Estimating the Average Treatment-on-the-Treated Effects of the DACA Program

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Abstract

I examine the labor market response of undocumented youth that participated in the Deferred Action for Childhood Arrivals (DACA). DACA provides temporary work authorization and deferral from deportation to eligible undocumented youth. I use data from the U.S. Citizenship and Immigration Services to construct a probabilistic measure for the unobserved DACA participation. Using ACS data, I estimate a two-sample model of the effect of participating in the DACA program. I also estimate the spillover effects of DACA on eligible but non-participating undocumented youth. I find that DACA significantly improved labor market outcomes of DACA recipients, with magnitude of the treatment-on-the-treated effects at least twice as large as the intent-to-treat estimates obtained from using only the observed eligibility indicator. I also find an increase in school attendance among DACA recipients. Evidence of a negative spillover effect on eligible non-participants is documented with a decrease in labor force participation and school attendance.

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1 Introduction

As of 2017, an estimated 10.5 million undocumented immigrants resided in the United States, representing 3.2% of the total population (Passel and Cohn, 2019). Whether congress should pass amnesty and in what form has been subject to heated debate. Considerable interest has been focused on the most recent attempt to regularize this population, the Deferred Action for Childhood Arrivals (DACA) program. Enacted on June 15, 2012 by President Obama through an executive memorandum, DACA grants eligible undocumented youth temporary protection from deportation and work authorization. These benefits are subject to renewal every two years. The DACA program eliminates considerable labor market barriers that recipients previously faced due to their lack of legal status.

In this paper, I examine how DACA *participation* impacted undocumented youth's labor market behavior. In addition, I test for possible spillover effects of the enactment of the DACA program on eligible non-participants. As of 2018, 840,000 individuals have participated in the DACA program with 620,000 maintaining an active status. Understanding the effect of *participating* in the program is of valuable information to policy makers on whether to continue or terminate DACA. Understanding the behavioral effects of both participants and of eligible but non-participating undocumented youth will also provide information on the effects of similar proposed amnesty programs considered by congress.

A growing literature has developed estimating the effects of DACA eligibility on various outcomes. Previous work has shown that DACA improves labor market outcomes (Pope, 2016; Amuedo-Dorantes and Antman, 2017), improves health outcomes among children and adults (Venkataramani et al., 2017; Hainmueller et al., 2017; Giuntella and Lonsky, 2020), reduces teenage pregnancy (Kuka et al., 2019), reduces the propensity to commit crime (Gunadi, 2019), and improves their sleep behavior (Giuntella et al., 2021). The effect of DACA eligibility on education has been mixed. Pope (2016), Amuedo-Dorantes and Antman (2017), and Hsin and Ortega (2018) show negative or insignificant effects on school attendance for those that are immediately eligi-

ble (meet the education requirement) while Kuka et al. (2020) and Ballis et al. (2020) find positive effects among those that may want to become eligible but do not yet meet the education requirement. Ballis et al. (2020) is the only other paper to estimate spillover effects of the DACA program. Ballis et al. (2020) finds evidence of spillover effects in educational achievement among students with more DACA-eligible peers.

The previous studies have focused exclusively on the effects of DACA on those that are eligible for the program. This has limited the discussion to the average intent-to-treat effects of DACA. The ability to extrapolate the average treatment-on-the-treated effects from the average intent-to-treat effects estimated in the literature requires the following strong assumptions: (1) no self-selection into the program and (2) no spillover effects on the non-participating population. Hipsman et al. (2016) estimate that 37% of immediately eligible undocumented immigrants did not participate in DACA. Given that these are strong assumptions the treatment-on-the-treated effects need to be estimated directly. Additionally, the assumption that eligible non-participants are not affected indirectly through increased labor market competition or behavioral changes from the changing legal environment needs to be empirically tested.

Researchers have also been limited to using lack of citizenship along with ethnicity as a proxy for undocumented status as there is no indicator for undocumented status in large representative datasets. With an estimated 39% of non-citizens age 18 to 35 being documented immigrants (Baker and Rytina, 2013), the current observable measure of eligibility are significantly contaminated with authorized non-citizens. Having up to 39% of the observed DACA-eligible population being false-positives will lead to estimates of the average intent-to-treat effects of DACA to be considerably attenuated towards zero. Only one other paper, Ballis et al. (2020), uses administrative data to reduce measurement error in the eligiblity indicator. Ballis et al. (2020) uses variation in the number of DACA applications relative to the size of the foreign-born population across zip code in Los Angeles in 2014 to proxy for likely-undocumented status. Focusing on only Hispanic or Mexican non-citizens also misses important heterogeneous effects across nationality and ethnicity. Understanding how non-Hispanics are affected by conditional amnesty is becoming more pertinent for

policy makers as this group continues to become a greater share of the undocumented population (Passel and Cohn, 2019).

In this paper, I expand on this literature by using publicly available administrative data from the U.S citizenship and Immigration Services (USCIS) to construct a probability measure of DACA participation. The USCIS data provides a total count of DACA recipients by country-of-origin for each year since the enactment of DACA up to 2018. Combining estimates of the DACA-eligible non-citizen population by country-of-origin using the ACS with the USCIS data allows me to construct a probabilistic measure for the unobserved DACA participation across country-of-origin and time. To estimate the treatment-on-the-treated effects of DACA on those who participated in the program, I merge this measure into the American Community Survey (ACS) and estimate a two-sample model. These are the best estimates available of the treatment-on-the-treated effects of DACA with currently available administrative data. In an alternative model, I include a probabilistic measure on the likelihood an eligible non-citizen is not a DACA recipient along with the probabilistic measure. This allows me to estimate both the spillover effects of DACA on eligible non-participants along with the direct treatment effects on DACA recipients using ineligible non-citizens as the control group.

I find that DACA significantly improved the labor market outcomes of recipients in the preferred model specification. DACA recipients increased the likelihood of working by 11.3 percentage points (p.p.) or 17.1% relative to non-participating non-citizens. With a total of 824,000 recipients, DACA moved 101,000 to 103,000 undocumented immigrants into employment in the 6 years following its introduction in 2012. This is driven by both movements into the labor force and out of unemployment. Pope (2016) estimated DACA moved 50,000 to 75,000 undocumented immigrants into employment in the first two years of the program. The effect of DACA on self-employment is an economically significant 18% decrease. As self-employment is used as a proxy for participating in the informal labor market, this shows DACA led to considerable shifts from the informal to the formal labor market. Receiving deferred action and work authorization also leads to an increase in school attendance by 3.4 p.p. or 13.5% increase from pre-DACA levels. Controlling for

spillover effects in the alternative model, the effects of DACA participation are slightly larger with the effects of DACA on self-employment is now significant.

The improvement of labor market outcomes led to an increase in total income of 102.6% after receiving deferred action and work authorization through DACA relative to non-participating non-citizens. This increase is driven almost entirely by increases in wage and salary income which saw a 108.1% increase. Given the average pre-DACA total income of $15,117, this is an average increase in total income of $15,510. With an estimated 824,000 total DACA recipients, this amounts to a $12.8 billion increase in total income for the entire DACA participating population. In the alternative model, the effects of DACA on wages is a significant 7.5% increase relative to ineligible non-citizens.

Comparing the treatment-on-the-treated estimates from the preferred model to the intent-to-treat estimates using only the observed DACA-eligible indicator provides suggestive evidence that there may be considerable self-selection into the program. The difference in magnitude between the the treatment-on-the-treated and intent-to-treat effects vary widely for each outcome of interest from 1.8 times higher for unemployment to 7.9 times higher for total income. These estimates vary considerably compared to the expected ratio of 2.61 under the assumption of no self-selection. While the differences in the expected ratio may be due to self-selection, I can not exclude that the differences are driven by heterogeneous effects across country-of-origin. I find that recipients from Asia had the largest labor market benefit from DACA. Latin Americans saw significantly lower labor market benefits compared to Mexican recipients but had the largest increase in school attendance from receiving deferred action and work authorization.

In the alternative model, eligible non-participants saw a 1.4 p.p. decrease in the likelihood of participating in the labor force driven by unemployed eligible non-participants leaving the labor force. Eligible non-participants also saw a 2.3 p.p. decrease in school participation. The spillover effect of DACA on the total income for eligible non-participants was a statistically significant 30.3% decrease. This is driven by a 20.3% decrease in wage income, a 14.7% decrease in income

from other sources, as well as an 11.7% decrease in hourly wage rate. Two important notes need to be made with regards to these estimates. First, as I can only estimate observed-eligible non-citizens this proxy is severely contaminated with authorized non-citizens which will attenuate the estimates towards zero. Second, these effects may be capturing eligible individuals attempting to become eligible but have not yet been approved at time t. The results may be driven by change in composition on who is classified as eligible non-participants over time. I control for this in an event study model by focusing on those eligible but never participated in DACA during the sample period.

A key assumption is that DACA recipients and Eligible non-participants would follow the same trends as ineligible non-citizens if not for DACA. construct a measure of ever participating in DACA to estimate an event study specification. I find insignificant pre-trends in support of the parallel trend assumption for most of the variables. When pre-trends are present, the trend is in the opposite direction of the effects of DACA. The event study specification also shows a decline in the effects of DACA on recipients after 2015.

To strengthen the validity of the assumptions made in the empirical models, I perform a number of robustness checks. First, The USCIS data also contains a total count of DACA recipients across state-of-residence and time. I construct an additional measure of DACA participation from the administrative data using variation in the number of DACA participants across state-of-residence. The results are robust to using this alternative proxy except for the effects on school attendance and hourly wage. I also perform a placebo test on naturalized citizens. If my constructed measures are only capturing DACA participation, then I should find no effect of DACA on this sample. The placebo test results are consistent with this assumption. A further robustness check takes advantage of a multiple proxy method proposed by Lubotsky and Wittenberg (Lubotsky and Wittenberg, 2006). This method includes both proxies simultaneously to minimize attenuation bias caused by proxy variables being mismeasured. The results are also robust to this alternative model.

This paper makes a number of important contributions to the emerging literature on the impact of DACA. First, I use administrative data to create a probability measure of DACA participation to estimate the treatment-on-the-treated effects of DACA. I also estimate the spillover effects DACA has on eligible non-participants. Second, I estimate the effect of DACA across different sources of income rather than total income alone. Desegregating the effect DACA has on total income across different income sources provides a better understanding on how DACA is affecting the labor market outcomes of recipients. It also of value to public policy if the increase in total income is driven by taxable income (wages and salaries), likely informal income (income from other sources), or if amnesty burdens the welfare system (income from welfare). Lastly, I contribute to the literature on DACA by expanding the number of years included in the sample to include the Trump presidency which experienced considerable changes and legal challenges.

This work also relates to the work done to estimate the effects on the 1986 Immigration Reform and Control Act (IRCA). IRCA granted 2.8 million undocumented immigrants amnesty and a pathway to citizenship (Baker, 2015). Most studies have found IRCA lead to an increase in participants income (Kossoudji and Cobb-Clark, 2000; Amuedo-Dorantes et al., 2007; Lozano and Sorensen, 2011). However, Amuedo-Dorantes et al. (2007) found a decrease in labor force participation and an increase in the unemployment.

This paper also relates to the strand of literature attempting to identify unobservable populations in survey data using secondary sources. Lozano and Sorensen (2011) predict undocumented status in the Census data using the Mexican Migration Project Survey which does ask about Mexican immigrants documentation status. Other work has focused on using the Survey of Income and Program Participation to predict undocumented status into Census surveys (Van Hook et al., 2015). Bollinger and Hagstrom (2008) and Bollinger and Hagstrom (2011) use administrative data to predict refugee status in the Current Population Survey. I expand on this work by using administrative data to create a probability measure of DACA participation in the ACS. As asking about legal status becomes a more sensitive status, identifying undocumented immigrants will become more difficult over time. Using administrative data will become an important method to estimate

the effects of policy on these unobserved populations.

The paper continues as follows. Section 2 details the institutional framework of DACA. Section 3 describes the empirical strategy followed by Section 4 which discusses the data and variable construction. Results of the effect of DACA on the labor market outcomes of DACA recipients are presented in Section 5. Section 6 provides estimates of the spillover effect on eligible non-participants. Estimates from an event study framework are presented in Section 6. Section 8 presents results of the robustness checks using an alternative measure and model. Finally, Section 9 provides concluding remarks.

2 Deferred Action for Childhood Arrivals

On June 15, 2012, through prosecutorial discretion, President Obama enacted an executive memorandum announcing the Deferred Action for Childhood Arrivals program. This executive decision was taken after the failed attempts in Congress to pass the DREAM Act in 2010 and 2011 which would have provided permanent residency to undocumented immigrants that came to the US as children. The DACA program is arguably the largest immigration reform impacting undocumented immigrants since the passage of the Immigration Reform and Control Act (IRCA) in 1986 where nearly 2.7 million undocumented immigrants were approved for permanent residency (Rytina, 2002). The memorandum provides eligible applicants with two key benefits. First, recipients receive two years of relief from deportation. Second, recipients receive work authorization through an Employment Authorization Document (EAD). With the EAD, individuals are allowed to apply for a Social Security Number (SSN). Both benefits are subject to renewal every two years. DACA does not provide any form of legal immigrant status or a pathway to citizenship. This is a *de facto* temporary legalization for the participating population.

On September 5, 2017, President Trump ordered the termination of the DACA program. Court challenges have led to a continuation of renewals for those who have already been approved prior to the termination of DACA but no new applications have been accepted since September

5, 2017. Following these legal challenges, the Supreme Court ruled that the administration acted arbitrarily and capriciously in ending the program and ruled that the rescission be vacated. After the 2020 presidential election, President Biden reinstated DACA in full.

2.1 Requirements for DACA Eligibility

The DACA program is specifically targeted towards undocumented immigrants that came to the US as children. In order to qualify for DACA, an applicant must meet the following six criteria:

1. have no lawful status as of June 15, 2012;
2. have come to the United States before the age of 16;
3. have been under the age of 31 as of June 15, 2012;
4. have continuously resided in the United States since June 15, 2007 and be physically present on June 15, 2012;
5. must be currently in school, have completed high school (or have obtained a General Education Development (GED)) certificate, or be an honorably discharged veteran of the United States military;[1]
6. cannot have been convicted of a felony, significant misdemeanor, or three or more other misdemeanors.

In addition to these requirements, an applicant has to pay a processing fee of $465 and be at least 15 years of age.

2.2 Size of the Eligible Population

In 2012, the Pew Research Center estimated 1.7 million of the 11.2 million undocumented immigrants are potentially eligible for DACA (Passel and Lopez, 2012). Of these, 950,000 were immediately eligible (satisfy criteria 1, 2, 3, 4, 5 and age 15 and older) at the announcement of DACA. Another 450,000 were potentially eligible by aging into the program (between the ages of 5 to 14).

[1] Very few DACA-eligible immigrants have used military service to satisfy this requirement. Approximately 820 DACA recipients are in the military (USCIS, 2017)

Given the age distribution of the those 5 to 14 years old, the number of children aging into the eligibility annually range from 80,000 to 90,000 between 2013 and 2016 (Batalova et al., 2014). Another 320,000 are potentially eligible by completing the education requirements (those aged 16 to 30 who do not have a high school diploma or GED and are not enrolled in school).

The above estimates of the number of potentially DACA-eligible immigrants does not take into account criteria 6 (not having been convicted of a felony or three serious misdemeanour) as neither the CPS nor ACS asks about the criminal history of participants. The Migration Policy Institute (MPI) estimates that 820,000 of the 11 million undocumented immigrants had criminal convictions (Rosenblum, 2015). Of those 820,000, Rosenblum (2015) estimate approximately 300,000 had a felony conviction (a conviction with a sentence 1 year of longer) and 390,000 had serious misdemeanours (a conviction with a sentence 90 days or longer) making them ineligible for DACA even if they satisfied all the other requirements. No information is available on the number of undocumented immigrants that have three or more misdemeanours, though, Rosenblum (2015) estimates at most 130,000 have at least one misdemeanour.

