Title

THE IMPACT OF DACA ON UNAUTHORIZED IMMIGRANTS:Analyzing Heterogeneous Treatment Effects of Temporary Work Authorization

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Publication Date
2019-03-16

Undergraduate

THE IMPACT OF DACA ON UNAUTHORIZED IMMIGRANTS:
Analyzing Heterogeneous Treatment Effects of Temporary Work Authorization

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March 16, 2019

Econ 196A

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ABSTRACT

The Deferred Action for Childhood Arrivals (DACA) program benefits hundreds of thousands of undocumented immigrant youths today. With the policy under threat of being rescinded, it is crucial to understand how it has affected these young unauthorized immigrants in order to understand the potential consequences of ending such a program. In order to fully assess the effects and possible incentives created by DACA, I use the program's eligibility requirement to construct a sample of potentially eligible individuals. Using a difference-In-differences method, I analyze the overall effect of this policy on different education and labor outcomes across different groups. I find that it has increased their likelihood of working by increasing the probability of entering the labor force and decreasing the probability of being unemployed. I also find evidence of heterogeneity across age and ethnic groups for some labor and educational outcomes. The results indicate that it incentivizes investment in education, at least at a high school level, while disincentivizing investment in higher levels of education for those who received the program at an older age. Further evidence suggests that eligible individuals who received DACA at a younger age are still more likely to invest in higher education at higher levels compared to those who received it at an older age. From this, I conclude that it not only helps this group enter the workforce but also partially increases investment in education thus creating a more capable and educated workforce which benefits the economy as a whole.

INTRODUCTION

Immigration has been at the forefront of heated political discussions across the world. With a large immigrant population, the United States has a long and contentious history attempting to figure out the proper way to regulate the constant influx of immigrants. The most recent wave from the American Community Survey estimates that there are about 44.7 million foreign-born individuals in the United States, with around 22.6 million of them classified as non-citizens.[1] This group consists of authorized immigrants, as well as unauthorized immigrants such as refugees and individuals temporarily protected from deportation under policies such as Temporary Protected Status (TPS) and Deferred Action for Childhood Arrivals (DACA). They've already contributed billions of dollars to GDP;[2] Increasing their access to education and better-paying jobs can only amplify that effect. In order to do so correctly and efficiently, it is important to first understand the economic impact and incentives created by existing policies like DACA. This knowledge can then be utilized to inform and help create more effective immigration policies to be implemented in the future.

In order to fully assess the effects and possible incentives created by DACA, I analyze the overall effect of DACA on different education and labor outcomes. Additionally, I focus on analyzing possible heterogeneity in the treatment effects on these outcomes. The presence of differences in the treatment effect may suggest that socioeconomic differences between different ethnic and age groups is affecting the way these groups respond to the changes in labor market frictions and returns to education caused by policies like DACA. Using a difference-In-differences method on various groups I can see how this policy has affected the labor and educational outcomes of those eligible for the program. I find that it has increased their likelihood of working by increasing the probability of entering the labor force and decreasing the probability of being unemployed. I find evidence of heterogeneity across age groups and ethnic for some labor and educational outcomes. These findings suggest that policies like DACA that intent to bring marginalized immigrant groups back into society, not only increase their access to the labor market but to education as well, creating a more capable and educated workforce which benefits the economy as a whole.

BACKGROUND

According to the U.S. Citizenship and Immigration Services (USCIS), DACA beneficiaries make up more than 650,000 of the estimated 11 million unauthorized immigrants as of September of 2019.[3] This group of unauthorized immigrants, also known as DREAMers, simultaneously experience full integration and marginalization in American society. They grow up side-by-side

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[1] "S0501: Characteristics of the Native and Foreign-Born Populations," United Sates Census Bureau, https://data.census.gov/cedsci/S05013ASELECTEDCHARACTERISTICSOFTHENATIVEANDFOREIGN-BORNPOPULATIONSACSST1Y2018S05012018

[2] Edwards, R., & Ortega, F. (2017). The economic contribution of unauthorized workers: An industry analysis. *Regional Science and Urban Economics*, *67*, 119-134.

[3] I-821 DACA

with native born American youth under the "legally protected status of K to 12 students," but are forced to face the social and economic limitations of living without legal status as they transition into adulthood.[4] They must cope with the constant fear of deportation and face barriers that limit their means of education and employment opportunities, ultimately confining them to low-wage jobs with little hope for upward mobility. Due to their unique circumstances, we have seen increased pressure for the government to provide a solution. Around 2001, legislation to address this issue was first introduced to Congress. If passed, The Development Relief and Education of Alien Minors Act bill, generally known as the Dream Act, would legalize the status of undocumented youth who entered the country at the age of 15 and under. [5]

Various versions have been introduced since then, none of them successful. In response to Congress's inability to provide a solution Dreamers, various states' implemented a series of laws to decrease barriers to higher education and provide sanctuary state protections. It is not until 2012, when President Obama introduced the DACA program, that we finally see a response at the Federal level.

The Deferred Action for Childhood Arrivals (DACA) is a temporary stopgap measure to provide temporary relief for Dreamers but does not serve as a permanent solution to the problem. The policy was also limited to a specific subset of unauthorized immigrants, leaving the large majority without any protection. In the case that individuals meet the policy's eligibility criteria, they would be granted a renewable 2-year deferral from deportation proceedings and temporary work authorization. Eligibility for the program required immigrant youth to be (1)under the age of 31 on June of 2012, (2) have entered under the age of 16, (3) have lived in the US for at least 5 years(since 2007), and finally, (4) be seeking an education or have obtained a high school degree or equivalent.[6] In addition to these restrictions, applicants must pay a fine of nearly $500, as well as fully disclose their identities to the federal government. Since then, the program had been running smoothly until President Trump's decision to terminate the program in 2017. It was blocked by several judges in states like California and New York the following year, allowing DACA recipients to continue to renew. Fearing the negative effects of ending the program, the decision to terminate is currently being reviewed by the United States Supreme Court.

LITERATURE REVIEW

Several key studies have been conducted that focus on the effects of the program experienced by DREAMers and unauthorized immigrants. While these studies cover a broad range of outcomes, including income, poverty, unemployment, education, and health, they are limited to observing very short-term results and an attenuated impact of the program caused by the lack of data regarding immigration status and the inability to observe DACA recipients directly.

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[4] Gonzales, Roberto G. "Learning to be illegal: Undocumented youth and shifting legal contexts in the transition to adulthood." https://doi.org/10.1177/0003122411411901

[5] American Immigration Council (AIC), 2019

[6] Additional discussion of eligibility criteria in Data section

Amuedo-Dorantes and Antman are two of the primary contributors to this literature. They first used the American Community Survey (2009-2014) to analyze if providing work authorization to unauthorized immigrants could help reduce the likelihood of poverty in those communities (Amuedo-Dorante & Antman 2016). In order to properly measure the effects of DACA, they restricted their observation to Mexican-noncitizens meeting the program's eligibility requirements. Using the Difference-in-Differences method, to observe the effect of receiving DACA for those eligible compared to those ineligible, they found that the program reduced the chances of poverty by approximately 38% of the sample average (Amuedo-Dorante & Antman 2016). They are essentially exploiting the discontinuity in the age-eligibility cut off to isolate the effect of DACA. This is assuming that the sample of individuals is representative of the into-to-treat group. Amuedo-Dorantes and Antman's restriction of the sample to individuals non-citizens of Mexican background (because the majority of DACA recipients are of Mexican descent) is a good start but maybe not fully solve the limitation of the ACS to accurately identify unauthorized immigrants. It could also be ignoring the possible heterogeneity in these results due to differences in ethnic background.

In a subsequent study by Amuedo-Dorantes and Antman (2017), the two estimate the schooling and labor market effects of temporary authorization using the Current Population Survey (200-2014). In order to deal with the CPS's lack of immigration status data, the authors once again take advantage of the DACA eligibility cutoffs using a Difference-in-Differences model. This time the sample is only restricted to non-citizens ages 18 to 24. One of the limitations is that the CPS sample is already so small. This means they most control for the omitted variable bias[7] by having the proxy variable for eligible include all the DACA requirements.[8] They also include extra covariates accounting factors, such as the number of years in the US. From the sample of foreign-born non-citizens who met DACA requirements, their results suggested that DACA reduced the probability of school enrollment (part-time and fulltime) by almost 28% and simultaneously increased the probability of working. Amuedo-Dorantes and Antman imply that work and school are treated as substitutes by DREAMers and they responded by shifting from education into labor. Moreover, they found heterogeneous effects by gender; while both DACA-eligible women and men experience a reduction in school enrollment and full-time enrollment, only men saw a statistically significant increase in the likelihood of employment. While their results have very interesting policy implications, it is important to understand that their study is limited to the effects on an older population (already out of high school) and undoubtedly limited by the small sample size of the CPS.

Adding to this discussion of the effects of education, Kuka, Shenhav, and Shih (2018) also analyzed the education decisions of DACA-eligible and ineligible individuals. Because DACA created a shock within the return rate in education, they can use it to analyze how it impacts youth investments in human capital. They use the ACS data from 2005-2015 and restrict the data to

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[7] caused by the lack of data available identifying DREAMer, DACA recipients in the Community Survey Data

[8] $Eligible_{it}$ indicates whether the individual meets all eligibility requirements observable to researchers: (1) being under the age of 31 in June 2012, (2) having entered the USA before his or her 16th birthday, and (3) having arrived prior to June 2007

match DACA requirements. Its treatment group included Hispanic noncitizen immigrants, which was compared to foreign-born citizens of the same age and with the same arrival year. The focus is very similar to Amuedo-Dorantes and Antman (2017), but this paper focuses mainly on the response from youth 14-18. The results show that the increased returns to education led to higher investments in education through increased school attendance and high school graduation rates. There also seemed to be some heterogeneity due to differences in gender, making the effect much stronger for Hispanic men. While they did test for heterogeneity, due to age differences by testing with an older group (19-22), the effect was not as clear for college attendance, as it proved to be for high school attendance. In general, the results show that the current educational attainment gap between non-citizen and citizen is mainly caused by the low benefits/returns of education for youths without legal status. The study suggests that providing incentives for education and reducing uncertainty over employment increase the effectiveness of immigration policies.

Hsin, Ortega(2018) also focused on the education-labor investment decisions that came about after DACA was implemented, but the key difference in this study is that the data, from a large University System, did accurately identify authorized immigrants. This means that the Difference-in-Differences model accurately shows the effects of the program on intent-to-treat groups. According to the study, DACA caused a 7.3 percentage point (p.p). increase in the dropout rate for undocumented students as 4-year colleges and decreased full-time attendance to 2-year colleges. These results show, once again, that DACA incentivizes undocumented immigrants to move from education to labor, suggesting that without the legal barriers to entering the workforce, a large majority of unauthorized immigrants would choose labor over education. The only small limitation to this study is that since it is only for one specific university system, presumably for one state, it does not show if these results vary across different states with different immigration policies.

