/2017/04/27/key-facts-about-the-u-s-h-1b-visa-program/)

An interesting theoretical study of the effects of DACA on the broader U.S. economy is by Ortega et al. (2018), which constructs a general-equilibrium model of the U.S. economy and allows for shifts between work, education and unemployment for DREAMers benefiting from DACA. The authors calibrate the model using data from an extract of the 2012 ACS containing imputed data on the immigration status of respondents, and find that DACA increased U.S. GDP by approximately $3.5 billion, or 0.02 percent, in the five years after its introduction in June 2012, corresponding to an increase of about $7,500 per employed DACA recipient. Their model also predicts that DACA increased wages of DACA recipients by approximately 12 percent, with no effect on wages of citizens.

My contribution is to address several of the issues found in previous studies on the effects of DACA on the DREAMer population, namely (i) being restricted to small sample sizes or by the short period of time for which DACA has been in effect and (ii) accurately identifying the immigration status of respondents in the survey, and therefore constructing an accurate treatment or intent-to-treat group. I use data from the 2005 to 2016 waves of the ACS, giving me a comprehensive data set with over 750,000 observations, including 120,000 potentially DACA-eligible individuals, capturing the vast majority of DACA applicants (as seen from the application data in Figure 1). Most importantly, I use data from the SIPP in order to predict the likelihood that an individual is undocumented, and then estimate a two-stage model using the ACS data, which addresses the concerns raised with Pope's identification strategy above. This approach is also arguably superior to and more comprehensive than the other papers that restrict their samples to Mexican noncitizens[10] in order to address the issue of identifying the undocumented, DACA-eligible population.

[10] Fifty-five percent of all unauthorized immigrants and 78 percent of DACA recipients were born in Mexico.

4. Conceptual Framework

DACA would affect labor market outcomes for DREAMers primarily through the elimination of labor market frictions that they face as a result of their undocumented status. Currently, unauthorized immigrants face significant obstacles to employment — the Immigration Reform and Control Act of 1986 made it illegal for employers to knowingly recruit or hire unauthorized immigrants,[11] and 20 states mandate the use of E-Verify, an online tool for checking employees' immigration status against data from the Department of Homeland Security, for some, if not all employers, and legislation has been introduced in Congress to mandate the use of E-Verify for all employers.[12] Therefore, undocumented immigrants are often restricted to employers who are willing to overlook their illegal status, and we would thus expect undocumented immigrants to face higher rates of unemployment and underemployment, as well as lower wages. This is borne out in the empirical data — for example, Hall et al. (2010) find that undocumented Mexican immigrants earn 17 percent less than legal ones.

Unauthorized immigrants also face other frictions and barriers in the labor market. Without documentation, they are unable to obtain bank accounts or driver's licenses, and they live in constant fear of deportation. This therefore further restricts access to jobs and labor mobility among the DREAMer population.

DACA reduces or eliminates entirely these labor market frictions by its provision of work authorization and temporary legal status to DREAMers. This therefore increases significantly the range and number of jobs for which DACA recipients are able to apply. As a result, we would expect DACA to reduce unemployment and underemployment among its recipients. Also, DACA should increase incomes among DREAMers, as more of them are employed and as they can now

[11] https://www.congress.gov/bill/99th-congress/senate-bill/1200
[12] http://www.ncsl.org/research/immigration/everify-faq.aspx

move to more high-paying jobs that they previously would not have been qualified for. By allowing its recipients to apply for bank accounts and driver's licenses, DACA also further improves labor mobility among the DREAMer population. We can see that DREAMers appear to be aware of these economic benefits of (even temporary) documented status, given the high application rate for the program in spite of the onerous documentation requirements and application process as well as the relatively expensive $465 application fee. This suggests that DREAMers foresee some economic benefit to the temporary protections afforded by DACA, presumably in terms of improved employment prospects and higher wages.

It is important to recognize that DACA does not necessarily shift the labor supply curve for DREAMers, instead increasing employment by reducing the significant frictions faced by DREAMers in the labor market. This results in an increase in the quantity of labor supplied in the broader labor market, as employers are now willing and able to hire these individuals. As a result, overall wages may fall; however, the numbers of DACA recipients are much smaller than the total U.S. workforce. There are 900,000 DACA recipients out of a total U.S. labor force of 155 million; I estimate that DACA has shifted 160,000 individuals into the labor force and a further 50,000 out of unemployment, while 10 million jobs were created in the U.S. between 2013 to 2016[13]. Therefore, the general equilibrium effects of DACA on wages should be minimal at best, especially compared to the benefits gained by DREAMers through the elimination of obstacles to employment. This is consistent with what has been modeled by Ortega et al. (2018), who find that DACA raised the wages of DREAMers by 12 percent but had no effect on the wages of citizens.

Work and education are often substitutes for each other, and DACA can have two competing effects on schooling among the DREAMer population. DACA can decrease school

[13] Data from Bureau of Labor Statistics data series LNS11000000 and CES0000000001.

attendance amongst DREAMers, as some may have chosen to attend school since they were unable to find employment because of their lack of legal status. Although DACA would not have shifted labor supply preferences, the increase in labor market opportunities and reduced risk of deportation associated with participating in the labor market would alter the return to working relative to the value of education. Therefore, DACA may have caused DREAMers to leave school and rejoin the workforce. However, DACA might also increase school attendance among the DACA-eligible population, as the additional employment opportunities afforded by the work authorization could encourage DREAMers to invest in higher education and their human capital. Therefore, it is also of interest to see which of these effects is greater.

5. Empirical Strategy

I utilize a difference-in-differences (DID) strategy similar to the one used by Pope (2016) in order to estimate the effects of DACA on the DREAMer population. DACA has certain specific and strict eligibility criteria, hence by comparing the differences in outcomes between the DACA-eligible and -ineligible populations both before and after the introduction of DACA in 2012, I am able to estimate the effect of DACA on the various labor, education and healthcare outcomes of interest.

The base DID model is identical to Pope's (2016), and is as follows:

$$Y_{it} = \beta_0 + \beta_1 AgeEligible_{it} * After_{it} + \beta_2 AgeEligible_{it} + \beta_3 After_{it} + \beta_4 X_{it} + \beta_5 W_{it} + \theta_t + \gamma_s + \gamma_s t + \varepsilon_{it} \quad (1)$$

where Y_{it} is the outcome of interest, and $AgeEligible_{it}$ is a dummy variable equal to 1 if the individual meets the age and age-of-arrival criteria for DACA, the construction of which is discussed further in §6.1.1. $After_{it}$ is a dummy equal to 1 for year greater than 2012, i.e. after the introduction of DACA,[14] X_{it} is a vector of individual demographic controls (gender, race, ethnicity, marital status, level of education, Spanish-speaking household and country of birth) and the state-level unemployment rate for that year, W_{it} corresponds to fixed effects for age and age the individual entered the U.S., θ_t *and* γ_s are year and state fixed effects, respectively, and $\gamma_s t$ are state-specific time trends. The coefficient of interest is β_1, the coefficient on the interaction between $AgeEligible_{it}$ and $After_{it}$, i.e. the effect of DACA on the outcome of interest.

It is important to note that the data from the ACS used to estimate this model does not include information about the immigration status of respondents, only collecting information on whether an individual is a citizen or not. Ideally, one would estimate the DID model on a sample of unauthorized immigrants, with the control group being DACA-ineligible immigrants and the intent-to-treat group being DACA-eligible immigrants, in order to obtain an estimate of the benefits of the legal status and protections afforded by DACA. However, as discussed in Section 3 above, using the ACS data we are only able to estimate this model on a sample of noncitizens. As a result, the sample will be contaminated with legal immigrants, such as F-1 and H-1B visa holders.

Therefore, the two groups in this estimation are *not* DACA-eligible and DACA-ineligible unauthorized immigrants, but rather noncitizens who meet the DACA age and age-of-arrival criteria (and may or may not actually be eligible for DACA, dependent on whether they possess legal status or not) and noncitizens who do not meet the DACA age criteria. Pope (2016) claims this will bias the DID estimates toward zero and underestimate the intent-to-treat effect, which is likely if legal immigrants are placed in the intent-to-treat group.

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[14] DACA was introduced in June 2012, however applications were only approved from 4Q 2012, and the bulk of approvals occurred in 2013. Unfortunately, the ACS does not include more granular time information, hence in this model we consider the post-intervention period to be 2013 and beyond.

Furthermore, the DID estimates obtained are *intent-to-treat* effects, not treatment effects, since the DACA eligibility criteria only allow us to identify individuals who potentially qualify for DACA, but do not tell us whether they have actually applied for and received deferred action.[15] Since it is estimated that only about 60 percent of the DREAMer population has applied for and been granted DACA (Batalova et al., 2014), the magnitudes of the actual treatment effects could be as much as 1.6–1.7 times as large as the intent-to-treat effects. Of course, this assumes that there are no differences between the DREAMers who apply for DACA and those who do not, which might not be a very valid assumption given the onerous application process involved in applying. Nevertheless, this issue of selection into DACA would not affect the intent-to-treat effects obtained by the DID analysis.

In order to address the problem of sample contamination by noncitizens, and obtain more accurate estimates of the intent-to-treat effect of DACA, I estimate a two-stage model as follows:

$$Unauthorized_{it} = \delta_0 + \delta_1 X_{it} + \delta_2 Age_{it} + \delta_3 Birth\_region_i + u_{it} \tag{2}$$

$$\begin{aligned} Y_{it} = {} & \beta_0 + \beta_1 AgeEligible_{it} * \widehat{Unauthorized}_{it} * After_{it} \\ & + \beta_2 AgeEligible_{it} * \widehat{Unauthorized}_{it} + \beta_3 After_{it} \\ & + \beta_4 \widehat{Unauthorized}_{it} + \beta_5 AgeEligible_{it} + \beta_6 X_{it} + \beta_7 W_{it} \\ & + \theta_t + \gamma_s + \gamma_s t + \varepsilon_{it} \end{aligned} \tag{3}$$

The first-stage model, equation (2), is a probit model where the dependent variable $Unauthorized_{it}$ is a dummy variable equal to 1 if the individual is an unauthorized immigrant and 0 otherwise. The independent variables are the same vector of demographic controls X_{it} as in equation (1), excluding country of birth and state unemployment rate, as well as controls for age (Age_{it}) and a set of

[15] The identification strategy is discussed further in §6.1.1.

dummies for region of birth ($Birth\_region_i$).[16] This model is estimated on a sample of noncitizen immigrants from the 2008 SIPP, which is one of the few large, nationally representative surveys that collects respondents' immigration status.

The estimated coefficients $\hat{\delta}_j$ obtained from the first stage can be used with the demographic information available in the ACS to predict the likelihood that an individual is unauthorized, $\widehat{Unauthorized}_{it}$. This method of using a "donor" sample to predict the immigration status of individuals in another data set has been commonly used throughout the immigration literature (Bachmeier et al., 2014; Capps et al., 2013).

We then estimate the second stage of the model, equation (3), on the ACS sample. Equation (3) is similar to the original DID model specified in equation (1), except that we now interact the DACA age and age-of-arrival eligibility dummy $AgeEligible_{it}$ by the probability that the individual in question is undocumented, $\widehat{Unauthorized}_{it}$. The coefficient of interest remains β_1, the coefficient of the interaction term $AgeEligible_{it} * \widehat{Unauthorized}_{it} * After_{it}$. However, the interpretation of the interaction term is different: the interaction variable $AgeEligible_{it} * \widehat{Unauthorized}_{it}$ is now an indicator for actual DACA eligibility. A one-unit shift in the variable $\widehat{Unauthorized}_{it}$ corresponds to a shift in the probability of being an unauthorized immigrant from zero to one, and DACA eligibility requires one to meet the age and age-of-arrival requirements as well as to be unauthorized. Hence, the coefficient on the interaction $AgeEligible_{it} * \widehat{Unauthorized}_{it} * After_{it}$ corresponds to the effect of DACA on the DACA-eligible population.

This therefore addresses the point raised above regarding the contamination of the sample by legal immigrants to an extent — even though the sample will still contain legal immigrants, some of whom meet the age and age-of-arrival criteria for DACA, they would no longer be

[16] Unlike the ACS, the SIPP only provides information regarding general birth regions, not specific birth countries.

included in the intent-to-treat group. As a result, the DID coefficient should no longer be biased toward zero and provide a more accurate estimate of the intent-to-treat effect of DACA on the DREAMer population. The sample construction for both the initial DID model and the two-stage DID model is discussed further in Section 6 below.

6. Data Description

6.1. *American Community Survey*

The American Community Survey (ACS) is a monthly, rolling sample of households in the U.S. administered by the U.S. Census Bureau, which is designed to replace the "long form" portion of the decennial U.S. census. The ACS samples roughly 295,000 households a month (242,000 from 2005–11), giving an annual sample of approximately 3.54 million households (2.9 million from 2005–11), i.e. an annual 1 percent sample of the U.S. population beginning in 2005.[17, 18] The ACS is the largest household survey conducted by the Census Bureau, and collects detailed information on demographics, education, labor outcomes and housing.

The sampling unit of the ACS is the household and all persons living in that household. Every month, the Census Bureau draws a systematic random sample of households from addresses in its Master Address File, representing each U.S. county or county equivalent, with areas of smaller populations being oversampled. The survey is mailed to the selected households at the beginning of each month, and nonrespondents are contacted via telephone for a phone interview a month later. A systematic sample of a third of the nonrespondents to both the mail survey and telephone interview is then drawn a month later, and this sample is then interviewed in-person.

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[17] https://www2.census.gov/programs-surveys/acs/methodology/design_and_methodology/acs_design_methodology_report_2014.pdf

[18] The ACS surveyed between 740,000 to 900,000 households annual from 2000 to 2004, i.e. approximately a 1-in-250 sample of the population.

The ACS covers almost 99 percent of all housing units in the United States,[19] and the Census Bureau reports that from 2005 to 2016, 62.2– 68.2% of households selected for the sample each year completed the survey, with a response rate of 89.9–98.0% for households selected for an in-person interview.[20] Given that the ACS covers effectively all the housing within the United States, and that samples are drawn systematically from the sampling frame, there is no reason to believe that unauthorized immigrants are under- or overrepresented in the ACS data, or that certain groups of unauthorized immigrants are more likely to be surveyed than others. Furthermore, like the U.S. Census, the ACS is conducted "without regard to legal status or citizenship," [21] hence we do not expect any differences in the survey or response rates of unauthorized immigrants compared to the rest of the population. The high response rates for the ACS also support the claim that the data in the ACS contains a representative sample of the unauthorized immigrant population of the U.S. In addition, Pope (2016) analyzes survey completion and individual-item response rates in the ACS data, and shows that neither immigration status nor DACA affected the completion and response rates in the data.

In this paper I use individual-level data from the 2005 to 2016 ACS surveys; with 2005 being the first year with a 1 percent sample of the population and 2016 being the latest sample available. This gives me eight years of data before the introduction of DACA[22] and four years post-DACA. I restrict my sample to noncitizens aged 18–35 with at least a high school degree, since the oldest group of DREAMers in 2012 (those who turn 31 just after June 15, 2012) would be 35 by the time of the 2016 ACS survey. Ideally, the sample would be restricted to unauthorized

[19] https://www.census.gov/acs/www/methodology/sample-size-and-data-quality/coverage-rates/
[20] https://www.census.gov/acs/www/methodology/sample-size-and-data-quality/sample-size/ and https://www.census.gov/acs/www/methodology/sample-size-and-data-quality/response-rates/index.php
[21] See note 17, p. 64.
[22] I count 2012 as part of the pre-DACA period; even though DACA was announced in June 2012, DHS did not begin taking applications until September and the first approvals were only received in 4Q 2012. Also, although the ACS is administered monthly, results are not broken down nor identified by month, only by year.

immigrants, as discussed in Section 5, but the ACS does not collect information on immigration status. The following subsection explains how I determine the control and intent-to-treat groups in this sample.

6.1.1. *Identification Strategy*

I utilize Pope's (2016) identification strategy in constructing the control and intent-to-treat groups in the ACS sample. The ACS collects detailed demographic information which can be used to determine if an individual meets the age and age-of-arrival criteria for DACA or not. DACA requires that an individual is under the age of 31 on June 15, 2012; the ACS does not provide exact dates of birth, only birth quarter and year, hence I consider individuals under 31 as of June 30 of a survey year to meet that eligibility criterion.[23] DACA also requires an individual to have come to the U.S. before their 16th birthday and to have resided in the U.S. since June 15, 2007 (i.e. for at least five years); the ACS asks noncitizens how long they have resided in the country, so I can use this information together with a respondent's age to calculate the age at which they arrived in the U.S. (to the nearest year), and determine whether they meet these two criteria.

Another requirement for DACA is for a recipient to either be currently in school or to possess a high school degree or its equivalent. The ACS collects respondents' educational attainment; hence I restrict my sample to all noncitizens who have a high school degree or equivalent. However, this does exclude individuals who are still completing high school or a GED, as well as those who have been honorably discharged from the armed forces, from the sample. There are probably few DREAMers who fall in the latter group; however, the numbers in the former group might be substantial. That said, this essay focuses on labor market outcomes of

[23] That is, all individuals 30 and under, as well as those aged 31 but born in the second half of the year.

DREAMers, and I expect that those still in high school would not also be working, nor would they be likely to move out of education and into work.

The information available in the ACS does not allow me to verify all the eligibility criteria for DACA. Most importantly, I cannot know if an individual is a legal or an unauthorized immigrant. Also, I do not have any information on individuals' criminal records (DACA requires that individuals have not been convicted of a felony or serious misdemeanor) nor on their military service. Nor is there information on whether individuals have left the U.S. and returned since coming to the country. However, I believe that these three criteria would only apply to, or exclude, a very small minority of DREAMers, and should not have any significant effect on the DID estimates.

Therefore, the three criteria from the ACS that I use to determine whether an individual is potentially eligible for DACA or not are (i) being under the age of 31 as of June 30 of the survey year; (ii) having come to the U.S. before age 16; and (iii) having resided in the U.S. for at least five years. I therefore use these criteria to construct the control or intent-to-treat groups for the difference-in-differences estimation: If an individual meets all 3 criteria, and therefore is *potentially* a DREAMer (which is ultimately dependent on immigration status, which we do not know), I set the variable $AgeEligible_{it}$ equal to 1. If not, the eligibility variable is set to 0. We can also see that this appears similar to a regression discontinuity design, and in Appendix I, I estimate models on various subsamples based on only criteria (i) and (ii) separately. The following subsection discusses the outcome variables I examine and gives the summary statistics for the two groups in the sample.