2.3 Size and Characteristics of DACA Recipients

The USCIS began accepting applications for DACA on August 15, 2012. Figure 1 displays the cumulative number of initial approvals from implementation in 2012 to the end of 2018 by quarter. Figure 2 shows cummulative number of initial approvals for Mexicans (a) and top 25 country-of-origin groups excluding Mexico (b). Data comes from publicly available quarterly reports published by the USCIS from 2013 to 2018 (USCIS, 2013-2017, 2018). By the end of 2013, the first full year of the program, 520,000 applications had been approved. The rate of new applications slowed beginning in 2014 and as of 2018 an estimated 824,000 undocumented immigrants have received deferred action and work authorization through DACA. A total of 80,400 applicants have had their initial applications denied. This is a take up rate of roughly 50% out of the estimated 1.7 million potentially eligible. Receiving work authorization through an EAD universally led to receiving a SSN. From October 1st, 2012 to June 30th, 2017, the Social Security Administration

assigned original SSNs to 838,058 non-citizens that had been granted DACA status (SSA, 2018).[2]

A total of 14,434 renewal applications have been denied by the end of 2018 (USCIS, 2013-2017). Investigations from the House and Senate Judiciary Committees in 2017 estimate 40,000 DACA participants were able to have their legal status changed as of August 2017 (Grassley, 2017). The Congressional investigations estimated 59,778 DACA recipients have applied for Lawful Permanent Resident (LPR) status through Advance Parole and 39,514 have been approved (4.8% of total DACA recipient) (Grassley, 2017). Of those who received LPR status, 2,181 have applied for U.S. citizenship and 1,056 have become U.S. citizens (Grassley, 2017). While DACA does not provide a formal "pathway to citizenship," DACA participants can take advantage of Advance Parole through an I-131 application for travel documents. Advance Parole is a formal procedure that allows DACA participants the ability to leave the country where they can then formally request an immigration status change in the US embassy in their home country. Without Advance Parole, an undocumented immigrant that leaves the U.S. will be banned from reentering the country for 3 or 10 years depending on how long they have been in the country without authorization. Given that 824,000 applicants were approved, 14,000 have had their status terminated, and 40,000 have transitioned to LPR, an estimated 92,000 (11%) DACA recipients have let their DACA status expire by the end of 2018. As of the end of 2018, there were approximately 680,000 active DACA recipients (USCIS, 2019).

The composition and geographic dispersion of DACA applicants is similar to that of the undocumented immigrant population as a whole. As of 2018, around 92% of approved applicants are from Central and South America and 76% are from Mexico alone (USCIS, 2013-2017). California and Texas account for over 229,000 and 127,000 of the initial approved applicants, respectively. Illinois, New York, and Florida have around 40,000 each (USCIS, 2013-2017, 2018). These five states make up 52% of the total number of applicants. Of those with active status as of November 2018, 47.3% are male, 79% are single, and are on average 24 years old (USCIS, 2019).

[2]The USCIS states that there have been a total of 792,000 application approvals as of June 30th, 2017 (USCIS, 2013-2017) leading to a discrepancy of 46,000 applicants between the number of DACA approvals given by the USCIS and the number of SSNs given to DACA recipients by the SSA.

3 Model Specification and Empirical Strategy

In an ideal situation, the ACS would have an indicator that would identify whether and when an individual was a recipient of deferred action and work authorization through DACA. Using a sample of non-citizens ages 18-35 with at least a high school degree, I would estimate the following reduced-form model specification:

$$Y_{icst} = \beta_0 + \beta^* Recipient_{icst} + \beta_2 X_{it} + \beta_3 W_{it} + \beta_4 Z_{st} + \gamma_c + \gamma_t + \gamma_s + \gamma_s t + \epsilon_{icst} \quad (1)$$

where Y_{icst} is the outcome of interest for non-citizen i from country c in state s in year t. The indicator $Recipient_{icst}$ takes the value of one if non-citizen i was ever a DACA recipient by time t and zero otherwise. The vectors X_{it}, W_{it}, and Z_{st} contain key demographic and state-by-year controls. The vectors γ_c, γ_t, and γ_s allow for country-of-origin fixed effects, time fixed effects, and state fixed effects, respectively. Lastly, $\gamma_s t$ allows for state-specific time trends.

The coefficient of interest, β^*, represents the treatment-on-the-treated effect of DACA. The control group would be all non-citizens in the sample that did not participate in the DACA program. This group contains both DACA ineligible non-citizens and Eligible non-participants. The coefficient, β^*, therefore represents the change in the outcome of interest after an individual becomes a DACA recipient relative to all non-citizens who did not participate in the DACA program. The key assumption to get unbiased estimates of β^* is that both the treated and control group would have followed similar trends had it not been for the enactment of DACA.

Unfortunately, large nationally-representative datasets commonly used by researchers, such as the ACS, do not ask whether an individual participated in DACA. As $Recipient_{icst}$ is unobserved, I cannot directly estimate the effect of DACA on recipients (β^*). To deal with this limitation, I consider the conditional expectations model of equation 1:

$$E[Y|C,T,E,X,W,Z,S] = \beta_0 + \beta^* E[R|C,T,E,X,W,Z,S] + \beta_2 X + \beta_3 W + \beta_4 Z + \gamma_c + \gamma_t + \gamma_s + \gamma_s t \quad (2)$$

Where R represents DACA participation. The expected conditional value of R can be represented as:

$$E[R|C,T,E,X,W,Z,S] = P(R = 1|C,T,E,X,W,Z,S) \tag{3}$$

Using publicly available data from the DHS on the total number of DACA recipients by country of birth in each year along with estimates of the total DACA eligible population using the ACS, I am able to construct the probability a non-citizen was ever a DACA recipient at time t.

$$P(R \widehat{= 1|C}, T, E) \tag{4}$$

The variable $P(R \widehat{= 1|C}, T, E)$ represents the probability a non-citizen i from country c had ever participated in DACA by time t. The probability is set to zero if the non-citizen does not meet any one of the observable DACA-eligibility requirements (E = 0) or if the year is 2012 or earlier.[3] The procedure of constructing this probability is detailed in Section 4. Under the assumption that the constructed probability is equal to the expected mean of the unobserved DACA participation or,

$$P(R \widehat{= 1|C}, T, E) = P(R = 1|C,T,E,X,W,Z,S) = E[R|C,T,E,X,W,Z,S] \tag{5}$$

I can plug in variable 4 into equation 2 and get the preferred model specification to be estimated in this paper:

$$E[Y|C,T,E,X,W,Z,S] = \beta_0 + \beta^* P(R \widehat{= 1|C}, T, E) + \beta_2 X + \beta_3 W + \beta_4 Z + \gamma_c + \gamma_t + \gamma_s + \gamma_s t \tag{6}$$

The assumption in equation 5 underlying the preferred model presumes the constructed probability is only capturing the unobserved participation decision. Specifically, that there are no unobserved time varying country-of-origin factors that are correlated with the unobserved participation decision and with outcomes. With this assumption the probability measure constructed

[3] While the program was announced in June 2012 and applications submitted by the end of 2012, very few applicants were approved in 2012. Additionally, the publicly available data does not provide the country-of-origin of those that were approved in 2012.

is an instrument for the unobserved treatment ($recipient_{icst}$). In a linear regression model, as the probabilities are instruments for the true unobserved treatment, the probability measure can be used as a regressor (Bollinger and Hagstrom, 2011). Under the assumption in equation 5 and the assumption that both treated and control groups would have similar trends if not for DACA equation 6 provides an unbiased estimate of β^*.

The sample in the preferred model of equation 6 comprises of all non-citizens ages 18 to 35 with at least a high school degree (or equivalent). The outcomes of interests are labor force participation, the likelihood of working, of being unemployed, the usual hours worked in a week, and likelihood of being self-employed. I look at total income and its subcomponents. The specific subcomponents are income from wage and salaries, welfare income, and income from other sources[4]. I also look at wage of employed individuals with positive hours of work. Additionally, I look at the likelihood of currently attending school.

The vector X contains demographic controls including education, sex, race, ethnicity, and marital status. The vector W includes fixed effects for individual $i's$ age and age when they arrived in the United States to control for the eligibility criteria. Vector Z is a vector of state-by-year controls. This vector includes the state unemployment rate, an indicator if the state has enacted universal E-Verify, if the state has enacted public E-Verify, an indicator if the state grants in-state tuition to undocumented immigrants, and an indicator if the state allows undocumented immigrants to obtain a driver's license at time t. The vector γ_c allow for country-of-origin fixed effects. The vectors γ_t and γ_s allow for time and state fixed effects, respectively. Lastly, $\gamma_s t$ allows for state-specific time trends. When estimating Equation 6, standard errors are clustered at the state-by-year level.[5]

A one unit change in the variable $P(\widehat{R = 1|C, T, E})$ corresponds to a shift in the probability of ever receiving DACA in year t from zero to one. The coefficient β^* therefore corresponds to the effect of having had received DACA by year t on the outcomes of interest relative to non-participating

[4]Income from other sources are income not from wages, welfare, farm or business/investments.

[5]Results are robust to clustering standard errors at the state level, and at the country-of-origin level.

non-citizens. Individuals that had received DACA may no longer have active status at time t and would no longer have the accompanying benefits. Due to this, the estimates of β^* will be a lower bound of the effects of DACA on active DACA recipients.

4 Data

To analyse the labor market effects of DACA participation, I use the ACS sourced from IPUMS (Ruggles et al., 2020). The main sample used is comprised of all non-citizens aged 18 to 35 with at least a high school degree (or equivalent) between the years 2005 to 2018. The choice of years was dictated by survey availability. The first year for which the nationally representative data were collected was 2005 and 2018 was the most recent sample available. The ACS contains key labor market outcomes including labor force participation, employment, unemployed, their usual hours worked, and their self-employment status. Information on individual's total income and by source. Sources analyzed in this paper are income from wages and salary, income from welfare, and income from other sources.

The ACS also contains important demographic and immigration related variables which are used to determine respondents' observable DACA eligibility status and assign a probability of DACA participation such as each immigrant's country-of-origin, their U.S. citizenship status, number of years spent in the U.S., quarter of birth, and educational attainment. The ACS does not contain data on non-citizens legal status and therefore undocumented status is proxied using non-citizenship. As is done in Pope (2016) and Giuntella and Lonsky (2020), I define non-citizens as being DACA-eligible as those who: (1) were under the age of 31 as of June 15, 2012; (2) have lived in the U.S. since June 15, 2007; (3) entered U.S. before reaching 16th birthday; (4) have at least a high school degree (or equivalent); (5) were born outside the U.S. or its territories; (6) are not U.S. citizens; and (7) at least 15 years of age.[6]

[6]To define the DACA-eligible population in year 2012 and before, the criteria are restricted to non-citizens who were: (1) under the age of 31 as of June 15 of the previous calendar year; (2) arrived to the U.S. prior to their 16th birthday, (3) have lived in the U.S. for at least 6 years, (4) have at least a high school degree (or equivalent); (5) were born outside the U.S.; and (6) are not U.S. citizens.

The key variable is the probability a non-citizen is a DACA recipient at time t. To construct this variable, I take advantage of administrative data from the USCIS that provides a total count of DACA recipients by country-of-origin and year (USCIS, 2013-2017, 2018). The USCIS data provides a total count for all countries only for the year 2018. For the years before 2018, only the 25 largest country-of-origin groups are observed. Using the 2018 total count, I do a linear extrapolation to estimate the total number of DACA recipients from countries not observed in the years 2013 to 2017 beginning at zero in 2012.[7] I use the ACS to estimate the average count of DACA-eligible non-citizens by country-of-origin from 2013 to 2018. Using the count provided in the administrative data and the estimate of the size of the observed DACA-eligible population, I construct an estimate of the probability a non-citizen i from country c at time t is a DACA recipient as follows:

$$\widehat{P(R = 1|C, T, E)} = \frac{(\text{Total DACA Recipients})_{ct}}{(\text{Total DACA Eligible Population})_{c}} \cdot Eligible_{it} \tag{7}$$

where the numerator is constructed from the USCIS data and the denominator is constructed from the ACS data. The average number of DACA-eligible non-citizens for each country-of-origin across all post DACA years is used to limit sampling error which can be an issue with nationalities that have small populations. Total DACA recipients is equal to zero in the pre-DACA years 2005 to 2012.[8] The indicator $Eligible_{it}$ is equal to one if an immigrant in the sample meets all observable DACA requirements and zero otherwise. For individuals who are not observed to be DACA-eligible, the probability of being a DACA recipient is set to zero. Each individual in the sample is assigned a probability of being a DACA recipient based on their observed eligibility status, country-of-origin, and year observed in the sample.

The administrative data also provides a total count of DACA recipients by state-of-residence for each year since the enactment of DACA up to the year 2018. Data is available for all states in all years. The same procedure as above is done to construct the probability measure of DACA

[7] Results are robust to using a sample of only the top 25 largest country-of-origin groups.

[8] While there was in fact a few number of approvals in the year 2012, they were at the very end of the calendar year and the total count publicly available are not desegregated at country-of-origin level.

participation across state-of-residence (S). I construct an estimate of the probability an observed DACA-eligible non-citizen i from state-of-residence s at time t is a DACA recipient as follows:

$$\widehat{P(R = 1|S, T, E)} = \frac{(\text{Total DACA Recipients})_{st}}{(\text{Total DACA Eligible Population})_{s}} \cdot Eligible_{it} \tag{8}$$

Each individual in the sample is assigned a probability of being a DACA recipient based on their observed eligibility status, state-of-residence, and year observed in the sample.

This creates two proxies for DACA participation using difference sources of variation. The proxy $\widehat{P(R = 1|C, T, E)}$ is the probability a non-citizen had ever participated in DACA by time t using variation across country-of-origin while $\widehat{P(R = 1|S, T, E)}$ is the probability a non-citizen had ever participated in DACA by time t using variation across state-of-residence.

4.1 Summary Statistics

Table 1 provides descriptive statistics of the constructed probability an observed DACA-eligible non-citizen ever participated in DACA for the 20 largest DACA approved countries in the year 2018. At a total of 643,373 approvals, Mexicans make up the overwhelming share of DACA recipients with 78% of all approvals. Observed DACA-eligible Mexicans have the largest share of DACA recipients at 71%. There is significant variation across countries and within regions. The share of DACA recipients in Asian countries range from 10.9% for Filipinos, Indians (11.8%), Chinese (3.4%), Koreans at 21.5%, and 24.1% for Indonesians. With 13% share of DACA-eligible non-citizens participating in DACA, Poland is the only European country in the top 30 list. For African countries, 20% of observed DACA-eligible Nigerians and 17.3% of Kenyans participated in DACA. With 990 approvals, only 3.2% of DACA-eligible non-citizens from Canada participated in DACA. There is a zero probability of an observed DACA-eligible non-citizen that migrated from England or Scotland is a DACA participant. [9] Figure 3 shows variation in the probability an observed

[9] Descriptive statistics of the constructed probability an observed DACA eligible non-citizen ever participated in DACA using variation across state-of-residence from equation 8 can be found in Table A.1.

DACA-eligible immigrant is a DACA recipient across time for the largest 25 country-of-origin groups.

The main source of variation in the measure comes from differences in the share of undocumented immigrants within each country's observable DACA-eligible population. Countries that have a high share of legal immigrants, such as Western European countries, China, Cuba, and Canada will have lower probability measures. Countries with a high share of undocumented immigrants, such as Mexico, Central and South American countries will have a higher probability measure. Additional variation is caused by differences in the participation rates across countries.

Table 2 provides descriptive statistics of the DACA recipients, eligible non-participants, ineligible non-citizens, and the full sample during the pre-DACA period (years 2005 to 2012). To produce summary statistics of the demographic characteristics of the DACA recipient population (column 1) prior to the enactment of DACA I assign the constructed probability a non-citizen ever participated in DACA by the year 2018 to all pre-DACA years. This probability is then multiplied by the ACS provided person-weight. To get descriptive statistics of the eligible non-participating population (column 2) I multiple the person weight by the probability a DACA eligible non-citizen was never a DACA participant.[10] To get descriptive statistics of the ineligible non-citizen population (column 3) I restrict the weighted sample to those that have the eligiblity indicator equal to zero. Column 4 shows the weighted summary statistics of the full sample. Recipients compose of 8.6% of the weighted sample. This equates to DACA recipients making up 57.2% of the observed DACA-eligible sample population. This values are similar to estimates of the share of DACA participants for the respective populations provided by Hipsman et al. (2016) and Passel and Lopez (2012).

Table 2 shows that, relative to eligible non-participants, DACA recipients are less likely to be in school (25.1% and 37.16%) and less likely to have a college degree (5.58% and 13.09%). Almost 92% of recipients are Hispanic, driven by 78% of recipients being from Mexico. Observed DACA-

[10] This is calculated by the equation non-participant = (1 - $P(recipient)_{ic,2018}$)* Eligible$_{it}$.

eligible non-participants are more likely to be from Latin America (31.51%), Asia (23.86%) and Europe (12.42%). The demographics are consistent with the observed DACA non-participating population having a significant proportion of documented immigrants. DACA-ineligible non-citizens are more likely to be recent immigrants with only 6.35 years living in the US compared to 15.7 years in the US for DACA recipients. Ineligible non-citizens are more likely to have entered the country as adults (22 years old vs. 8.5 years old) and are twice as likely to be married than eligible non-citizens.

In Table 2, a number of differences are shown in each group's labor market outcomes pre-DACA. While DACA recipients are 2.6 percentage points more likely to work and work 1.3 more hours a week than their non-participating eligible counterparts, they earn roughly $1,300 less in total income. DACA-ineligible non-citizens have considerably higher total income at $23,929 or 1.6 times larger than DACA-participants. DACA-ineligible non-citizens are also 3.7 percentage points less likely to be unemployed, work an hour more a week, and 1.5 percentage points more likely to be self-employed.