Finally, we have Pope (2016), who examines the effects of DACA on the labor market outcomes and education of DACA-eligible immigrants through the reduction of labor market barriers/frictions. Pope similarly uses a difference-in-differences strategy based on the eligibility criteria for DACA. He restricts the ACS data (2005-2014) sample to non-citizen immigrants who already have a high school diploma and meet all other DACA qualifications. Pope finds that DACA increases the probability of working by increasing labor force participation and decreasing the unemployment rate for DACA-eligible individuals. He also found that the program increases the income of unauthorized immigrants at the bottom of the income distribution. Unlike most of the other studies, Pope finds very little evidence that DACA affects the likelihood of attending school and no statistically significant differences in the coefficients between men and women. He concludes by connecting DACA and DAPA, Deferred Action for Parents of Americans/Lawful Permanent Residents, claiming that it would have similar effects moving over thousands of undocumented immigrants into employment.

While there is quite extensive literature on the different effects of DACA on outcomes such as Poverty, Education, Healthcare, Unemployment, etc., in this paper I will (1) analyze the labor and educational outcomes over a longer period of time (5 years after DACA implementation), providing the ability to look at more long term effects, and (2) assess the sources of variation within the treatment across individuals of different age groups and different ethnic groups. While this contribution to the literature may not be considered groundbreaking, looking at heterogeneous treatment effects of the program can be very helpful, as it can evaluate what causes the difference between the intended and the actual observed results. Not only is this sample much larger than any used before, but there is also the added element of including younger individuals in the age analysis section. This data is also not solely limited to high school graduates, as it includes individuals who are still in the process of completing high school diploma or equivalent test such as the General Educational Development(GED) test.

CONCEPTUAL FRAMEWORK

Individuals who meet the DACA eligibility criteria, first get approved for a 2-year deferral from deportation proceedings, then become able to apply for their work authorization card and social security number. Obtaining this legal documentation has opened up new forms of access, both directly and indirectly, for this immigrant group.

Working can become a replacement for going to school, especially for low income individuals who may not be able to afford an education and need to work to support themselves and their families. This may be stronger for immigrants, as many find themselves critically needing income in order to provide support for their families in their native country. By eliminating the legal barriers to entry, DACA has largely increased labor market prospects and access to higher paying jobs for eligible unauthorized individuals. This extended legal protection can indirectly increase the returns of higher education as well, consequently increasing the likelihood of upward mobility through education. Depending on which effect is stronger, it is possible to see a simultaneous increase in the likelihood of being in school along with an expected increase in the probability of working for DACA eligible individuals. Due to the differences between the age groups, and possibly even between different ethnic groups, we can anticipate variation in the treatment effects of DACA.

This paper will analyze the heterogeneity in treatment effects for individuals of different age groups when the policy was implemented. This analysis includes individuals who were 23 years of age and under in June 2012 compared to individuals who were between 24 and 31 years old in June of 2012. When facing changes in returns to labor and school as a result of DACA, key differences present between the different age groups may cause them to respond differently. The driving factors include basic behavioral differences in age group which can further affect their level of social integration. There may also be the additional factor of how the extended protection from deportation after high school may indirectly increase motivation to attend college and obtain a higher level of education in order to obtain higher wage jobs. When combined with the reduction of labor market friction through work authorization, it can reduce financial barriers to higher education by allowing unauthorized immigrants to work through college to pay off their tuition. This means the increased legal protections provided by DACA may result in a higher likelihood of upward mobility through education, essentially increasing the returns on education. These effects may be stronger for younger groups.

To begin with, it is known the schools' socialization mechanisms promote assimilation of these individuals,[9] therefore younger individuals and those more likely to be in school, or just coming out of high school, may exhibit behaviors that are more similar to American native-born individuals when presented with the chance to further their education under extended protection from deportation. Seeing as this group is more likely to still be in school and living with their parents, expenses such as rent, food, gas, etc. are less of a pressure. On the other hand, the older group (23-32) has already been out of high school for a couple years now, and without DACA, their legal protections have ceased after high school. Their chances for upward mobility through the means of education has been seen to be limited, corresponding to a decline in their educational motivation.[10] Additionally, this group has already fully transitioned into adulthood, becoming accustomed to the limitations arising from their lack of legal status compared to the younger group. The older group is more likely to be independent and may even have a family of their own, in this way direct entry into the workforce makes more sense to them rather than going back to school. Due to this, even when granted the same legal protection as the younger group, it can be believed they will be less likely to seek upward economic mobility through the means of higher levels of education and instead, will do so through the traditional routes: entering the workforce.

Some states have additionally introduced in-state tuition programs which greatly reduced the financial burden of attending college. It should be considered that undocumented immigrants are more likely to enroll in school when working is not a viable option,[11] meaning undocumented immigrants treat school and work as substitutes. While the behavior of the older group may support this idea, behavioral evidence from the younger group suggests DACA causes youth to invest more in education (at least, a high school education).[12]

It is intended to analyze any heterogeneity in treatment effects for different ethnic groups as it is acknowledged that the immigrant population in America is a very diverse group. Figure 1 shows the variation within the DACA eligible groups by birthplace from the main sample. While the majority seemed to be Mexican there are some large groups from countries in Asia, Africa, Europe, Central and South America. Based on data from the Pew Research Center, a shift in the composition of the non-authorized immigrant groups is being seen with the decrease in arrival of Mexican immigrants and a simultaneous increase in arrival rates for individuals from Central America, Asia and the rest of the world.[13] They even go as far as to project that by 2055, Asians will surpass Hispanics and become the largest immigrant group in the U.S. When looking at heterogeneous effects across these groups, the main idea is that there is a socioeconomic difference, such as income mobility and access to education and jobs, between ethnic groups. A cause could be that the program disproportionally benefits one group over another. Pew Research

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[9] Gonzales, Roberto G. "Learning to be illegal: Undocumented youth and shifting legal contexts in the transition to adulthood." https://doi.org/10.1177/0003122411411901

[10] Gonzales, Roberto G. "Learning to be illegal: Undocumented youth and shifting legal contexts in the transition to adulthood." https://doi.org/10.1177/0003122411411901

[11] Amuedo-Dorantes and Antman (2017)

[12] Kuka, Shenhav, and Shih (2018)

[13] https://www.pewresearch.org/fact-tank/2019/06/12/us-unauthorized-immigrant-population-2017/ft_19-06-12_unauthorizedimmigration_recent-arrivals-northern-triangle-asia-mexico-2/

Center also found that increasing fault lines of inequality along race and ethnicity can have a large effect on labor outcomes for unauthorized immigrants.[14] Furthermore, there is existing literature suggesting that socioeconomic backgrounds are good predictors of labor and educational outcomes (Portes & Rumbaut, 2001; Terriquez, 2014), and that differences in skill levels and the amount of resources for different immigrants groups lead to inequalities in mobility opportunities and social/economic incorporation in general (Feliciano, 2008; Zhou & Kim, 2006). If the ethnicity analysis shows that socioeconomic differences between ethnic groups, indeed causes heterogeneous treatment effects, then it can be accounted for it in future programs and policies if their goal is to reduce inequalities between undocumented immigrants groups.

DATA

The data used is individual level data from the American Community Survey (ACS) recorded by the Census Bureau. The IPUMS extract is pooled cross-sectional data which ranges from 2005 to 2018, providing seven years of data before DACA is officially implemented and 6 years after. The ACS data is a good fit because it includes questions regarding the outcomes of interests, as well as a large set of demographic variables which can be used to identify the unauthorized population using the DACA eligibility criteria.[15] Furthermore, the survey's random sampling methods and interview process means it's representative of the whole US population and since the survey isn't based on legal status, it is also representative of the unauthorized immigrants population.[16]

The most important variable used for this analysis is the DACA eligibility variable which will be used to identify those who are most likely to be undocumented immigrants. One of the key limitations of the data is that it doesn't report legal status which affects my ability to accurately estimate the DACA treatment effect. The initial data extract is made up of foreign-born non-citizen ages 16 to 37 since the oldest eligible individuals would be around the age of 37 in 2018. This group includes authorized immigrants (Legal Permanent Residents (LPRs) or "green card" holders, non-naturalized immigrants, Legal visitors to the U.S. that are not citizens) and unauthorized immigrants, such as TPS[17] and DACA beneficiaries. Using the "residual method,"[18] the DHS estimates that out of the 22.6 million non-citizens, around 51% were unauthorized immigrants.[19] The inclusion of authorized immigrants means that generally the effect of DACA will be under-estimated in my model. That being said, they do include variables regarding citizenship status, birth year, country of origin, and the amount of year's an individual has been in the country; these and additional demographic variables can be used to estimate the unauthorized population. The DACA eligibility criteria, allows me to create a variable which identifies who is most likely to be unauthorized and a DREAMER at the individual level. I begin by excluding

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[14] https://www.pewresearch.org/fact-tank/2019/06/12/us-unauthorized-immigrant-population-2017/
[15] https://www.uscis.gov/archive/consideration-deferred-action-childhood-arrivals-daca
[16] https://www2.census.gov/programs-surveys/acs/design _methodology
[17] https://www.uscis.gov/humanitarian/temporary-protected-status
[18] https://www.pewresearch.org/fact-tank/2019/06/12/us-unauthorized-immigrant-population-2017/
[19] https://www.dhs.gov/sites/default/files/publications/18_1214_PLCY_pops-est-report.pdf

anyone with less than a high school degree who was not currently attending school in order to meet program's educational requirement. It requires an individual to either have a high school degree/GED or at least be in school, so limiting the data this way allows me to include younger individuals who may still be in the process of finishing high school. This makes my sample much larger compared to previous researchers who include only those with at least a high school diploma or equivalent. Using the individual's age and quarter of the year in which they were born, I calculated their age in June of 2012 to make sure they were under the age of 31. Then, using the amount of years they've been in the U.S., I created a variable for how many years they would have been residing in country by 2012. I also calculated the year and age of arrival, to ensure that they had been residing in the U.S since 2007 and arrived before the age of 16.[20] Using the age in June of 2012, age of arrival and the amount of years in the U.S I created the variable Eligible which is equal to 1 if individuals meet the DACA eligibility requirements and 0 is they don't.[21] The Eligible group will become the treatment group while the Ineligible group will become the control group.