6.1.2. *Outcome Variables*

There are four main outcomes of interest in this paper, namely employment, income, schooling and health insurance coverage. Employment can be measured in several ways: whether an individual is in the labor force, and if so, whether they are employed or not; as well as the amount an individual works as measured in hours worked per week. The ACS provides a dummy variable for labor force participation, as well as a categorical variable for whether an individual is employed, unemployed or not in the labor force, which I recode as binary variables for employment and unemployment. Additionally, the ACS data also contains another binary variable for whether an individual has worked in the past year. These four variables therefore can show whether DACA has shifted DREAMers into the labor force, as well as from unemployment into employment. The ACS also contains a variable on the average number of hours worked per week, as well as a dummy for whether an individual is self-employed; these provide further information as to if and how DACA has affected or changed the nature of work performed by DREAMers.

In order to measure the effect of DACA on wages, I look at three income variables: total personal income, total wage income and the hourly wage rage. The first two variables are given directly in the ACS and report respondents' total pre-tax income in the 12 months prior to the survey; the former records income from all sources while the latter records wage and salary income. I find similar results regardless of measure chosen, hence for the remainder of this paper I use total income as the variable of interest; results using wage income are available in Appendix II. The hourly wage rate can be constructed from three variables available in the ACS, from dividing total wage income by the product of average hours worked per week and the number of weeks worked in the past 12 months. The resulting values are then trimmed to remove any extreme outliers (wage rates of less than \$4/hour and greater than \$250/hour), and in my analysis I also exclude individuals who worked for less than half a year (under 26 weeks) in the preceding 12-month period. Examining changes in wage rates can provide information on whether DACA has allowed DREAMers to move to better jobs.

As for schooling and health insurance coverage, I use the indicator variables for school attendance and being covered by health insurance available in the ACS. The frame of reference for school attendance for the ACS is within the past three months of the survey being administered, and schooling is defined as attending a nursery school, kindergarten, elementary school and any schooling leading toward a high school diploma or college degree. The ACS began including questions regarding health insurance coverage starting from 2008, hence for that variable we have five years of pre-DACA information and four years post-DACA. An individual is defined to have health insurance if he is covered by any type of health insurance, e.g. from an employer, from Medicare or Medicaid, or self-purchased insurance.

6.1.3. Summary Statistics

Table 1 on the following page reports the summary statistics from the ACS 2005–2016 data, restricted to individuals aged 18 to 35 with at least a high school degree, and split between individuals identified as meeting the DACA age and age-of-arrival criteria as defined in §6.1.1 (and who therefore are potentially DREAMers, dependent on immigration status which is unobserved) and individuals who do not meet the criteria. In total there are 528,296 observations in this sample, corresponding to about 44,000 observations per year, with 120,839 or 23% being age-eligible and the remaining 407,457 or 77% ineligible.

We can see from Table 1 that the individuals who meet the age criteria for DACA are, on average, younger, entered the U.S. at a younger age and have spent more time in the country than

Variable	Mean: DACA Age-Eligible	Mean: DACA Age-Ineligible	Difference	*t*-statistic
Outcome variables				
Working	66.2	66.1	0.1	0.2
Worked in past year	75.7	73.4	2.4	6.4
Hours worked per week	27.3	28.3	-1.0	-6.4
Self-employed	3.9	5.2	-1.4	-13.8
Unemployed	8.2	5.2	3.0	17.6
In labor force	74.4	71.4	3.0	9.2
Total income	16,189	25,002	-8,812.1	-31.9
Total wage income	15,149	23,340	-8,190.7	-30.6
Hourly wage	14.10	19.64	-5.54	-27.6
Attending school	31.8	22.1	9.7	27.0
Has health insurance†	51.5	62.7	-11.2	-18.1
Demographics				
Age	24.0	28.7	-4.7	-152.4
Years in U.S.	15.7	6.3	9.3	129.4
Age entered U.S.	8.3	22.3	-14.0	-248.1
Male	52.6	51.7	1.0	4.4
Married	24.0	51.0	-27.0	-96.2
White	50.3	42.7	7.6	9.7
Black	9.3	9.2	0.1	0.2
Asian	14.2	32.2	-18.0	-27.9
Hispanic	66.2	40.8	25.4	22.9
Speaks Spanish at home	58.3	37.2	21.1	14.5
Born in Latin America	73.1	46.0	27.0	31.9
High school degree	49.5	36.2	13.3	33.7
Some college	40.3	25.4	15.0	47.4
College degree	10.2	38.5	-28.3	-66.9
Observations	120,839	407,457		
Percent	22.8%	77.2%		

Table 1. Summary statistics.

Sample consists of noncitizens in ACS 2005–2016 aged 18–35 with at least a high school degree (N = 528,296). Binary variables are given in percentage terms. t-statistics are calculated using robust standard errors clustered at the state-year level. Observations are weighted using person weights in the ACS.
† The ACS only began collecting information on health insurance from 2008; for that variable there are 92,884 observations in the DACA-eligible group and 303,107 in the ineligible group.

the ineligible group. They are also significantly more likely to be of Hispanic ethnicity, speak Spanish at home and to have been born in Latin America. However some, if not most, of this difference is probably due to contamination of the sample by lawful immigrants, who tend to come from countries such as India and China and who are more likely to be ineligible for DACA,[24] while most of the unauthorized immigrant population is from Mexico and Latin America. The DACA age-eligible population is also relatively less educated than the ineligible population, but this might also be suggestive of sample contamination by F-1 and H-1B visa holders.

Examining the outcome variables, we see that the two groups have similar rates of working and labor force participation; however, the DACA age-eligible group is more likely to be unemployed and uninsured than the ineligible group. Also, the DACA age-eligible group has significantly lower incomes, on average, than the DACA-ineligible group; however, this again might be due to sample contamination by H-1B visa holders and other lawful immigrants.

6.2. *Survey of Income and Program Participation*

In order to address the problem of legal immigrants being present in the sample, and specifically in the intent-to-treat and potentially DACA-eligible group, I use data from the second wave of the Survey of Income and Program Participation (SIPP) 2008 to estimate a first-stage model based on certain demographic parameters that predicts the likelihood of a noncitizen being an unauthorized immigrant, as discussed in Section 5.

The Survey of Income and Program Participation is a longitudinal survey of American households, carried out over a period of two-and-a-half to four years by the U.S. Census Bureau, to collect information regarding income, labor force participation and eligibility for and participation in public assistance programs.[25] At first glance, it might not be apparent why the SIPP is useful for predicting an individual's legal status. However, the SIPP is actually the only nationally representative survey that includes questions regarding immigration history and the

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[24] See Section 3 and note 9.

[25] https://www.census.gov/programs-surveys/sipp/about/sipp-introduction-history.html

legal status of noncitizens (Capps et al., 2013), specifically in one of the topical modules found in the 2004 and 2008 SIPP. Hence the SIPP has often been used in the immigration literature as a "donor" sample in order to predict the immigration status of individuals in other data sets (Bachmeier et al., 2014; Capps et al., 2013), especially since the SIPP samples are still relatively small, and in this case also because it does not extend to the period when DACA was introduced.

Each SIPP panel comprises 14,000 to 52,000 U.S. households, drawn from a stratified sample of the U.S. civilian population, and a panel lasts between 2.5 and 4 years. The 2008 SIPP contained 52,031 eligible households interviewed over four years.[26] Every household in the panel is interviewed at four-month intervals, known as waves. Each wave consists of a set of core questions relating to income, work and labor force and program participation, as well as a topical module specific to that wave. The first, second and sixth waves were conducted in person, with interviews for all other waves conducted via telephone.[27] The 2008 SIPP had a response rate of 80.8% at the first wave and 74.2% at the second wave, corresponding to 37,471 households interviewed in the second wave.[28]

The second wave of the 2008 SIPP (administered between September 2008 and March 2009) included a topical module on migration, with questions pertaining to immigration status; I use the data in this module as well as the associated core module for this wave to obtain demographics about the authorized and unauthorized immigrant populations in the United States. In this wave, all respondents not born in the U.S. were asked about their citizenship status as well as their immigration status upon their entry to the country, i.e. whether they were lawful permanent residents or not. Those who did not enter the U.S. as a lawful permanent resident were then asked

[26] https://www.census.gov/programs-surveys/sipp/methodology/organizing-principles.html
[27] https://www.census.gov/programs-surveys/sipp/methodology/organizing-principles/mode-of-data-collection.html
[28] https://www2.census.gov/programs-surveys/sipp/tech-documentation/complete-documents/2008/sipp-2008-panel-wave-02-nonresponse-bias-analysis-alys-13.pdf

if they had adjusted to lawful status since entering the country. Therefore, even though the survey does not directly ask if one is an unauthorized immigrant or not, I can infer that noncitizens who did not enter with lawful status and who have not obtained permanent residency are unauthorized immigrants.[29]

	Mean			
Variable	Unauthorized	Authorized	Difference	*t*-statistic
Age	29.1	30.3	-1.3	-3.0
Male	56.2	49.3	6.8	2.5
Married	49.8	56.9	-7.0	-2.6
White	69.1	61.1	8.0	2.3
Black	9.6	13.9	-4.3	-1.5
Asian	18.5	22.1	-3.5	-1.0
Hispanic	56.6	39.4	17.2	4.1
Speaks Spanish at home	56.4	44.1	12.2	3.3
Born in Latin America	67.2	55.1	12.1	2.5
High school degree	50.1	37.9	12.2	4.0
Some college	10.2	17.2	-6.9	-3.9
College degree	39.7	44.9	-5.3	-2.6
Observations	764	1,374		
Percentage	35.7%	64.3%		

Table 2. Summary statistics.

Sample consists of noncitizens in the second wave of SIPP 2008 aged 18–40 with at least a high school degree ($N = 2{,}138$). Binary variables are given in percentage terms. *t*-statistics are calculated using robust standard errors clustered at the state level. Observations are weighted using person weights in the SIPP.

Table 2 above reports the summary statistics for the demographics of the sample from the second wave of the 2008 SIPP, restricted to noncitizens aged 18 to 40 and separated by immigration status as inferred from their responses to the migration module. This sample contains 2,138 individuals, of which 764 (35.7%) are inferred to be unauthorized immigrants and the remaining 1,375 (64.3%) are legal immigrants. From the data we can see that unauthorized immigrants are more likely to be male, Hispanic, Spanish-speaking and born in Latin America, which is consistent with what we know about the unauthorized population in the United States

[29] It is possible that this group will also encompass a small number of legal, temporary nonimmigrants, such as students or temporary workers.

(Baker, 2014). Unauthorized immigrants are also on average less educated than their authorized peers. I use these demographics to estimate a probit model for the probability that a noncitizen is an unauthorized immigrant.

7. Results and Discussion

7.1. *Graphical Results*

I first begin the difference-in-differences analysis using a straightforward, graphical method, plotting the differences between the means of the outcome variables for individuals in the ACS who meet the age criteria for DACA (i.e. are potentially DREAMers) versus those who do not, without any demographic controls or other fixed effects. This can show us if DACA has had any effect on these variables — if so, we expect to see a change in the differences of the means from 2013 onward. This graphical approach also checks for any sort of differential pre-trends between the two groups which might render the DID estimates invalid, if the parallel trend assumption required for DID does not hold. Figures 2 to 5 on the following pages show the graphs of these outcome variables.

Figure 2 on page 32 shows the difference in means between the two groups for three variables associated with working: (a) whether an individual is working or not, (b) whether the individual worked in the past year and (c) the average number of hours worked in the past week. We can see that prior to the introduction of DACA in June 2012 (the shaded area on the graph), the difference in the means of the two groups is relatively constant, suggesting that the parallel trend hypothesis required for the validity of the DID estimates holds. We also see that DACA has had a strong effect on all these three outcome variables: in Figure 2(a), DACA appears to have

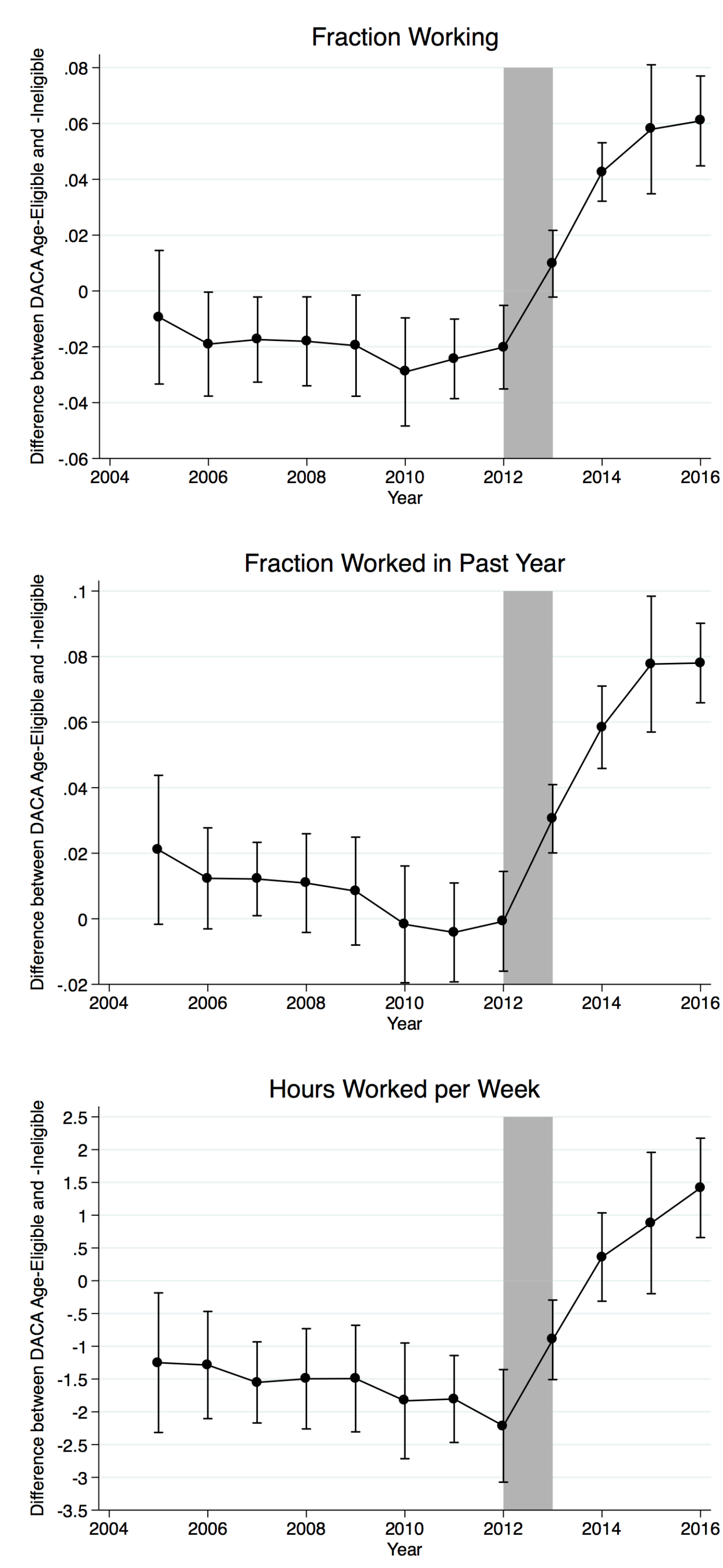

Figure 2. Differences in means of (a) fraction working, (b) fraction worked in the past 12 months and (c) average hours worked per week between individuals who meet the age eligibility criteria for DACA and who do not. Sample contains all noncitizens in 2005–2016 ACS aged 18–35 with at least a high school degree. Vertical bars correspond to 95% confidence intervals, calculated with robust standard errors clustered at the state-year level. Observations are weighted using person weights in the ACS. The shaded area represents the period in which DACA was introduced.