5 Results

The estimates of the preferred model from equation 6 of the effect of DACA on labor market outcomes of DACA recipients are reported in Table 3. Row 2 of Table 3 show the pre-DACA means of the labor market outcomes for DACA recipients. The results reveal DACA has significantly improved the labor market outcomes of recipients relative to the control group. In the preferred model, the control group is composed of both DACA-eligible non-participants and DACA-ineligible non-citizens.

Column 2 of Table 3 shows that DACA recipients are 11.3 p.p. more likely to be working compared to the control group after receiving deferred action and work authorization through DACA. With an estimated 66% of DACA recipients being employed prior to 2012, the estimates translate to an increase in the likelihood of working of 17.1%. This is a little less than 3 times larger than the

attenuated intent-to-treat effects of DACA on the observed DACA eligible population in the first two years of the program estimated in Pope (2016). The increase in the likelihood of working is driven by individuals entering the labor force and individuals moving out of unemployment. Column 1 shows DACA increased the likelihood a DACA recipient is in the labor force by 9.6 p.p. while Column 3 shows that DACA recipients decreased the likelihood of being unemployed by 3.0 p.p.. Column 4 indicates DACA recipients work 3.802 more hours a week relative to the control group. This outcome is an alternative measure for working. The estimates can be viewed as DACA leading to one additional full-time job (40 hours per week) per 10.5 DACA recipients. For reference, Pope (2016) estimated an increase of one additional full-time job per 23 DACA-eligible individuals. These estimates indicate lack of work authorization and fear of deportation are severe frictions limiting undocumented immigrants from entering the labor force and acquiring employment when they do enter. The effects of DACA on self-employment is statistically significant and the magnitude of the coefficient indicates a 18% decrease in the likelihood of self-employment. As self-employment is more likely to indicate employment in the informal sector this indicates economically and statistically significant movement from the informal to the formal labor market.

I also estimate the effect of DACA on recipient's school attendance. Column 6 of Table 3 shows DACA recipients are 3.4 p.p. (13.5%) more likely to be enrolled in school relative to the control group. This is in contrast with the difference-in-differences results from Pope (2016), Amuedo-Dorantes and Antman (2017), and Hsin and Ortega (2018) on the effect of DACA on DACA-eligible non-citizens but consistent with the results from Kuka et al. (2020) and Ballis et al. (2020).

Estimates from the preferred model of the effect of DACA on the income of DACA recipients are reported in Table 4. Row 2 of Table 4 shows the pre-DACA means of income for DACA recipients. The income outcomes are transformed by their inverse hyperbolic sine so that the coefficients are interpreted as percent changes. A benefit of this transformation rather than a simple log-transformation is that I am able to include those in the sample with zero income.

The results reveal DACA has significantly increased the total income of DACA recipients relative

to eligible non-participants and ineligible non-citizens. Column 1 in Table 4 shows that DACA recipients saw an increase in total income of 102.6% after DACA relative to the control group. The pre-DACA income of DACA recipients was $15,117, indicating DACA lead to an increase in total income of $15,510 for the average DACA recipient. Pope (2016) did not find a significant average effect of DACA-eligibility on total income but did note an increase of 5-20% in total income for those the income distribution between the 30th and 60th percentile, or around an increase of 400 to 800 dollars.

The increase in total income is driven almost entirely by a 108.1% increase in income from wage and salaries (Column 2). DACA had no effect on income from other sources (Column 3). Column 5 of Table 4 shows the effect of DACA on recipients hourly wage. Hourly wage is constructed by diving wage income by usual hours worked in a week times weeks worked in a year. The inverse hyperbolic sine transformation is also taken so that the estimated effects translate to percent changes. I find DACA recipients had a statistically insignificant 1.6% increase in wages relative to the control group.

While undocumented immigrants, including DACA recipients, are ineligible to participate in federal welfare programs, some states do provide undocumented immigrants access to certain state funded welfare programs. Column 4 shows the estimates of DACA on recipient's welfare income. DACA did not have a statistically significant effect on welfare income of DACA recipients. Extrapolating this estimate to future amnesty programs should be taken with caution though as participating in a permanent amnesty program will provide participants access to federal welfare programs and as such may lead to an increase in welfare expenditure.

5.1 Relationship To Intent-to-Treat Estimates.

To be able to extrapolate the average treatment-on-the-treated effects from the intent-to-treat estimates in the literature we must make a number of strong assumptions. First, due to data limitations, the literature on DACA has focused on estimating the effects of being an observed DACA-eligible non-citizen as undocumented status (and criminal history) is unobserved. The observed

DACA eligibility indicator is contaminated with authorized (DACA-ineligible) non-citizens. This will cause the estimates of the intent-to-treat effects to be attenuated towards zero. Assuming DACA does not have an effect on observed eligible non participants, the degree of attenuation can be characterized by the following equation:

$$\widehat{\beta^{ITT}} = \beta^{ITT} \cdot P(E^* = 1|E = 1) + 0 \cdot P(E^*1 = 0|E = 1) \tag{9}$$

or,

$$\beta^{ITT} = \widehat{\beta^{ITT}} \cdot \frac{1}{P(E^* = 1|E = 1)} \tag{10}$$

Where E represents observed eligible and E^* represents the true unobserved eligibility status. The coefficient β^{ITT} is the true intent-to-treat effects and the coefficient $\widehat{\beta^{ITT}}$ is the attenuated intent-to-treat estimate from the observed eligibility indicator. The scaling factor to get the true intent-to-treat from the attenuated estimate is 1 over the probability an observed eligible noncitizen is actually eligible. Disregarding criminal history, the scaling factor will be 1 over the probability an observed DACA eligible non-citizen is actually an undocumented immigrant.

Next, to extrapolate the treatment-on-the-treated effects from the intent-to-treat effects we must assume that (1) there is no self-selection into the participation decision and (2) there are no spillover effects. Note that the intent-to-treat effects can also be written as;

$$\beta^{ITT} = \beta^* \cdot P(R = 1|E^* = 1) + 0 \cdot P(R = 0|E^* = 1) \tag{11}$$

Where R represents DACA participation. The probability$P(R = 1|E^* = 1)$ is the probability a DACA-eligible immigrant participated in DACA. The probability$P(R = 0|E^* = 1)$ is the probability a DACA-eligible immigrant did not participate in DACA. The coefficient, β^*, is again the treatment-on-the-treated effects of DACA. Plugging in equation 10 into equation 11, we get the relationship between the attenuated intent-to-treat estimates and the assumed treatment-on-the-treated effects if the above assumptions hold.

$$\widehat{\beta^{ITT}} \cdot \left[\frac{1}{P(E^* = 1|E = 1)} \cdot \frac{1}{P(R = 1|E^* = 1)} \right] = \beta^* \tag{12}$$

Equation 12 shows that the attenuated intent-to-treat estimates must be scaled by 1 over the probability an observed DACA eligible non-citizen is actually an undocumented immigrant times 1 over the participation rate of DACA eligible immigrants. Estimates from the DHS indicate the share of unauthorized immigrants among the non-citizen population aged 18-35 is around 61% (Baker and Rytina, 2013), indicating the attenuated estimates need to be scaled by 1.64 to derive the true intent-to-treat estimates. As an estimated 63% of DACA-eligible individuals participated in the DACA program (Hipsman et al., 2016), the assumed treatment-on-the-treated effects should be 1.59 times larger than the true intent-to-treat effects. In other words, under the assumption of no self-selection into the program and no spillover effects, the treatment-on-the-treated effects should be (1.64*1.59 =) 2.61 times larger than the attenuated estimates using the observed eligibility indicator.

I now compare the treatment-on-the-treated estimates in this paper to those of the attenuated intent-to-treat estimates using the observed eligibility indicator. A benefit of this exercise is that it will provide some evidence of whether self-selection is taking place among DACA recipients. If the assumptions of no self-selection and no spillover effects hold, the ratio between the two estimates should be around 2.61. Although it provides suggestive evidence, I can not rule out other possible mechanisms, such as heterogeneous treatment effects across country-of-origin as a possible source if the scaling factor is not equal to 2.61.

To do the comparison, I estimate a similar difference-in-differences model as in Pope (2016) using

the same sample and controls as in equation 6.[11]

$$Y_{icst} = \beta_0 + \beta_1 eligible_{it} \cdot post_t + \beta_2 eligible_{it} + \beta_3 X_{it} + \beta_4 W_{it} + \beta_5 Z_{st} + \gamma_t + \gamma_s + \gamma_s t + \epsilon_{icst} \tag{13}$$

The coefficient , β_1 , is the effect of DACA on DACA-eligible non-citizens relative to ineligible non-citizens. This captures the attenuated intent-to-treat effects of DACA ($\widehat{\beta^{ITT}}$). All other controls are the same as in equation 6 so as to make sure the results are not driven by differences in model specification or sample selection. Standard errors are clustered at the state-year level.

Table 5 reports the effect of observed DACA eligibility on labor market outcomes. The second row shows the ration between the estimated treatment-on-the-treated effects and the estimated attenuated intent-to-treat effects. These estimates compare closest to those in Table 3 Row C in Pope (2016). The Magnitude of the attenuated intent-to-treat effects are lower compared to Pope's estimates. This is driven by my sample having six post DACA years compared to Pope (2016) which only estimated the effect of DACA on the first two years of the program. The model specification also includes country-of-origin fixed effects and state-year immigration controls not included in Pope (2016).

The treatment-on-the-treated effects are considerably larger and vary widely relative to the attenuated intent-to-treat effects. The effects of DACA on recipient's labor market outcomes range from 1.88 larger than the attenuated intent-to-treat (likelihood of being unemployed) to 5.66 times larger (usual hours worked). The treatment effects of DACA on the likelihood of working are 3.77 times larger and 5.05 times larger for likelihood of being in the labor force than the intent-to-treat effects. Looking at the effect of DACA eligiblity on schooling would give insignificant results. The effect on recipients is 4.25 times larger and significant. The scaling factor for self-employment and schooling are 3.00.

[11] Of course, this is not an exact comparison. In the preferred model, the estimated treatment-on-the-treated effects are the contemporaneous effects of participating in DACA at time t. In the difference-in-differences model, the intent-to-treat effects are the average effects in all post DACA years.

Table 6 reports the effect of observed DACA-eligibility on income. The second row shows the estimated treatment-on-the-treated effects over the estimated attenuated intent-to-treat effects. The treatment effects of DACA on recipient's total income is 7.87 times larger than when using the observed eligiblity indicator. The scaling factor for the effects on wage and salary income 5.60, while it is 0.13 for income for other sources, and 2.30 for welfare income. The effect of DACA-eligiblity on hourly wage is of opposite sign and significant at a 6% decrease giving a scaling factor of -0.26.

This results demonstrate that it is difficult to extrapolate the treatment-on-the-treated effects from intent-to-treat estimates and therefore needs to be empirically estimated directly as is done in this paper. A possible reason for this is that the assumption of no self-selection into the program may not be valid. Although, I also cannot rule out other possible mechanisms such as heterogeneous treatment effects. For policy makers, the intent-to-treat estimates may not be as informative in understanding the effects of amnesty programs on actual participants.

5.2 Heterogeneous Effects Across Region-of-Birth

The difference between the treatment-on-the-treated Estimated from the preferred model and those of the intent-to-treat estimates using the observed eligbility indicator may be a result of heterogeneous effects of DACA across country of origin. Such that individuals from countries whose observed DACA-eligible non-citizen population have a higher probability of participating in DACA also benefit the most from participating in DACA. I next estimate equation 6 where the probabilistic measure is interacted with indicators for region-of-birth. The regions considered are Latin America (Excluding Mexico), Asia, Europe, and all other countries (Rest).

Table 7 and Table 8 shows the heterogeneous effect of DACA on recipients. As the excluded group is Mexicans, the coefficient on $P(R|C,T,E)$ measure the effect of DACA on Mexican Recipients. The coefficients on the interaction terms are the relative effects compared to Mexican recipients. Significant Heterogeneity in the effect of DACA is documented.

Recipients from Asian countries have the largest documented treatment-on-the-treated effects on

labor market outcomes and Income. Latin Americans have significantly lower labor market outcomes compared to Mexicans but have the highest increase in school attendance. This result shows even within ethnicity, considerable heterogeneous effects are at play. The effects on Europeans and Rest of countries are mostly statistically insignificant or have unrealistic coefficient estimates. This is likely due to Europeans and Rest making up less than 1% of the DACA participating population each.

These results shows a significant limitation in the previous literature. Past work has focused on estimating the effects of DACA on a sub-sample of Hispanics only or Mexicans only as those groups have the highest share of DACA participants across their non-citizen populations. As non-Hispanics make up a small fraction of DACA participants, prior work has not focused on them. Focusing on only Hispanics misses important race-ethnicity heterogeneity that needs to be further studied. Asian DACA-participants appear to benefit the most from conditional amnesty provided by DACA. This is important for policy makes as Non-Hispanics continue to make up a greater share of the undocumented population (Passel and Cohn, 2019). Further work needs to examine why Asian undocumented immigrants have the highest benefits from DACA but yet have some of the lowest participation rates (Hipsman et al., 2016). These results also indicate that the variability in the ratio between the treatment-on-the-treated estimates and the intent-to-treat estimates are likely caused by heterogeneous effects. Whether and to how much self-selection plays a role needs further examination.

6 Spillover Effects on Eligible Non-participants

An estimated 37% of DACA eligible immigrants have not applied for deferred action and work authorization through DACA (Hipsman et al., 2016). The announcement of DACA and the regularization of 824,000 similar undocumented immigrants may have impacted this eligible non-participating group. This spillover can be caused by increased competition driven by the large increase in labor force participation documented in Section 5. The announcement of DACA may also have led to behavioral changes if it altered their expected probability they are staying in

the country or if those individuals want to apply but cannot afford the financial and legal costs. Spillover effects on this population will alter the cost and benefits of amnesty and regularization programs such as DACA and need to be analyzed. Controlling for the effect of DACA on eligible non-participants will also more accurately estimate the effect of DACA participants. The control group in the preferred model of equation 6 is composed of two distinct populations, non-citizens eligible for DACA but did not participate and non-citizens that are ineligible for DACA. If there is in fact significant spillover effects on eligible non-citizens (control group) then the estimated results from Section 5 will be biased.

Given the policy importance of estimating spillover effects to understand the total effect of DACA and to more accurately estimate the effect of DACA participation, I expand on equation 6 by including a measure of the probability an observed DACA eligible no-citizen did not receive deferred action and work authorization through DACA by time.

$$P(R = \widehat{0|C,T}, E = 1) = \left(1 - \frac{(\text{Total DACA Recipients})_{ct}}{(\text{Total DACA Eligible Population})_c}\right) \cdot Eligible_{it} \tag{14}$$

Where $P(R = \widehat{0|C,T}, E = 1)$ is zero for years 2005 to 2012 and if the non-citizen is DACA-ineligible. I estimate the following equation:

$$\begin{aligned} E[Y|C,X,W,Z,S] = \beta_0 + \beta_1 P(R = \widehat{1|C,T}, E) + \beta_2 P(R = \widehat{0|C,T}, E = 1) \\ + \beta_3 X + \beta_4 W + \beta_5 Z + \gamma_c + \gamma_t + \gamma_s + \gamma_s t \end{aligned} \tag{15}$$

all other controls are the same as in equation 6. Standard errors are clustered at the state-year level. The control group is now composed of only DACA-ineligible non-citizens.

The first coefficient of interest is β_1. This corresponds to the effect of DACA on DACA recipients relative to ineligible non-citizens. The coefficient β_1 is analogous to β^* in equation 6 except that the control group is composed of only ineligible non-citizens. If there are no spillover effects then

β_1 will equal the estimates of β^* in Section 5.

The second coefficient of interest, β_2, corresponds to the effect of DACA on observed DACA-eligible non-participants relative to ineligible non-citizens. When discussing the spillover effects of DACA on observed eligible non-participants, I am including authorized immigrants that meet the observed DACA eligiblity requirements (age and education). As the eligiblity indicator is heavily contaminated with authorized immigrants, the coefficient β_2 will be a lower bound on the spillover effect of DACA on actual DACA-eligible non-participants.

Prior to discussing the results, it is of value to discuss what might be causing the surprisingly low participation rates (given the perceived benefits) in the program. As stated above, an estimated 63% of the immediately eligible population and roughly 50% of the potentially eligible population applied and received deferred action and work authorization through the DACA program (Hipsman et al., 2016). The participation rate is surprisingly low given the high perceived benefits associated with DACA and the actual benefits estimated in this paper.