Furthermore, I use variables regarding employment and educational attainment and status to analyze the policy's impact on education and labor outcomes. Firstly, I look at the likelihood of an individual to be working/employed. To measure this outcome, I look at five binary ACS variables: (1) whether an individual worked in the last week, (2) whether an individual has worked in past year, (3) whether an individual is in the labor force, (4) whether an individual is unemployed , and (5) whether an individual is self-employed. These variables allow me to see how DACA affects employment status, labor force participation, and employment type. Finally, I look at the likelihood of an individual to be attending school and to obtain a bachelor's degree or higher using another 3 binary variables: (6) whether an individual is attending/ in school, and (7) whether an individual has a bachelor's degree or higher. This way I can see if DACA increases investments in higher education.

In summary, the main sample I created from the data extract consists of foreign-born non-citizens, ages 16-37, who are enrolled in school or have at least a high school diploma or equivalent. It includes a total of 779,910 observations, with 202,439 eligible individuals. It's important to note that while including 16-17-year-olds in the main sample is useful when looking at the educational outcomes, this can also lead to slight bias in the estimates since they tend to have very different schooling and labor outcomes.[22] Additionally, since age has a large confounding effect on education and employment, comparing groups even with a two to three-year difference

[20] While DACA requirements specify that they must have entered before the age of 16 and have continuously resided in the US since June of 2007, there is no data available regarding the exact date of arrival. This makes it impossible to tell whether they arrived before or after June and also makes it difficult to calculate the exact age of arrival. Due to these limitations. I use less strict requirements using on the year of arrival alone and include those who arrived at 16 as eligible.

[21] This variable excludes DACA's criteria which says applicants cannot have committed a felony or significant misdemeanor and the sample excludes DREAMERS who are eligible because of they've served the Armed Forces or Coast Guard as this information isn't not recorded by the ACS.

[22] All those under 18 are much more likely to be in school and less likely to be working. This could cause differences between the control and treatment groups because the eligible group is more likely to include a younger population. It may lead to upward biased educational outcome estimates and downward biased labor outcome estimates when compared to the ineligible group.

leads to large differences between the group, making them less comparable. And since the DACA eligibility criteria causes the ineligible group to be slightly older, restricting the main sample to those 18 or older can help give a better idea of how similar the groups actually are. **Table 1**. shows summary statistics for the main sample of non-citizens from 2005 to 2018 but restricted to individuals 18-37. The first two columns show the group means for the Eligible and Ineligible group. The third column shows the difference between the group means and the fourth column shows the t-statistic when testing the difference between the means. We that can see the largest difference between the groups comes from difference in age, age of arrival, and the amount of years an individual has been in the USA. The eligible group also seems to be more likely to be Hispanic than the ineligible group. The majority of these demographic differences are taken into account in the main regression model in the form of controls and fixed effects.

Table 1 Summary Statistics

	Mean			
	Ineligible	Eligible	Difference	t-Statistic
Working	59.7	56.3	3.5	24.4
In labor force	69.7	69.3	0.4	2.8
Unemployed	4.9	7.9	-3.0	-40.3
Self Employed	5.7	3.8	1.9	32.1
Worked in past year	72.6	71.8	0.8	6.2
Age	29.6	23.5	6.1	471.0
Years in US	6.7	14.7	-8.0	-453.4
Age Entered US	22.9	8.7	14.1	949.4
Male	49.3	52.2	-2.9	-20.2
Hispanic	36.0	65.4	-29.4	-214.3
White	42.1	50.8	-8.7	-60.7
Black	8.4	8.3	0.1	1.6
Asian	36.3	15.9	20.5	180.7
Married	55.9	22.9	33.0	261.9
In School	23.9	40.8	-16.9	-122.8
Less than high school	1.8	7.6	-5.8	-83.3
High school/GED	30.7	44.6	-13.9	-98.9

Note: The sample for summary statistics consists of non-citizens ages 18-37 with atleast of a Highschool degree/GED or in school. Binary variables shown in percent terms

	Ineligible	Eligible
Observations	559,215	153,892
Percent	78.4	21.6

EMPIRICAL STRATEGY

In order to estimate the effect of DACA I use a Difference-in-Differences(DID) estimator, most commonly used by researchers to analyze effects of policy change on different groups. It allows me to estimate the policy's treatment effect by comparing the differences between the control and treatment group before and after the policy is implemented. The DID estimate is essentially the treatment effect as long as the model's parallel trends assumption is met. The main regression model used in this paper is as follows:

$$\text{Eq. (1)} \qquad Y_{it} = \beta_0 + \beta_1 Eligible_{it} * After_t + \beta_2 Eligible_{it} + \beta_3 After_t + \beta_4 X_{it} + \beta_4 W_{it} + \theta_t + \gamma_s + \gamma_s t + \varepsilon_{it}$$

Y_{it} is one of the outcome variables and represents the probability being equal to 1 for each individual i in year t. $Eligible_{it}$ is equal to 1 if the individual meets the DACA eligibility criteria and 0 otherwise. $After_{it}$ is a binary variable that indicates whether it's the period before or after DACA is implemented. It is equal to 1 if the year 2013-18 and 0 if it is 2005-2012. β_1, the coefficient on the interaction between the eligibility indicator and post 2012 period indicator, is the coefficient of interest. It estimates the difference in average outcome in the treatment group before and after treatment minus the difference in average outcome in the control group before and after treatment. The model also includes additional control variables. X_{it}, a set of control variables for education, sex, race, ethnicity, language spoken at home, marital status and number of children. W_{it} accounts for age fixed effects and controls for the number of years the individual has been in the country. θ_t allows for time fixed effects and γ_s allows for state fixed effects. Finally $\gamma_s t$ allows state specific time trends as well as state level unemployment rates and labor force trends. All result tables report robust standard errors which are clustered at the state-year level.

Equation 1 is estimated across various subsamples for the main analysis and the heterogeneity analysis. The main analysis, which just estimates the effect on the general DACA eligible population, uses the main sample describe in the data section and two other subsamples. Panel A, which is also used for the summary statistics in **Table 1**, is constructed from the main sample but is limited to individuals 18 and older. Since it excludes 16 and 17-year-olds the eligible and ineligible groups become more comparable. This is important because the Difference-In-Differences estimator assumes that the control and treatments groups follow parallel pre-trends in the absence of the treatment. The more comparable the groups are higher the likelihood that they will follow parallel trends which ensures that the estimator is valid. The yearly trends for Panel A are shown in **Figures 16-22** in the appendix. With the same idea in mind, Panel H, is constructed with the purpose of reducing the differences between the control and treatment groups before DACA is implemented. It consists of non-citizens 18 and older, who were between the ages of 22-32 and had been in the country for at least 4 years by June of 2012. Although the sample size is much smaller, Panel H has the most similar pre-pretends which can be seen in **Figures 2-8.** The results for these three samples are shown in **Table 2**. With these samples, each with slight variations, I can get baseline estimates and ensure that the estimated effect is robust and consistent.