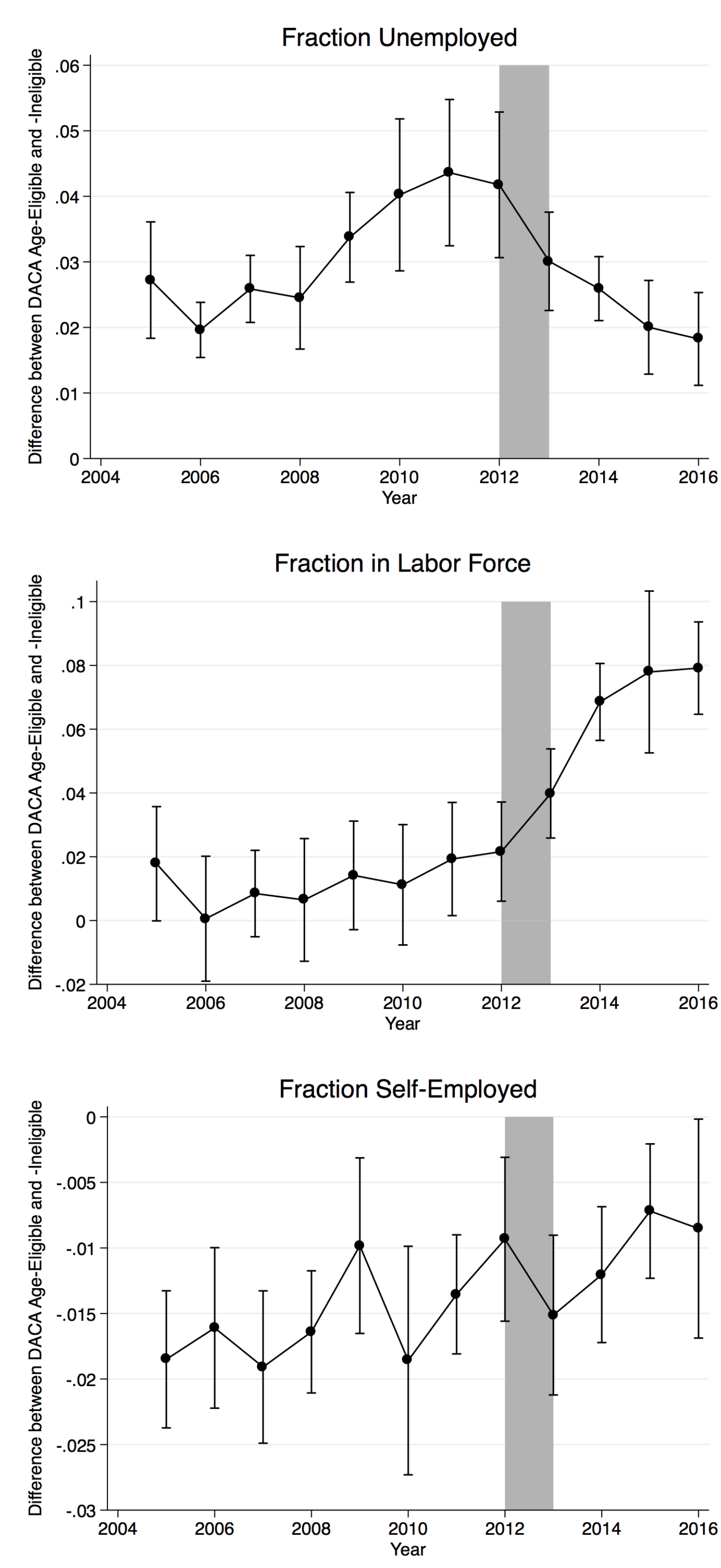

Figure 3. Differences in means of (a) fraction unemployed, (b) labor force participation rate and (c) fraction self-employed between individuals who meet the age eligibility criteria for DACA and who do not. Sample contains all noncitizens in 2005–2016 ACS aged 18–35 with at least a high school degree. Vertical bars correspond to 95% confidence intervals, calculated with robust standard errors clustered at the state-year level. Observations are weighted using person weights in the ACS. The shaded area represents the period in which DACA was introduced.

increased the likelihood of an individual who meets the age and age-of-arrival eligibility criteria working by about 6 percentage points relative to an ineligible individual between 2012 and 2014, and in Figure 2(c) we see that DACA has increased the average number of hours worked per week by about 2.5 hours for DACA age-eligible individuals relative to ineligible ones. Also, we see that the differences in means between the two populations has continued to widen in 2015 and 2016, even though the bulk of new DACA applications and approvals occurred in 2013–14; which suggests that DREAMers continue to experience the benefits of deferred action conferred by DACA, and that the effect of DACA has increased over time.

Figure 3 on page 33 plots the difference in means for three more labor market outcomes: (a) unemployment, (b) labor force participation and (c) the fraction self-employed. The results here are mixed — we see in Figure 3(b) that post-DACA the labor force participation rate for age-eligible individuals has increased about 5.5 percentage points relative to ineligible individuals between 2012 and 2014, which is similar to the results for the likelihood of working. However, the results for unemployment appear weaker: DACA appears to have reduced the difference in unemployment between the two populations from 2012, but there is a strong upward trend in the differences from 2008 to 2012, presumably corresponding to the Great Recession and some differential effects between the two groups; hence the decrease in the difference in means post-2012 might also be due to the subsequent economic recovery. Also, we see no discernible trend or effect of DACA on the fraction of individuals who are self-employed.

Figure 4 on the next page shows the graphs of the differences in the means of total personal income and log hourly wage between the two populations. We can see in Figure 4(a) that there appears to be a strong downward trend in the differences even pre-DACA, and no significant effect

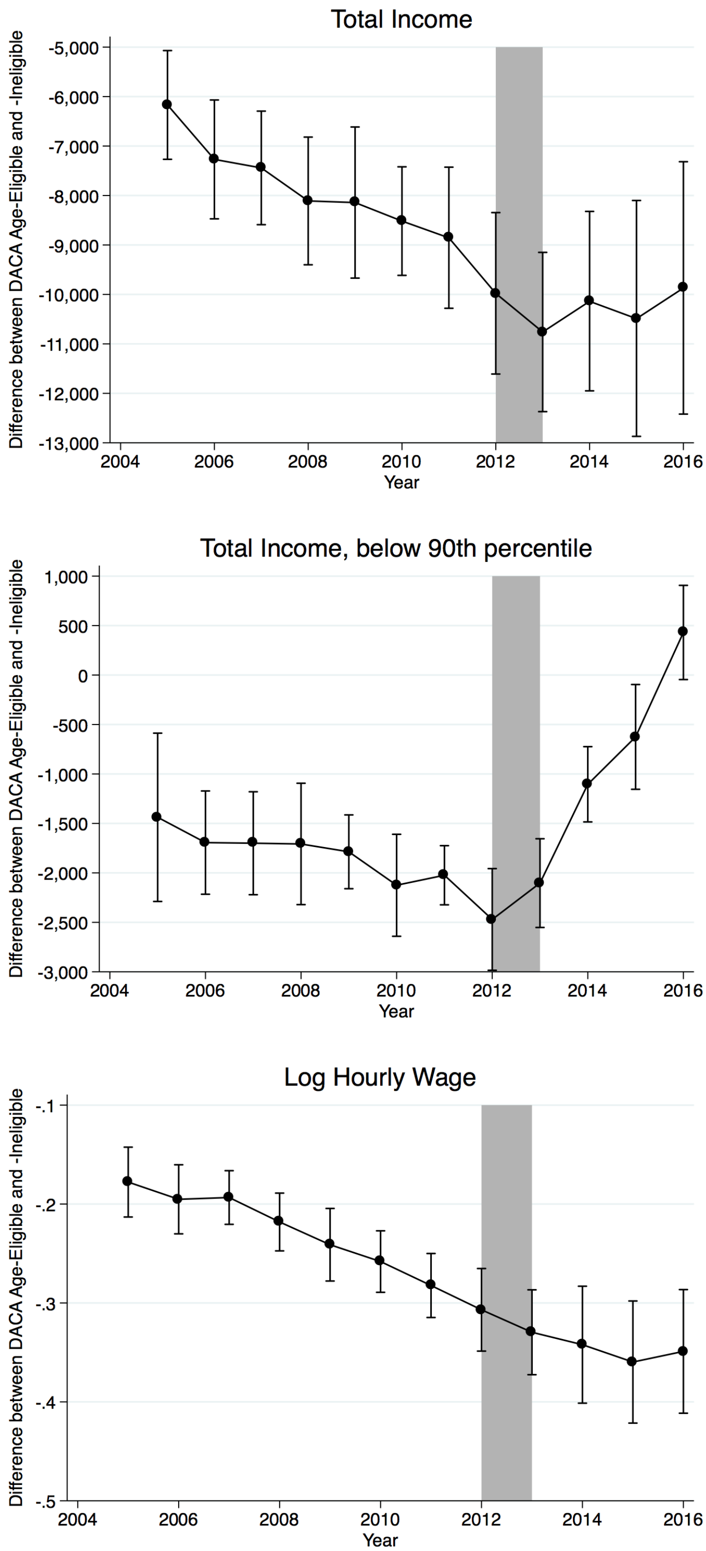

Figure 4. Differences in means of (a) and (b) total personal income and (c) log hourly wage between individuals who meet the age eligibility criteria for DACA and who do not. Sample contains (a) all noncitizens in 2005–2016 ACS aged 18–35 with at least a high school degree, (b) restricted to individuals with total incomes below the 90th percentile, and (c) restricted to individuals who worked for at least half of the prior 12-month period. Income are in nominal U.S. dollars unadjusted for inflation. Vertical bars correspond to 95% confidence intervals, calculated with robust standard errors clustered at the state-year level. Observations are weighted using person weights in the ACS. The shaded area represents the period in which DACA was introduced.

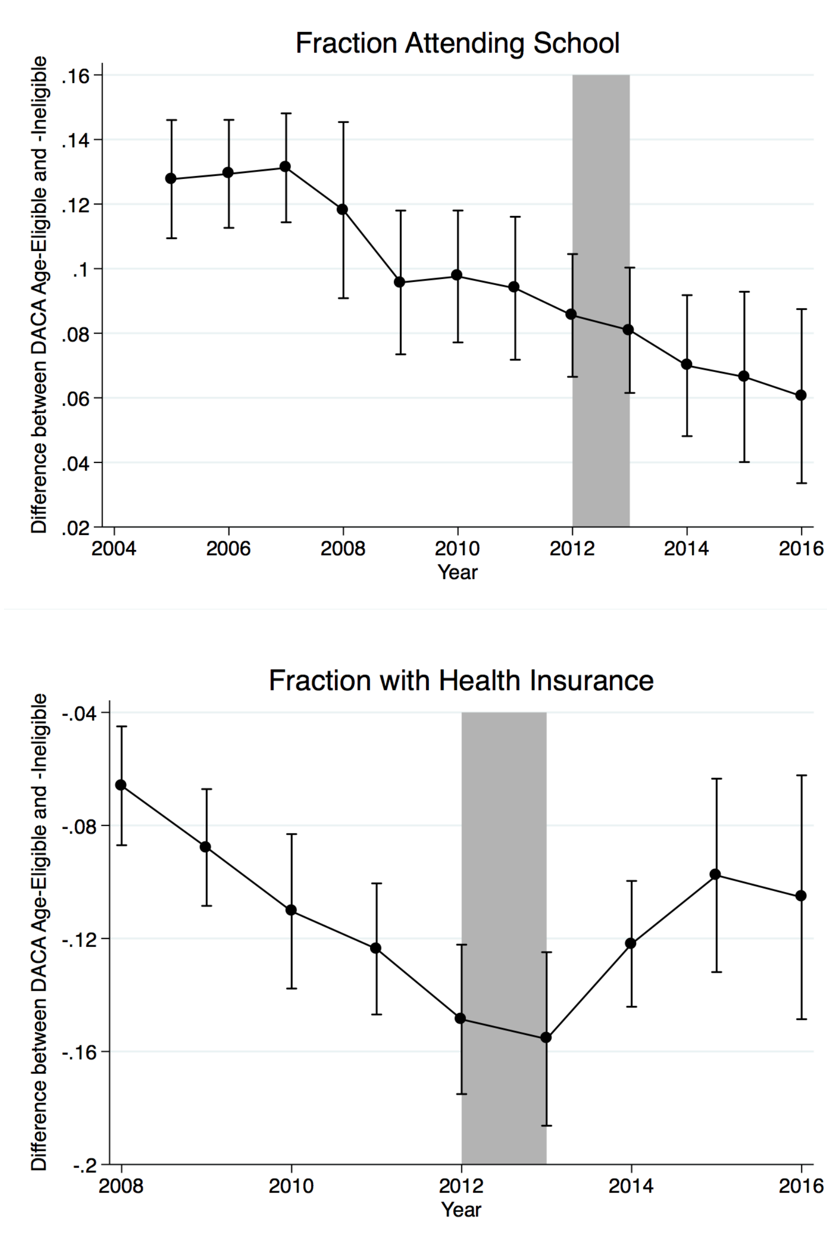

Figure 5. Differences in means of (a) fraction attending school and (b) fraction with any health insurance coverage between individuals who meet the age eligibility criteria for DACA and who do not. Sample contains all noncitizens in (a) 2005–2016 ACS and (b) 2008–2016 ACS aged 18–35 with at least a high school degree. Vertical bars correspond to 95% confidence intervals, calculated with robust standard errors clustered at the state-year level. Observations are weighted using person weights in the ACS. The shaded area represents the period in which DACA was introduced.

post-DACA; however, this seems to be driven strongly by differences in the top decile of the income distribution — when we restrict our sample to the bottom 90 percent of the income distribution in Figure 4(b), we see that the differential pre-trend disappears, and that DACA has had a strong effect on incomes of those individuals who meet the age and age-of-arrival eligibility criteria relative to those who do not. Post-DACA, the difference in mean income between the age-eligible and -ineligible groups has decreased by about \$1,500 between 2012 and 2014. However, this increase in income appears to not have been driven by an increase in hourly wage rates — in Figure 4(c) we see a strong negative differential trend in the wage differential between the two groups, and no apparent effect from DACA.

Figure 5 on the previous page provides the graphical analysis for the effects of DACA on schooling and healthcare. The preliminary results in both cases are considerably weaker: in Figure 5(a), we see that there is a strong negative pre-trend in the differences in school attendance before the introduction of DACA, and DACA does not appear to have had much of an effect on school attendance from 2013 onward; instead the negative trend continues. In Figure 5(b), we see a similar strong negative pre-trend for health insurance coverage; however, in this case DACA appears to have reduced the differences in means between the eligible and ineligible populations between 2013 and 2015 by about 6 percentage points, relative to a base level of 51 percent coverage for the intent-to-treat group and 63 percent for the control group.

7.2. *Initial Difference-in-Differences Results*

We can now introduce controls and fixed effects in order to estimate the initial difference-in-differences model specified in equation (1) in Section 5. The results of this estimation are shown in Table 3 on the following page. Each column in Table 3 corresponds to a separate regression for each outcome variable on a sample of noncitizens aged 18 to 35 with at least a college degree in the 2005–2016 ACS (2008–2016 for healthcare). The coefficient of interest is the coefficient on the interaction term between DACA age-eligibility and the dummy signifying after the introduction of DACA, which provides the estimated intent-to-treat effect of DACA on the particular outcome variable.

From the results in Table 3 we can see that DACA increased the likelihood of an individual meeting the age and age-of-arrival criteria for DACA (and who is therefore potentially a DREAMer) working by 4.4 percentage points (column 1). With an estimated DREAMer population of 1.5 million, this corresponds to approximately 65,000 more DREAMers working as a result of DACA. Also, this is an intent-to-treat effect, and since only about 60% of eligible DREAMers have applied for DACA, the actual treatment effect could be up to 1.67 times larger, i.e. up to 7.3 percentage points.

The increase in the number of DREAMers working post-DACA can arise from two possible pathways. First, DACA might reduce unemployment among DREAMers currently in the labor force, by reducing barriers to employment and labor market frictions. In column (4), we estimate the effect of DACA on unemployment, and find that the introduction of DACA has led to the reduction of unemployment by approximately 1.6 percentage points from a pre-DACA level of 11.6 percent, significant at the 1% level, which corresponds to approximately 18,000 DACA-eligible individuals shifting from unemployment into employment.[30] Second, DACA can increase the likelihood of work by shifting DREAMers into the labor force, again by reducing or eliminating labor market frictions. In column (5) we see that DACA has increased the labor force participation rate of the DACA-eligible group by 3.6 percentage points from a pre-DACA 73.8

[30] I obtain this figure of 18,000 since there are approximately 1.5 million DREAMers, with an LFPR of about 74 percent (Table 2).

VARIABLES	(1) Working	(2) Worked in past year	(3) Hours worked per week	(4) Unemployed	(5) Labor force status	(6) Self-employed	(7) Total personal income	(8) Total personal income, bottom 90%	(9) Log hourly wage	(10) Attending school	(11) Has health insurance
Age-Eligible*After	0.0437***	0.0373***	1.175***	-0.0155***	0.0355***	0.00102	-1,177**	574.7***	-0.0462***	-0.00247	0.0237***
	(0.00564)	(0.00567)	(0.282)	(0.00357)	(0.00515)	(0.00184)	(578.3)	(168.0)	(0.0125)	(0.00544)	(0.00827)
Age-Eligible	0.0678***	0.0601***	2.426***	-0.00955**	0.0664***	0.00510*	6,606***	1,243***	0.0801***	-0.0323***	-0.0487***
	(0.00523)	(0.00483)	(0.213)	(0.00385)	(0.00497)	(0.00288)	(549.8)	(173.1)	(0.00975)	(0.00508)	(0.00754)
Age-eligible sample mean, pre-DACA	0.652	0.757	27.6	0.116	0.738	0.0378	16,025	14,180	2.436	0.320	0.481
Observations	528,296	528,296	528,296	369,509	528,296	528,296	528,294	476,565	295,132	395,991	528,296
R-squared	0.130	0.126	0.186	0.031	0.132	0.021	0.217	0.204	0.355	0.221	0.132

Table 3. Difference-in-differences estimates of the effect of DACA on various labor market, education and healthcare outcomes.

Each column corresponds to a separate regression for the corresponding outcome variable by estimating equation (1) on a sample containing noncitizens aged 18–35 with at least a college degree in the 2005–2016 ACS (2008–2016 for health insurance coverage). The coefficient of interest is the coefficient on the *AgeEligible*After* interaction term. Income in columns 7 and 8 measured in nominal U.S. dollars and uncorrected for inflation. Log hourly wage in column 9 is restricted to individuals who worked for at least half the prior 12-month period. Coefficients for demographic controls, fixed effects and state-year time trends are not shown. The row *Age-eligible sample mean, pre-DACA* gives the sample mean for individuals before 2012 who meet the age eligibility criteria for DACA. Observations are weighted using person weights in the ACS. Robust standard errors clustered at the state-year level in parentheses.
*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

percent, also significant at the 1% level, which equates to approximately 50,000 more DREAMers entering the labor force.

Also, I examine the effect of DACA on the average number of hours worked per week in column (3). The introduction of DACA has increased the average hours worked per week by an individual who meets the DACA age-eligibility criteria by 1.2 hours per week; this effect is also significant at the 1% level. We can thus see from our results in columns (1) through (5) that DACA has had a strong effect on the employment outcomes of the age-eligible group, i.e. the group of potential DREAMers. However, there is no apparent effect of DACA on the likelihood of being self-employed (column 6). This is not surprising given the graphical results in Figure 3(c) which show no DID effect; this might also be due to the very small number of self-employed individuals in the sample and in the general population.

Next, we look at the effect of DACA on income and wages in columns (7) and (8) of Table 3. From column (7) it appears that the introduction of DACA has *decreased* the total income of the DACA age-eligible population; however, from the graphical analysis in Section 7.1 we know that this is effect is probably driven by the top decile of the income distribution, and that there is a strong negative pre-trend present as well. When we restrict the sample to individuals with total incomes below the 90^{th} percentile, we see that DACA has increased total incomes by \$575 on average, or 41 percent from the sample mean pre-DACA; this effect is also more significant. The choice of income variable does not appear to make much of a difference to the results: the results when I regress on total wage income instead of total income are similar and available in Appendix II. However, in column (9) there appears to be a small *negative* effect on the hourly wages of the individuals who meet the age eligibility criteria for DACA, although the strong negative differential trend in wages observed in the graphical analysis in Figure 4(c) suggest that this is due to the pre-trend and not to DACA itself.