The National UnDACAmented Research Project (NURP) is the first national survey of DACA recipients (and non-participants). While not a representative sample, the NURP survey provides valuable information on the barriers that have limited participation into DACA. The NURP survey is a national survey of 2,684 DACA-eligible individuals between the age of 18 to 32 conducted in 2013 (Gonzalez and Bautista-Chavez, 2014). Among the 2,684 respondents, 2,2440 DACA-eligible youth had been approved for DACA. The remaining 244 individuals who met the DACA requirements had not yet applied to the program. While the fee appears to be trivial compared to the benefits of receiving DACA, Gonzalez and Bautista-Chavez (2014) show more than 43% of DACA-eligible non-applicants stated that they could not afford the $465 application fee. Indicating that financial constraints are a considerable barrier for not applying. Lack of understanding of the benefits associated with DACA also appear to play a role as 30% of non-applicants stated they are waiting for better options (Gonzalez and Bautista-Chavez, 2014). Other factors documented in Gonzalez and Bautista-Chavez (2014) that prevented DACA-eligible immigrants from applying

are missing paperwork (22%), legal reasons (17%), fear of sending their personal information to the government (15%), and 10% indicated they did not know how to apply.

Table 9 and Table 10 provide the estimated effects of DACA on recipients and the spillover effects of DACA on eligible non-participants for labor market outcomes and income respectively relative to non-citizens. Row 1 on both tables provides the estimated effects of DACA on recipients (β_1). Row 2 on both tables provides the estimated effects of DACA on eligible non-participants (β_2).

In relation to the preferred model, the estimated effects of DACA on the labor market outcomes, school attendance, and income of DACA recipients are similar in magnitude once separating out the spillover effects of DACA on eligible non-participants. Schooling is 1.1 p.p. larger than in the preferred model. The effect of DACA on recipients likelihood of self-employment shows a statistically significant 1.0 p.p. (20%) decrease. The biggest difference is on the effects of DACA on recipients hourly wage. The effect on hourly wage when using only DACA-ineligible non-citizens as a control group is now a statistically significant 7.5% increase.

For eligible non-participants, DACA did not have an impact in the likelihood of working. A 1.4 p.p. decrease in the probability of participating in the labor force is documented driven by unemployed leaving the labor force. School attendance among DACA eligible non-participants decreased by 2.3 p.p. DACA had significant negative spillover effects on eligible non-participants income. Relative to ineligible non-citizens DACA eligible non participants saw a 30.3% decrease in total income driven by a 20.3% decrease in wage and salary income, a 14.7% decrease in income from other sources, and a 11.7% decrease in hourly wages.

Two important notes need to be made with regards to these estimates. Second, as I can only estimate observed-eligible non-citizens this proxy is severely contaminated with authorized non-citizens which will attenuate the estimates towards zero. Second, these effects may be capturing eligible individuals attempting to become eligible but have not yet been approved at time t. The results may be driven by change in composition on who is classified as eligible non-participants

over time. In the next section, I deal with this concern in an event study framework where I analyze the effects of DACA-eligible non-citizens who never participated in DACA.

As the model estimates the effect of DACA on eligible non-participants at time t, the coefficient is capturing the effect of DACA on two groups. One group are eligible non-participants at time t that will eventually apply and be approved for DACA k periods in the future. For instance, individuals who do not yet have the financial means to apply for DACA may seek employment first to save for the cost of the application process. The results may also be driven by change in composition on who is classified as eligible non-participants by time t. A second group is composed on eligible non-participants that have no intention of ever participating in DACA due to seeking other options or not meeting the other requirements (criminal history) that are not observable in the ACS data. Additionally, due to contamination in the observed DACA eligible indicator, the estimated spillover effects of DACA on the Eligible non-participating population are attenuated towards zero.

7 Event Study Model

Identification in the prior sections relies on the assumption that in the absence of DACA, DACA participants would have exhibited similar trends to ineligible non-citizens that did not participate in DACA. To test the plausibility of this assumption I estimate an event study model. There are two benefits of this model; (1) the parallel trends assumption can be tested by comparing the conditional trends prior to the enactment of DACA and (2) one can visualize any dynamic effects of DACA participation on labor market outcomes and income.

I construct a measure for each non-citizen in the sample of the probability of ever participating in DACA during the years 2013 to 2018. This is equivalent to assigning $P(R|C, T, E)$ at year 2018 to all years. To test the parallel trend assumption for eligible non-participants, I also construct a measure of the probability an eligible non-citizen never participated in DACA during years 2013 to 2018. This also alleviates concerns that the spillover effects in the prior section are driven by

compositional changes between the participating and eligible non-participating populations.

The event study model is as follows:

$$
\begin{aligned}
E[Y|C,T,E,X,W,Z,S] = & \sum_{j \neq t^*-1} \delta_j \cdot YEAR_{j=t} \cdot P(R = 1|\widehat{C,T = 2018}, E) \\
& + \sum_{j \neq t^*-1} \alpha_j \cdot YEAR_{j=t} \cdot P(R = 0|C,\widehat{T = 2018}, E = 1) \\
& + \beta_1 P(R = 1|\widehat{C,T = 2018},) + \beta_2 P(R = 0|C,\widehat{T = 2018}, E = 1) \\
& + +\beta_3 X + \beta_4 W + \beta_5 Z + \gamma_c + \gamma_t + \gamma_s + \gamma_s t
\end{aligned} \tag{16}
$$

The variable $P(R = 1|\widehat{C,T = 2018}, E)$ is the probability a non-citizen was ever a DACA recipient. The variable $P(R = 0|C,\widehat{T = 2018}, E = 1)$ is the probability an eligible non-citizen never participated in DACA during the post DACA period. Each measure is interacted with year dummies. The year 2012 is the reference year and omitted. The control group are ineligible non-citizens. All other controls are the same as Equation 6. Standard errors are clustered at the state-year level.

Column (a) in Figure 4 and Figure 5 shows the event study estimates of the effect of DACA participation on labor market outcomes and schooling. The figures show that there was no pre-existing trends between DACA recipients and DACA ineligible non-citizens prior to 2013 for labor force participation, working, unemployment, and school attendance. Self-employment shows differential pre-trends, though, the pre-trend is counter to the effects of DACA on self-employment. Accounting for potential differential linear pre-trends in the outcome by participation status will indicate DACA participation led to significant decrease in self-employment rates. Some noticeable differences from the estimates in the alternative model are seen in unemployment which is no longer significant. The effects of wages are negative and insignificant relative to 2012 compared to the 7.5% increase documented in the alternative model.

Column (a) in Figure 6 and Figure 7 shows the event study estimates of the effect of DACA participation on income. The coefficients in the year prior to DACA are insignificant except for year

2010 in the effects of total income and wage and salary income.

Immediately after the enactment of DACA, large effects are estimated for nearly all variables for DACA participants. After 2015, the effects have been decreasing with sharp drops in 2017 and 2018. A number reasons can be attributed for the decrease in the estimates labor market effects of DACA after 2015. First, the effects of DACA on school show a delayed response with a rapid rise in school attendance after 2015. This indicates a shift from the labor market to schooling. Second, almost 15% of DACA participants have had their status terminated or have let their status expire. Without work authorization these undocumented immigrants can no longer legally participate in the labor market. Third is the start of the Trump administration which has attempted to fully terminate DACA since 2017. Any change in participants perceived risk or deportation or their expected time in the US will have an impact on their labor market outcomes.

Column (b) in Figures 4, 5, 6, and 7 shows the event study estimates of DACA on eligible non-participants. The pre-trends provide evidence of the validity of the parallel trend assumption. The results show eligible non-participants experienced and immediate drop unemployment rate relative to 2012 but a gradual decrease in labor force participation reaching a significant 5 p.p. reduction by 2018. Across income sources, only income from other sources show a significant impact. The results of spillover effects on total income, wage income, and hourly wage of eligible non-participants are not robust.

8 Robustness Checks

The estimates from the preferred model in Section 5 and the modified model controling for possible spillover effects on DACA-eligible non-participants in Section 6 are the best available estimates of the average treatment-on-the-treated effects of DACA with data that is publicly available. The results indicate that DACA has lead to significant improvements in on the labor market outcomes and the incomes of those that participated in the program relative to other non-citizens.

The fundamental assumption needed for the treatment-on-the-treated estimates produced above

to be unbiased is the assumption that the variation in the share of DACA participants across country-of-origin and time only affect outcomes through the unobserved participation decision. If the constructed probability is measuring other time varying country specific unobserved variables besides the participation decision that are correlated with the outcome of interest across time, the results will be biased.

Another issue with the preferred model is that I am using a proxy variable that only takes advantage of variation across country-of-origin rather than the ideal indicator of DACA participation, there will be issues relating to mis-measurement. One source of this mis-measurement comes from using observed DACA eligiblity requirements to identify eligibility which misses the non-citizens' unobserved undocumented status and their unobserved criminal history. This means I am assigning a positive probability to documented immigrants and ineligible undocumented immigrants that meet the observed education and age requirements. The country-of-origin proxy also misses important demographic and geographic variation among DACA participants that would allow for finer estimation of the average treatment-on-the-treated effects. There is also mis-measurement in the administrative data on DACA. In the data some participants have demographic characteristics that fail the requirements for eligibility or are missing (USCIS, 2018). In 2018, the USCIS did not have country-of-origin data for 2,100 DACA recipients recipients (USCIS, 2018).

To strengthen the validity of the estimates presented so far, I perform a number of robustness checks. First, I take advantage of state-level variation in the share of DACA participation among DACA eligible non-citizens. Second, I perform a placebo test of naturalized immigrants. Third, I perform an alternative approach suggested by Lubotsky and Wittenberg (2006) that takes advantage of all available sources of variation available simultaneously.

8.1 Variation in DACA Participation Across State-of-Residence

The preferred model uses variation in the probability an observed DACA-eligible non-citizen is a DACA recipient across country-of-birth and time. I create a similar measure using variation across state-of-residence. This variable is defined in equation 8. Using this alternative measure is

less preferred than using country-of-variation. First, there is considerably less variation with 50 states (plus DC). Second the model controls for state fixed effects and state time trends. This will cause the model absorb considerable variation in this instrument.

Even with these drawbacks, estimating the model using the alternative measure will provide a valuable robustness checks on the results of the preferred model. I take advantage of this other source of variation by estimating equation 6 and replacing the country-of-origin measure with the alternative state-of-residence measure.

$$E[Y|C, X, W, Z, S] = \beta_0 + \beta^* P(\widehat{R = 1|S, T, E}) + \beta_2 X + \beta_3 W + \beta_4 Z + \gamma_c + \gamma_t + \gamma_s + \gamma_s t \tag{17}$$

where $P(\widehat{R = 1|S, T, E})$ is the probability of a DACA eligible non-citizen being a DACA recipient at time t using variation across state s. All other controls are the same as with the preferred equation 6. Errors are clustered at the state-year level.

As with the preferred model, I make the key assumption that the constructed probability only affects outcome y through the unobserved DACA participation, or that

$$P(\widehat{R = 1|S, T, E}) = P(R = 1|C, T, E, X, W, Z, S) = E[R|C, T, E, X, W, Z, S] \tag{18}$$

If the assumption made in both equation 5 and equation 18 hold, both models should provide similar average treatment-on-the-treated effects of DACA.

Row 1 of Table A.2 shows the effect of DACA on labor market outcomes using variation across state-of-residence. Row 1 of Table A.3 shows the effect of DACA on income using variation across state-of-residence. As would be expected from the state fixed effects and the state time trends absorbing considerable variation in the variable of interest, the standard errors are considerably larger than in the preferred model. Even with the larger standard errors the estimated effects are still statistically significant as in the preferred model. The magnitude of the effects of DACA on recipients likelihood of working are similar. The magnitude on the effect of DACA on recipients

labor force participation, usual hours worked, total income, income from wages and are smaller than in the preferred model. The magnitude of the effects on the likelihood of being unemployed and income from other sources are larger magnitude than in the preferred model.

The most noticeable difference are found in the effect of income from other sources, school attendance, and wages. Using the alternative proxy produces and effect on income from other sources that is negative at a 19% compared to a positive 7% increase in the preferred model. The effect on schooling is statistically and economically insignificant compared to a significant 2 p.p. decrease. Lastly, the effect of DACA on recipients wages is now negative when using state variation.

In nearly all outcomes of interest, there is a downward change in the estimates using the state-of-residence measure compared to the preferred model using country-of-origin measure. As the alternative measure uses significantly less variation, considerably more non-citizens in the sample will be mis-measured which will attenuate the results towards zero. For instance, an observed eligible immigrant from England living in California will have a constructed probability of 0.491 rather than the actual probability of 0. This though, will not explain why some estimates are more negative then the preferred model.

8.2 Placebo Test - Naturalized Citizens

A major concern in the estimates produced in the preferred model is in the underlying assumption that there are no country-year unobservable covariates that are correlated with the constructed measure and outcomes interest. For the case of the measure using state variation, that there are no state-year unobservable covariates correlated with the constructed measure and outcomes of interest. In other words, that the measures are capturing only the participation decision and nothing else. I perform a placebo test on naturalized citizens to test this assumption. If there are other unobserved time varying factors at the country-level or state-level that are being captured by the constructed measures, then the coefficient on the DACA recipient measures using a sample of naturalized citizens citizens should be similar.

I estimate equation 6 and 17 on a sample of naturalized citizens ages 18-35 with a high school degree or more. I treat all naturalized citizens as non-citizens and perform the same procedure to assign a probability to to each. Table A.4 shows the placebo test for the labor market outcomes while Table A.5 shows the placebo test for income outcomes. For each Table, Row 1 uses the country-of-origin variation measure as in the preferred model. Row 2 uses the state-of-residence variation measure.

The placebo results are consistent with the key assumption being satisfied. Only 4 of the 22 regressions produced a marginally statistically significant effect. For 3 of the 4 significant coefficients, the magnitude of the effects are a fifth or half the size compared to the preferred model. Only one coefficient, on the effect of DACA on hourly wages using state-of-residence measure, has a similar magnitude.

8.3 Lubotsky and Wittenberg (2006) Approach

A disadvantage of the prior models estimates is that they are using each source of variation separately. I next implement an interpretation approach suggested by Lubotsky and Wittenberg (2006) (henceforth L-W). The L-W method includes all variables that proxy for the unobserved variable of interest in the estimating question. I estimate equation 6 but include the two constructed probability measures.

$$E[Y|C,X,W,Z,S] = \beta_0 + \beta_c^* P(\widehat{R=1|C},T,E) + \beta_s^* P(\widehat{R=1|S},T,E) + \beta_2 X + \beta_3 W + \beta_4 Z + \gamma_c + \gamma_t + \gamma_s + \gamma_s t \quad (19)$$

L-W show that the weighted sum of the coefficients of the multiple proxy variables that measures the same unobserved variable of interest minimizes the attenuation bias from the mis-measured proxies. The attenuation minimizing estimate of β^* is written as

$$b^\rho = \rho_c \cdot \beta_c^* + \rho_s \cdot \beta_s^* \quad (20)$$

Where b^{ρ} is the minimizing attenuation bias estimate of β^*. The weight of each proxy ρ_j must be estimated. The estimate of ρ_j is $\hat{\rho_j} = \frac{cov(y,P(recipient)_j)}{cov(y,P(recipient)_1)}$. The weights are to ensure all variables are scaled the same and the weights must be scaled so that one weight is equal to one. The weight for the probability measure using country-of-origin variation is chosen as the base ($\rho_c = 1$) so that they can be compared to the estimates from Table 3 and Table 4.

Under the assumption that both variables only capture the underlying unobserved variable (recipient), the estimated effects for all outcomes of interest in this specification will be larger than in the preferred model using the mis-measured constructed probability the greater the measurement error. Row 1 of Table A.6 shows the estimates of the L-W approach for labor market outcomes. Row 1 of Table A.7 shows the estimates from the L-W method for the income outcomes. In the L-W model There is no significant difference between the coefficients produced in the preferred model using variation across country-of-origin and taking advantage of both sources of variation using the L-W method. Besides for estimates in the effect of DACA on recipient's income from other sources and usual hours of work, the magnitude in the L-W estimates are slightly lower. Nearly all the coefficients are larger than the estimates from the preferred model using variation across state-of-residence. This would be consistent with state-of-residence recipient measure having more measurement error. The estimate of the effect of DACA on wages using both measures is of opposite sign and statistically insignificant.

The effects on school attendance is now positive and a large but statistically insignificant 22.3 p.p. compared to a 34 p.p. decrease in the preferred model. This is an unrealistic increase. One possible explanation for this is the fact the weights have to be estimated. As the purpose of the weights is for scaling and given the design of the two variables capture the probability an individual is a DACA recipient, an assumption can be made that the weights should equal one. In fact, this will come from the assumptions made to derive assumption 5 and assumption 18.

Row 2 of Table A.6 and Row 2 of Table A.7 shows the estimates of the the weight $\hat{\rho_s} = \frac{cov(y,P(recipient)_s)}{cov(y,P(recipient)_c)}$.[12].

[12]The weight $\hat{\rho_c}$ is set equal to 1 as it is the reference weight used for the scaling.