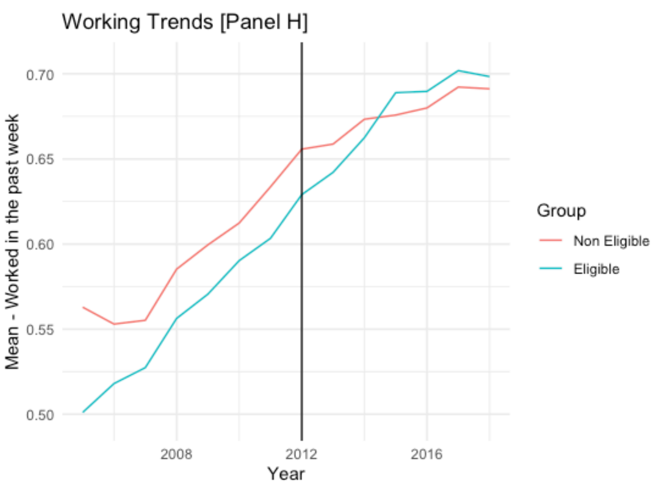

Figure 2

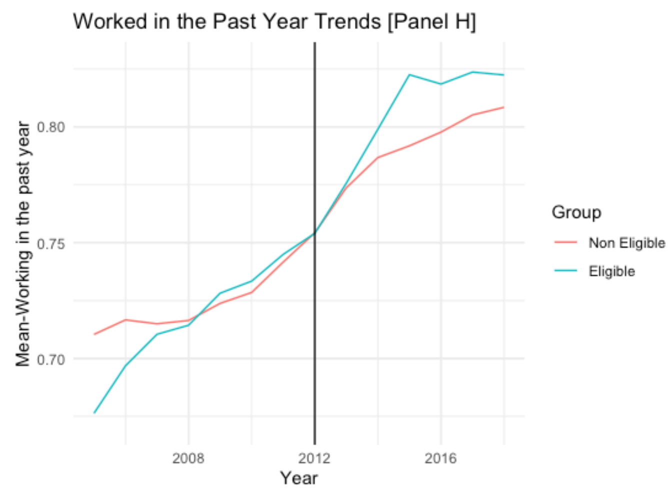

Figure 3

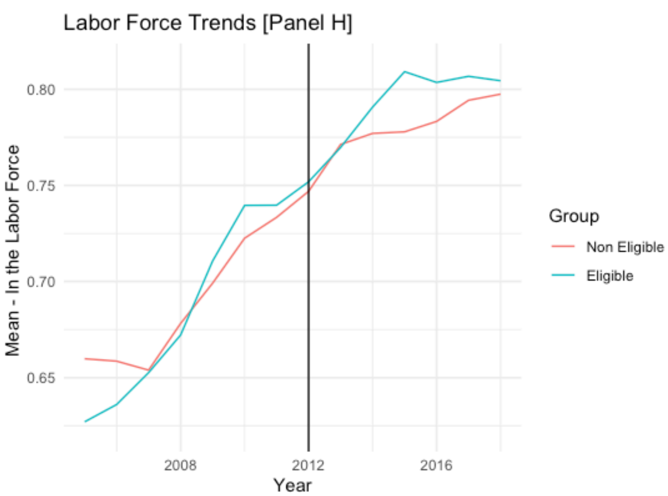

Figure 4

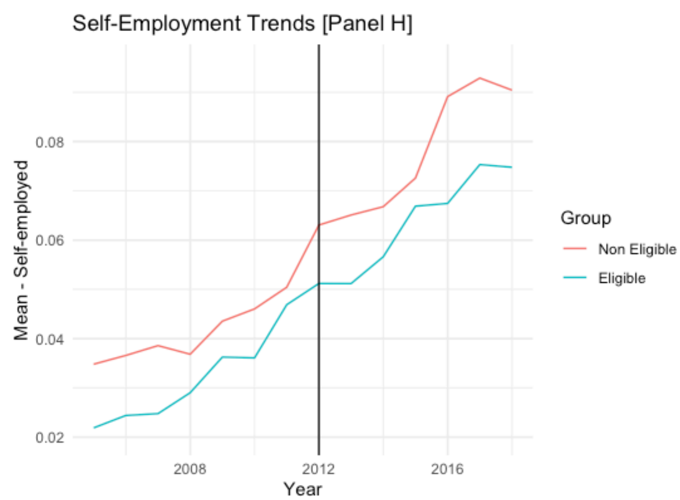

Figure 5

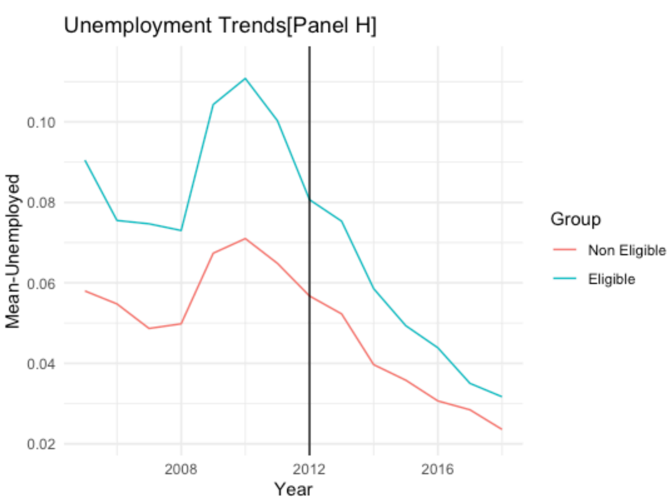

Figure 6

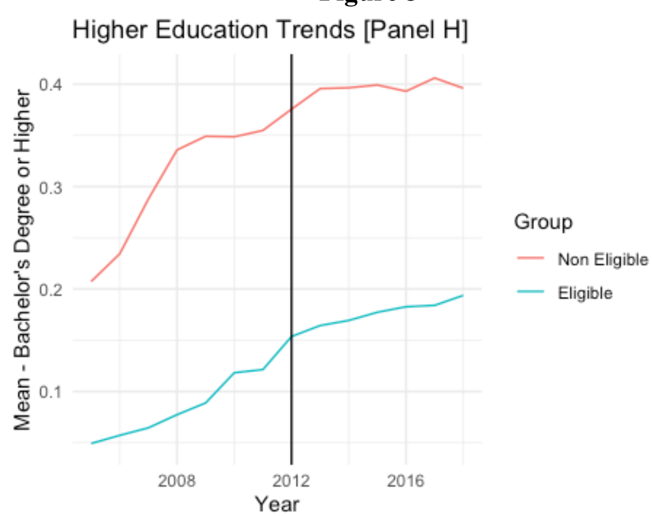

Figure 7

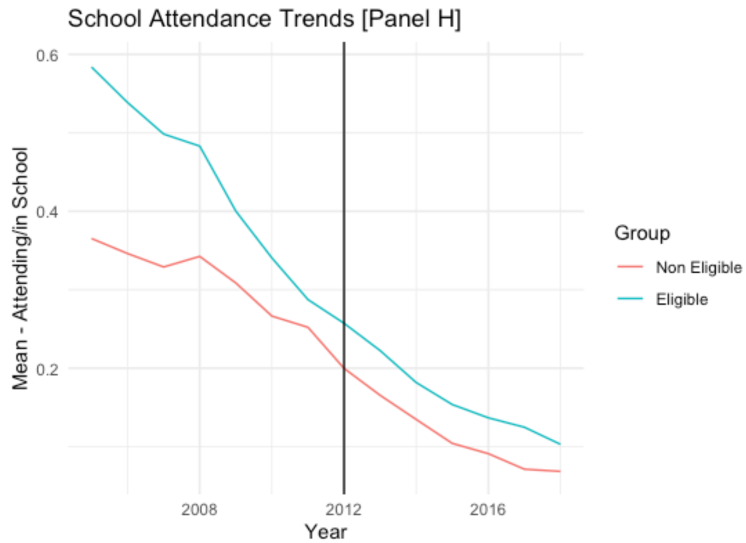

Figure 8

When analyzing potential heterogeneity in the treatment effects for different age groups, I created three subsamples: Panel C, Panel D and Panel E. Beginning with Panel C by restricting the main sample to individuals who were 31 and younger in June of 2012. This helps make sure that the groups are similar, since they already meet the age in 2012 requirement, the only difference between the groups is that the ineligible arrived after the age of 16 or entered the country after 2007. This subsample consists of non-citizens age 16 and older in order to include a slightly younger populations and hopefully get a good measure of the educational effects of DACA. Panel C is then split into a younger and an older group. The younger group, Panel D, is created by additionally restricting Panel C to individuals wo were under the age of 24 in June of 2012. In doing so, the group is also limited to non-citizens ages 16-30, this is because those who were 23-24 in 2012 can't be older than 30 by 2018. The older group, Panel E, is created by restricting Panel C to individuals who were around the age of 24 to 31 in June of 2012. Once again this puts a limit on the age of the individuals; since someone who was 24-25 in June 2012 can be no younger than 17-18, this group is limited to non-citizens ages 18-31. Results for all three are shown in **Table 3**. First, Equation 1 is estimated on D and E to see if there are differences in the treatment effect, estimated by β_1. Since age has a significant effect on whether someone is working or in school, it's possible that maybe be that these difference in age can lead to bias estimates that may falsely suggest the existence of heterogeneity in the treatment effect. So in order to back up those estimates from Panels D and E, Panel C is used to run a triple interaction test using Equation 2. The model is as follows:

Eq. (2)

$$Y_{it} = \beta_0 + \beta_1(Eligible_{it} * Older_{it} * After_{it}) + \beta_2(Eligible_{it} * After_{it}) + \beta_3(Eligible_{it} * Older_{it}) + \beta_4(Older_{it} * After_{it}) + \beta_5 Eligible_{it} + \beta_6 After_t + \beta_7 Older_{it} + \beta_8 X_{it} + \beta_9 W_{it} + h_t + c_s + c_s t + e_{it}$$

This model is identical to Equation 1 but includes an additional triple interaction term between the variables Eligible, After and Older. The variable $Older_{it}$ is a binary variable equal to 1 if the individual is 24 or older in June 2012 and 0 if they're younger. The coefficient of interest β_1 estimates the difference between the older and younger, eligible and ineligible groups, before and after DACA is implemented. This a triple interaction model is helpful because it allows me to tests whether the heterogeneity in treatment effects found in the previous two panels is statistically significant without having to worry about potential bias cause by age differences.

When looking at possible heterogeneity across ethnic groups, my goal was to look at possible variations of the treatment effect on different Panels for each major ethnic group in the main sample. Figure 1 in the appendix shows the DACA eligible group by country of origin. We can see that there's a large number of ethnic groups. Because of this, estimating the treatment effects using these separate panels creates a problem because the subsample sizes would be significantly smaller than the main sample. This may lead to biased results and with so many regressions it could also affect my ability to effectively compare the size of the treatment effect with one another. On the other hand, comparing the groups using multiple interaction terms, like Equation 2, with 4-5 groups isn't quite as simple and would require additional assumptions to be met. Ultimately, this method would require more advanced knowledge of econometrics than I currently possess. Nonetheless, we can still conduct a much simpler analysis by comparing a homogenous group made up of the largest ethnic group, Mexicans (Panel F), to a heterogenous sample containing the rest of the ethnic groups(Panel G). I compare the results from both panels and the main analysis to see if there are any significant differences. The results for these two panels are shown in **Table 4**.

In addition to the result tables, the figures plotting group means for each year can be used to ensure that the DID estimator's assumptions are met. As I mentioned previously, in order for the DID estimated to be valid, several assumptions must be met. The most important one is the parallel trends assumption. The fact that the data used includes multiple years before and after the treatment allows us to see if there are any pre-existing differences in trends.[23] Using the figures we can see that for the most part, the main sample and subsamples show parallel pre-trends for labor outcomes. These will be further discussed in the results section. However , **Figures 7 , 8 , 21** and **22** show that the main sample does not satisfy this assumption for the educational outcomes. This means that the estimates for these outcomes are most likely invalid. This may be caused by difference in age and age of arrival shown in the summary statistics in **Table 1**. As previously mentioned in the data section, the non-eligible group seemed to be older and have arrived in the US at a later age[24]. On top of that, the confounding effect that age has on education, can lead to large differences in pre-trends for the education outcome variables. While including age fixed effects in Equations 1 and 2 may help, there is no way to control for large differences in the age of arrival. Since it is a variable used to identify the treatment group, including it in the regression

[23] https://eml.berkeley.edu/~webfac/saez/e131_s04/diff.pdf

[24] It makes sense that age of arrival difference leads to non-parallel schooling pretends. Immigrants in the ineligible group who are at high school age but arrived when they were already 17 or 18 may be less unlikely to be attending school, where as the eligible group who has an average arrival age of 8 and has consistently been attending school in the US since elementary school have much higher probability of being in school at the age of 16-18.

causes a multicollinearity problem. This will be discussed further in the results section by comparing the table estimates to the trends shown in **Figures 9-13**.

Finally, when interpreting the results we must take into account other sources of bias. For example, the main sample consists of foreign non-citizen which also include authorized immigrants. As discussed in the data section, this mean that's the DID estimates will be systematically biased toward zero. Since the DHS estimates authorized immigrants to be about around 45-50% of the foreign-born non-citizen population, the actual treatment effect on unauthorized immigrants may be around approximately 1.5 times larger than the model estimates. Furthermore, USCIS latest report estimates that there were about 652,880 active DACA recipients as of September 2019[25] but since the ACS does not observe participation in the program directly, we must take into consideration that the DACA eligible group is merely an estimate of the DACA recipients. So the estimates don't directly report the effected on the treated population because only a portion of the eligible apply and get approved for the program.

RESULTS

In this section, I will look at the regression results reported in **Tables 2, 3,** and **4**. For each table, the column headers list the education and labor market outcome variables discussed in the data section. For each Panel, the first rows report the estimates for the effect of DACA eligibility and the second row reports the estimate for the interaction term of interest, out difference in difference estimate.