The last two columns of Table 3 examine the effect of DACA on attending school (column 10) and health insurance coverage (column 11). DACA appears to have no significant effect on the school attendance of DACA age-eligible individuals, with the coefficient on the DID term being negligible and insignificant. On the other hand, the introduction of DACA is associated with a 2.4 percentage point increase in the number of potential DREAMers with some sort of health insurance coverage; this effect is significant at the 1% level. However, from the graphical results in Section 7.1, we see a strong negative pre-trend in the difference in the means of health insurance coverage in Figure 5(b), which might suggest that the parallel trend assumption required for the validity of the DID model might not hold.

In order to more rigorously test for differential trends between the control and intent-to-treat groups, I adopt the method used by Pope (2016), wherein I estimate equation (1) with the $AgeEligible_{it}$ variable interacted with a dummy variable for each year. This is equivalent to investigating how the effect of DACA eligibility varies by year. If there is no differential pre-trend, then I expect that the coefficients on the interaction terms with the years before the introduction of DACA (i.e. 2011 and before) should be insignificant, while the interactions of the eligibility variable with the years after the introduction of DACA (i.e. 2013 and beyond) should be significant (since these are equal to the DID estimates for each separate year). However, if a pre-trend does exist, then the coefficients on the interaction terms with the years before the introduction of DACA would also be significant, implying that there already was a differential trend between the DACA age-eligible and -ineligible groups even prior to the introduction of DACA.

Table 4 on the following page presents the results of this analysis. Again, each column corresponds to a separate regression for each outcome variable. Table 4 reports the coefficients on the interaction of the eligibility dummy and each year dummy; the interaction $AgeEligible_{it}*2012$ is the omitted category given how DACA was introduced midway through that year.

We can see from the results in Table 4 that for the labor market outcomes in columns (1) through (5), the coefficients on the post-DACA interaction terms, i.e. the effect of DACA on that outcome variable for that year, are all statistically significant and similar in magnitude and sign to the estimates obtained from the base DID model in Table 3. More interestingly, the magnitude of the coefficients increases from 2013 to 2016. This may be because additional DREAMers apply for DACA each year; however, given that the bulk of DACA applications were received in 2013 (Figure 1), it is also possible that this might imply that the benefits of DACA increase over time: with legal status DREAMers are able to move on to better jobs, allowing them to gain valuable work experience and invest in their skills and human capital, hence making them even more employable and further improving labor market outcomes.

Looking at the pre-DACA interaction terms in columns (1) through (5), we observe that there are no discernible pre-trends for the likelihood of working, hours worked or labor force participation, which is heartening; however, there is a negative pre-trend for unemployment between 2006 and 2008. This might not be that significant of an issue, since there is no pre-trend in the period immediately preceding the introduction of DACA (from 2009 to 2011), and since 2006–208 correspond to the years immediately preceding the Great Recession when the U.S. economy was at or near full employment,[31] hence employers short on labor might be more likely

[31] Bureau of Labor Statistics data series LNS14000000 (U.S. monthly unemployment rate, seasonally adjusted)

VARIABLES	(1) Working	(2) Worked in past year	(3) Hours worked per week	(4) Unemployed	(5) Labor force status	(6) Self-employed	(7) Total personal income	(8) Total personal income, bottom 90%	(9) Log hourly wage	(10) Attending school	(11) Has health insurance
Age-Eligible*2016	0.0542***	0.0556***	2.369***	-0.0316***	0.0337***	-0.00367	-366.6	1,814***	-0.0168	0.0139	0.0667***
	(0.0117)	(0.0104)	(0.630)	(0.00807)	(0.00972)	(0.00494)	(1,460)	(373.1)	(0.0282)	(0.0146)	(0.0191)
Age-Eligible*2015	0.0598***	0.0625***	2.273***	-0.0323***	0.0394***	-0.000703	-617.8	1,150***	-0.0275	0.00539	0.0704***
	(0.0144)	(0.0136)	(0.731)	(0.00787)	(0.0147)	(0.00381)	(1,504)	(418.0)	(0.0316)	(0.0121)	(0.0128)
Age-Eligible*2014	0.0535***	0.0511***	2.156***	-0.0255***	0.0388***	-0.00440	-110.1	1,034***	-0.0158	-0.000200	0.0377***
	(0.0105)	(0.0108)	(0.609)	(0.00732)	(0.00940)	(0.00389)	(1,279)	(352.1)	(0.0305)	(0.0132)	(0.0104)
Age-Eligible*2013	0.0282***	0.0306***	1.198**	-0.0165**	0.0184**	-0.00615	-661.7	243.1	-0.0253	0.00731	-0.00343
	(0.0103)	(0.0108)	(0.602)	(0.00830)	(0.00899)	(0.00437)	(1,236)	(345.7)	(0.0241)	(0.0120)	(0.0107)
Age-Eligible*2011	-0.00293	-0.00215	0.454	0.00310	-0.000667	-0.00380	480.9	345.3	-0.00757	0.000394	0.00871
	(0.0107)	(0.0112)	(0.562)	(0.00870)	(0.0107)	(0.00370)	(1,111)	(318.1)	(0.0210)	(0.0119)	(0.0102)
Age-Eligible*2010	-0.00581	0.00232	0.507	0.000688	-0.00614	-0.00869*	399.0	244.0	0.0151	0.00274	0.0140
	(0.0129)	(0.0124)	(0.649)	(0.0101)	(0.0106)	(0.00504)	(1,112)	(395.6)	(0.0219)	(0.0123)	(0.0102)
Age-Eligible*2009	0.00829	0.0168	1.078	-0.0113	0.000905	0.000751	914.0	643.3*	0.0284	-0.00164	0.0310***
	(0.0141)	(0.0135)	(0.688)	(0.00814)	(0.0126)	(0.00441)	(1,222)	(364.0)	(0.0202)	(0.0146)	(0.00978)
Age-Eligible*2008	0.0128	0.0219*	1.259**	-0.0227***	-0.00331	-0.00604	834.3	834.8**	0.0322	0.00866	0.0462***
	(0.0109)	(0.0119)	(0.623)	(0.00801)	(0.0106)	(0.00370)	(1,085)	(418.6)	(0.0197)	(0.0123)	(0.00954)
Age-Eligible*2007	0.0101	0.0206**	1.049*	-0.0188**	-0.00397	-0.00813**	925.9	654.5**	0.0472***	0.0215*	
	(0.0104)	(0.00978)	(0.546)	(0.00743)	(0.00892)	(0.00406)	(1,035)	(332.9)	(0.0181)	(0.0129)	
Age-Eligible*2006	0.00955	0.0219*	1.354**	-0.0262***	-0.0105	-0.00498	1,121	643.7*	0.0461**	0.0211*	
	(0.0124)	(0.0118)	(0.628)	(0.00706)	(0.0122)	(0.00428)	(973.4)	(358.6)	(0.0201)	(0.0122)	
Age-Eligible*2005	0.0127	0.0255*	1.097	-0.0167*	0.000720	-0.00796**	1,475	583.9	0.0405**	0.0228**	
	(0.0134)	(0.0135)	(0.689)	(0.00911)	(0.0106)	(0.00390)	(1,003)	(451.2)	(0.0189)	(0.0115)	
Age-eligible sample mean, pre-DACA	0.652	0.757	27.6	0.116	0.738	0.0378	16,025	14,180	2.436	0.320	0.481
Observations	528,296	528,296	528,296	369,509	528,296	528,296	528,294	476,565	295,132	528,296	395,991
R-squared	0.130	0.126	0.186	0.031	0.133	0.021	0.217	0.204	0.356	0.304	0.222

Table 4. Estimates of the effect of DACA age-eligibility by year.

Each column corresponds to a separate regression for the corresponding outcome variable by estimating equation (1) but with $AgeEligible_{it}$ interacted with each year dummy. The interaction *AgeEligible**2012 is the omitted category. Each row corresponds to the coefficient on the interaction terms. Regressions are estimated on a sample containing noncitizens aged 18–35 with at least a college degree in the 2005–2016 ACS (2008–2016 for health insurance coverage). Income in columns 7 and 8 measured in nominal U.S. dollars and uncorrected for inflation. Log hourly wage in column 9 is restricted to individuals who worked for at least half the prior 12-month period. Coefficients for year dummies, demographic controls, fixed effects and state-year time trends are not shown. The row *Age-eligible sample mean, pre-DACA* gives the sample mean for individuals before 2012 who meet the age eligibility criteria for DACA. Observations are weighted using person weights in the ACS. Robust standard errors clustered at the state-year level in parentheses.
*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

to overlook their lack of documentation and hire DREAMers, which would account for the closing of the gap in unemployment rates during this time period.

As is consistent with the results in Table 3, we do not see any significance on any of the interaction terms in columns (6) and (7), corresponding to the rate of self-employment and to total personal income, respectively. However, again when we exclude the top decile of income earners, in column (8) the coefficients on the post-DACA interaction terms are large and significant and increasing over time. In column (9) we observe some pre-trends in hourly wage rates from 2005 to 2007, however these do not explain the results for wages which we see in Table 3.

There are no significant coefficients for the regression on schooling in column (10), both on the pre- and post-DACA interaction terms; the magnitudes of the coefficients are also very small. As for health insurance coverage in column (11), we observe a strong significant post-DACA effect, but there is also a significant pre-trend for 2008 and 2009 which makes one wary of reading too much into these results.

Table 5 on the next page gives the results of a second specification which tests explicitly for pre-trends in the ACS data. Here, I estimate equation (1) but with the age-eligibility variable $AgeEligible_{it}$ interacted with a linear pre-trend equal to min(*year* – 2012, 0) and year dummies for years after 2012, i.e. after the introduction of DACA. The coefficient on the interaction with the pre-trend term would tell if any significant pre-trend exists, while the estimates for the post-DACA interactions provide information on any trends arising from the introduction of DACA.

We observe that the coefficients on the post-DACA interaction terms in Table 5 are very similar to the results obtained in Table 4; however, some additional pre-trends appear for a number of our variables. We see a statistically significant negative pre-trend for the likelihood of working in the previous year in column (2), but the magnitude of this pre-trend is negligible relative to the

VARIABLES	(1) Working	(2) Worked in past year	(3) Hours worked per week	(4) Unemployed	(5) Labor force status	(6) Self-employed	(7) Total personal income	(8) Total personal income, bottom 90%	(9) Log hourly wage	(10) Attending school	(11) Has health insurance
Age-Eligible*2016	0.0572***	0.0574***	2.121***	-0.0342***	0.0347***	-0.00158	-507.5	1,623***	-0.0148	0.0180	0.0695***
	(0.00982)	(0.00833)	(0.508)	(0.00635)	(0.00840)	(0.00430)	(1,274)	(300.9)	(0.0246)	(0.0123)	(0.0184)
Age-Eligible*2015	0.0628***	0.0643***	2.024***	-0.0349***	0.0405***	0.00139	-758.7	959.2***	-0.0254	0.00947	0.0732***
	(0.0129)	(0.0121)	(0.628)	(0.00609)	(0.0138)	(0.00292)	(1,320)	(354.8)	(0.0285)	(0.00934)	(0.0119)
Age-Eligible*2014	0.0565***	0.0529***	1.907***	-0.0281***	0.0398***	-0.00231	-251.0	843.1***	-0.0138	0.00388	0.0405***
	(0.00832)	(0.00877)	(0.482)	(0.00535)	(0.00801)	(0.00302)	(1,058)	(274.5)	(0.0272)	(0.0107)	(0.00921)
Age-Eligible*2013	0.0311***	0.0324***	0.949**	-0.0191***	0.0194***	-0.00406	-802.6	52.57	-0.0233	0.0114	-0.000639
	(0.00813)	(0.00881)	(0.472)	(0.00663)	(0.00751)	(0.00362)	(1,007)	(266.6)	(0.0197)	(0.00913)	(0.00960)
Age-Eligible	-0.00243*	-0.00431***	-0.171**	0.00404***	0.000554	0.000796*	-178.6*	-86.06**	-0.00785***	-0.00390***	-0.0114***
*linear pre-trend	(0.00136)	(0.00136)	(0.0699)	(0.000921)	(0.00123)	(0.000437)	(105.2)	(42.83)	(0.00207)	(0.00132)	(0.00214)
Age-eligible sample mean, pre-DACA	0.652	0.757	27.6	0.116	0.738	0.0378	16,025	14,180	2.436	0.320	0.481
Observations	528,296	528,296	528,296	369,509	528,296	528,296	528,294	476,565	295,132	528,296	395,991
R-squared	0.130	0.126	0.186	0.031	0.133	0.021	0.217	0.204	0.356	0.304	0.222

Table 5. Testing for pre-trends.

Each column corresponds to a separate regression for the corresponding outcome variable by estimating equation (1) but with $AgeEligible_{it}$ interacted with a linear pre-trend equal to min(*year*–2012, 0) and with year dummies for years after 2012. Each row corresponds to the coefficient on the interaction terms. Regressions are estimated on a sample containing noncitizens aged 18–35 with at least a college degree in the 2005–2016 ACS (2008–2016 for health insurance coverage). Income in columns 7 and 8 measured in nominal U.S. dollars and uncorrected for inflation. Log hourly wage in column 9 is restricted to individuals who worked for at least half the prior 12-month period. Coefficients for year dummies, demographic controls, fixed effects and state-year time trends are not shown. The row *Age-eligible sample mean, pre-DACA* gives the sample mean for individuals before 2012 who meet the age eligibility criteria for DACA. Observations are weighted using person weights in the ACS. Robust standard errors clustered at the state-year level in parentheses.
*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

sample mean of the eligible population, as well as the post-DACA effects. Of more concern is the positive pre-trend of about 0.4 percentage points observed for unemployment in column (4), which is also significant at the 1% level. This corresponds to the pre-DACA increase in unemployment for the DACA-eligible population, which we also see in the graphical results in Figure 3(a), and therefore suggests that our DID estimates for the effect of DACA on unemployment are potentially less valid.

Similarly, we see in columns (10) through (12) strong negative pre-trends for hourly wage rates, school attendance and health insurance coverage. This also corresponds to the differential trends observed in the graphical results in Figures 4 and 5, and again imply that the DID estimates obtained for these outcome variables might not be accurate.

Overall, the initial DID analyses in Tables 3 through 5 therefore show that DACA has had a strong, positive impact on the labor market outcomes of individuals who meet the age and age-of-arrival criteria for DACA, and thus are potential DREAMers, specifically in terms of shifting them into the labor force, out of unemployment and into work. DACA has also increased the average hours worked by these individuals, as well as the incomes of those in the bottom 90th percentile of the income distribution (i.e. the large majority of them). All these effects also appear to be increasing over time. However, DACA appears to have not have had an effect on hourly wages, which is interesting and unexpected, although this result is considerably weaker given the strong negative pre-trend observed in the data. DACA also looks to have increased health insurance coverage among the eligible population, although the results for this are weaker and less conclusive. On the other hand, DACA seems to have had no impact on the likelihood of attending school.

These results thus far appear strong and compelling; however, as discussed in Section 5 an issue with this DID strategy is the contamination of the sample with legal immigrants who also meet the DACA age-eligibility criteria and are placed in the intent-to-treat pool, thereby biasing the DID coefficient estimates toward zero. Therefore, in the following subsection I provide a two-stage DID model that attempts to address this issue.

7.3. *Two-stage Difference-in-Differences Model*

As discussed in Sections 5 and 6, one can use a "donor" sample, in this case the 2008 SIPP, to estimate a model giving the likelihood that an individual is undocumented based on certain demographic characteristics. Then, one can use this model to predict the likelihoods that the individuals in a "recipient" sample, here the 2005–2016 ACS, are undocumented. I subsequently estimate the second-stage DID model in equation (3), weighting the DACA eligibility term by the probability of an individual being undocumented, in order to obtain a more accurate intent-to-treat group and thus more accurate coefficient estimates. This section discusses the results obtained from this approach.

7.3.1. *First-Stage Results*

The first stage of this model estimates equation (2) using a probit model on a sample of noncitizens aged 18–40 with at least a high school degree in the second wave of the 2008 SIPP, in order to create a model which provides the likelihood of a noncitizen being an unauthorized or a legal immigrant. The right-hand side variables in this model correspond to the same demographic controls used in estimating the DID models in equations (1) and (3), i.e. gender, marital status, race, ethnicity, whether Spanish is spoken at home and dummies for education level; as well as additional controls for age and region of birth. The results from this estimation are given in Table 6 on the following page. Column (1) reports the probit coefficients while column (2) gives average marginal effects.

From our results in Table 6, we can see that age is a strong predictor of undocumented status, with younger noncitizens more likely to be unauthorized. Men are on average 4.1 percent more likely to be undocumented than women, and single individuals are on average 5.5 percent more likely to be undocumented than married ones. Both observations are in agreement with estimates in the immigration literature as well. Race is not a good predictor of undocumented status; however, being Hispanic is associated with a 7.7 percent higher likelihood of being unauthorized, even conditional on controls for region on birth, although this is only significant at the 10 percent level. Again, this is reasonable and perhaps expected, given that 55 percent of unauthorized immigrants come from Mexico and a further 27 from Central and South America (Baker, 2014). However, speaking Spanish at home is not a good predictor of unauthorized status.

The age at which an individual entered the U.S. is also a significant predictor of their undocumented status; interestingly enough, the coefficient is opposite to the coefficient on age — i.e. an individual who came to the U.S. a year younger is on average 1.0 percent *less* likely to be an unauthorized immigrant.