The range of values in the weights vary considerably. In the case of unemployment, the weight is negative. For schooling, the weight is a large 2.2 and negative. This is over twice as large as the other weights and of opposite sign. Aside from concerns in the estimation of the weight, the variables may also be capturing additional unobservable covariates aside from individuals DACA recipient status.

Rather than estimate the weight, I next implement the L-W method assuming ρ is equal to one as implied by assumption 5 and assumption 18. Row 2 of Table A.6 shows the estimates of the L-W approach for labor market outcomes while Row 2 of Table A.7 shows the estimates from the L-W method for the income outcomes when ρ is assumed to be equal to one. The estimates are larger for likelihood of working, likelihood of of being unemployed, and income from other sources. The estimated effects of other outcomes are slightly lower when using $\rho = 1$ rather than the estimated *rho*. Notably, the effect on schooling is a statistically insignificant 1.2 p.p. increase. While the effect on wages are a significant 10.4% decrease which is similar to that when using state-of-residence measure.

9 Concluding Remarks

I construct a novel measure of DACA participation using publicly available data from the USCIS to estimate the effect of DACA on recipients. This allows for the first estimation of the treatment-on-the-treated effects of the DACA program. These are the best estimates available with currently available administrative data. I find that the reduction of labor market frictions through deferred action and work authorization from participating in the DACA program increased the likelihood of working by 11.3 percentage points (p.p.) or 17.1%. This is driven by a 9.6 p.p. increase in labor force participation and a 3.0 p.p. decrease in unemployment among DACA recipients. I find statistically significant decrease in the likelihood of a DACA recipient being self-employed with a magnitude that is economically meaningful at 18%. As self-employment is a proxy for informal employment among the undocumented population, this implies economically significant movement from the informal to the formal labor market after participating in DACA. Unlike previous

studies on DACA, I find positive effects on school attendance on DACA recipients. The effects are delayed with increases occurring after 2015.

DACA recipients saw an increase in total income of 108.1%, equivalent to a $15,510 increase in total income from their pre-DACA levels. The increase in total income is driven entirely by increases in wage and salary income. With a total of 824,000 participants since its enactment in 2012, DACA moved 101,000 to 103,000 undocumented youth into employment. The effect on income implies a $12.8 billion increase in total income for the entire DACA participating population.

Similar results are obtained when using alternative measure constructed from variation in the participation rate among DACA-eligible non-citizens across state-of-residence. The results are also robust to using an alternative method, the L-W method, that takes advantage of all variation from both proxies. Although the effects on wages and education are not robust to the primary measure using variation across country-of-origin.

The scaling factor between the estimated treatment-on-the-treated effects and intent-to-treat effects in this paper ranges from 1.8 to 7.9 times larger depending on the outcome of interest. This shows the treatment effects on recipients of deferred action can not simply be extrapolated from the effects on those eligible using the standard assumptions. While self-selection is a likely source of the significant variation in the scaling factor, this paper can not exclude the possibility the differences are driven by heterogeneous effects of DACA. I find significant heterogeneity in the treatment-on-the-treated effects across region-of-origin. I find that recipients from Asia had the largest labor market benefit from DACA. Latin Americans saw significantly lower labor market benefits compared to Mexican recipients but had the largest increase in school attendance from receiving deferred action and work authorization. As non-Mexicans become a larger share of the undocumented population, understanding these heterogeneous effects are important to estimate the cost and benefits of future amnesty programs.

I also document negative spillover effects on Eligible non-participants. I find eligible non-participants

had 1.4 p.p. decrease in labor force participation, driven by those in unemployment. Eligible non-participants also reduced their likelihood of attending school after DACA is announced. Policy makers should carefully understand why certain eligible undocumented immigrants are not participating in the program to better designed amnesty proposals that meet their objectives. Policy makers must also take into account spillover effects on this group to see how the costs and benefits of the proposed programs are altered.

References

AMUEDO-DORANTES, C. AND F. ANTMAN (2017): "Schooling and labor market effects of temporary authorization: Evidence from DACA," *Journal of population economics*, 30, 339–373.

AMUEDO-DORANTES, C., C. BANSAK, AND S. RAPHAEL (2007): "Gender differences in the labor market: Impact of IRCA," *American Economic Review*, 97, 412–416.

BAKER, B. AND N. RYTINA (2013): "Estimates of the unauthorized immigrant population residing in the United States: January 2012," *Department of Homeland Security, March*, Link.

BAKER, S. R. (2015): "Effects of immigrant legalization on crime," *American Economic Review*, 105, 210–13.

BALLIS, B. ET AL. (2020): "Does Peer Motivation Impact Educational Investments? Evidence From DACA," .

BATALOVA, J., S. HOOKER, AND R. CAPPS (2014): "DACA at the Two-Year Mark: A National and State Profile of Youth Eligible and Applying for Deferred Action." *Migration Policy Institute*.

BOLLINGER, C. R. AND P. HAGSTROM (2008): "Food stamp program participation of refugees and immigrants," *Southern Economic Journal*, 665–692.

——— (2011): "The poverty reduction success of public transfers for working age immigrants and refugees in the United States," *Contemporary Economic Policy*, 29, 191–206.

GIUNTELLA, O. AND J. LONSKY (2020): "The effects of DACA on health insurance, access to care, and health outcomes," *Journal of Health Economics*, 102320.

GIUNTELLA, O., J. LONSKY, F. MAZZONNA, AND L. STELLA (2021): "Immigration policy and immigrants' sleep. Evidence from DACA," *Journal of Economic Behavior & Organization*, 182, 1–12.

GONZALEZ, R. G. AND A. M. BAUTISTA-CHAVEZ (2014): *Two Years and Counting: Assessing the Power of DACA.*, American Immigration Council, Link.

GRASSLEY, C. (2017): "Data Indicate Unauthorized Immigrants Exploited Loophole To Gain Legal Status, Pathway To Citizenship," .

GUNADI, C. (2019): "Does Immigrant Legalization Affect Crime? Evidence from Deferred Action

for Childhood Arrivals in the United States," Link.

HAINMUELLER, J., D. LAWRENCE, L. MARTÉN, B. BLACK, L. FIGUEROA, M. HOTARD, T. R. JIMÉNEZ, F. MENDOZA, M. I. RODRIGUEZ, J. J. SWARTZ, ET AL. (2017): "Protecting unauthorized immigrant mothers improves their children's mental health," *Science*, 357, 1041–1044.

HIPSMAN, F., B. GÓMEZ-AGUIAGA, AND R. CAPPS (2016): "DACA at Four: Participation in the Deferred Action Program and Impacts on Recipients.","*Notes*, 1, 228–000, Link.

HSIN, A. AND F. ORTEGA (2018): "The effects of deferred action for childhood arrivals on the educational outcomes of undocumented students," *Demography*, 55, 1487–1506.

KOSSOUDJI, S. A. AND D. A. COBB-CLARK (2000): "IRCA's impact on the occupational concentration and mobility of newly-legalized Mexican men," *Journal of Population Economics*, 13, 81–98.

KUKA, E., N. SHENHAV, AND K. SHIH (2019): "A Reason to Wait: The Effect of Legal Status on Teen Pregnancy," in *AEA Papers and Proceedings*, vol. 109, 213–17.

——— (2020): "Do Human Capital Decisions Respond to the Returns to Education? Evidence from DACA," *American Economic Journal: Economic Policy*, 12, 293–324.

LOZANO, F. A. AND T. SORENSEN (2011): "The labor market value to legal status," .

LUBOTSKY, D. AND M. WITTENBERG (2006): "Interpretation of regressions with multiple proxies," *The Review of Economics and Statistics*, 88, 549–562.

PASSEL, J. S. AND D. COHN (2019): "Mexicans decline to less than half the US unauthorized immigrant population for the first time," *Pew Research Center*, Link.

PASSEL, J. S. AND M. H. LOPEZ (2012): "Up to 1.7 million unauthorized immigrant youth may benefit from new deportation rules," *Washington, DC: Pew Hispanic Center*, Link.

POPE, N. G. (2016): "The effects of DACAmentation: The impact of Deferred Action for Childhood Arrivals on unauthorized immigrants," *Journal of Public Economics*, 143, 98–114.

ROSENBLUM, M. R. (2015): "Understanding the potential impact of executive action on immigration enforcement," *Migration Policy Institute*, 11.

RUGGLES, S., S. FLOOD, R. GOEKEN, J. GROVER, AND E. MEYER (2020): "Jose Pacas, and Matthew Sobek. 2020. Ipums usa: Version 10.0 [dataset]," *Minneapolis, MN: IPUMS*, 10, D010.

RYTINA, N. (2002): *IRCA legalization effects: Lawful permanent residence and naturalization through*

2001, Office of Policy and Planning, Statistics Division, US Immigration and Naturalization Service, Link.

SSA (2018): "Social Security Benefits Paid to Non-citizens Granted Deferred Action for Childhood Arrivals Status," .

USCIS (2013-2017): "Deferred Action for Childhood Arrivals (DACA) Quarterly Report," .

——— (2017): "Deferred Action for Childhood Arrival (DACA) Recipients Serving in the Military," .

——— (2018): "The Department of Homeland Security's Response to Representative King's January 16, 2018 Letter on DACA Characteristics Data," .

——— (2019): "DACA Characteristics Data: Approximate Active DACA Recipients as of Nov. 30, 2018," .

VAN HOOK, J., J. D. BACHMEIER, D. L. COFFMAN, AND O. HAREL (2015): "Can we spin straw into gold? An evaluation of immigrant legal status imputation approaches," *Demography*, 52, 329–354.

VENKATARAMANI, A. S., S. J. SHAH, R. O'BRIEN, I. KAWACHI, AND A. C. TSAI (2017): "Health consequences of the US Deferred Action for Childhood Arrivals (DACA) immigration programme: a quasi-experimental study," *The Lancet Public Health*, 2, e175–e181.

Tables

Table 1: Descriptive Statistics of the Constructed Probability by Country-of-Origin (2018)

Country of Origin	(1) Eligible Population	(2) Total Approvals	(3) Constructed Probability
Mexico	906,643	643,372	0.710
El Salvador	61,697	29,459	0.477
Guatemala	42,562	20,721	0.487
Honduras	29,776	18,962	0.637
Peru	21,526	9,249	0.430
Korea	41,638	8,967	0.215
Brazil	17,497	7,555	0.432
Ecuador	17,789	6,842	0.385
Colombia	30,475	6,710	0.220
Argentina	8,957	4,917	0.549
Philippines	4,3801	4,766	0.109
Jamaica	27,908	3,505	0.126
India	27,523	3,242	0.118
Dominican Republic	38,775	3,240	0.084
Venezuela	14,020	3,172	0.226
Trinidad and Tobago	13,118	2,620	0.200
Uruguay	3,740	2,464	0.659
Bolivia	4,260	2,107	0.495
Costa Rica	5,248	2,093	0.399
Poland	14,253	1,852	0.130
Chile	4,524	1,784	0.394
Pakistan	8,898	1,720	0.193
Nicaragua	14,458	1,645	0.114
Nigeria	6,626	1,320	0.199
Guyana/British Guiana	8,416	1,293	0.154
Belize/British Honduras	2,856	1,021	0.358
Canada	30,571	990	0.032
China	28,986	982	0.034
Kenya	5,063	874	0.173
Indonesia	3,479	836	0.241

Notes: Authors own calculations for the constructed probability in the year 2018. Eligible population is calculated using ACS data from 2013 to 2018. Total approvals are from 2018 USCIS publicly available data (USCIS, 2018). Constructed Probability measure is the ration between total approvals over eligible population.

Table 2: Pre-DACA Characteristics of Participants and Comparison Groups

Variables	(1) Recipients	(2) Eligible Non-Participants	(3) DACA Ineligible	(4) Full Sample
Individual Characteristics				
Age	23.9	23.8	28.6	27.6
Years in US	15.7	15.2	6.4	8.3
Age enter US	8.2	8.7	22.3	19.3
In School	25.1	37.2	21.1	23.1
HS Degree	59.5	43.4	38.2	41.4
Some College	35.0	43.5	25.3	28.3
College Degree	5.6	13.1	36.5	30.3
Male	53.1	52.6	52.0	52.4
Married	27.9	21.7	51.8	46.0
White	2.6	17.4	17.4	16.2
Black	1.9	13.6	8.2	8.4
Asian	3.3	22.7	29.1	25.5
Hispanic	91.6	44.3	43.2	48.2
Born in Mexico	77.7	23.1	27.5	32.0
Born in Europe	1.0	12.4	10.5	10.0
Born in Asia	3.5	23.9	32.3	28.0
Born in Latin America	17.2	31.5	21.2	22.2
C. Outcomes				
Labor Force Participation	74.7	72.9	72.5	72.3
Working	66.2	63.9	67.0	66.8
Unemployed	11.3	12.4	7.6	8.4
Usual Hours Worked	27.9	26.7	29.0	28.0
Self-Employed	5.0	4.5	6.6	6.1
Total Income	$15,117	$16,255	$23,929	$22,132
Wage Income	$14,165	$15,155	$22,309	$20,649
Other Income	$245	$329	$406	$374
Welfare Income	$40	$35	$31	$32
D. Identifiers				
Observed Eligible	100.0	100.0	0	23.5
Probability Recipient	57.2	27.7	0	8.6

Notes: The sample for the summary statistics includes non-citizens who are ages 18–35 and have at least a high school degree in the years 2005 to 2012. All binary variables are represented in percent (%) terms. All values represent the weighted sum using ACS weights times the respective weight. The weights used for each column are as follows; (1)person weight times probability DACA recipient, (2) person weight times probability eligible non-participant, (3) person weight times indicator DACA ineligible, and (4) person weight.

Table 3: The Effects of DACA on Labor Market Outcomes

Variables	(1) Labor Force	(2) Working	(3) Unemployed	(4) Usual Hours Worked	(5) Self-Employed	(6) School
DACA Recipient	0.096***	0.113***	-0.030***	3.802***	-0.009*	0.034**
	(0.012)	(0.012)	(0.006)	(0.591)	(0.004)	(0.012)
Pre-DACA Mean	0.747	0.662	0.113	27.929	0.050	0.251
N	618,450	618,450	432,284	618,450	498,081	618,450
R^2	0.152	0.146	0.034	0.201	0.029	0.333

Standard errors in parenthesis

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

Notes: *Labor Force* -binary var. equal 1 if individual currently participates in the labor force; *Working* - binary var. equal 1 if individual is currently working; *Unemployed* - binary var. equal 1 if individual is currently unemployed; *Usual Hours Worked* - number of hours per week respondent usually worked in past 12 months; *Self-Employed* - binary var. equal 1 if individual is currently self-employed. *School* - binary var. equal 1 if individual is currently in school. Estimates are derived from a sample of non-citizen immigrants ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2005-2018 waves of ACS. All regressions control for demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age,age of entering U.S., education attainment), country-of-origin fixed effects, state fixed effects, year fixed effects, state-specific time trends, and state-year controls (state unemployment, dummies for Universal E-Verify laws, Public E-Verify, instate tuition laws, driver's license laws). Standard errors are clustered at state-year level

Table 4: The Effects of DACA on Income (IHS)

Variables	(1) Total Income	(2) Wage Income	(3) Other Income	(4) Welfare Income	(5) Wage
DACA Recipient	1.026***	1.081***	-0.015	-0.023	0.016
	(0.131)	(0.132)	(0.036)	(0.013)	(0.024)
Pre-DACA Mean	$15,117	$14,165	$245	$40	$12.63
N	618,450	618,450	618,450	618,450	423,477
R^2	0.181	0.159	0.026	0.014	0.300

Standard errors in parenthesis
* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: *Total Income* - inverse hyperbolic sine (IHS) transformation of individual's total pre-tax personal income from all sources for the previous 12 months. *Wage Income* - inverse hyperbolic sine (IHS) transformation of individual's total pre-tax wage and salary income for the previous 12 months. *Other Income* - inverse hyperbolic sine (IHS) transformation of individual's total income from sources not included in the other IPUMS person-record income variables for the previous 12 months. *Welfare Income* - inverse hyperbolic sine (IHS) transformation of individual's pre-tax income (if any) the respondent received from various public assistance programs commonly referred to as "welfare" during the previous 12 months. *Wage* - inverse hyperbolic sine (IHS) transformation of constructed wage. Estimates are derived from a sample of non-citizen immigrants ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2005-2018 waves of ACS. All regressions control demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age,age of entering U.S., education attainment), country-of-origin fixed effects, state fixed effects, year fixed effects, state-specific time trends, and state-year controls (state unemployment, dummies for Universal E-Verify laws, Public E-Verify, instate tuition laws, driver's license laws). Standard errors are clustered at state-year level.