Table 2 shows the main analysis results from Equation 1ffi on the main sample and two other subsamples. In Column 1, the main sample indicates that DACA eligible individuals are more likely to be working by 2.04 percentage points (pp) than ineligible individuals after DACA is introduced. Panel A, which is limited to those above 18 and has more comparable groups, indicates the eligible groups is 2.06 pp more likely to be working than the ineligible individuals. The results are pretty consistent but Panel H, the most similar pre-trends, suggests that the treatment effect is slight smaller at 1.48 pp. This means that DACA increases the likelihood of individuals to be working by around 1.5 to 2.1 pp, which is a much smaller effect to the results seen in previous literature; more specifically looking at Pope's findings of a 4.8 pp increase. However, we still must consider that the results could be 1.5 times larger as discussed previously. This leaves us with treatment effect of 2.3 to 3.2 pp. In Column 2, the main sample reports an increase of 1.13 in the likelihood of working in the past 12 months for the eligible group compared to the ineligible group after DACA become available. Panel A reports this increase to be bigger at 1.36 pp while Panel H significantly underestimates this effect at .98 pp. Nonetheless, the overall treatment effect is between 1 to 1.2 pp indicates that DACA increases the likelihood of eligible individuals to find jobs. This increasing in the likelihood of working could be coming from more individuals entering the labor force or from a reduction in unemployment. These effects are reported in columns 3 and 4. Column 3 reports an increase in the likelihood of being in the workforce of .81 to 1.3 pp and column 4 indicates a reduction in the likelihood of being

[25] I-821 DACA

unemployed of 1 to 1.7 pp. This means that DACA had a larger effect by moving more people from unemployment to employment for those who were already in the labor force than by bringing new individuals into the labor force. I found no statistically significant effects on the probability of being self-employed. In general, the effects on labor outcomes are consistent to previous literature in direction but not in magnitude.

Columns 6 and 7 report the effects on educational outcomes. In column 6, the main sample reports that the eligible group was more likely to be attending school by 1.52 pp compared to the ineligible group after DACA became available. This effect is bigger for Panel A at 2.27 pp and 1.87 pp for Panel H. Overall ,this reports that DACA increases the likelihood of individuals to be in school. In column 7, the main sample and Panel A report a decrease in the likelihood of having a bachelor's degree or higher for eligible individuals compared to ineligible individuals after DACA is implemented. Panel H's estimates are inconsistent with the last to results. It estimates a much larger effect at nearly -8.6 pp, but this maybe cause by some mistake in the regression. In general these results are the opposite to what is seen in some of the previous literature since Pope's

Table 2 Main Analysis

	Dependent variable:						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Working	Worked in Past Year	In Labor Force	Unemployed	Self Employed	Attending	Higher level Ed
Main Sample: all non-citizens ages 15-37							
Eligible	-0.0279***	-0.0221***	-0.0128***	0.0243***	-0.0136***	-0.0309***	0.0911***
	(0.0018)	(0.0010)	(0.0021)	(0.0014)	(0.0011)	(0.0028)	(0.0032)
Eligible*After	0.0204***	0.0113***	0.0086***	-0.0128***	-0.0017	0.0152***	-0.0162***
	(0.0021)	(0.0016)	(0.0024)	(0.0019)	(0.0016)	(0.0041)	(0.0049)
Observations	779,910	779,910	779,910	779,910	779,910	779,910	779,910
R^2	0.8474	0.9372	0.8429	0.1396	0.0794	0.6658	0.6087
Panel A: all non-citizens ages 18-37							
Eligible	-0.0267***	-0.0245***	-0.0149***	0.0279***	-0.0160***	-0.0423***	0.0982***
	(0.0020)	(0.0013)	(0.0023)	(0.0016)	(0.0012)	(0.0038)	(0.0033)
Eligible*After	0.0206***	0.0136***	0.0128***	-0.0169***	-0.0005	0.0227***	-0.0260***
	(0.0025)	(0.0019)	(0.0029)	(0.0024)	(0.0017)	(0.0051)	(0.0045)
Observations	713,107	713,107	713,107	713,107	713,107	713,107	713,107
R^2	0.8503	0.9384	0.8480	0.1318	0.0805	0.5606	0.6180
Panel H: non-citizens ages 18-37 who were 22-31 on June of 2012							
Eligible	-0.0077***	-0.0108***	-0.0087***	0.0101***	-0.0076***	-0.0055	0.0627***
	(0.0026)	(0.0018)	(0.0029)	(0.0020)	(0.0016)	(0.0037)	(0.0044)
Eligible*After	0.0148***	0.0098***	0.0081**	-0.0104***	-0.0007	0.0187***	-0.0857***
	(0.0035)	(0.0027)	(0.0033)	(0.0027)	(0.0026)	(0.0052)	(0.0066)
Observations	266,073	266,073	266,073	266,073	266,073	266,073	266,073
R^2	0.8490	0.9414	0.8612	0.1320	0.0790	0.5357	0.5350

Note: Table 2 reports the estimates from Eq. (1) for 3 separate samples of non-citizens. Main Sample with no restrictions. Panel A, non-citizens between the ages of 18-37. Panel H non-citizens 18 and older, who were between the ages of 22-32 and had been in the country for at least 4 years by June of 2012. Robust standard errors are clustered at the State-Year level. $^{*}p<0.1$ $^{**}p<0.05$ $^{***}p<0.01$

results actually showed a decrease in the likelihood of being in school. The difference in the direction of the results may be coming from the fact that Equation 1 included control from employment status for the educational outcomes.[26] However, when we looker closer at the educational pre-trends from Panels A (**Figures 21-22**) and H (**Figures 7-8**) we see that neither show parallel pre-trends, as discussed in the empirical strategy, these results are most likely invalid. Keeping that in mind, the direction of these results, showing an increase in the likelihood of being in school but a reduction in the likelihood of pursuing higher education could mean that, DACA incentivizes going to school only to meet the DACA educational requirement since there's no increase in the likelihood of having a degree beyond the high school level or equivalent.

For the age analysis, we look at **Table 3** which reports the estimates from Equation 1 on Panels C, D and E to see if there any significant differences in the treatment effects across different age groups. Starting by comparing Panel C baseline results for the treatment effect to the main analysis results. If we look at the first row of Panel C it actually reports the interaction term for eligibility and post DACA period. For column 1, the estimate of 3.34 pp is larger compared the he main analysis results. For column 2 the estimates are closest to Panel H's estimates and for columns 3, 4 and 5, again we get an overestimation. Finally, for columns 6 the estimate is more consistent with. Panel A and for column 7 its surprisingly consistent with Panel H. In general the direction of effects is consistent with slight variations in the magnitude.

Now we look at the heterogeneity present between Panels D and E and compare them with the estimated from the triple interaction term from Panel C. In column 1, Panels D and E report that DACA eligible individuals who were under the age of 24 in 2012 experience a treatment effect that is .44[27] pp larger than the treatment effect experienced by eligible individuals who were over the age of 24, when compare to ineligible individuals of the same age group. Panel C suggests the difference between these groups may be double that, reporting that the older group experiences a treatment effect that is .85 pp smaller than the younger. This estimate is statistically significant at the 5 percent level, meaning there is a significant difference in the treatment effects on the likelihood of working for these two age groups. Column 2 indicates that the older group experience a larger effect on the likelihood of working the past year than the younger group. Panels D and E suggest the difference is about .81 p.p. while Panel C suggests it's about .99 p.p. and is statistically significant at the 1% significance level. While this difference seems small, it is positive and significant thus suggesting that the older groups saw a larger treatment effect on the likelihood of working in the past year.

Columns 3 and 4 show the treatment effect differences between the groups for the likelihood of being in the labor force and the likelihood of being unemployed. In column 4, Panel D and E suggest a difference in the treatment effects of -.44 pp between the younger and older groups. Panel C indicated the difference is much larger at -1.24 pp and is statistically significant

[26] These controls for employment status(employed, unemployed, not in the labor force) and class of worker(work for wages or self-employed) were only included in the education outcome estimations not in the labor outcome estimations.

[27] Percentage point differences are calculated by subtracting the estimate on the interaction terms for Panels D and E (Panel E- Panel D)

at the 5% level. This means that the group of eligible individuals who were older when DACA took effect experienced an increase in the likelihood of entering the labor force which was .4 to 1.2 pp bigger than the effect experienced by eligible individuals who were younger at that time. In column 4 shows that the reduction in unemployment effect was .42 pp larger for the older group compared to the younger group. Once again Panel C suggest that the difference is slightly bigger at .52 but is not statistically significant which means that we cannot reject the idea that there is no heterogeneity in the treatment effects on unemployment between the older and younger group. Much like the main analysis results, I find so significant effect or difference in effect for the likelihood of self-employment.

When we look at the educational outcomes in column 6 and 7 we see that there seems to be heterogeneity in the educational effects for the younger and the older group. Column 6 indicates that DACA reduced the likelihood of being in school for the younger group by 1.37 pp while increasing the likelihood of being in school for the older group by 2.81 pp. This is supported by Panel C which estimates that the treatment effect on the older group is 7.05 pp larger than the treatment effect on the younger group and is significant at the 1% level. This may further support the idea that older individuals are actually going to school to meet the DACA educational requirement as we see in the main analysis. Column 7 indicates that the reduction on the likelihood

Table 3 Age Analysis

	Dependent variable:						
	(1) Working	(2) Worked in Past Year	(3) In Labor Force	(4) Unemployed	(5) Self Employed	(6) Attending	(7) Higher level Ed
Panel D: Younger Group							
Eligible	-0.0240***	-0.0148***	-0.0132***	0.0219***	-0.0038**	0.0010	0.0772***
	(0.0031)	(0.0023)	(0.0045)	(0.0029)	(0.0017)	(0.0050)	(0.0054)
Eligible*After	0.0324***	0.0098***	0.0282***	-0.0236***	0.0004	-0.0137**	-0.0960***
	(0.0034)	(0.0026)	(0.0044)	(0.0034)	(0.0018)	(0.0062)	(0.0055)
Observations	231,068	231,068	231,068	231,068	231,068	231,068	231,068
R^2	0.7838	0.9268	0.7787	0.2204	0.0428	0.8150	0.5029
Panel E: Older Group							
Eligible	-0.0197***	-0.0167***	-0.0262***	0.0223***	0.0016	-0.0121**	0.0648***
	(0.0026)	(0.0016)	(0.0032)	(0.0019)	(0.0015)	(0.0058)	(0.0042)
Eligible*After	0.0280***	0.0179***	0.0238***	-0.0243***	-0.0059**	0.0281***	-0.1096***
	(0.0035)	(0.0027)	(0.0036)	(0.0028)	(0.0025)	(0.0059)	(0.0083)
Observations	273,299	273,299	273,299	273,299	273,299	273,299	273,299
R^2	0.8561	0.9403	0.8585	0.1190	0.3959	0.4429	0.6482
	Triple Interaction Test -Treatment Effect Heterogeneity						
Panel C: under 32 in June 2012							
Eligible:After	0.0334***	0.0099***	0.0270***	-0.0256***	-0.0035**	-0.0246***	-0.0684***
	(0.0032)	(0.0027)	(0.0039)	(0.0032)	(0.0017)	(0.0059)	(0.0069)
Eligible:After:Older	-0.0085**	0.0099***	-0.0124**	0.0052	0.0029	0.0705***	-0.0604***
	(0.0042)	(0.0034)	(0.0048)	(0.0034)	(0.0027)	(0.0074)	(0.0102)
Observations	520,565	520,565	520,565	520,565	520,565	520,565	520,565
R^2	0.8294	0.9331	0.8277	0.1604	0.2977	0.7000	0.5961

*Note:*Table 3 reports estimates from Eq.(1) on subsamples restricted by age in 2012. Panel D includes non-citizens who were under the age of 24 in June 2012. Panel E consists of non-citizen who were 24-31 in June of 2012 Panel C consists of non-citizens ages 16-37 who were age 31 and younger in June 2012. Panel C is used to test if any difference between the older and younger group show in Panels D and E are statistically significant using a triple interaction test(Eq.(2)). Standard Errors are clustered at the State-Year level.*p**p***p<0.01

of having a bachelor's degree or higher is bigger for the larger group compared to the younger and is supported by Panel C estimate showing a -6.04 pp difference which is significant at the 1% level. This could mean that although DACA seems to be decreasing the likelihood of individuals to have a bachelor's degree or higher, the effect isn't as large on the younger population which means those who received DACA when they were younger are still more likely to invest in higher education compared to those who received DACA when they were older. To look more closely at this we can compare the educational trends for Panel D and E.