Unauthorized immigrants are also more likely to be less educated than their legal immigrant peers: the coefficients for the dummies for having some college education or a college degree or higher are negative (with having only a high school degree being the omitted category). Country or region of birth is also a very strong predictor of immigration status: individuals born in Europe or Asia are on average between 9.3 to 28.2 percent less likely to be unauthorized than

	(1)	(2)
	Unauthorized	
VARIABLES	*Probit coefficients*	*Marginal effects*
Age	-0.0401***	-0.0135***
	(0.00714)	(0.00235)
Male	0.124*	0.0417*
	(0.0638)	(0.0215)
Unmarried	0.160**	0.0548**
	(0.0772)	(0.0265)
Black	-0.00965	-0.00326
	(0.134)	(0.0452)
Asian	-0.0102	-0.00343
	(0.141)	(0.0477)
Hispanic	0.228*	0.0770*
	(0.131)	(0.0440)
Age entered U.S.	0.0296***	0.0100***
	(0.00528)	(0.00173)
Spanish spoken at home	-0.138	-0.0467
	(0.107)	(0.0361)
Some college education	-0.408***	-0.138***
	(0.101)	(0.0336)
College degree or higher	-0.0316	-0.0107
	(0.0794)	(0.0268)
Born in Northern/Western Europe	-0.883***	-0.282***
	(0.236)	(0.0625)
Born in Southern/Eastern Europe	-0.581***	-0.201***
	(0.194)	(0.0624)
Born in East Asia	-0.270	-0.0993
	(0.216)	(0.0779)
Born in South/Central Asia	-0.252	-0.0926
	(0.198)	(0.0720)
Born in Southeast/West Asia	-0.620***	-0.213***
	(0.193)	(0.0623)
Born in Africa	-0.357*	-0.129*
	(0.202)	(0.0707)
Born in the Caribbean	-1.171***	-0.341***
	(0.187)	(0.0430)
Born in South America	-0.208	-0.0770
	(0.160)	(0.0588)
Observations	2,138	2,138
R-squared	0.0893	0.0893

Table 6. First-stage probit model estimating likelihood that a noncitizen is unauthorized.

Table is obtained by estimating equation (2) with a probit model on a sample of noncitizens aged 18–40 with at least a high school degree or equivalent in Wave 2 of the 2008 SIPP. The dependent variable is whether individual is an unauthorized immigrant. Column (1) reports probit coefficients while column (2) gives average marginal effects. Omitted category for race is white. Omitted category for education is having a high school degree only. Omitted category for birthplace is Mexico/Central America. Observations are weighted by person weights in the SIPP. Robust standard errors clustered at the state level in parentheses.
*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

individuals born in Mexico or Central America (the omitted category for region of birth). Again, this is in broad agreement with available data or estimates for the unauthorized population of the United States.

7.3.2. *Second-Stage Results*

We can use the results from the first stage of the model to predict the likelihood that a noncitizen in the ACS is undocumented, and then use these predicted probabilities to estimate the second stage of our model, i.e. the difference-in-differences equation (3). Table 7 presents the results of this second-stage estimation. Again, each column in the table corresponds to a separate regression for the outcome variable of interest; in this case, the coefficient of interest and the measure of the impact of DACA on the outcome of interest is the coefficient on the interaction of DACA age-eligibility weighted by the probability of being unauthorized and the dummy for the post-DACA period. A one-unit change in the variable $\widehat{Unauthorized}_{it}$ corresponds to a shift in the probability of being unauthorized from zero to one, and since DACA eligibility requires both meeting the age requirements and being unauthorized, the coefficient on the interaction $AgeEligible_{it} * \widehat{Unauthorized}_{it} * After_{it}$ corresponds to the effect of DACA on the DACA-eligible population.

From Table 7 we see that in our two-stage model, the effects of DACA on the labor market outcomes in columns (1) through (5) are between 2.3 to 3.2 times larger than the estimates obtained in the simple DID model using equation (1) in Table 3; furthermore, all these effects are all significant at the 1% level as well. In the two-stage model, DACA appears to have increased the probability of an eligible individual working by 12.7 percentage points, compared to 4.4 percentage points in the simple DID model in Table 3. This corresponds to approximately 200,000

VARIABLES	(1) Working	(2) Worked in past year	(3) Hours worked per week	(4) Unemployed	(5) Labor force status	(6) Self-employed	(7) Total personal income	(8) Total personal income, bottom 90%	(9) Log hourly wage	(10) Attending school	(11) Has health insurance
Age-Eligible *Pr(Unauthorized)*After	0.127***	0.113***	3.797***	-0.0377***	0.108***	-0.00341	-2,854*	2,324***	-0.115***	-0.00103	0.0850***
	(0.0157)	(0.0153)	(0.720)	(0.0107)	(0.0136)	(0.00523)	(1,657)	(432.5)	(0.0370)	(0.0170)	(0.0291)
Age-Eligible*Pr(Unauthorized)	-0.0495***	-0.0607***	0.781	0.0493***	0.000267	0.0215***	7,774***	1,079**	0.173***	-0.253***	-0.0819***
	(0.0190)	(0.0182)	(0.706)	(0.0126)	(0.0175)	(0.00640)	(1,004)	(497.4)	(0.0246)	(0.0188)	(0.0230)
Pr(Unauthorized)	0.0391***	-0.0133	-0.928*	-0.0679***	-0.0166	0.00725	-7,721***	-1,621***	-0.116***	-0.0119	-0.304***
	(0.0135)	(0.0120)	(0.493)	(0.00892)	(0.0133)	(0.00564)	(773.7)	(344.1)	(0.0178)	(0.0139)	(0.0241)
Age-Eligible	0.0848***	0.0792***	2.188***	-0.0265***	0.0670***	-0.000578	4,072***	851.2***	0.0239**	0.0430***	-0.0274***
	(0.00746)	(0.00691)	(0.261)	(0.00541)	(0.00652)	(0.00328)	(502.7)	(232.3)	(0.0101)	(0.00592)	(0.00888)
Age-eligible sample mean, pre-DACA	0.652	0.757	27.6	0.116	0.738	0.0378	16,025	14,180	2.436	0.320	0.481
Observations	528,296	528,296	528,296	369,509	528,296	528,296	528,294	476,565	295,132	528,296	395,991
R-squared	0.130	0.126	0.186	0.031	0.133	0.021	0.218	0.204	0.356	0.305	0.224

Table 7. Second-stage difference-in-differences estimates of the effect of DACA on various labor market, education and healthcare outcomes.

Each column corresponds to a separate regression for the corresponding outcome variable by estimating equation (3) on a sample containing noncitizens aged 18–35 with at least a college degree in the 2005–2016 ACS (2008–2016 for health insurance coverage). The coefficient of interest is the coefficient on the *AgeEligible*Unauthorized*After* interaction term. Income in columns 7 and 8 measured in nominal U.S. dollars and uncorrected for inflation. Log hourly wage in column 9 is restricted to individuals who worked for at least half the prior 12-month period. Coefficients for demographic controls, fixed effects and state-year time trends are not shown. The row *Age-eligible sample mean, pre-DACA* gives the sample mean for individuals before 2012 who meet the age eligibility criteria for DACA. Observations are weighted using person weights in the ACS. Robust standard errors clustered at the state-year level in parentheses.
*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

additional DREAMers working as a result of DACA. Similarly, we see that DACA has increased the labor force participation rate among DREAMers by 10.8 percentage points, and decreased unemployment by 3.8 percentage points, i.e. shifting about 160,000 DREAMers into the labor force and moving 50,000 DREAMers out of unemployment.

Although these estimates may appear unrealistically large at first glance, other smaller, more qualitative studies have actually observed similar, sharp increases in employment and labor force participation among DACA recipients. For example, Wong et al. (2017) surveyed 3,063 DACA recipients and reported that 54.2% of all respondents and 35.3% of respondents 25 and older obtained their first job after approval of their DACA applications. This suggests that the estimates I obtain from this two-stage model are realistic and in fact very likely to be a lower bound on the effect of DACA on DREAMers, given how these estimates are intent-to-treat effects and that not all DREAMers have applied for and received DACA.

Comparing column (8) in Tables 3 and 7, we also see that the effect of DACA on total income is now four times as large as the initial estimate from the simple DID model. From Table 7, we see that an unauthorized immigrant earns on average \$1,620 less than a legal immigrant; however, with the introduction of DACA, the average income of a DACA-eligible individual has increased by \$2,324, or by about 16 percent from the pre-DACA sample mean, significant at the 1% level. Again, this is a not unsubstantial amount, but still very likely understates the gains to DREAMers from DACA: Wong et al. (2017) report in their study the that median annual earnings among DACA recipients was \$19,000 pre-DACA and \$32,000 post-DACA, corresponding to a \$13,000 increase in annual income. Looking at the results in column (9) of Table 7, we see that this increase in income is not due to an increase in the hourly wage; in fact, it appears that DACA has decreased the average hourly wage of DREAMers. However, this result should be viewed with some caution given the strong negative pre-trend in wages that we have observed in Figure 4(c) and Table 5, suggesting that the parallel trend assumption required for the validity of our DID estimate does not hold.

The results when we examine the effect of DACA on school attendance and healthcare are similar to that in the initial single-stage DID model in the previous section. DACA still appears to not have any effect on school attendance for DREAMers: the coefficient on the interaction term is small and insignificant. This supports the results from Pope (2016), who also finds that the effect of DACA on school attendance is inconclusive, and is contrary to the findings of Hsin and Ortega (2017), who demonstrate that DACA shifted individuals out of school and into the workforce. The fact that the DID coefficient is small and insignificant suggests that the two competing effects on school attendance (either where DACA reduces labor market frictions, encouraging DREAMers to move from school into work, or where DACA makes it more attractive for DREAMers to attend school in order to improve their human capital and skills) tend to cancel each other out.

The DID estimate for the effect of DACA on health insurance coverage is, however, is 3.6 times that of the estimate from the single-stage DID model; I find that the rate of health insurance coverage for unauthorized immigrants is almost 30 percentage points lower than for legal immigrants; however, DACA has increased the fraction of DREAMers with health insurance coverage by 8.5 percentage points.

From these results in Table 7 we can therefore see that DACA has had a much larger effect on labor market outcomes, wages and healthcare coverage on DREAMers than we had expected from a simple difference-in-differences estimation. The results from this two-stage model are also closer to other empirical estimates observed in the literature, suggesting that contamination of our original sample by legal immigrants had indeed biased the original estimates downward, and that this two-stage model is an appropriate way to correct for this. Furthermore, it is also important to remember that the estimates from this model are estimates of the intent-to-treat effect of DACA, and since only about 60% of DREAMers have applied for deferred action the actual treatment effects may be up to 1.67 times larger than what we have observed in our data.

7.4. *Subsamples and Robustness Checks*

I move on to estimating the second stage of the two-stage difference-in-differences model on various subsamples of the ACS data, in order to investigate if there are any differential effects of DACA based on income levels, gender or ethnicity, i.e. if some groups benefit more from DACA than others. These results are presented in Tables 8 through 10 below.

Table 8 shows the differential effects of DACA on various subsamples based on total income: (a) for individuals below the 90^{th} percentile of income, (b) for individuals below the median income and (c) for individuals above the median income. From our results in Figure 4 and Tables 3 and 7 we already know that DACA appears to not have an effect on income when we estimate the DID models on the entire ACS sample, but after excluding the top decile of earners we find that DACA has actually raised the income significantly of individuals below the 90^{th} percentile of the income distribution. Therefore, it would be interesting to see if there are any differential effects based on income, which we do in Table 8 on the next page.

VARIABLES	(1) Working	(2) Worked in past year	(3) Hours worked per week	(4) Unemployed	(5) Labor force status	(6) Self-employed	(7) Total personal income	(8) Log hourly wage	(8) Attending school	(9) Has health insurance
Below 90th percentile income										
Age-Eligible *Pr(Unauthorized)*After	0.151***	0.136***	4.685***	-0.0399***	0.133***	-0.00548	2,324***	-0.0227	-0.0167	0.0750***
	(0.0155)	(0.0150)	(0.625)	(0.0103)	(0.0140)	(0.00519)	(432.5)	(0.0175)	(0.0158)	(0.0263)
Age-Eligible*Pr(Unauthorized)	-0.0851***	-0.0912***	-0.981	0.0580***	-0.0324*	0.0215***	1,079**	0.0821***	-0.243***	-0.0715***
	(0.0201)	(0.0191)	(0.690)	(0.0131)	(0.0182)	(0.00633)	(497.4)	(0.0193)	(0.0186)	(0.0233)
Pr(Unauthorized)	0.0629***	0.00180	0.177	-0.0756***	0.00231	0.00739	-1,621***	-0.0477***	-0.0269*	-0.313***
	(0.0146)	(0.0127)	(0.520)	(0.00973)	(0.0142)	(0.00565)	(344.1)	(0.0160)	(0.0147)	(0.0242)
Age-Eligible	0.0781***	0.0728***	1.883***	-0.0285***	0.0597***	0.00293	851.2***	-0.0123	0.0515***	-0.0364***
	(0.00786)	(0.00730)	(0.268)	(0.00581)	(0.00696)	(0.00337)	(232.3)	(0.00864)	(0.00612)	(0.00903)
Age-eligible sample mean, pre-DACA	0.645	0.752	27.2	0.119	0.733	0.0361	14,180	2.390	0.325	0.474
Observations	476,565	476,565	476,565	319,117	476,565	476,565	476,565	245,484	476,565	355,668
R-squared	0.126	0.125	0.178	0.027	0.133	0.021	0.204	0.186	0.316	0.196
Below median income										
Age-Eligible *Pr(Unauthorized)*After	0.177***	0.168***	4.646***	-0.0710***	0.161***	-0.00956	1,088***	-0.00602	-0.0166	0.0859***
	(0.0199)	(0.0215)	(0.699)	(0.0201)	(0.0195)	(0.00699)	(182.3)	(0.0238)	(0.0182)	(0.0315)
Age-Eligible*Pr(Unauthorized)	-0.170***	-0.180***	-4.615***	0.178***	-0.0783***	0.00173	-1,159***	-0.0168	-0.253***	-0.102***
	(0.0281)	(0.0286)	(0.884)	(0.0262)	(0.0272)	(0.00893)	(242.6)	(0.0319)	(0.0234)	(0.0275)
Pr(Unauthorized)	0.0598***	-0.00978	-0.143	-0.120***	-0.0227	0.0288***	-62.14	-0.00277	-0.0136	-0.299***
	(0.0183)	(0.0186)	(0.695)	(0.0201)	(0.0192)	(0.00625)	(175.3)	(0.0230)	(0.0189)	(0.0286)
Age-Eligible	0.0791***	0.0747***	1.587***	-0.0783***	0.0461***	0.00134	496.9***	0.0270*	0.0708***	-0.0324***
	(0.0121)	(0.0125)	(0.404)	(0.0135)	(0.0117)	(0.00500)	(107.1)	(0.0145)	(0.00881)	(0.0120)
Age-eligible sample mean, pre-DACA	0.424	0.564	16.8	0.230	0.550	0.033	3,902	1.955	0.449	0.422
Observations	264,317	264,317	264,317	118,906	264,317	264,317	264,317	54,313	264,317	201,131
R-squared	0.072	0.085	0.105	0.030	0.092	0.023	0.099	0.061	0.390	0.210

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VARIABLES	(1) Working	(2) Worked in past year	(3) Hours worked per week	(4) Unemployed	(5) Labor force status	(6) Self-employed	(7) Total personal income	(8) Log hourly wage	(8) Attending school	(9) Has health insurance
Above median income										
Age-Eligible	0.0287***	0.0182***	0.761	-0.00917	0.0200***	0.00420	-8,985***	-0.119***	0.0245	0.0401
*Pr(Unauthorized)*After	(0.0101)	(0.00511)	(0.499)	(0.00733)	(0.00635)	(0.00762)	(2,655)	(0.0359)	(0.0191)	(0.0319)
Age-Eligible*Pr(Unauthorized)	0.0145	0.0131**	3.206***	0.00182	0.0168*	0.0319***	12,335***	0.129***	-0.152***	0.00605
	(0.0121)	(0.00589)	(0.585)	(0.00952)	(0.00870)	(0.0106)	(1,522)	(0.0244)	(0.0196)	(0.0291)
Pr(Unauthorized)	0.0756***	0.0405***	0.807**	-0.0307***	0.0474***	-0.0124	-8,844***	-0.139***	-0.00973	-0.289***
	(0.00954)	(0.00573)	(0.369)	(0.00606)	(0.00799)	(0.00829)	(1,188)	(0.0185)	(0.0122)	(0.0259)
Age-Eligible	0.0305***	0.0209***	0.182	-0.00332	0.0279***	0.000174	2,971***	0.0240**	0.0131**	-0.0308***
	(0.00478)	(0.00228)	(0.195)	(0.00349)	(0.00327)	(0.00545)	(708.8)	(0.00959)	(0.00648)	(0.0118)
Age-eligible sample mean, pre-DACA	0.927	0.990	40.6	0.0376	0.964	0.0435	30,600	2.599	0.165	0.556
Observations	263,979	263,979	263,979	250,603	263,979	263,979	263,977	240,819	263,979	194,860
R-squared	0.020	0.029	0.046	0.007	0.028	0.023	0.220	0.360	0.136	0.255

Table 8. Two-stage DID estimates of the effect of DACA on various labor market, education and healthcare outcomes by income level.

Each column corresponds to a separate regression for the corresponding outcome variable by estimating equation (3) on the sample in Table 7 restricted to (a) individuals below 90^{th} percentile for income, (b) individuals below median income and (c) individuals above median income. The coefficient of interest is the coefficient on the *AgeEligible*Unauthorized*After* interaction term. Income is measured in nominal U.S. dollars and uncorrected for inflation. Log hourly wage in column 8 is restricted to individuals who worked for at least half the prior 12-month period. Coefficients for demographic controls, fixed effects and state-year time trends are not shown. The row *Age-eligible sample mean, pre-DACA* gives the sample mean for individuals before 2012 who meet the age eligibility criteria for DACA. Observations are weighted using person weights in the ACS. Robust standard errors clustered at the state-year level in parentheses.

*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

However, a possible issue with the results in this table is that we are partially conditioning on some of our outcome variables; for example, since the average number of hours worked in the past year will affect total income, then whether an individual is below the 90th (or 50th) percentile of income can also be influenced by the dependent variable.[32]

From Table 8, we can see that the effect of DACA on various labor market outcomes is indeed concentrated toward the bottom of the income distribution. We can see that the coefficients on the interaction terms for the labor market outcomes in columns (1) through (5) are greater in magnitude when the top decile of earners is excluded, and even larger when we look at the bottom half of the income distribution. On the other hand, we now no longer see an effect of DACA on unemployment or hours worked per week in the top half of the income distribution, and the effects on the likelihood of working and of labor force participation are significantly smaller.