Table 5: The Effects of DACA-Eligibility on Labor Market Outcomes

Variables	(1) Labor Force	(2) Working	(3) Unemployed	(4) Usual Hours Worked	(5) Self-Employed	(6) School
eligible x Post	0.019***	0.030***	-0.016***	0.671**	-0.003	0.008
	(0.005)	(0.005)	(0.003)	(0.261)	(0.002)	(0.005)
Recipient/Eligible	5.05	3.77	1.88	5.66	3.00	4.25
N	618,450	618,450	432,284	618,450	498,081	618,450
R^2	0.130	0.129	0.031	0.183	0.023	0.334

Standard errors in parenthesis

* $p < .1$, ** $p < .05$, *** $p < .01$

Notes: *Labor Force* -binary var. equal 1 if individual currently participates in the labor force; *Working* - binary var. equal 1 if individual is currently working; *Unemployed* - binary var. equal 1 if individual is currently unemployed; *Usual Hours Worked* - number of hours per week respondent usually worked in past 12 months; *Self-Employed* - binary var. equal 1 if individual is currently self-employed. *Income (IHS)* - inverse hyperbolic sine (IHS) transformation of individual's total pre-tax personal income from all sources for the previous 12 months. *School* - binary var. equal 1 if individual is currently in school. Estimates are derived from a sample of non-citizen immigrants ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2005-2018 waves of ACS. All regressions control for Post-DACA implementation dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age,age of entering U.S., education attainment), state fixed effects, year fixed effects, state-specific time trends, and state-year controls (state unemployment, dummies for Universal E-Verify laws, Public E-Verify, instate tuition laws, driver's license laws). Standard errors are clustered at state-year level.

Table 6: The Effects of DACA-Eligibility on Income (IHS)

Variables	(1) Total Income	(2) Wage Income	(3) Other Income	(4) Welfare Income	(5) Wage
eligible x Post	0.127**	0.193***	-0.075***	-0.010	- 0.061***
	(0.055)	(0.057)	(0.016)	(0.006)	(0.011)
Recipient/Eligible	7.87	5.60	0.13	2.30	-0.26
N	618,450	618,450	618,450	618,450	423,477
R^2	0.168	0.139	0.011	0.010	0.30

Standard errors in parenthesis
* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: *Total Income* - inverse hyperbolic sine (IHS) transformation of individual's total pre-tax personal income from all sources for the previous 12 months. *Wage Income* - inverse hyperbolic sine (IHS) transformation of individual's total pre-tax wage and salary income for the previous 12 months. *Other Income* - inverse hyperbolic sine (IHS) transformation of individual's total income from sources not included in the other IPUMS person-record income variables for the previous 12 months. *Welfare Income* - inverse hyperbolic sine (IHS) transformation of individual's pre-tax income (if any) the respondent received from various public assistance programs commonly referred to as "welfare" during the previous 12 months. Estimates are derived from a sample of non-citizen immigrants ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2005-2018 waves of ACS (Panel A) and 2005-2016 for Panel B. All regressions control for Post-DACA implementation dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), state fixed effects, year fixed effects, state-specific time trends, and state-year controls (state unemployment, dummies for Universal E-Verify laws, Public E-Verify, instate tuition laws, driver's license laws). Standard errors are clustered at state-year level.

Table 7: Heterogeneity in the Effects of DACA on Labor Market Outcomes

Variables	(1) Labor Force	(2) Working	(3) Unemployed	(4) Usual Hours Worked	(5) Self-Employed	(5) School
$P(R\|C,T,E)$	0.093***	0.102***	-0.021***	3.590***	-0.003	0.016
	(0.008)	(0.008)	(0.005)	(0.441)	(0.004)	(0.010)
$P(R\|C,T)$*latin	-0.070***	-0.037*	-0.033**	-3.118***	-0.039***	0.059***
	(0.016)	(0.019)	(0.012)	(0.774)	(0.011)	(0.016)
$P(R\|C,T)$*asia	0.159*	0.158**	-0.012	2.683	0.060	0.040
	(0.062)	(0.061)	(0.044)	(2.259)	(0.038)	(0.054)
$P(R\|C,T,E)$*euro	-0.142	-0.165	0.052	-12.029*	-0.229**	-0.042
	(0.127)	(0.141)	(0.098)	(5.207)	(0.079)	(0.110)
$P(R\|C,T,E)$*rest	-0.033	0.002	-0.037	-5.679	0.044	-0.540***
	(0.157)	(0.163)	(0.157)	(6.479)	(0.096)	(0.149)
N	618,450	618,450	432,284	618,450	498,081	618,450
R^2	0.152	0.147	0.034	0.201	0.030	0.334

Standard errors in parenthesis
* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: *Labor Force* -binary var. equal 1 if individual currently participates in the labor force; *Working* - binary var. equal 1 if individual is currently working; *Unemployed* - binary var. equal 1 if individual is currently unemployed; *Usual Hours Worked* - number of hours per week respondent usually worked in past 12 months; *Self-Employed* - binary var. equal 1 if individual is currently self-employed. *School* - binary var. equal 1 if individual is currently in school. Estimates are derived from a sample of non-citizen immigrants ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2005-2018 waves of ACS. All regressions control for demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age,age of entering U.S., education attainment), country-of-origin fixed effects, state fixed effects, year fixed effects, state-specific time trends, and state-year controls (state unemployment, dummies for Universal E-Verify laws, Public E-Verify, instate tuition laws, driver's license laws). Standard errors are clustered at state-year level

Table 8: Heterogeneity in the Effects of DACA on Income (IHS)

Variables	(1) Total Income	(2) Wage Income	(3) Other Income	(4) Welfare Income	(5) Wage
$P(R\|C,T,E)$	0.938***	0.956***	-0.011	-0.019	0.013
	(0.096)	(0.098)	(0.030)	(0.011)	(0.020)
$P(R\|C,T,E)$*latin	-0.640***	-0.297	-0.127*	0.014	-0.027
	(0.176)	(0.210)	(0.058)	(0.022)	(0.025)
$P(R\|C,T,E)$*asia	0.152	0.699	-1.132***	-0.070	-0.903***
	(0.614)	(0.595)	(0.270)	(0.071)	(0.108)
$P(R\|C,T,E)$*euro	-2.691*	-0.494	-1.551**	0.375	-1.277***
	(1.261)	(1.385)	(0.509)	(0.226)	(0.267)
$P(R\|C,T,E)$*rest	-1.946	-2.097	-0.036	0.376	-0.750**
	(1.690)	(1.828)	(0.595)	(0.325)	(0.232)
N	618,450	618,450	618,450	618,450	423,477
R^2	0.181	0.159	0.026	0.014	0.300

Standard errors in parenthesis
* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: *Total Income* - inverse hyperbolic sine (IHS) transformation of individual's total pre-tax personal income from all sources for the previous 12 months. *Wage Income* - inverse hyperbolic sine (IHS) transformation of individual's total pre-tax wage and salary income for the previous 12 months. *Other Income* - inverse hyperbolic sine (IHS) transformation of individual's total income from sources not included in the other IPUMS person-record income variables for the previous 12 months. *Welfare Income* - inverse hyperbolic sine (IHS) transformation of individual's pre-tax income (if any) the respondent received from various public assistance programs commonly referred to as "welfare" during the previous 12 months. *Wage* - inverse hyperbolic sine (IHS) transformation of constructed wage. Estimates are derived from a sample of non-citizen immigrants ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2005-2018 waves of ACS. All regressions control demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age,age of entering U.S., education attainment), country-of-origin fixed effects, state fixed effects, year fixed effects, state-specific time trends, and state-year controls (state unemployment, dummies for Universal E-Verify laws, Public E-Verify, instate tuition laws, driver's license laws). Standard errors are clustered at state-year level.

Table 9: The Spillover Effects of DACA on Labor Market Outcomes

Variables	(1) Labor Force	(2) Working	(3) Unemployed	(4) Usual Hours Worked	(5) Self-Employed	(6) School
DACA Recipient	0.103***	0.115***	-0.024***	4.250***	-0.010*	0.045***
	(0.012)	(0.013)	(0.006)	(0.606)	(0.005)	(0.012)
Eligible Non-Participant	-0.014*	-0.004	-0.011**	-0.869**	0.003	-0.023***
	(0.007)	(0.007)	(0.004)	(0.284)	(0.004)	(0.005)
N	618,450	618,450	432,284	618,450	498,081	618,450
R^2	0.152	0.146	0.034	0.201	0.029	0.334

Standard errors in parenthesis

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

Notes: *Labor Force* -binary var. equal 1 if individual currently participates in the labor force; *Working* - binary var. equal 1 if individual is currently working; *Unemployed* - binary var. equal 1 if individual is currently unemployed; *Usual Hours Worked* - number of hours per week respondent usually worked in past 12 months; *Self-Employed* - binary var. equal 1 if individual is currently self-employed. *School* - binary var. equal 1 if individual is currently in school. Estimates are derived from a sample of non-citizen immigrants ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2005-2018 waves of ACS. All regressions control for demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age,age of entering U.S., education attainment), country-of-origin fixed effects, state fixed effects, year fixed effects, state-specific time trends, and state-year controls (state unemployment, dummies for Universal E-Verify laws, Public E-Verify, instate tuition laws, driver's license laws). Standard errors are clustered at state-year level

Table 10: The Spillover Effects of DACA on Income (IHS)

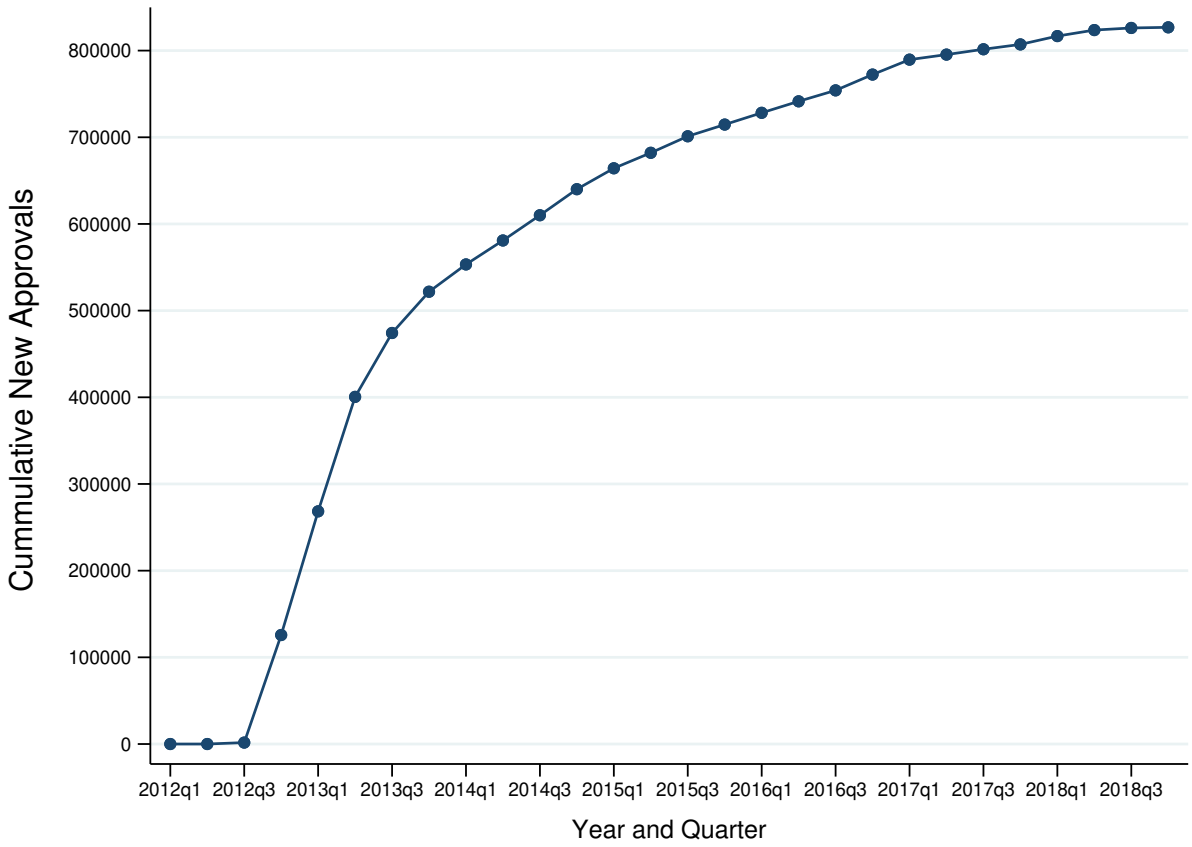
Variables	(1) Total Income	(2) Wage Income	(3) Other Income	(4) Welfare Income	(5) Wage
DACA Recipients	1.182***	1.185***	0.061	-0.025	0.075**
	(0.138)	(0.143)	(0.036)	(0.014)	(0.025)
Eligible Non-Participants	-0.303***	-0.203**	-0.147***	0.003	-0.117***
	(0.065)	(0.070)	(0.022)	(0.010)	(0.012)
N	618,450	618,450	618,450	618,450	423,477
R^2	0.181	0.159	0.026	0.014	0.300

Standard errors in parenthesis
* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: *Total Income* - inverse hyperbolic sine (IHS) transformation of individual's total pre-tax personal income from all sources for the previous 12 months. *Wage Income* - inverse hyperbolic sine (IHS) transformation of individual's total pre-tax wage and salary income for the previous 12 months. *Other Income* - inverse hyperbolic sine (IHS) transformation of individual's total income from sources not included in the other IPUMS person-record income variables for the previous 12 months. *Welfare Income* - inverse hyperbolic sine (IHS) transformation of individual's pre-tax income (if any) the respondent received from various public assistance programs commonly referred to as "welfare" during the previous 12 months. *Wage* - inverse hyperbolic sine (IHS) transformation of constructed wage. Estimates are derived from a sample of non-citizen immigrants ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2005-2018 waves of ACS (Panel A) and 2005-2016 for Panel B. All regressions control for Post-DACA implementation dummy, demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), state fixed effects, year fixed effects, state-specific time trends, and state-year controls (state unemployment, dummies for Universal E-Verify laws, Public E-Verify, instate tuition laws, driver's license laws). Standard errors are clustered at state-year level.

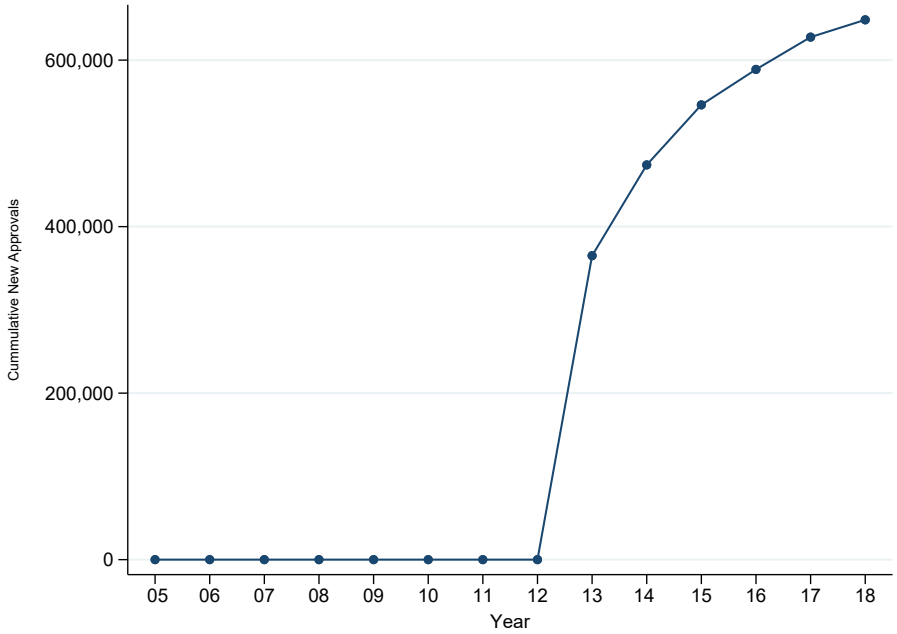
Figures

Figure 1: Cumulative number of Initial Applications Approved by Quarter

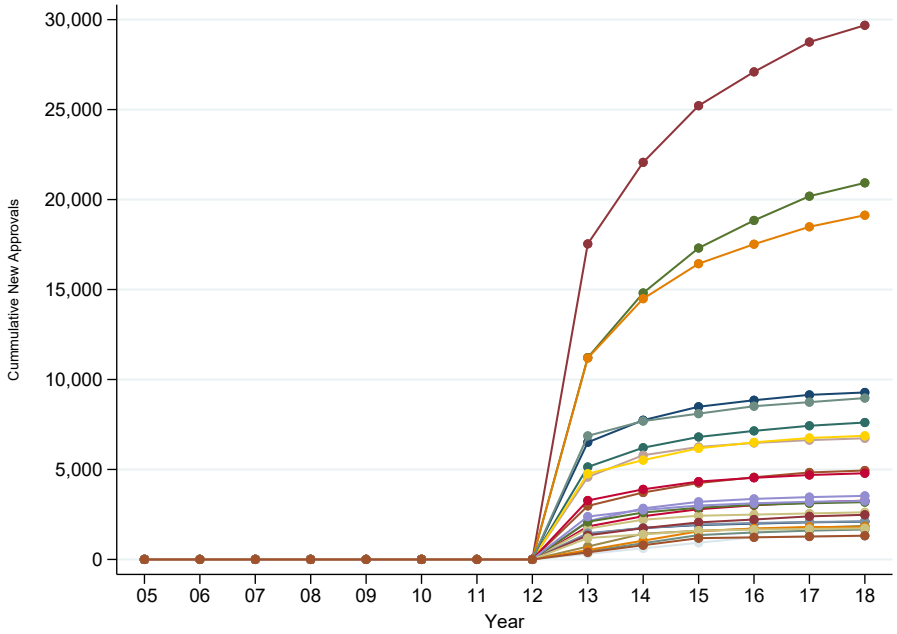


Notes - This figure shows cumulative new approvals number approved in each quarter through 2018 quarter 3. Data comes from publicly available quarterly reports published by the USCIS from 2013 to 2018 (USCIS, 2013-2017)