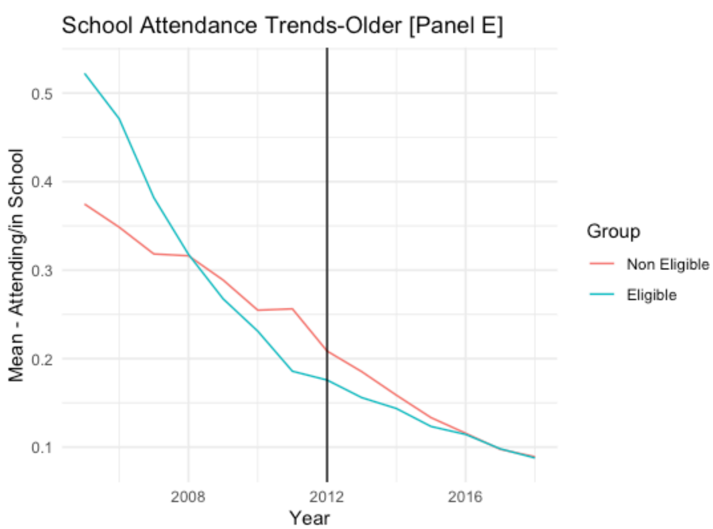

Figure 9

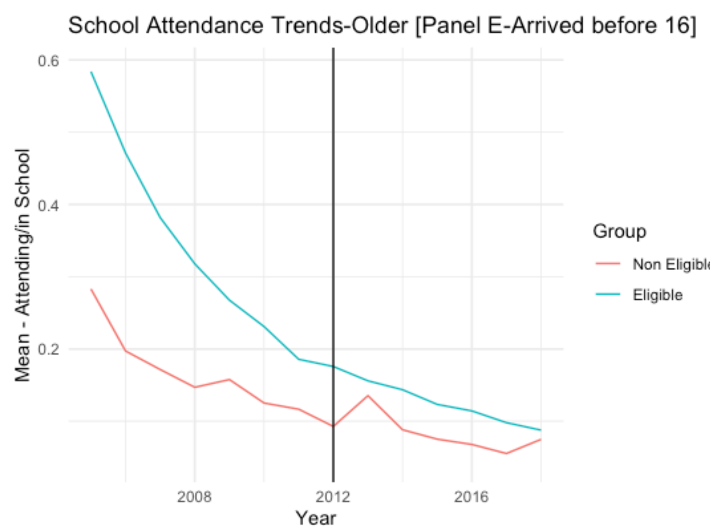

Figure 10

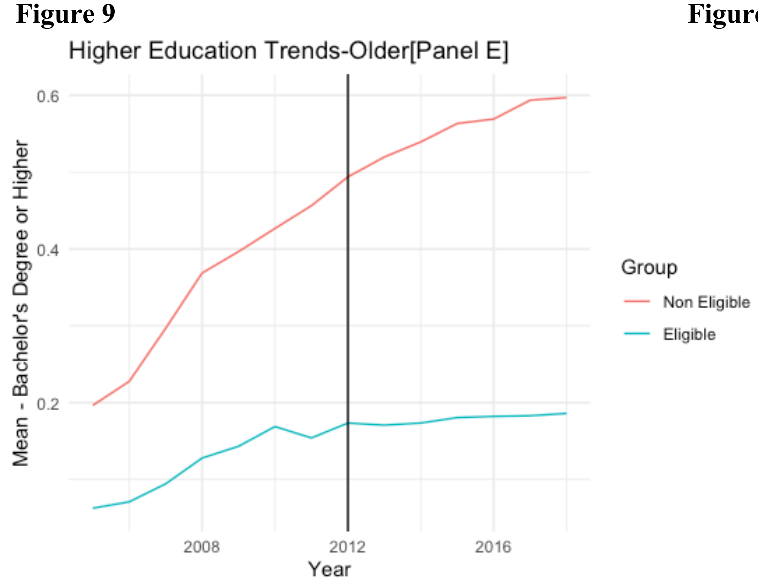

Figure 11

Figure 9 show the that Panel E doesn't show parallel pretends for school attendance which may invalidate Panels E estimates from column 6 in Table 3. However, In **Figure 10** we further limit the group to only those who arrived before the age of 16 to adjust for age of arrival differences and make the groups more comparable. This shows that the difference in school attendance does in fact decrease before and after DACA which supports the validity of the estimates. Additionally, in **Figure 11** Panel E seems to have fairly parallel trends for the higher education variable so the estimates may still be valid. This means that indeed DACA seems to decrease the likelihood of pursuing higher education for those who were over the age of 24 when DACA became available.

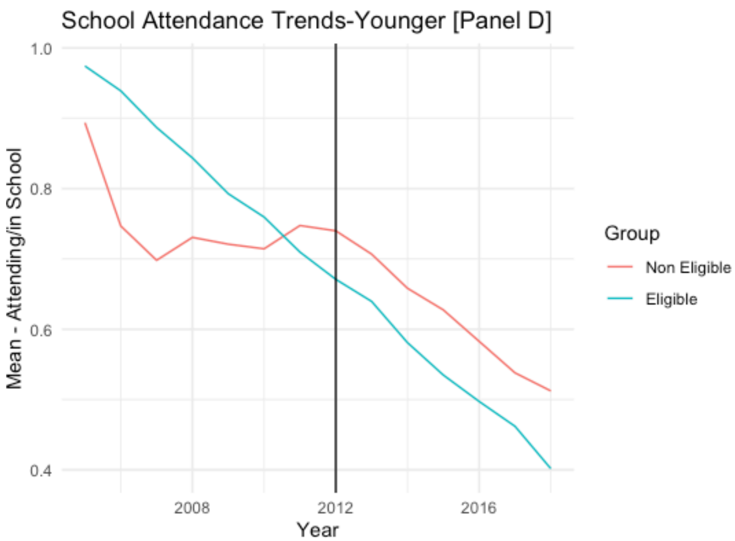

Figure 12

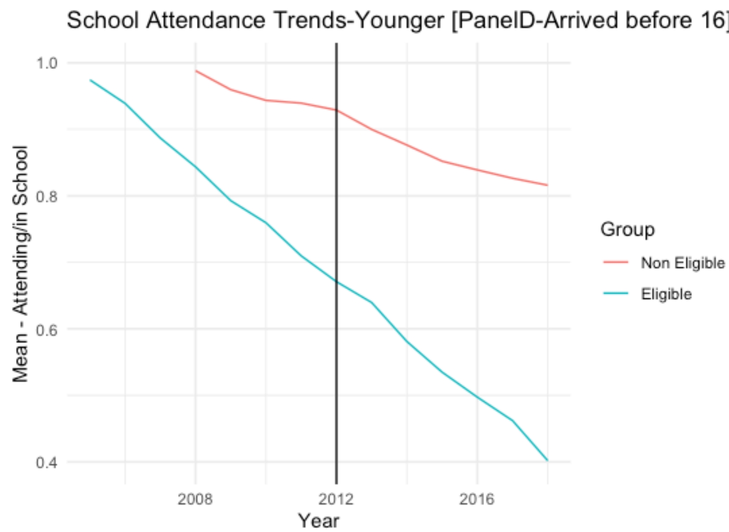

Figure 13

Looking at **Figure 12**, we can see that Panel D definitely doesn't have parallel pre-trend for the attendance variable so the estimates for the effect on the younger group showing in column 6 of Table 3 is invalid. When we limit the subsample to individuals who arrived before 16, show in **Figure 13**, we see that the trends for the eligible group doesn't seem to change before and after DACA. This means that DACA may not affect the likelihood of being in school for the younger eligible individuals.

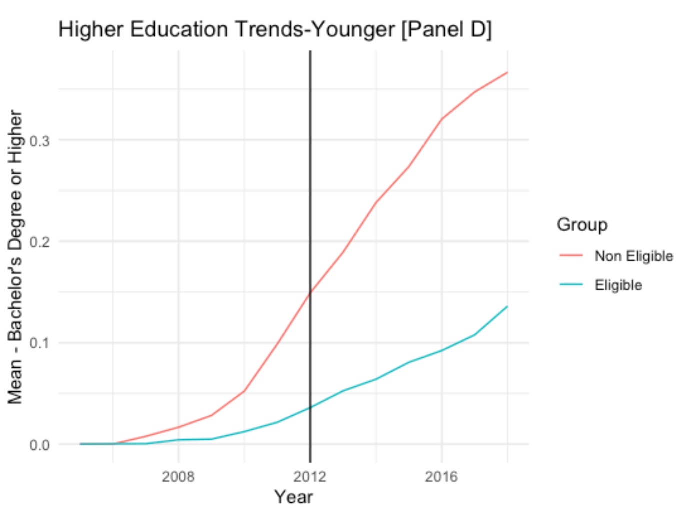

Figure 14

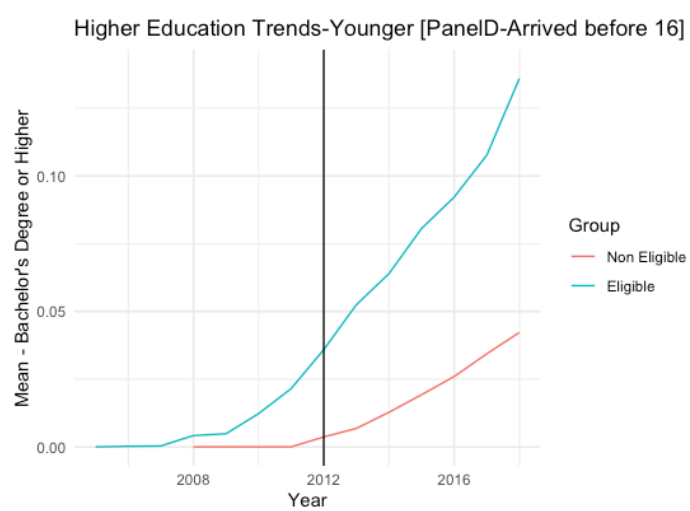

Figure 15

When we look at the pre-trends for higher education for Panel D, we see something very interesting. Firstly, **Figure 14** suggests that the eligible and ineligible groups in Panel D don't show parallel pre-trends so the estimate for the younger in column 7 of **Table 3** are most likely invalid. In fact, if we limit the sample to those who arrived before the age of 16 in order to adjust for differences in age of arrival and make the groups more comparable, the trends in Figure 15 show completely opposite trends. While **Figure 14** shows that the ineligible group always has higher levels of education, **Figure 15** shows that it's actually the eligible group who always has higher levels of education. In fact, the difference between the two groups increases significantly after 2012. This further invalidates the decrease that is shown in table 3 and actually may suggest that the opposite is true. With this in mind, the fact that the estimates for the higher education for the older group are valid suggests that there is definitely heterogeneity in the treatment effects on educational outcomes between these too groups.