For example, DACA has reduced unemployment among DREAMers earning less than the median income by more than 7 percentage points (compared to a full-sample effect of a 3.8 percentage point decrease, and a 4.0 percentage point reduction in the bottom 90 percent) but had no effect on DREAMers in the top half of the income distribution. DACA has increased the likelihood of a DREAMer in the bottom half of the income distribution working by 17.7 percentage points (relative to 12.7 percentage points in the full sample and 15.1 percentage points in the below-90th percentile sample), compared to a 2.8 percentage point increase among DREAMers in the top half of the income distribution.

We also see similar trends in health insurance coverage. From our results we see that DACA has increased the fraction of DREAMers with health insurance coverage by 8.6 percentage

[32] This is especially problematic with the income variable itself, and a possible way to address this would be to use quantile regression; however, given the size of the data set and the number of controls and fixed effects I was unable to achieve convergence in STATA when estimating a quantile regression model.

points for those earning less than the median income, but only by 4.0 percentage points for those earning more than the median income. On the other hand, we do not see any significant effect for DACA on school attendance in any of the three subsamples we consider.

The results for income are more interesting, however. DACA increased total income among the bottom 90 percent of earners by $2,324, but only by $1,088 when we look at individuals below the median income. However, if we consider that the pre-DACA mean income among DACA-eligible individuals in the bottom 90 percent of earners is $14,180, while the mean income in the bottom half of the distribution is $3,902, we can again see that DACA has had a much larger impact on DREAMers earning below the median income. Expressing the effects in percentage terms, we see that DACA has raised incomes in the below-90th percentile sample by 16% relative to the sample mean, but in the below-median sample it has raised incomes by 28% relative to the mean.

Therefore, from Table 8 we see that the effects of DACA are to be unequally distributed based on income (and by extension, socioeconomic status): DACA appears to have the strongest effects on individuals near the bottom of the income distribution, and minimal effect for individuals at the top. This is unsurprising, given how the poorest individuals are the ones most likely to face labor market frictions and barriers, and how these barriers tend to be larger as well. Hence, we can expect that poorer individuals will probably benefit the most from the elimination of these labor market obstacles with DACA, and this is indeed borne out in the results in Table 8.

Table 9 on the next page gives the results from estimating the two-stage DID model by gender. Although the DID estimates for the likelihood of working and the average number of hours worked are similar for men and women, the effect of DACA on two other labor market outcomes — unemployment and labor force participation — appear to diverge. We see that DACA has

VARIABLES	(1) Working	(2) Worked in past year	(3) Hours worked per week	(4) Unemployed	(5) Labor force status	(6) Self-employed	(7) Total personal income	(8) Total personal income, bottom 90%	(9) Log hourly wage	(10) Attending school	(11) Has health insurance
Male											
Age-Eligible	0.110***	0.0920***	3.615***	-0.0488***	0.0773***	-0.00934	-4,455**	2,152***	-0.118***	-0.00778	0.0824***
*Pr(Unauthorized)*After	(0.0169)	(0.0158)	(0.725)	(0.0130)	(0.0140)	(0.00668)	(2,174)	(536.9)	(0.0395)	(0.0170)	(0.0290)
Age-Eligible*Pr(Unauthorized)	-0.00447	-0.0246	2.906***	0.0283*	0.0373**	0.0308***	17,741***	3,909***	0.192***	-0.189***	-0.0510*
	(0.0208)	(0.0190)	(0.884)	(0.0158)	(0.0187)	(0.00943)	(1,544)	(671.7)	(0.0297)	(0.0221)	(0.0295)
Pr(Unauthorized)	0.189***	0.134***	4.946***	-0.0883***	0.125***	-0.00603	-5,665***	1,201**	-0.135***	-0.0107	-0.302***
	(0.0137)	(0.0119)	(0.561)	(0.00991)	(0.0140)	(0.00789)	(1,014)	(499.1)	(0.0243)	(0.0160)	(0.0254)
Age-Eligible	0.0623***	0.0613***	1.366***	-0.0101	0.0499***	-0.000503	2,352***	208.3	0.0131	0.0180**	-0.0286**
	(0.00860)	(0.00669)	(0.319)	(0.00703)	(0.00696)	(0.00480)	(778.3)	(346.8)	(0.0136)	(0.00779)	(0.0118)
Age-eligible sample mean, pre-DACA	0.711	0.816	31.2	0.113	0.801	0.0475	18,958	16,508	2.466	0.288	0.445
Observations	263,649	263,649	263,649	212,625	263,649	263,649	263,648	227,701	176,555	263,649	197,673
R-squared	0.147	0.142	0.198	0.037	0.149	0.027	0.244	0.219	0.363	0.311	0.243
Female											
Age-Eligible	0.132***	0.129***	3.327***	-0.0110	0.138***	0.00494	-1,987	1,779***	-0.119***	0.00351	0.0869**
*Pr(Unauthorized)*After	(0.0224)	(0.0240)	(1.015)	(0.0161)	(0.0208)	(0.00792)	(1,224)	(576.8)	(0.0439)	(0.0236)	(0.0356)
Age-Eligible*Pr(Unauthorized)	0.135***	0.102***	7.338***	-0.00315	0.163***	-0.000837	12,244***	5,056***	0.293***	-0.304***	-0.114***
	(0.0263)	(0.0260)	(1.002)	(0.0229)	(0.0248)	(0.00925)	(1,117)	(614.1)	(0.0368)	(0.0260)	(0.0302)
Pr(Unauthorized)	-0.148***	-0.194***	-7.970***	-0.0180	-0.185***	0.0368***	-7,886***	-4,625***	-0.0994***	0.00244	-0.303***
	(0.0190)	(0.0179)	(0.714)	(0.0133)	(0.0183)	(0.00741)	(817.1)	(450.9)	(0.0280)	(0.0165)	(0.0274)
Age-Eligible	0.0348***	0.0336***	0.299	-0.0261***	0.0203**	0.00246	850.1*	-453.1	-0.00369	0.0592***	-0.0289**
	(0.0107)	(0.0103)	(0.403)	(0.00768)	(0.00973)	(0.00419)	(468.2)	(290.8)	(0.0139)	(0.00774)	(0.0122)
Age-eligible sample mean, pre-DACA	0.587	0.692	23.5	0.120	0.667	0.0269	12,733	11,610	2.393	0.356	0.521
Observations	264,647	264,647	264,647	156,884	264,647	264,647	264,646	248,864	118,577	264,647	198,318
R-squared	0.083	0.082	0.096	0.025	0.087	0.016	0.151	0.142	0.338	0.304	0.198

Table 9. Two-stage DID estimates of the effect of DACA on various labor market, education and healthcare outcomes by gender.

Each column corresponds to a separate regression for the corresponding outcome variable by estimating equation (3) on the sample in Table 7 restricted to (a) males and (b) females. The coefficient of interest is the coefficient on the *AgeEligible*Unauthorized*After* interaction term. Income in columns 7 and 8 is measured in nominal U.S. dollars and uncorrected for inflation. Log hourly wage in column 9 is restricted to individuals who worked for at least half the prior 12-month period. Coefficients for demographic controls, fixed effects and state-year time trends are not shown. The row *Age-eligible sample mean, pre-DACA* gives the sample mean for individuals before 2012 who meet the age eligibility criteria for DACA. Observations are weighted using person weights in the ACS. Robust standard errors clustered at the state-year level in parentheses.
*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

VARIABLES	(1) Working	(2) Worked in past year	(3) Hours worked per week	(4) Unemployed	(5) Labor force status	(6) Self-employed	(7) Total personal income	(8) Total personal income, bottom 90%	(9) Log hourly wage	(10) Attending school	(11) Has health insurance
Hispanic ethnicity											
Age-Eligible	0.120***	0.108***	3.365***	-0.0319***	0.107***	-0.0122*	-952.4	700.3	-0.105***	-0.00500	0.0349
*Pr(Unauthorized)*After	(0.0167)	(0.0153)	(0.615)	(0.0121)	(0.0141)	(0.00651)	(657.7)	(452.7)	(0.0202)	(0.0146)	(0.0222)
Age-Eligible*Pr(Unauthorized)	-0.151***	-0.133***	-4.464***	0.0864***	-0.0816***	0.0221**	-3,966***	-3,470***	-0.0808**	-0.326***	-0.0668**
	(0.0312)	(0.0286)	(1.098)	(0.0173)	(0.0266)	(0.00963)	(956.8)	(762.2)	(0.0320)	(0.0193)	(0.0279)
Pr(Unauthorized)	0.0579***	-0.0116	0.340	-0.100***	-0.0269*	0.0162*	1,970***	873.8*	0.0418*	-0.0351***	-0.443***
	(0.0190)	(0.0144)	(0.614)	(0.0132)	(0.0148)	(0.00845)	(645.4)	(490.7)	(0.0222)	(0.0134)	(0.0408)
Age-Eligible	0.0674***	0.0550***	1.433***	-0.0334***	0.0408***	0.00163	830.2*	1,155***	0.0181	0.140***	-0.0226*
	(0.0124)	(0.0111)	(0.435)	(0.00763)	(0.0104)	(0.00493)	(448.0)	(318.7)	(0.0132)	(0.00806)	(0.0115)
Age-eligible sample mean, pre-DACA	0.675	0.769	28.7	0.110	0.758	0.0393	15,374	14,265	2.374	0.247	0.394
Observations	226,488	226,488	226,488	168,295	226,488	226,488	226,487	220,275	133,222	226,488	165,944
R-squared	0.135	0.144	0.199	0.031	0.137	0.016	0.177	0.226	0.162	0.253	0.113
Born in Mexico											
Age-Eligible	0.121***	0.110***	3.563***	-0.0221	0.118***	-0.0194**	-1,082	434.0	-0.0959***	-0.0190	0.0413
*Pr(Unauthorized)*After	(0.0193)	(0.0181)	(0.772)	(0.0145)	(0.0152)	(0.00949)	(824.2)	(607.8)	(0.0279)	(0.0177)	(0.0259)
Age-Eligible*Pr(Unauthorized)	-0.465***	-0.436***	-17.67***	0.173***	-0.350***	0.00589	-12,505***	-11,440***	-0.184***	-0.410***	-0.147***
	(0.0305)	(0.0278)	(1.163)	(0.0196)	(0.0275)	(0.0144)	(1,126)	(814.1)	(0.0425)	(0.0252)	(0.0381)
Pr(Unauthorized)	-0.0362	-0.191***	-5.646***	-0.125***	-0.154***	-0.0191	7,133***	3,775***	0.374***	0.0129	0.355***
	(0.0373)	(0.0301)	(1.394)	(0.0325)	(0.0309)	(0.0222)	(1,519)	(994.2)	(0.0582)	(0.0222)	(0.0497)
Age-Eligible	0.166***	0.151***	5.405***	-0.0656***	0.121***	0.00317	3,288***	3,405***	0.0476***	0.195***	0.0210
	(0.0129)	(0.0120)	(0.504)	(0.00909)	(0.0115)	(0.00690)	(569.3)	(390.6)	(0.0173)	(0.00950)	(0.0162)
Age-eligible sample mean, pre-DACA	0.668	0.761	28.6	0.110	0.750	0.0399	14,686	13,715	2.343	0.219	0.359
Observations	147,035	147,035	147,035	107,802	147,035	147,035	147,035	143,968	85,663	147,035	106,526
R-squared	0.165	0.179	0.232	0.035	0.170	0.015	0.190	0.246	0.149	0.251	0.107

Table 10. Two-stage DID estimates of the effect of DACA on various labor market, education and healthcare outcomes by ethnicity and country of birth.

Each column corresponds to a separate regression for the corresponding outcome variable by estimating equation (3) on the sample in Table 7 restricted to (a) individuals of Hispanic ethnicity and (b) individuals born in Mexico. The coefficient of interest is the coefficient on the *AgeEligible*Unauthorized*After* interaction term. Income in columns 7 and 8 is measured in nominal U.S. dollars and uncorrected for inflation. Log hourly wage in column 9 is restricted to individuals who worked for at least half the prior 12-month period. Coefficients for demographic controls, fixed effects and state-year time trends are not shown. The row *Age-eligible sample mean, pre-DACA* gives the sample mean for individuals before 2012 who meet the age eligibility criteria for DACA. Observations are weighted using person weights in the ACS. Robust standard errors clustered at the state-year level in parentheses.
*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

reduced unemployment for male DREAMers by 4.9 percentage points, significant at the 1% level, but has had no effect on unemployment among female DREAMers. Conversely, DACA has increased labor force participation for female DREAMers by 13.8 percentage points, but only by 7.7 percentage points for male DREAMers. This is probably because men were more likely than women to already be in the labor force pre-DACA — we can see from the pre-DACA sample means of the eligible populations that men had a labor force participation rate of 80.1 percent compared to 66.7 percent for women. This is interesting, as it shows that the pathway by which DACA increased employment among DREAMers differs by gender, with men more likely to move from unemployment into work, but with women more likely to move into the labor force and employment. This also stands in contrast to the results by Pope (2016), where he finds no difference in the effect of DACA on unemployment and labor force participation between the genders.

Moving on to the other outcomes of interest, we see that DACA appears to have increased incomes more for men than for women, but men earn more than women to begin with (in our sample, the bottom 90 percent of men earn $16,508 on average, compared to $11,610 for women), and in percentage terms women actually see a greater increase in their incomes as a result of DACA (15% versus 13%). DACA had no effect on school attendance for both men and women, and increased health insurance coverage between both groups by about the same amount.

Table 10 on the previous page gives the results from the DID model on two subsamples: the first of all individuals with Hispanic ethnicity, and the second of all individuals born in Mexico. These subsamples were chosen because a large majority of DREAMers and DACA applicants are Mexican (65 percent and 78 percent, respectively). Also, this choice of subsamples serves as a robustness check for our results, as well as an alternative identification strategy — other authors have used being a noncitizen from Mexico as a proxy for being an unauthorized immigrant, in order to perform various DID analyses with the ACS (for example, Amuedo-Dorantes and Antman, 2016) — we should expect to see similar results in these subsamples.

Indeed, we observe that the DID estimates for the various labor market outcomes such as fraction working, hours worked, labor force participation and unemployment for these two subsamples are very close to the estimates obtained for the whole sample in Table 7. However, the DID estimates for income and health insurance coverage are now smaller and no longer significant. This might be because of the differential pre-trends observed for these variables, or a function of the relatively smaller sample size.

Table 11 on the following pages gives a series of robustness checks, by estimating equation (3) with varying amounts of controls and fixed effects. When we estimate the model without any controls or fixed effects, in Table 11(a), we see that the estimates we obtain are about 1.5 times the magnitude of our baseline specification in Table 7 (with the full set of demographic controls, state and year fixed effects and state-year time trends). Interestingly, the DID estimate for school attendance is negative and significant. Adding only demographic controls in 11(b) gives us results that are now close to the estimates obtained with our full specification, and bringing in year and state fixed effects together with demographic controls in Table 11(c) gives results that are effectively identical to the full specification which includes state-year time trends.

Also, as discussed in §6.1.1, the identification strategy for individuals who meet the age and age-of-arrival eligibility criteria for DACA contains regression discontinuity (RD) elements, and it is therefore as a robustness check it is possible to estimate RD models using discontinuities in only one of the DACA eligibility criteria. I do this in Appendix I, and the qualitative results obtained are broadly similar to the results from the full model as well.

VARIABLES	(1) Working	(2) Worked in past year	(3) Hours worked per week	(4) Unemployed	(5) Labor force status	(6) Self-employed	(7) Total personal income	(8) Total personal income, bottom 90%	(9) Log hourly wage	(10) Attending school	(11) Has health insurance
No controls											
Age-Eligible	0.187***	0.169***	6.831***	-0.0492***	0.163***	0.00794	-4,694**	4,274***	-0.249***	-0.104***	0.00103
*Pr(Unauthorized)*After	(0.0182)	(0.0183)	(0.837)	(0.0134)	(0.0160)	(0.00544)	(1,824)	(609.0)	(0.0511)	(0.0202)	(0.0427)
Age-Eligible*Pr(Unauthorized)	-0.168***	-0.177***	-4.956***	0.0848***	-0.112***	0.0544***	5,672***	-5,182***	0.0453	-0.334***	-0.215***
	(0.0198)	(0.0190)	(0.768)	(0.0137)	(0.0171)	(0.00622)	(1,141)	(528.4)	(0.0368)	(0.0187)	(0.0299)
Pr(Unauthorized)	0.0941***	0.0747***	2.750***	-0.0380***	0.0706***	-0.0774***	-20,379***	-6,236***	-0.664***	-0.0381***	-0.510***
	(0.0117)	(0.0109)	(0.447)	(0.00835)	(0.0131)	(0.00483)	(1,523)	(378.4)	(0.0537)	(0.0119)	(0.0346)
Age-Eligible	0.0360***	0.0630***	-0.0999	0.0154***	0.0507***	-0.0347***	-11,185***	-820.3***	-0.297***	0.204***	-0.0773***
	(0.00737)	(0.00732)	(0.298)	(0.00438)	(0.00646)	(0.00229)	(496.2)	(200.9)	(0.0151)	(0.00514)	(0.00964)
R-squared	0.001	0.002	0.002	0.004	0.002	0.003	0.020	0.006	0.059	0.014	0.043
Observations	528,296	528,296	528,296	369,509	528,296	528,296	528,294	476,565	295,132	528,296	395,991
Demographic controls only											
Age-Eligible	0.130***	0.119***	4.110***	-0.0394***	0.111***	-0.00505	-2,887*	2,501***	-0.116***	-0.00476	0.0882**
*Pr(Unauthorized)*After	(0.0157)	(0.0153)	(0.732)	(0.0111)	(0.0136)	(0.00547)	(1,533)	(465.2)	(0.0332)	(0.0183)	(0.0416)
Age-Eligible*Pr(Unauthorized)	-0.0578***	-0.0689***	0.203	0.0502***	-0.00869	0.0195***	7,816***	840.3*	0.192***	-0.244***	-0.0664**
	(0.0194)	(0.0186)	(0.707)	(0.0128)	(0.0176)	(0.00643)	(1,004)	(497.8)	(0.0253)	(0.0188)	(0.0281)
Pr(Unauthorized)	0.0407***	-0.000866	-1.037**	-0.0765***	-0.0214	-0.00974*	-7,787***	-1,624***	-0.101***	0.00336	-0.253***
	(0.0144)	(0.0126)	(0.517)	(0.00968)	(0.0135)	(0.00533)	(829.8)	(380.1)	(0.0243)	(0.0134)	(0.0362)
Age-Eligible	0.0869***	0.0802***	2.301***	-0.0267***	0.0692***	0.000150	4,073***	891.4***	0.0207**	0.0398***	-0.0371***
	(0.00758)	(0.00701)	(0.263)	(0.00544)	(0.00659)	(0.00326)	(468.4)	(230.7)	(0.00977)	(0.00590)	(0.0109)
R-squared	0.127	0.122	0.182	0.030	0.129	0.019	0.212	0.200	0.344	0.301	0.204
Observations	528,296	528,296	528,296	369,509	528,296	528,296	528,294	476,565	295,132	528,296	395,991