Figure 2: Cumulative number of Initial Applications Approved by Country-of-Origin



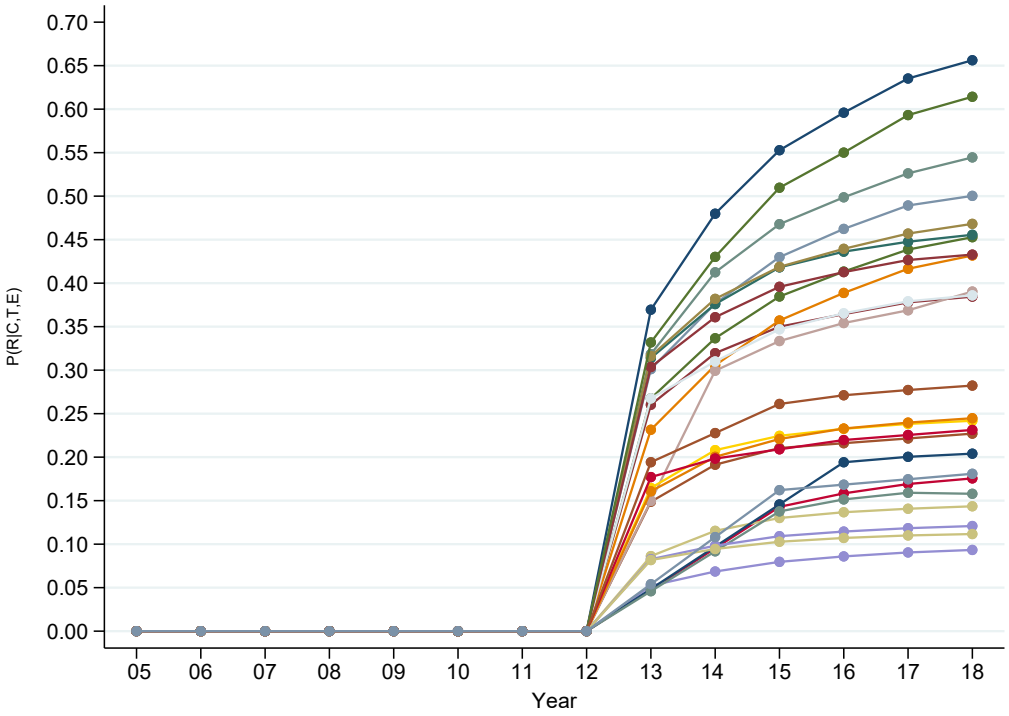
(A) Mexico



(B) Top 25 - Excluding Mexico

Source - This figure shows cumulative new approvals number approved in each year through 2018 for the top 25 countries. Data comes from publicly available quarterly reports published by the USCIS from 2013 to 2018 (USCIS, 2013-2017, 2018)

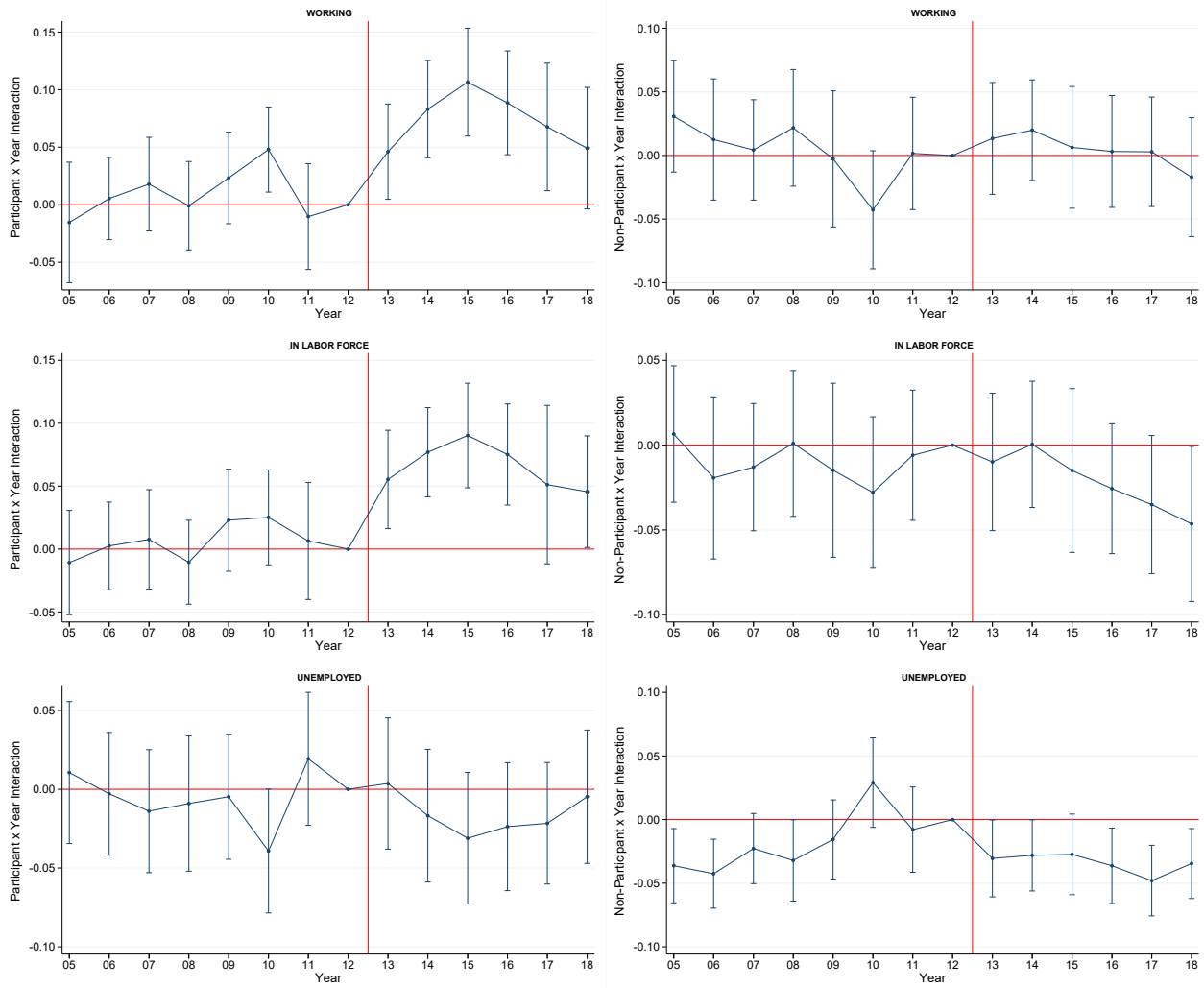
Figure 3: Variation in DACA Participation Measure



(A) Top 25 Countries

Source - This figure shows cumulative probabily an observed DACA eligible immigrant is a DACA recipient in each year through 2018 for the top 25 countries. Data comes from publicly available quarterly reports published by the USCIS from 2013 to 2018 (USCIS, 2013-2017, 2018)

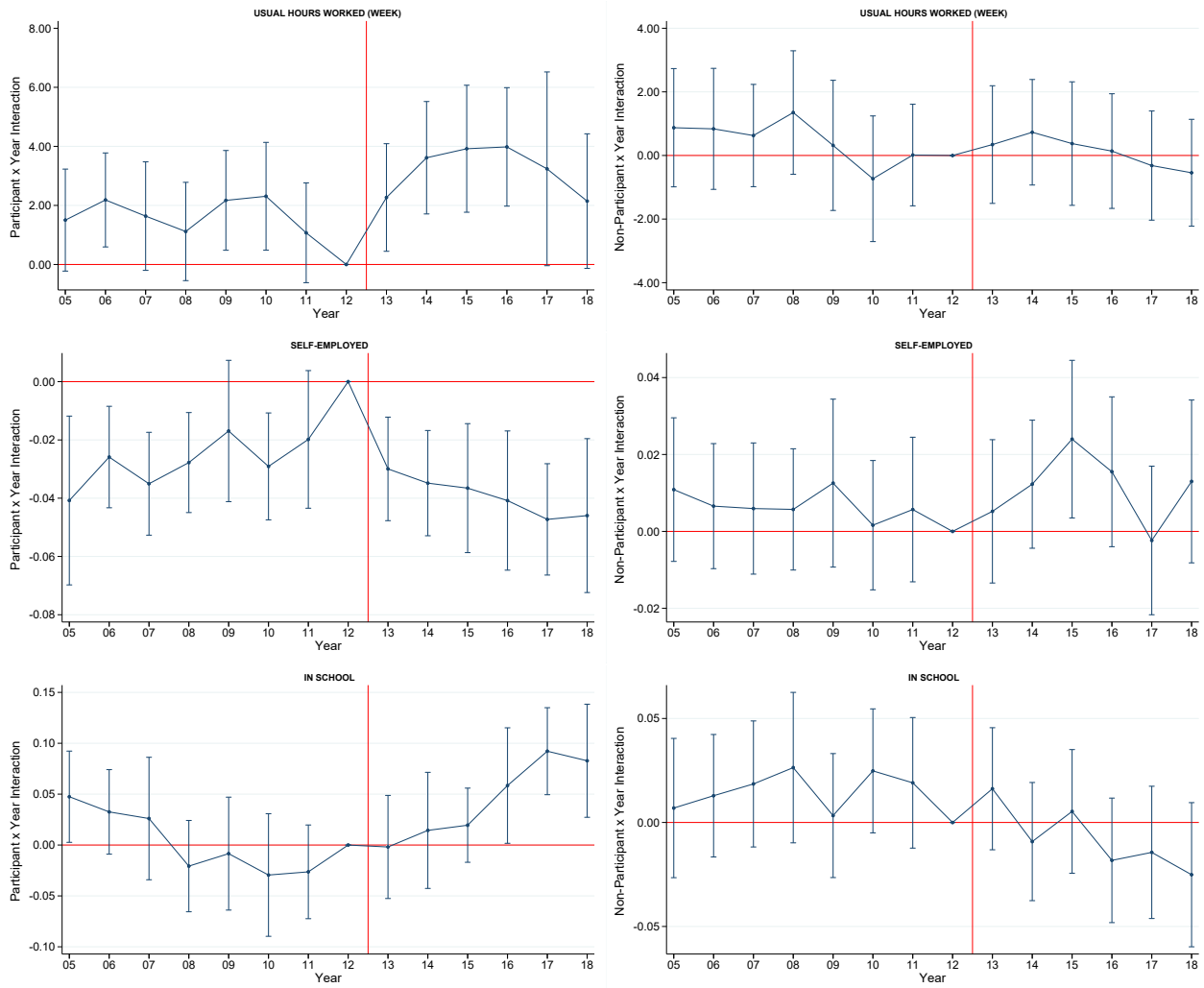
Figure 4: Event Study: DACA on Labor Market Outcomes I



(A) DACA Recipient (B) Eligible Non-Participant

Notes - The figure on the first column plots the coefficients obtained estimating Equation (xx) with the variable P(R=1—C,T) interacted with a binary variable for each year (2012 is the omitted interaction). The figure on the second column plots the coefficients obtained estimating Equation (xx) with the variable P(ENP=1—C,T) interacted with a binary variable for each year (2012 is the omitted interaction). Following dependent variables were used in the regressions (up-to-down, starting with the first row): *In Labor Force* - binary var. equal 1 if individual currently participates in the labor force; *Working* - binary var. equal 1 if individual is currently working; *Unemployed* - binary var. equal 1 if individual is currently unemployed. Estimates are derived from a sample of non-citizen immigrants ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2005-2018 waves of ACS. All regressions control for demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), state fixed effects, year fixed effects, state-specific time trends, and state-year controls (state unemployment, state minimum wage, dummies for Universal E-Verify laws, Public E-Verify, instate tuition laws, driver's license laws). Standard errors are clustered at state-year level.

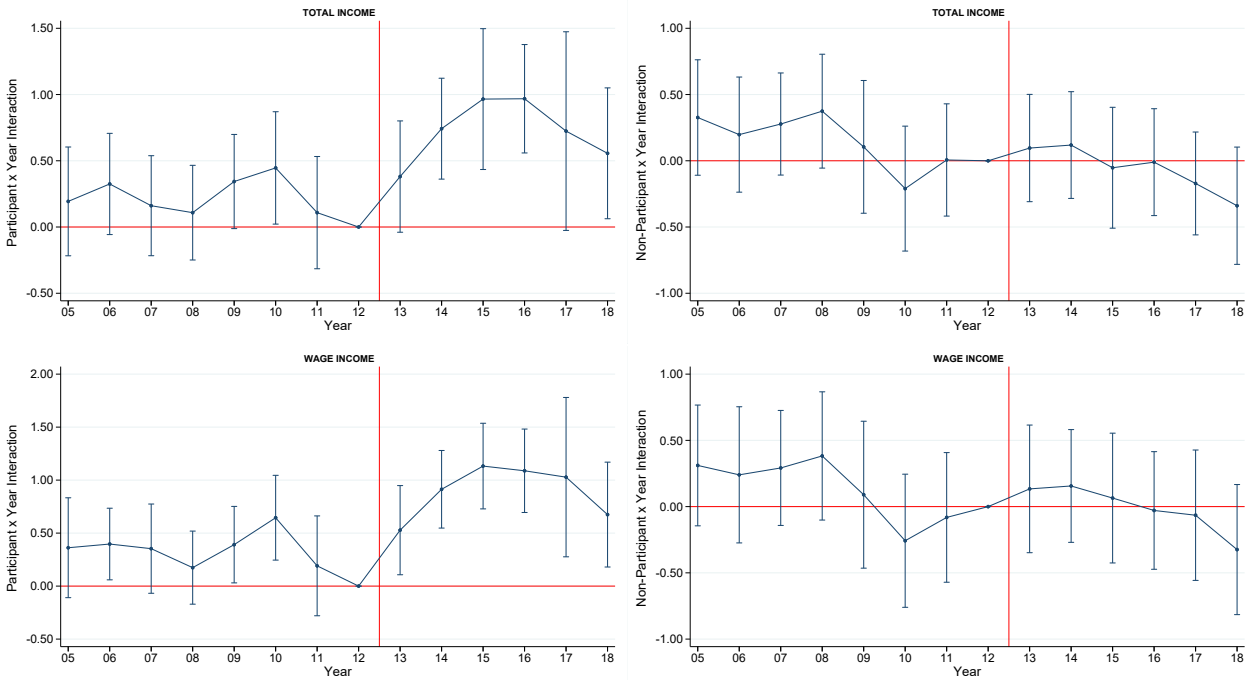
Figure 5: Event Study: DACA on Labor Market Outcomes II



(A) DACA Recipient (B) Eligible Non-Participant

Notes - The figure on the first column plots the coefficients obtained estimating Equation (xx) with the variable P(R=1—C,T) interacted with a binary variable for each year (2012 is the omitted interaction). The figure on the second column plots the coefficients obtained estimating Equation (xx) with the variable P(ENP=1—C,T) interacted with a binary variable for each year (2012 is the omitted interaction). Following dependent variables were used in the regressions (up-to-down, starting with the first row):*Usual Hours Worked* - number of hours per week respondent usually worked in past 12 months; *Self-Employed* - binary var equal 1 if individual is currently self-employed; *School* - binary var equal 1 if individual is currently in school. Estimates are derived from a sample of non-citizen immigrants ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2005-2018 waves of ACS. All regressions control for demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), state fixed effects, year fixed effects, state-specific time trends, and state-year controls (state unemployment, state minimum wage, dummies for Universal E-Verify laws, Public E-Verify, instate tuition laws, driver's license laws). Standard errors are clustered at state-year level.