Finally, **Table 4** shows the results from a simple test for heterogeneity of treatment effects through the comparison of the estimates on Panel F and G. Both panels are created from the Main sample without any other restrictions by age or age of arrival. The main idea behind this test is that if there truly is no difference in effect across different ethnic groups, then pulling out one of those groups shouldn't change the results of the same regression. The estimates can be used to give me a general idea of the treatment effects and show if there is any difference between the Mexican sample and the heterogenous sample containing the other ethnic groups.

The first column shows the estimates of the effect on the likelihood of working for the eligible group compared to the ineligible group after DACA was implemented for both panels; we can see that there is quite a large difference in the estimates for Panel F and G. Comparing these

Table 4 Ethnicity Analysis

	Dependent variable:						
	Working	Worked in Past Year	In Labor Force	Unemployed	Self Employed	Attending	Higher Level Ed
Panel F: Mexican							
Eligible	-0.0066**	-0.0090***	-0.0004	0.0105***	-0.0041**	0.0045	0.0343***
	(0.0026)	(0.0015)	(0.0030)	(0.0018)	(0.0018)	(0.0045)	(0.0027)
Eligible*After	0.0267***	0.0085***	0.0132***	-0.0090***	0.0022	0.0049	-0.0147***
	(0.0032)	(0.0017)	(0.0036)	(0.0022)	(0.0021)	(0.0047)	(0.0032)
Observations	217,997	217,997	217,997	217,997	217,997	217,997	217,997
R^2	0.8447	0.9533	0.8625	0.1529	0.3992	0.7181	0.3000
Panel G: Heterogenous							
Eligible	-0.0271***	-0.0151***	-0.0206***	0.0299***	-0.0041***	-0.0186***	0.0547***
	(0.0022)	(0.0013)	(0.0026)	(0.0018)	(0.0014)	(0.0032)	(0.0048)
Eligible*After	0.0073***	0.0074***	-0.0031	-0.0134***	-0.0019	0.0135***	-0.0214***
	(0.0026)	(0.0018)	(0.0031)	(0.0024)	(0.0021)	(0.0041)	(0.0071)
Observations	561,913	561,913	561,913	561,913	561,913	561,913	561,913
R^2	0.8487	0.9445	0.8359	0.1374	0.3600	0.6622	0.7154

Note: Table 4 reports the estimates from Eq.(1) for 2 subsamples with differences in Ethinicty. The subgroups from the main sample are split using individuals Birthplace with out any age restrictions. Panel F consists only of Mexican born non-citizens while Panel G consists non-citzens from all Birthplace groups expecpt for Mexico. Standard Errors are clustered at the State-Year level. *p**p***p<0.01

results to the main sample results in Table 1, It seems that the Mexican sample has a large influence on the treatment effect for the eligible group as whole. The fact that the main sample estimate is smaller than that of the Mexican sample, and the estimate for the heterogenous group is much smaller than both of these, could suggest there are other sources of heterogeneity. In the second column, the difference between the effects isn't ass as large and since the main sample estimate was around 1%, it suggests that there isn't much ethnicity-based heterogeneity in the treatment effect for the likelihood of working in the past year. The third column indicates that there is definitely ethnicity-based heterogeneity in the treatment effect on the likelihood of entering the labor force. While estimates for the Mexican sample is consistent with Panel A in showing in increase in the probability of being in the labor force, Panel G actually shows a decrease in the probability of entering the work force.

For the treatment effect on unemployment in the fourth column, we can see there seems to be differences in the effect experience by the Mexican sample and the rest of the ethnic groups. The decrease in unemployment is much larger for the other ethnic groups than it is for Mexicans alone which means there is heterogeneity in the treatment effect on this outcome. For Self-employment, we see the same trend, very small and un significant effects for all subsamples. However, there is a difference in the direction of the effects. The Mexican estimate and is positive while all the others are negative. While this isn't statistically significant it may be a sign that there is heterogeneity.

For the Attending column, the larger effect seems to be coming from Panel G whose estimate is consistent with Panel A and the main sample. There isn't even a significant effect shown for the Mexican sample. This may suggest that Hispanic groups, like Mexicans, may not see an increase as large as other ethnic groups from Europe, Asia, Africa and the rest of the world. In the last column, we do see differences between the groups, but they don't see to vary too far from the results in the main analysis. For both of these educational outcomes it is difficult to see if there really is heterogeneity for ethnic because as we've been seen previously, the main sample doesn't satisfy the parallel trends assumption.

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CONCLUSION

As a country of immigrants, immigration policy will always be a topic of debate in the United States. The government will constantly encounter dilemmas regarding management in guiding these marginalized groups into society without creating the wrong incentives. The U.S has many policy options available to deal with this issue. This includes programs that provide temporary benefits or permanent ones, they can be specific to certain groups or granting different levels of protection, from simple deferral from deportation to complete amnesty. Each program will have different effects and provide different incentive which is why understanding the policy implication of the research done on current policy is important.

We can start by understanding how temporary authorization policies, like DACA, affected young unauthorized immigrants. Using differences-in-differences method can help us analyze the effects of DACA and how they vary across different subgroups. The results show that it increased the likelihood of eligible individuals to be working by around 2 percentage points compared to the ineligible population and seems to be larger for individuals who received DACA when they were under the age of 24 compared to those who received it after the age of 24. This effect comes from an increase in the likelihood of being in the labor force of about 1pp and a decrease in the likelihood of being unemployed of about1.3 pp. The results also show that the labor force effects were larger for those were received DACA at a younger age while the unemployment effect seems to be larger for the those who received DACA at an older age. In addition, it increased the probability of working in the past year by a little over 1 pp, which was larger for those who received it at an older age, but it doesn't seem to have any significant effect on self-employment for any groups. The program potentially increased the likelihood of being in school by around 2 pp and decreased the likelihood of having a bachelor's degree or higher by a little over 2pp. Both of these effects appear to be larger for those who received it at an older age.

These results and the yearly trends imply that DACA may be pushing older individuals to attend school in order to meet the high school level DACA requirements. It also suggests that the effect from there reduction of barriers to enter the labor market was larger than the effects from the increased returns to education for the older group. For those who received DACA at a younger age these effects aren't quite as strong and although there is a decrease in the probability of pursuing higher education, it is much smaller when compared to the older group. The yearly trends further suggest that there may actually be in increase in the likelihood of pursuing an education which could mean that DACA incentivizes investment in higher education for the younger group despite having the opposite effect on the older group.

In addition, I can speculate that heterogenous treatment effects are present on in the effect an individual's likelihood to be working, in the labor force, and unemployed. Therefore, you cannot deny that heterogeneity across ethnic groups may exist, but we cannot definitively say it does exist without further research.

Overall, we can see the policy had positive effects on this young authorized group but since DACA was implemented through prosecutorial discretion it is at risk of being rescinded. As political tensions continue to rise over the immigration crisis and President Trump continues to divide the country with anti-immigrant rhetoric, understanding the effects of the immigration policy, that he is so eager to end, is crucial to understanding the economic implications of ending the program. This could have detrimental economic consequences for the young undocumented individuals who currently have DACA and may even put them at risk for mass deportation under Trump's government. Furthermore, we know that not only is the program temporary, but it also only benefits the 5% of unauthorized immigrants who have obtained deferred action and work authorization through DACA. Perhaps by extending the temporary program or granting permanent amnesty can provide deferral from deportation and work authorization to a much larger population of unauthorized immigrants. Since the presence of differences in the treatment effect suggests different ethnic and age groups respond differently to the changes in the labor market frictions and returns education, the results of a large amnesty program may vary from the result from DACA. Nevertheless, we cannot deny the need for a more inclusive and permanent solution for this immigrant group.