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VARIABLES	(1) Working	(2) Worked in past year	(3) Hours worked per week	(4) Unemployed	(5) Labor force status	(6) Self-employed	(7) Total personal income	(8) Total personal income, bottom 90%	(9) Log hourly wage	(10) Attending school	(11) Has health insurance
Demographic controls with state and year fixed effects											
Age-Eligible *Pr(Unauthorized)*After	0.127***	0.115***	3.911***	-0.0378***	0.108***	-0.00416	-2,554	2,445***	-0.104***	-0.00283	0.0931***
	(0.0159)	(0.0154)	(0.724)	(0.0108)	(0.0138)	(0.00524)	(1,594)	(454.3)	(0.0366)	(0.0173)	(0.0299)
Age-Eligible*Pr(Unauthorized)	-0.0499***	-0.0616***	0.734	0.0489***	-0.000424	0.0219***	7,650***	1,051**	0.169***	-0.252***	-0.0857***
	(0.0191)	(0.0182)	(0.708)	(0.0126)	(0.0176)	(0.00637)	(999.2)	(502.5)	(0.0246)	(0.0189)	(0.0231)
Pr(Unauthorized)	0.0394***	-0.0127	-0.890*	-0.0681***	-0.0164	0.00713	-7,641***	-1,601***	-0.114***	-0.0124	-0.303***
	(0.0135)	(0.0119)	(0.490)	(0.00893)	(0.0133)	(0.00562)	(773.7)	(346.1)	(0.0179)	(0.0140)	(0.0242)
Age-Eligible	0.0850***	0.0792***	2.186***	-0.0266***	0.0671***	-0.000604	4,060***	848.7***	0.0241**	0.0429***	-0.0274***
	(0.00747)	(0.00692)	(0.262)	(0.00541)	(0.00653)	(0.00328)	(502.5)	(232.5)	(0.0102)	(0.00593)	(0.00895)
R-squared	0.130	0.126	0.185	0.031	0.132	0.021	0.218	0.203	0.355	0.305	0.223
Observations	528,296	528,296	528,296	369,509	528,296	528,296	528,294	476,565	295,132	528,296	395,991

Table 11. Robustness checks with varying levels of controls and fixed effects.

Each column corresponds to a separate regression for the corresponding outcome variable by estimating equation (3) on the sample in Table 7 but (a) without controls or fixed effects, (b) with demographic controls only or (c) with demographic controls and state and year fixed effects. The coefficient of interest is the coefficient on the *AgeEligible*Unauthorized*After* interaction term. Income in columns 7 and 8 is measured in nominal U.S. dollars and uncorrected for inflation. Log hourly wage in column 9 is restricted to individuals who worked for at least half the prior 12-month period. Coefficients for demographic controls, fixed effects and state-year time trends are not shown. Observations are weighted using person weights in the ACS. Robust standard errors clustered at the state-year level in parentheses.
*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

7.5. *Significance and Policy Implications*

From our results we see that DACA has had a significant impact on the labor force outcomes of DREAMers. DACA has shifted approximately 200,000, or about 10 percent of the total estimated DREAMer population into employment, reducing unemployment among DREAMers by an estimated 3.8 percentage points and increasing labor force participation by 10.8 percentage points. DACA has also increased incomes significantly, by about 16 percent for the bottom 90 percent of the income distribution and 28 percent for individuals earning below median income. It is also important to recognize that these DID estimates are intent-to-treat effects, and since only an estimated 60 percent of DREAMers have actually applied for DACA (Batalova et al., 2014), the actual magnitudes of the effect of DACA can be close to 1.67 times larger than the estimates obtained here.

These results therefore illustrate the magnitude of the impact of DACA on the DREAMer population, and show that DACA has brought about significant economic benefit for DREAMers. Also, the results demonstrate that the largest effects of DACA are felt by DREAMers lower in the income distribution, hence the welfare benefits of DACA may be even greater, since the marginal benefit of, for example, an increase in income would be greatest for these individuals.

DACA thus appears to be broadly beneficial for the DREAMer population, and the economic case for DACA from the DREAMer perspective thus appears rather clear-cut. The benefits of DACA for the broader U.S. population, however, are harder to quantify, and although not exactly within the scope of this paper still worth considering nonetheless. The estimates obtained from my analysis are partial equilibrium effects, but by increasing the supply of labor in the overall workforce, DACA might cause overall wages to fall. I believe that this is highly unlikely: The U.S. economy is at or near full employment right now, and over 10 million jobs were created between 2013 to 2016, which dwarfs the number of DREAMers shifted into the labor force by DACA, or even the total number of DREAMers. Therefore, I do not believe that DACA would lead to negative general equilibrium effects on wages or employment among the broader population. Furthermore, the positive impact of DACA among DREAMers would far outweigh any negative impacts — as a very rough calculation, if DACA increased annual incomes among DREAMers by $2,000 on average, as estimated in Table 7, this would translate to approximately a $900 million increase in GDP. Theoretical general equilibrium modeling of the effect of DACA on the broader U.S. economy by Ortega et al. (2018) appears to confirm this: they find that DACA increased wages of DACA recipients by 12% on average, but did not affect citizen wages; also, they calculate that DACA increased U.S. GDP by approximately $3.5 billion in the 5 years since 2012, i.e. by approximately $700 million per year.

This therefore makes the case that DACA is beneficial both for DREAMers and for the country as a whole, and also suggests that repeal of DACA, as proposed by the Trump administration, would have significant economic consequences. The repeal of DACA would be equivalent to reintroducing the frictions and barriers faced by DREAMers in the labor market, and therefore it makes sense to expect that the effects of repeal should be the opposite of what we have estimated in this paper: i.e., that repeal would decrease the likelihood of DREAMers working by about 12 percentage points, would increase unemployment among DREAMers by 3.8 percentage points and lower incomes by about 15%. More broadly, repeal would translate to about a $700 million to $900 million reduction in U.S. GDP, using the estimates above. Also, we have observed that the positive impacts of DACA appear to strengthen over the period for which DACA has been in effect, so the potential loss in GDP and other negative outcomes could be even greater. Moreover, repeal of DACA would expose DREAMers to the risk of deportation again — which in and of itself has significant negative consequences for the DREAMer population.

We can also consider the potential effects of the opposite of repeal — the expansion of DACA protections, for example through the loosening of the eligibility criteria in order to grant deferred status to a larger group of unauthorized immigrants. This is actually what the Obama administration attempted to do in 2014, when President Obama announced that he would expand DACA to include unauthorized immigrants of any age who entered the country before the age of 16 and had lived in the U.S. continuously since 2010, as well as introducing a new program, Deferred Action for Parents of Americans and Lawful Permanent Residents (or DAPA for short), that would grant deferred action to undocumented parents of U.S. citizens or permanent residents.[33] The Migration Policy Institute in Washington, D.C. has estimated that the expanded policy could apply to up to as many as 3.7 million unauthorized immigrants, or close to a third of the unauthorized immigrant population in the United States.[34] If we assume that the potential impacts of this expansion are similar to our estimates of the effect of DACA, this would translate to about 400,000 additional immigrants moved into employment, and about a $2 billion increase in U.S. GDP, which is a considerable amount. However, the expansion of DACA and introduction of DAPA was blocked in the courts after 24 states filed suit, and eventually repealed by the Trump administration in 2017. Nevertheless, we see from our results that any expansion of DACA introduced by a future administration or Congress could bring about significant economic benefit to the unauthorized immigrant population, as well as to the broader economy.

[33] https://www.uscis.gov/archive/2014-executive-actions-immigration
[34] https://www.migrationpolicy.org/news/mpi-many-37-million-unauthorized-immigrants-could-get-relief-deportation-under-anticipated-new

8. Conclusion

This paper has examined the impact of DACA on the group of unauthorized immigrants known as DREAMers, and found that DACA has brought about significant labor market benefits to the DREAMer population. DACA has moved DREAMers into work by increasing labor force participation and decreasing unemployment, although these effects differ by gender. DACA has also increased incomes, with the largest increases at the bottom of the income distribution. Also, DACA has increased health insurance coverage among the DREAMer population. These results therefore demonstrate the value of the legal status and work authorization provided by DACA, and conversely also show how undocumented status had previously affected the DREAMer population. And as DACA continues to be debated in Congress and the courts and as the fate of DREAMers remains in limbo, it is therefore important to understand that the case for DACA is not just a moral but also an economic one, and it is hoped that this paper has provided some insight on the economic benefits of DACA for DREAMers.

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APPENDIX I: Regression Discontinuity Specifications

The models we estimate in the main body of the paper are DID models with some regression discontinuity (RD) elements arising from the criteria for DACA; we can estimate pure RD models by performing the DID estimation on subsamples that only differ by only one of the criteria for DACA. Table A1 on the next page presents the results of estimating equation (1) on (a) a sample of noncitizens below the age of 31 who entered the U.S. between ages 12 and 19 (i.e. the discontinuity being the DACA cutoff for entering before age 16) and (b) a sample of noncitizens aged between 27 and 34 who entered the U.S. before age 16 (i.e. the discontinuity being the DACA cutoff for being under 31 on June 15, 2012).

Table A2 on the following page presents the results of estimating the two-stage DID model specified in equation (3) on the same two subsamples as in Table A1. We see from the results in Tables A1 and A2 that the RD method gives qualitatively similar estimates of the effect of DACA on the various outcomes of interest, especially in the two-stage model. However, some effects are weaker or absent, most likely due to the smaller sample sizes involved. Both sets of RD specifications provide further evidence to the robustness of our results in the main text.

VARIABLES	(1) Working	(2) Worked in past year	(3) Hours worked per week	(4) Unemployed	(5) Labor force status	(6) Self-employed	(7) Total personal income	(8) Total personal income, bottom 90%	(9) Log hourly wage	(10) Attending school	(11) Has health insurance
Under 31, entered U.S. between 12 and 19											
Age-Eligible*After	0.0509***	0.0427***	1.758***	-0.0121**	0.0449***	-0.00123	296.0	727.7***	-0.0214*	-0.0276***	0.00593
	(0.00831)	(0.00871)	(0.338)	(0.00568)	(0.00814)	(0.00327)	(344.0)	(232.3)	(0.0112)	(0.00823)	(0.00895)
Age-Eligible	-0.0350***	-0.0425***	-0.802**	-0.0124	-0.0491***	-0.00155	-592.9**	-140.9	-0.00591	-0.0435***	0.00249
	(0.0103)	(0.0104)	(0.363)	(0.0101)	(0.0112)	(0.00334)	(271.3)	(202.5)	(0.0159)	(0.00906)	(0.0106)
Age-eligible sample mean, pre-DACA	0.669	0.766	28.3	0.105	0.747	0.0402	15,974	14,331	2.408	0.303	0.451
Observations	122,037	122,037	122,037	80,355	122,037	122,037	122,037	118,544	60,741	122,037	91,380
R-squared	0.150	0.141	0.229	0.031	0.158	0.018	0.200	0.247	0.233	0.421	0.199
Between 27 and 34, entered U.S. under 16											
Age-Eligible*After	0.0227**	0.0177*	0.585	-0.0119	0.0146	0.0103	1,215	-32.23	0.0189	0.00724	-0.0345**
	(0.0112)	(0.00961)	(0.419)	(0.00852)	(0.00914)	(0.00777)	(772.4)	(450.4)	(0.0145)	(0.00996)	(0.0142)
Age-Eligible	0.00962	0.0116	0.394	-0.00400	0.00637	-0.00806	697.5	1,105**	0.0123	-0.0140	0.0436**
	(0.0164)	(0.0139)	(0.566)	(0.0106)	(0.0148)	(0.0108)	(989.8)	(533.4)	(0.0214)	(0.0102)	(0.0190)
Age-eligible sample mean, pre-DACA	0.758	0.841	33.7	0.0839	0.828	0.0617	25,765	21,746	2.642	0.115	0.553
Observations	43,870	43,870	43,870	35,429	43,870	43,870	43,870	40,525	30,223	43,870	33,954
R-squared	0.058	0.070	0.106	0.024	0.066	0.016	0.137	0.117	0.179	0.087	0.124

Table A1. Regression discontinuity design estimates of the effect of DACA on various labor market, education and healthcare outcomes.

Each column corresponds to a separate regression for the corresponding outcome variable by estimating equation (1) on a sample from the 2005 –2016 ACS containing (a) noncitizens under the age of 31 who entered the U.S. between age 12 and 19 and (b) noncitizens aged 27 to 34 who entered the U.S. before age 16. The coefficient of interest is the coefficient on the *AgeEligible*After* interaction term. The coefficient of interest is the coefficient on the *AgeEligible*After* interaction term. Income in columns 7 and 8 measured in nominal U.S. dollars and uncorrected for inflation. Log hourly wage in column 9 is restricted to individuals who worked for at least half the prior 12-month period. Coefficients for demographic controls, fixed effects and state-year time trends are not shown. The row *Age-eligible sample mean, pre-DACA* gives the sample mean for individuals before 2012 who meet the age eligibility criteria for DACA. Observations are weighted using person weights in the ACS. Robust standard errors clustered at the state-year level in parentheses.
*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

VARIABLES	(1) Working	(2) Worked in past year	(3) Hours worked per week	(4) Unemployed	(5) Labor force status	(6) Self-employed	(7) Total personal income	(8) Total personal income, bottom 90%	(9) Log hourly wage	(10) Attending school	(11) Has health insurance
Under 31, entered U.S. between 12 and 19											
Age-Eligible	0.106***	0.0896***	3.703***	-0.0199	0.0936***	-0.00479	901.9	1,913***	-0.0306	-0.0454**	0.0381
*Pr(Unauthorized)*After	(0.0216)	(0.0219)	(0.832)	(0.0154)	(0.0204)	(0.00893)	(897.9)	(593.3)	(0.0305)	(0.0199)	(0.0259)
Age-Eligible*Pr(Unauthorized)	-0.150***	-0.132***	-5.185***	0.0475**	-0.131***	0.00273	100.5	-1,761**	0.0333	0.112***	0.0251
	(0.0302)	(0.0269)	(1.072)	(0.0221)	(0.0270)	(0.00996)	(1,015)	(744.7)	(0.0366)	(0.0243)	(0.0330)
Pr(Unauthorized)	0.0941***	0.0421**	2.276***	-0.0733***	0.0444*	0.0156**	868.8	540.4	0.0207	-0.108***	-0.301***
	(0.0228)	(0.0206)	(0.861)	(0.0173)	(0.0252)	(0.00740)	(783.7)	(577.3)	(0.0278)	(0.0232)	(0.0333)
Age-Eligible	0.0226	0.00803	1.181**	-0.0310**	0.00124	-0.00239	-637.6	503.5	-0.0211	-0.0867***	-0.00907
	(0.0148)	(0.0139)	(0.525)	(0.0122)	(0.0147)	(0.00438)	(438.6)	(321.4)	(0.0202)	(0.0121)	(0.0154)
Age-eligible sample mean, pre-DACA	0.669	0.766	28.3	0.105	0.747	0.0402	15,974	14,331	2.408	0.303	0.451
Observations	122,037	122,037	122,037	80,355	122,037	122,037	122,037	118,544	60,741	122,037	91,380
R-squared	0.150	0.141	0.229	0.031	0.158	0.018	0.200	0.247	0.233	0.421	0.201
Between 27 and 34, entered U.S. under 16											
Age-Eligible	0.0862***	0.0794***	2.586**	-0.0203	0.0741***	0.00562	3,318	4,312***	0.0962**	0.0439*	-0.116***
*Pr(Unauthorized)*After	(0.0313)	(0.0267)	(1.254)	(0.0219)	(0.0279)	(0.0202)	(2,044)	(1,232)	(0.0463)	(0.0232)	(0.0439)
Age-Eligible*Pr(Unauthorized)	0.0597	-0.0426	-0.0545	-0.101**	-0.0240	0.0557	7,355*	-2,330	0.0185	-0.185***	0.120
	(0.0635)	(0.0510)	(2.296)	(0.0492)	(0.0474)	(0.0393)	(3,748)	(2,332)	(0.0836)	(0.0384)	(0.0829)
Pr(Unauthorized)	0.0272	0.0581	1.056	-0.0157	0.0121	-0.0607	-11,771***	1,312	-0.176*	0.175***	-0.219***
	(0.0667)	(0.0572)	(2.498)	(0.0493)	(0.0502)	(0.0441)	(3,917)	(2,449)	(0.100)	(0.0422)	(0.0782)
Age-Eligible	-0.000581	0.0206	0.424	0.0137	0.0110	-0.0160	-585.7	1,251*	0.00825	0.0224	0.0145
	(0.0209)	(0.0176)	(0.762)	(0.0130)	(0.0181)	(0.0129)	(1,302)	(726.4)	(0.0261)	(0.0137)	(0.0259)
Age-eligible sample mean, pre-DACA	0.758	0.841	33.7	0.0839	0.828	0.0617	25,765	21,746	2.642	0.115	0.553
Observations	43,870	43,870	43,870	35,429	43,870	43,870	43,870	40,525	30,223	43,870	33,954
R-squared	0.059	0.070	0.107	0.025	0.066	0.016	0.137	0.118	0.179	0.088	0.124

Table A2. Second-stage regression discontinuity estimates of the effect of DACA on various labor market, education and healthcare outcomes.