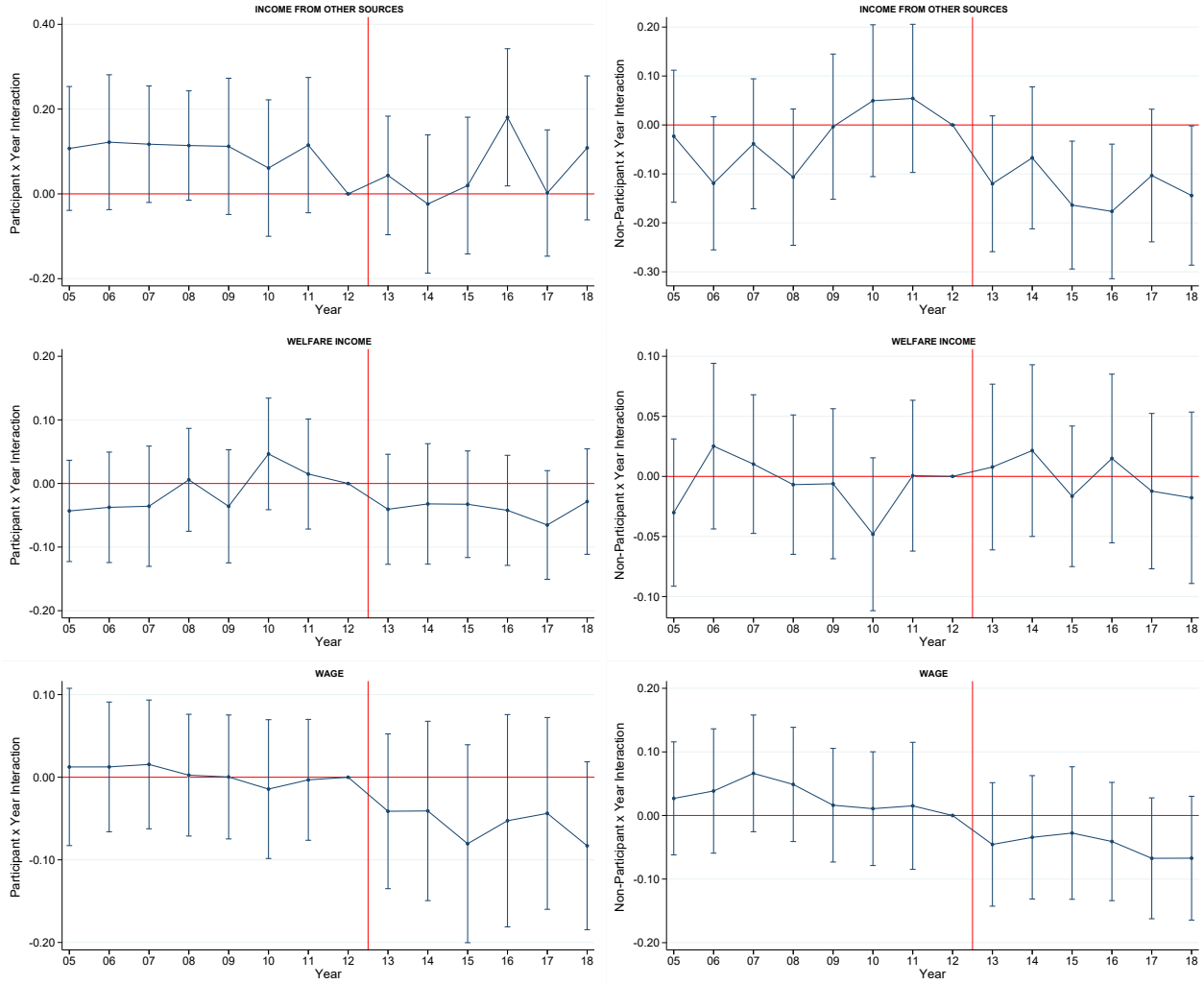
Figure 6: Event Study: DACA on Income I



(A) DACA Recipient (B) Eligible Non-Participant

Notes - The figure on the first column plots the coefficients obtained estimating Equation (xx) with the variable P(R=1—C,T) interacted with a binary variable for each year (2012 is the omitted interaction). The figure on the second column plots the coefficients obtained estimating Equation (xx) with the variable P(ENP=1—C,T) interacted with a binary variable for each year (2012 is the omitted interaction). Following dependent variables were used in the regressions (up-to-down, starting with the first row): *Total Income* - inverse hyperbolic sine (IHS) transformation of individual's total pre-tax personal income from all sources for the previous 12 months. *Wage Income* - inverse hyperbolic sine (IHS) transformation of individual's total pre-tax wage and salary income for the previous 12 months. Estimates are derived from a sample of non-citizen immigrants ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2005-2018 waves of ACS. All regressions control for demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), state fixed effects, year fixed effects, state-specific time trends, and state-year controls (state unemployment, state minimum wage, dummies for Universal E-Verify laws, Public E-Verify, instate tuition laws, driver's license laws). Standard errors are clustered at state-year level.

Figure 7: Event Study: DACA on Income II



(A) DACA Recipient (B) Eligible Non-Participant

Notes - The figure on the first column plots the coefficients obtained estimating Equation (xx) with the variable P(R=1—C,T) interacted with a binary variable for each year (2012 is the omitted interaction). The figure on the second column plots the coefficients obtained estimating Equation (xx) with the variable P(ENP=1—C,T) interacted with a binary variable for each year (2012 is the omitted interaction). Following dependent variables were used in the regressions (up-to-down, starting with the first row):*Other Income* - inverse hyperbolic sine (IHS) transformation of individual's total income from sources not included in the other IPUMS person-record income variables for the previous 12 months. *Welfare Income* - inverse hyperbolic sine (IHS) transformation of individual's pre-tax income (if any) the respondent received from various public assistance programs commonly referred to as "welfare" during the previous 12 months; *Wages* - inverse hyperbolic sine (IHS) transformation of individuals constructed wage. Estimates are derived from a sample of non-citizen immigrants ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2005-2018 waves of ACS. All regressions control for demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age, age of entering U.S., education attainment), state fixed effects, year fixed effects, state-specific time trends, and state-year controls (state unemployment, state minimum wage, dummies for Universal E-Verify laws, Public E-Verify, instate tuition laws, driver's license laws). Standard errors are clustered at state-year level.

Appendix

A Tables

Table A.1: Descriptive Statistics of the Constructed Probability by State-of-residence

State of Residence	(1) Eligible Population	(2) Total Approvals	(3) Constructed Probability
California	467,454	229,335	0.491
Texas	278,271	127,555	0.458
Florida	135,568	35,682	0.263
New York	129,052	45,335	0.351
Illinois	83,039	43,443	0.523
New Jersey	61,906	23,471	0.379
Arizona	57,769	28,483	0.493
Georgia	51,906	24,907	0.480
North Carolina	43,668	27,866	0.638
Washington	43,256	18,483	0.427
Virginia	34,642	12,821	0.370
Colorado	32,330	17,676	0.547
Maryland	29,534	10,367	0.351
Massachusetts	28,637	8,687	0.303
Nevada	28,524	13,379	0.469
Pennsylvania	25,540	6,500	0.254
Oregon	21,066	11,534	0.548
Michigan	19,364	6,840	0.353
Utah	18,102	9,878	0.546
Connecticut	17,416	5,265	0.302

Notes: The DACA-eligible population for each state-of-residence is estimated using the eligiblity procedure defined in Section 4. Total DACA approvals by state-of-residence up to march 2018 come from the publicly available USCIS data. The constructed probability is constructed by the author by dividing total approvals by estimated size of the observed DACA-eligible population for each state-of-residence. The 20 states with largest eligible population are displayed.

Table A.2: The Effects of DACA on Labor Market Outcomes

State-of-Residence Variation

Variables	(1) Labor Force	(2) Working	(3) Unemployed	(4) Usual Hours Worked	(5) Self-Employed	(6) School
DACA Recipient	0.085***	0.110***	-0.038***	3.109***	-0.007	0.009
	(0.013)	(0.013)	(0.007)	(0.670)	(0.006)	(0.013)
Pre-DACA Mean	0.747	0.662	0.113	27.929	0.050	0.251
N	618,450	618,450	432,284	618,450	498,081	618,450
R^2	0.151	0.146	0.034	0.201	0.029	0.333

Standard errors in parenthesis

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

Notes: *Labor Force* -binary var. equal 1 if individual currently participates in the labor force; *Working* - binary var. equal 1 if individual is currently working; *Unemployed* - binary var. equal 1 if individual is currently unemployed; *Usual Hours Worked* - number of hours per week respondent usually worked in past 12 months; *Self-Employed* - binary var. equal 1 if individual is currently self-employed. *School* - binary var. equal 1 if individual is currently in school. Estimates are derived from a sample of non-citizen immigrants ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2005-2018 waves of ACS. All regressions control for demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age,age of entering U.S., education attainment), country-of-origin fixed effects, state fixed effects, year fixed effects, state-specific time trends, and state-year controls (state unemployment, dummies for Universal E-Verify laws, Public E-Verify, instate tuition laws, driver's license laws). Standard errors are clustered at state-year level

Table A.3: The Effects of DACA on Income (IHS)

State-of-Residence Variation

Variables	(1) Total Income	(2) Wage Income	(3) Other Income	(4) Welfare Income	(5) Wage
DACA Recipient	0.741***	0.871***	-0.152***	-0.019	-0.113***
	(0.145)	(0.139)	(0.041)	(0.015)	(0.028)
Pre-DACA Mean	$15,117	$14,165	$245	$40	$12.63
N	618,450	618,450	618,450	618,450	423,477
R^2	0.181	0.158	0.026	0.014	0.300

Standard errors in parenthesis

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

Notes: *Total Income* - inverse hyperbolic sine (IHS) transformation of individual's total pre-tax personal income from all sources for the previous 12 months. *Wage Income* - inverse hyperbolic sine (IHS) transformation of individual's total pre-tax wage and salary income for the previous 12 months. *Other Income* - inverse hyperbolic sine (IHS) transformation of individual's total income from sources not included in the other IPUMS person-record income variables for the previous 12 months. *Welfare Income* - inverse hyperbolic sine (IHS) transformation of individual's pre-tax income (if any) the respondent received from various public assistance programs commonly referred to as "welfare" during the previous 12 months. *Wage* - inverse hyperbolic sine (IHS) transformation of constructed wage. Estimates are derived from a sample of non-citizen immigrants ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2005-2018 waves of ACS. All regressions control demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age,age of entering U.S., education attainment), country-of-origin fixed effects, state fixed effects, year fixed effects, state-specific time trends, and state-year controls (state unemployment, dummies for Universal E-Verify laws, Public E-Verify, instate tuition laws, driver's license laws). Standard errors are clustered at state-year level.

Table A.4: Placebo Test on Naturalized Citizens (Labor Market)

Variables	(1) Labor Force	(2) Working	(3) Unemployed	(4) Usual Hours Worked	(5) Self-Employed	(6) School
$P(R\|C,T,E)$	0.019*	0.017	0.002	0.225	0.005	0.001
	(0.009)	(0.010)	(0.005)	(0.384)	(0.006)	(0.010)
$P(R\|S,T,E)$	-0.001	0.001	-0.002	-0.635	-0.004	-0.002
	(0.009)	(0.010)	(0.005)	(0.393)	(0.006)	(0.008)

Standard errors in parenthesis
* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: *Labor Force* -binary var. equal 1 if individual currently participates in the labor force; *Working* - binary var. equal 1 if individual is currently working; *Unemployed* - binary var. equal 1 if individual is currently unemployed; *Usual Hours Worked* - number of hours per week respondent usually worked in past 12 months; *Self-Employed* - binary var. equal 1 if individual is currently self-employed. *School* - binary var. equal 1 if individual is currently in school. Estimates are derived from a sample of naturalized immigrants ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2005-2018 waves of ACS. All regressions control for demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age,age of entering U.S., education attainment), country-of-origin fixed effects, state fixed effects, year fixed effects, state-specific time trends, and state-year controls (state unemployment, dummies for Universal E-Verify laws, Public E-Verify, instate tuition laws, driver's license laws). Standard errors are clustered at state-year level

Table A.5: Placebo Test on Naturalized Citizens (Income)

Variables	(1) Total Income	(2) Wage Income	(3) Other Income	(4) Welfare Income	(5) Wage
$P(R\|C,T,E)$	0.165*	0.087	-0.016	-0.005	-0.073
	(0.082)	(0.101)	(0.041)	(0.016)	(0.085)
$P(R\|S,T,E)$	-0.093	-0.112	-0.085*	-0.014	-0.220*
	(0.093)	(0.108)	(0.038)	(0.017)	(0.101)

Standard errors in parenthesis
* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: *Total Income* - inverse hyperbolic sine (IHS) transformation of individual's total pre-tax personal income from all sources for the previous 12 months. *Wage Income* - inverse hyperbolic sine (IHS) transformation of individual's total pre-tax wage and salary income for the previous 12 months. *Other Income* - inverse hyperbolic sine (IHS) transformation of individual's total income from sources not included in the other IPUMS person-record income variables for the previous 12 months. *Welfare Income* - inverse hyperbolic sine (IHS) transformation of individual's pre-tax income (if any) the respondent received from various public assistance programs commonly referred to as "welfare" during the previous 12 months. *Wage* - inverse hyperbolic sine (IHS) transformation of constructed wage. Estimates are derived from a sample of non-citizen immigrants ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2005-2018 waves of ACS. All regressions control demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age,age of entering U.S., education attainment), country-of-origin fixed effects, state fixed effects, year fixed effects, state-specific time trends, and state-year controls (state unemployment, dummies for Universal E-Verify laws, Public E-Verify, instate tuition laws, driver's license laws). Standard errors are clustered at state-year level.

Table A.6: The Effects of DACA on Labor Market Outcomes

Lubotsky and Wittenberg (2006)

Variables	(1) Labor Force	(2) Working	(3) Unemployed	(4) Usual Hours Worked	(5) Self-Employed	(6) School
$\rho = \hat{\rho}$	0.095***	0.113***	-0.025 ***	4.005 ***	-0.007	0.223***
	(0.012)	(0.012)	(0.006)	(0.570)	(0.006)	(0.042)
$\hat{\rho}$	0.774	0.754	0.481	0.532	1.007	- 2.265
$\rho = 1$	0.090***	0.115***	-0.039 ***	3.329***	-0.007	0.012
	(0.013)	(0.014)	(0.007)	(0.698)	(0.006)	(0.013)

Standard errors in parenthesis

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

Notes: *Labor Force* -binary var. equal 1 if individual currently participates in the labor force; *Working* - binary var. equal 1 if individual is currently working; *Unemployed* - binary var. equal 1 if individual is currently unemployed; *Usual Hours Worked* - number of hours per week respondent usually worked in past 12 months; *Self-Employed* - binary var. equal 1 if individual is currently self-employed. *School* - binary var. equal 1 if individual is currently in school. Estimates are derived from a sample of non-citizen immigrants ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2005-2018 waves of ACS. All regressions control for demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age,age of entering U.S., education attainment), country-of-origin fixed effects, state fixed effects, year fixed effects, state-specific time trends, and state-year controls (state unemployment, dummies for Universal E-Verify laws, Public E-Verify, instate tuition laws, driver's license laws). Standard errors are clustered at state-year level

Table A.7: The Effects of DACA on Income (IHS)

Lubotsky and Wittenberg (2006)

Variables	(1) Total Income	(2) Wage Income	(3) Other Income	(4) Welfare Income	(5) Wage
$\rho = \hat{\rho}$	0.960***	1.023 ***	-0.029	-0.020	-0.042
	(0.136)	(0.136)	(0.035)	(0.016)	(0.027)
$\hat{\rho}$	0.772	0.801	0.711	1.065	0.828
$\rho = 1$	0.809***	0.9344 ***	-0.140***	-0.020	-.104 ***
	(0.152)	(0.146)	(0.041)	(0.015)	(0.029)

Standard errors in parenthesis

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

Notes: *Total Income* - inverse hyperbolic sine (IHS) transformation of individual's total pre-tax personal income from all sources for the previous 12 months. *Wage Income* - inverse hyperbolic sine (IHS) transformation of individual's total pre-tax wage and salary income for the previous 12 months. *Other Income* - inverse hyperbolic sine (IHS) transformation of individual's total income from sources not included in the other IPUMS person-record income variables for the previous 12 months. *Welfare Income* - inverse hyperbolic sine (IHS) transformation of individual's pre-tax income (if any) the respondent received from various public assistance programs commonly referred to as "welfare" during the previous 12 months. *Wage* - inverse hyperbolic sine (IHS) transformation of constructed wage. Estimates are derived from a sample of non-citizen immigrants ages 18-35 with at least a high school diploma (or equivalent). Data are taken from the 2005-2018 waves of ACS. All regressions control demographic characteristics (sex, race, ethnicity, marital status), DACA eligibility criteria dummies (age,age of entering U.S., education attainment), country-of-origin fixed effects, state fixed effects, year fixed effects, state-specific time trends, and state-year controls (state unemployment, dummies for Universal E-Verify laws, Public E-Verify, instate tuition laws, driver's license laws). Standard errors are clustered at state-year level.