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APPENDIX

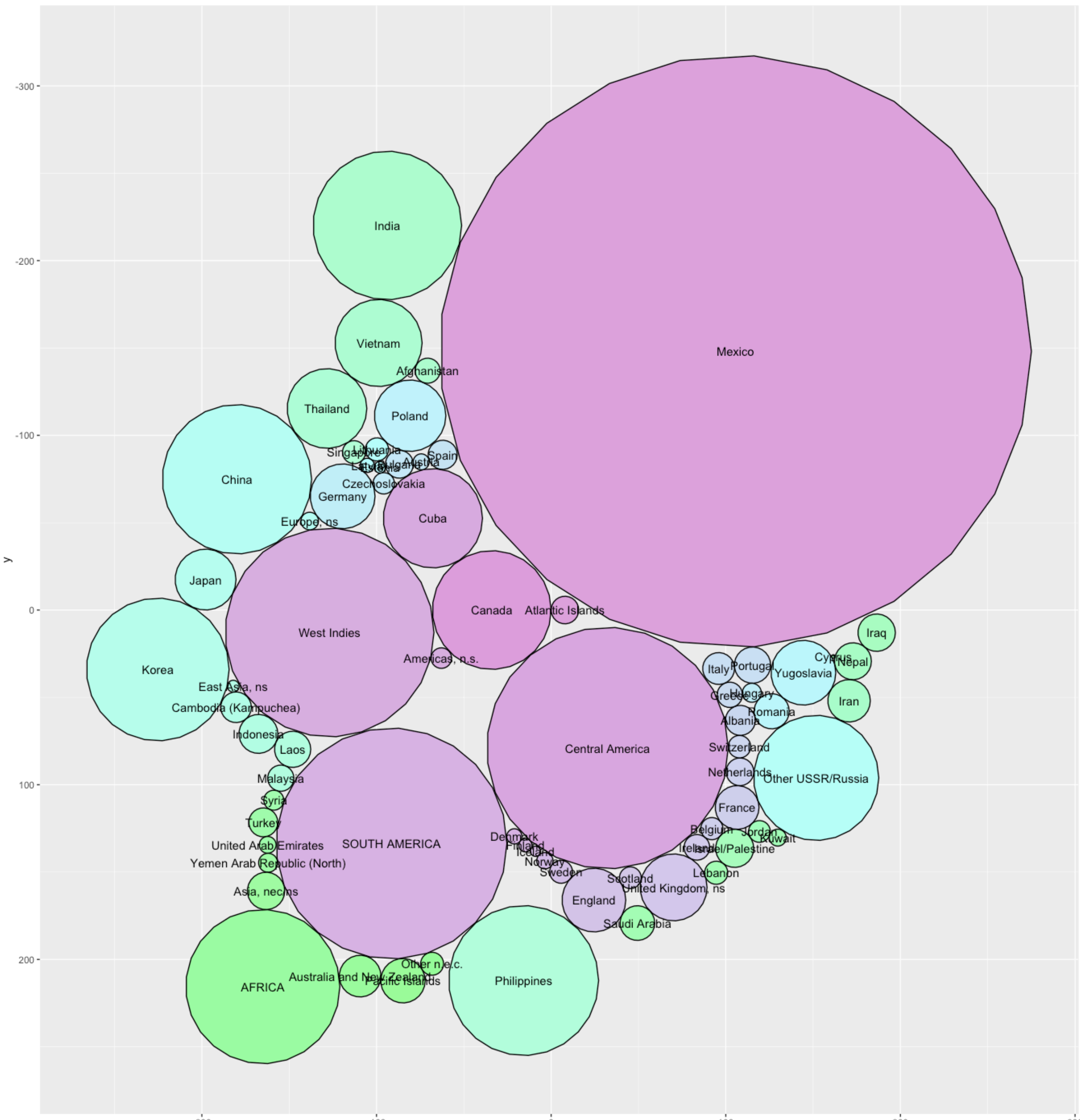


Figure 1. DACA Eligible by Birthplace

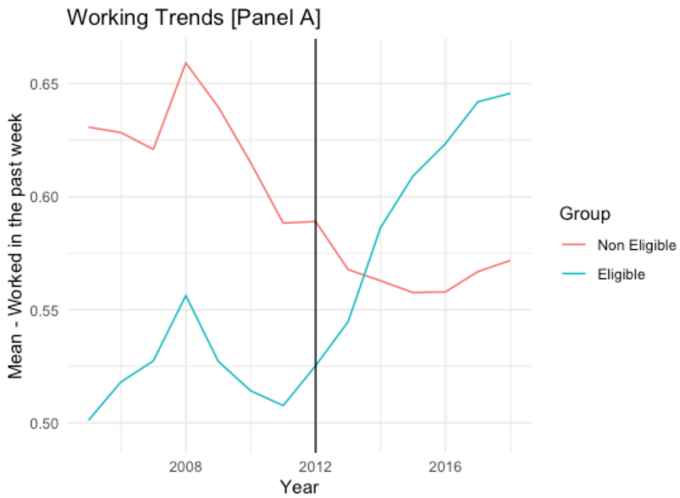


Figure 16

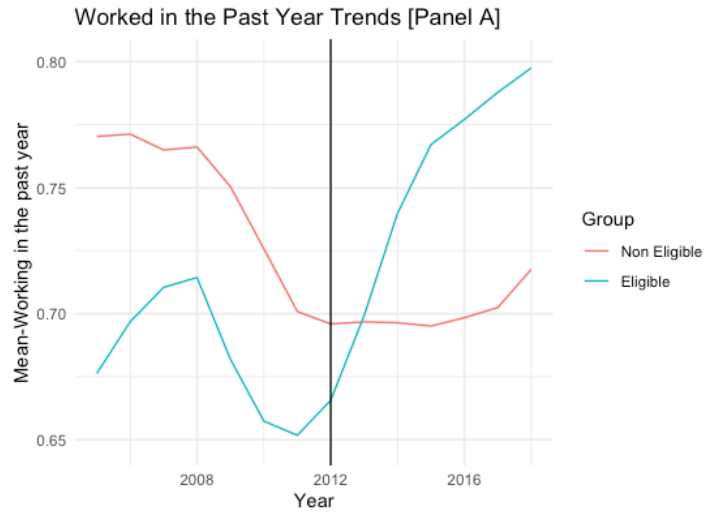
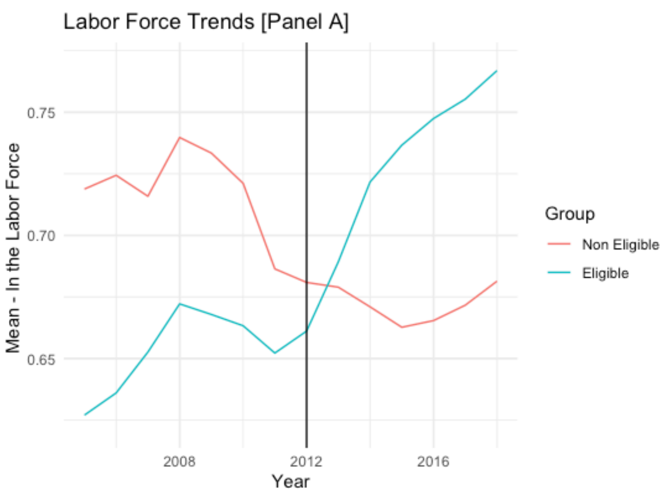


Figure 17



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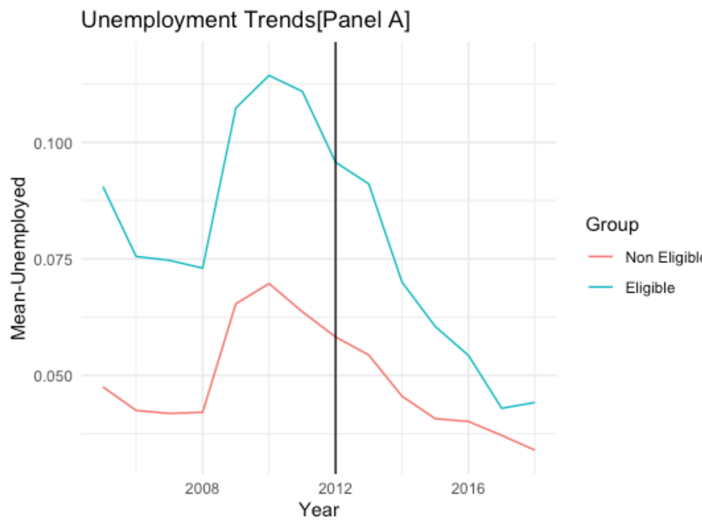

Figure 19

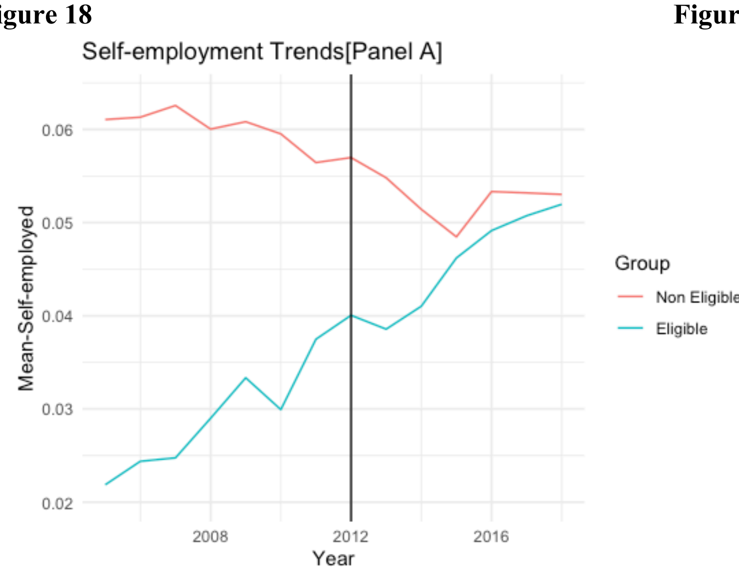

Figure 20

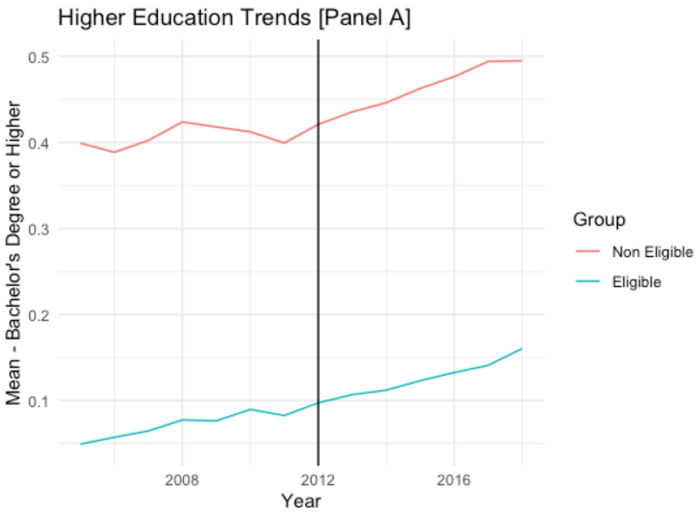

Figure 21

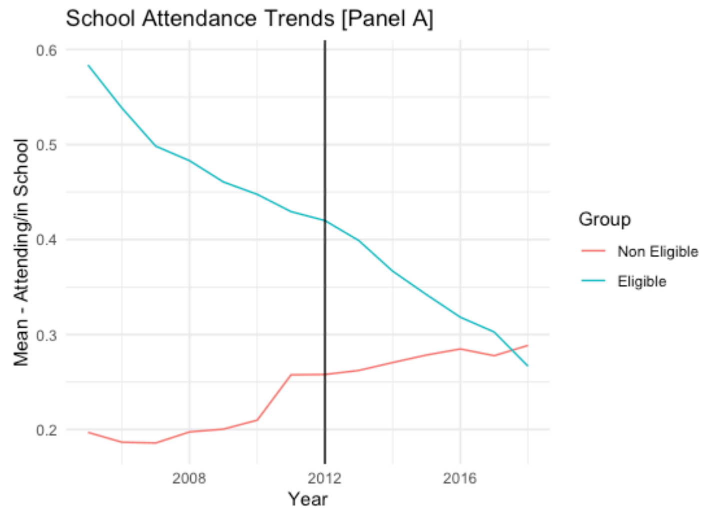

Figure 22