Each column corresponds to a separate regression for the corresponding outcome variable by estimating equation (3) on a sample from the 2005–2016 ACS containing (a) noncitizens under the age of 31 who entered the U.S. between age 12 and 19 and (b) noncitizens aged 27 to 34 who entered the U.S. before age 16. The coefficient of interest is the coefficient on the *AgeEligible*Unauthorized*After* interaction term. Income in columns 7 and 8 measured in nominal U.S. dollars and uncorrected for inflation. Log hourly wage in column 9 is restricted to individuals who worked for at least half the prior 12-month period. Coefficients for demographic controls, fixed effects and state-year time trends are not shown. The row *Age-eligible sample mean, pre-DACA* gives the sample mean for individuals before 2012 who meet the age eligibility criteria for DACA. Observations are weighted using person weights in the ACS. Robust standard errors clustered at the state-year level in parentheses.
*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

APPENDIX II: Alternative Income Variables

The ACS provides multiple income variables; the regressions in the main body of the paper are run using total personal income as one of the outcome variables. However, we can also use total wage income as a dependent variable, obtaining similar results. This section replicates Figure 4(ab) and the relevant columns in Tables 3 through 5, 7, 9 and 10, as well as all of Table 8, using total wage income in place of total income, in Figure A1 and Tables A3 through A8. We see that the estimates obtained are very similar to the results in the main text, except for a strong, negative linear pre-trend for total wage income in Table A6.

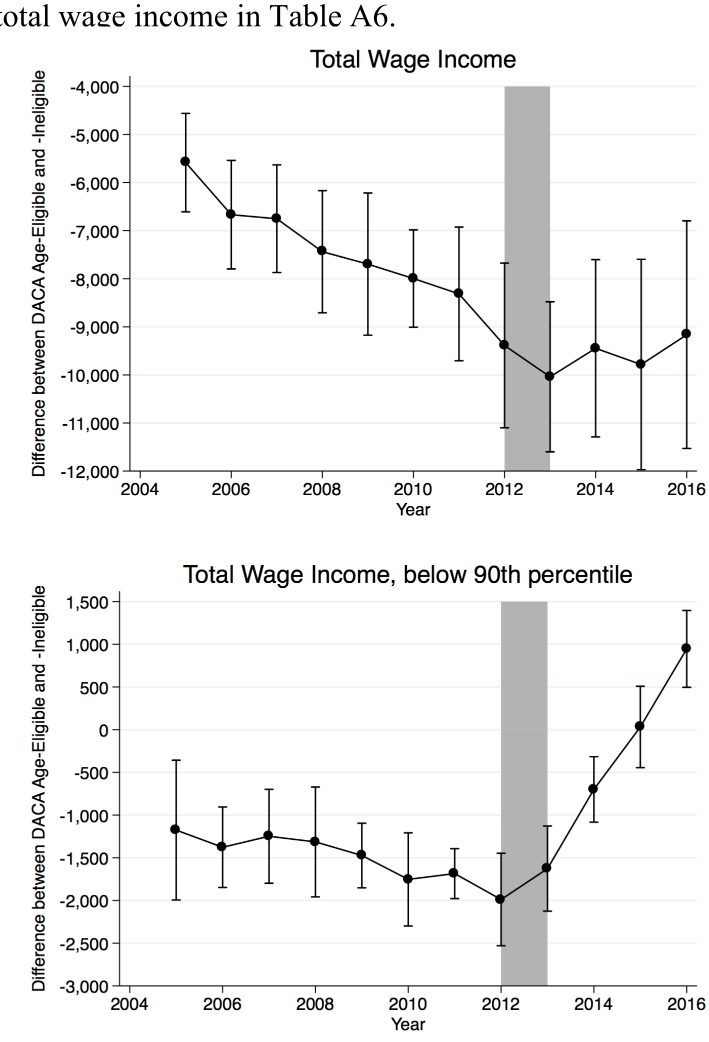

Figure A1. Differences in means of total wage income between individuals who meet the age eligibility criteria for DACA and who do not. Sample contains (a) all noncitizens in 2005–2016 ACS aged 18–35 with at least a high school degree, (b) restricted to individuals with total wage incomes below the 90th percentile. Amounts are in nominal U.S. dollars unadjusted for inflation. Vertical bars correspond to 95% confidence intervals, calculated with robust standard errors clustered at the state-year level. Observations are weighted using person weights in the ACS. The shaded area represents the period in which DACA was introduced.

VARIABLES	(7) Total wage income	(8) Total wage income, bottom 90%
Age-Eligible*After	-1,090**	698.8***
	(545.4)	(166.8)
Age-Eligible	6,819***	1,347***
	(505.1)	(191.1)
Age-eligible sample mean, pre-DACA	14,994	13,384
Observations	528,296	479,491
R-squared	0.212	0.180

Table A3. Difference-in-differences estimates of the effect of DACA on total wage income.

This corresponds to columns (7) and (8) in Table 3 in the main text, with total personal income replaced by wage income. The coefficient of interest is the coefficient on the *AgeEligible*After* interaction term. Income is measured in nominal U.S. dollars and uncorrected for inflation. Coefficients for demographic controls, fixed effects and state-year time trends are not shown. Observations are weighted using person weights in the ACS. Robust standard errors clustered at the state-year level in parentheses.
*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

VARIABLES	(7) Total wage income	(8) Total wage income, bottom 90%
Age-Eligible *Pr(Unauthorized)*After	-2,751*	2,518***
	(1,540)	(419.3)
Age-Eligible*Pr(Unauthorized)	6,881***	589.0
	(978.4)	(501.7)
Pr(Unauthorized)	-6,363***	-603.4
	(732.6)	(370.8)
Age-Eligible	4,588***	1,137***
	(463.4)	(247.7)
Age-eligible sample mean, pre-DACA	14,994	13,384
Observations	528,296	479,491
R-squared	0.213	0.180

Table A4. Second-stage DID estimates of the effect of DACA on total wage income.

This corresponds to columns (7) and (8) in Table 6 in the main text, with total personal income replaced by wage income. The coefficient of interest is the coefficient on the *AgeEligible*Unauthorized*After* interaction term. Income is measured in nominal U.S. dollars and uncorrected for inflation. Coefficients for demographic controls, fixed effects and state-year time trends are not shown. Observations are weighted using person weights in the ACS. Robust standard errors clustered at the state-year level in parentheses.
*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

	(7)	(8)
VARIABLES	Total wage income	Total wage income, bottom 90%
Age-Eligible*2016	-199.6	1,889***
	(1,381)	(353.8)
Age-Eligible*2015	-485.1	1,351***
	(1,415)	(384.8)
Age-Eligible*2014	-4.258	969.7***
	(1,265)	(343.2)
Age-Eligible*2013	-548.5	230.5
	(1,225)	(357.5)
Age-Eligible*2011	450.3	214.2
	(1,098)	(319.4)
Age-Eligible*2010	378.6	170.3
	(1,079)	(397.2)
Age-Eligible*2009	806.0	499.2
	(1,191)	(365.4)
Age-Eligible*2008	973.4	790.4*
	(1,072)	(419.0)
Age-Eligible*2007	1,103	662.7*
	(1,005)	(344.6)
Age-Eligible*2006	1,213	549.4
	(973.5)	(364.0)
Age-Eligible*2005	1,582	453.8
	(1,002)	(448.7)
Age-eligible sample mean, pre-DACA	14,994	13,384
Observations	528,296	479,491
R-squared	0.212	0.180

Table A5. Estimates of the effect of DACA age-eligibility by year for wage income.

This corresponds to columns (7) and (8) in Table 4 in the main text, with total personal income replaced by wage income. Each column corresponds to a separate regression for the corresponding outcome variable by estimating equation (1) but with $AgeEligible_{it}$ interacted with each year dummy. The interaction *AgeEligible**2012 is the omitted category. Each row corresponds to the coefficient on the interaction terms. Income is measured in nominal U.S. dollars and uncorrected for inflation. Coefficients on year dummies, demographic controls, fixed effects and state-year time trends are not shown. Observations are weighted using person weights in the ACS. Robust standard errors clustered at the state-year level in parentheses.
*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

VARIABLES	(7) Total wage income	(8) Total wage income, bottom 90%
Age-Eligible*2016	4,212***	3,246***
	(652.5)	(249.1)
Age-Eligible*2015	2,827***	2,332***
	(892.9)	(287.0)
Age-Eligible*2014	1,939**	1,463***
	(821.8)	(248.6)
Age-Eligible*2013	765.8	441.6*
	(744.5)	(237.4)
Age-Eligible *linear pre-trend	-336.5***	-380.9***
	(111.2)	(44.90)
Age-eligible sample mean, pre-DACA	14,994	13,384
Observations	528,296	479,491
R-squared	0.020	0.006

Table A6. Testing for pre-trends for wage income.

This corresponds to columns (7) and (8) in Table 5 in the main text, with total personal income replaced by wage income. Each column corresponds to a separate regression for the corresponding outcome variable by estimating equation (1) but with $AgeEligible_{it}$ interacted with a linear pre-trend equal to min(*year*–2012, 0) and with year dummies for years after 2012. Each row corresponds to the coefficient on the interaction terms. Income is measured in nominal U.S. dollars and uncorrected for inflation. Coefficients on year dummies, demographic controls, fixed effects and state-year time trends are not shown. Observations are weighted using person weights in the ACS. Robust standard errors clustered at the state-year level in parentheses.
*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

VARIABLES	(1) Working	(2) Worked in past year	(3) Hours worked per week	(4) Unemployed	(5) Labor force status	(6) Self-employed	(7) Total wage income	(8) Log hourly wage	(9) Attending school	(10) Has health insurance
Below 90th percentile income										
Age-Eligible	0.153***	0.137***	4.752***	-0.0403***	0.134***	-0.00434	2,518***	-0.0205	-0.0181	0.0745***
*Pr(Unauthorized)*After	(0.0155)	(0.0149)	(0.623)	(0.0103)	(0.0141)	(0.00550)	(419.3)	(0.0174)	(0.0159)	(0.0265)
Age-Eligible*Pr(Unauthorized)	-0.0831***	-0.0902***	-0.903	0.0578***	-0.0303*	0.0242***	589.0	0.0821***	-0.243***	-0.0714***
	(0.0201)	(0.0191)	(0.689)	(0.0131)	(0.0182)	(0.00649)	(501.7)	(0.0193)	(0.0186)	(0.0232)
Pr(Unauthorized)	0.0617***	0.00184	0.131	-0.0750***	0.00157	0.00446	-603.4	-0.0474***	-0.0264*	-0.312***
	(0.0145)	(0.0127)	(0.522)	(0.00964)	(0.0142)	(0.00576)	(370.8)	(0.0159)	(0.0148)	(0.0240)
Age-Eligible	0.0783***	0.0733***	1.903***	-0.0287***	0.0598***	0.00231	1,137***	-0.0126	0.0505***	-0.0359***
	(0.00784)	(0.00729)	(0.268)	(0.00574)	(0.00695)	(0.00343)	(247.7)	(0.00863)	(0.00611)	(0.00902)
Age-eligible sample mean, pre-DACA	0.645	0.752	27.2	0.119	0.733	0.0375	13,384	2.392	0.325	0.474
Observations	479,491	479,491	479,491	321,446	479,491	479,491	479,491	246,893	479,491	357,774
R-squared	0.126	0.125	0.178	0.027	0.133	0.023	0.180	0.189	0.316	0.197
Below median income										
Age-Eligible	0.181***	0.177***	4.997***	-0.0691***	0.166***	0.00629	1,099***	0.00251	-0.0185	0.0919***
*Pr(Unauthorized)*After	(0.0196)	(0.0211)	(0.701)	(0.0192)	(0.0199)	(0.00930)	(172.1)	(0.0266)	(0.0186)	(0.0325)
Age-Eligible*Pr(Unauthorized)	-0.164***	-0.176***	-4.309***	0.171***	-0.0723***	-0.00718	-899.9***	-0.0182	-0.263***	-0.0992***
	(0.0280)	(0.0284)	(0.895)	(0.0268)	(0.0266)	(0.0110)	(209.2)	(0.0346)	(0.0234)	(0.0282)
Pr(Unauthorized)	0.0642***	0.000955	-0.213	-0.119***	-0.0163	0.0367***	8.032	0.00233	-0.0153	-0.310***
	(0.0185)	(0.0185)	(0.674)	(0.0204)	(0.0192)	(0.00909)	(158.4)	(0.0246)	(0.0183)	(0.0272)
Age-Eligible	0.0794***	0.0782***	1.703***	-0.0725***	0.0484***	0.0123*	472.0***	0.0289*	0.0675***	-0.0402***
	(0.0117)	(0.0121)	(0.408)	(0.0132)	(0.0108)	(0.00648)	(96.90)	(0.0156)	(0.00867)	(0.0115)
Age-eligible sample mean, pre-DACA	0.416	0.557	16.7	0.238	0.545	0.057	3,043	1.938	0.445	0.422
Observations	272,970	272,970	272,970	122,729	272,970	272,970	272,970	48,698	272,970	208,142
R-squared	0.071	0.083	0.106	0.030	0.091	0.070	0.063	0.061	0.393	0.212

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VARIABLES	(1) Working	(2) Worked in past year	(3) Hours worked per week	(4) Unemployed	(5) Labor force status	(6) Self-employed	(7) Total wage income	(8) Log hourly wage	(9) Attending school	(10) Has health insurance
Above median income										
Age-Eligible	0.0159*		0.116	-0.0105	0.00582	-0.00664	-9,545***	-0.119***	0.0297	0.0382
*Pr(Unauthorized)*After	(0.00846)		(0.450)	(0.00672)	(0.00508)	(0.00425)	(2,683)	(0.0357)	(0.0185)	(0.0312)
Age-Eligible*Pr(Unauthorized)	0.00120		2.788***	0.00279	0.00404	0.0270***	12,391***	0.136***	-0.133***	0.0125
	(0.0111)		(0.489)	(0.00922)	(0.00728)	(0.00668)	(1,510)	(0.0229)	(0.0187)	(0.0301)
Pr(Unauthorized)	0.0343***		-0.720*	-0.0246***	0.0106**	-0.0157***	-8,917***	-0.150***	0.00945	-0.282***
	(0.00707)		(0.382)	(0.00558)	(0.00483)	(0.00525)	(1,207)	(0.0179)	(0.0121)	(0.0266)
Age-Eligible	0.0106**		-0.771***	-0.00119	0.00957***	0.00147	2,906***	0.0196**	0.0248***	-0.0287**
	(0.00437)		(0.166)	(0.00325)	(0.00278)	(0.00334)	(636.9)	(0.00937)	(0.00622)	(0.0121)
Age-eligible sample mean, pre-DACA	0.939		40.8	0.0333	0.972	0.0142	29,472	2.579	0.169	0.557
Observations	255,326		255,326	246,780	255,326	255,326	255,326	246,434	255,326	187,849
R-squared	0.009		0.041	0.006	0.013	0.013	0.240	0.365	0.124	0.260

Table A7. Two-stage DID estimates of the effect of DACA on various labor market, education and healthcare outcomes by wage income level.

This corresponds to Table 8 in the main text but with subsamples based on total wage income. The regression for working in the past year for the subsample with above median wage income omitted because all observations in the sample worked the previous year. The coefficient of interest is the coefficient on the *AgeEligible*Unauthorized*After* interaction term. Income is measured in nominal U.S. dollars and uncorrected for inflation. Log hourly wage in column 8 is restricted to individuals who worked for at least half the prior 12-month period. Coefficients for demographic controls, fixed effects and state-year time trends are not shown. The row *Age-eligible sample mean, pre-DACA* gives the sample mean for individuals before 2012 who meet the age eligibility criteria for DACA. Observations are weighted using person weights in the ACS. Robust standard errors clustered at the state-year level in parentheses.
*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Male		*Female*		*Hispanic ethnicity*		*Born in Mexico*	
VARIABLES	Total wage income	Total wage income, bottom 90%	Total wage income	Total wage income, bottom 90%	Total wage income	Total wage income, bottom 90%	Total wage income	Total wage income, bottom 90%
Age-Eligible *Pr(Unauthorized)*After	-4,414**	2,430***	-1,744	1,927***	-785.4	777.9*	-661.6	719.0
	(2,007)	(514.6)	(1,173)	(573.1)	(632.7)	(440.7)	(774.7)	(594.6)
Age-Eligible*Pr(Unauthorized)	15,910***	2,492***	11,752***	4,988***	-4,226***	-3,555***	-12,199***	-11,030***
	(1,496)	(678.6)	(1,085)	(611.0)	(915.4)	(754.9)	(1,081)	(876.0)
Pr(Unauthorized)	-4,140***	2,299***	-7,120***	-3,917***	2,668***	1,536***	7,540***	4,822***
	(1,011)	(507.6)	(772.9)	(458.7)	(632.9)	(512.9)	(1,470)	(1,037)
Age-Eligible	3,351***	773.4**	1,037**	-296.1	1,237***	1,211***	3,559***	3,353***
	(700.6)	(370.4)	(459.0)	(303.7)	(412.6)	(328.0)	(534.2)	(438.8)
Age-eligible sample mean, pre-DACA	17,737	15,591	11,915	10,944	14,459	13,508	13,795	12,967
Observations	263,649	229,591	264,647	249,900	226,488	220,965	147,035	144,338
R-squared	0.239	0.186	0.147	0.129	0.166	0.197	0.179	0.215

Table A8. Two-stage DID estimates of the effect of DACA on wage income by (a) gender and (b) ethnicity and country of birth.

Columns (1) to (4) correspond to columns (7) and (8) in Table 9 in the main text. Columns (5) to (8) correspond to columns (7) and (8) in Table 10 in the main text. Each column corresponds to a separate regression for the corresponding outcome variable by estimating equation (3) on the sample in Table 7 restricted to (1-2) males, (3-4) females, (5-6) individuals of Hispanic ethnicity and (7-8) individuals born in Mexico. The coefficient of interest is the coefficient on the *AgeEligible*Unauthorized*After* interaction term. Income is measured in nominal U.S. dollars and uncorrected for inflation. Coefficients for demographic controls, fixed effects and state-year time trends are not shown. The row *Age-eligible sample mean, pre-DACA* gives the sample mean for individuals before 2012 who meet the age eligibility criteria for DACA. Observations are weighted using person weights in the ACS. Robust standard errors clustered at the state-year level in parentheses.
*** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.