Policy Impacts in the Age of Trump: Evidence from DACA

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Abstract

Enacted in 2012, the Deferred Action of Childhood Arrivals (DACA) provided almost 800,000 undocumented immigrants with temporary work authorization and deportation relief but was substantially challenged by the Trump Administration in 2017. This paper explores the labor market responses of DACA recipients to the uncertainty and volatility that accompanied the policy. Using a difference-in-difference methodology and relying on a discontinuity in DACA's eligibility criteria, I estimate the effects of DACA on labor market and education outcomes between 2012 and 2019. Contrary to previous literature studying DACA, I do not use non-citizenship as a proxy for unauthorized status. I rather impute undocumented status using a residual method, that allows selecting a sample more closely aligned with likely undocumented individuals. Results show that DACA had significant positive effects on employment and negative effects on education. In the wake of the uncertainty instigated in 2017, DACA's impact on labor market outcomes mostly disappeared, while the negative effects of DACA on the likelihood of attending schools increased in magnitude. Finally, I document stark heterogeneity across gender, ethnicity, and political environments.

Keywords: Employment; Labor Market; Labor Force; School; Immigration; Illegal Immigrant; Unauthorized Immigrant; DACA; Deferred Action of Childhood Arrivals; Public Policy; Policy Fluctuations; Migration Policy

JEL Codes: J18, J15, J24, J68

Declarations of interest: None

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“ DACA is dead ...”

— President Donald J. Trump[1]

“ [DACA] brought me confidence into my life and happiness because I wasn’t afraid anymore to go to places [...]. DACA helped me push forward to achieve my registered nurse license. [...]. If DACA was to come to an end, everything I worked so hard for, everything I have built and everything I accomplished will be worth nothing. All the time invested will be long gone and worth nothing. Without DACA, I will go back to being an immigrant student with dreams...”

— Leyni Rosas Cuevas, 25, California[2]

1 Introduction

For the past two decades, the gap in political views between Republicans and Democrats has been widening (Gallup Polls, 2017). Polls show that individuals often view their opposing party’s policies, whether economy, migration, or healthcare related, as a threat (Pew Research, 2014). As a result, consecutive presidencies have revoked policies enacted by previous administrations, shortly after their implementation and regardless of their impacts. This was especially evident after the unexpected election of President Trump in 2016. In his days in office, President Trump proposed and conducted changes to numerous policies, including rolling back the Affordable Care Act, cutting the budget of Medicaid, limiting H-1B visas, and building a wall along the border with Mexico.

When policies face the risk of cancellation, recipients are subjugated to uncertainty even if the policies are factually unchanged. A temporary policy that is not set in stone might generate differential effects based on its perception as permanent versus temporary. Nonetheless, the extent to which varying expectations towards a policy alter its outcomes has not been extensively explored in the literature. In this paper, I demonstrate how variation in risk and uncertainty towards a temporary policy affects its benefits by focusing on the most relevant immigration-related executive action in recent history: the Deferred Action of Childhood Arrivals (DACA). In particular, I estimate the effects of DACA on eligible undocumented

[1] @realDonaldTrump Tweet on April 2, 2018.

[2] Shalby, C., & Kim, K. (2017, September 26). IN THEIR WORDS ‘Dreamers’ tell us what the end of DACA would mean for them. Los Angeles Times. Retrieved March 14, 2021, from https://www.latimes.com/projects/la-na-daca-recipients/.

immigrants and examine how the policy's outcomes evolved after it was challenged by the Trump administration. I explore whether the latter persisted or were depressed by the change in expectations towards the policy's permanency.

The undocumented population in the U.S. includes almost 11 million individuals, constituting 30% of the country's foreign-born population in 2008 (Passel and Cohn, 2008). Undocumented immigrants cannot access jobs, welfare benefits, or credit, affecting their human capital accumulation. Descriptive statistics show that undocumented immigrants have lower income and returns to educations than natives or legal immigrants (Rivera-Batiz, 1999). In addition, undocumented men have a higher labor supply, that is less responsive to wage changes (Borjas, 2017). Wage gaps increase over the life cycle of undocumented immigrants and have been attributed to occupational barriers (Borjas and Cassidy, 2019; Ortega and Hsin, 2018). Accordingly, multiple attempts for immigration reform have been made in the U.S. since the 1980s, seeking to enhance the livelihoods of undocumented immigrants, while at the same time curbing illegal immigration.

On June 15^{th}, 2012, President Obama passed DACA through an executive order, providing undocumented immigrants with work authorization and deferring their removal action for 2 years, subject to renewal, if they satisfy certain requirements (USCIS). Almost 826,000 individuals have benefited from DACA since it has been passed (American Progress, 2020). The policy primarily focused on undocumented individuals who had reached the US before their 16^{th} birthday. However, it did not provide a permanent solution to undocumented immigrants, nor did it grant them citizenship or lawful status. After its passage in 2012, lawsuits were filed in multiple states to challenge the policy and limit its expansion. The situation was exacerbated by the Trump administration, culminating in the rescission of DACA in September 2017. DACA recipients were allowed to renew their status and technically receive the policy's benefits thereafter, but new applications were not considered. Thus, recipients have experienced a great deal of uncertainty regarding their status, and their perceived risk of deportation significantly varied during the 2012-2019 time period.

In light of the uncertainty, two opposing channels might have altered DACA's initial outcomes. The net effect is ambiguous and depends on the magnitude of each channel. First, an increase in the risk of cancellation of the policy might be translated as an increase in the perceived risk of deportation. This is especially true for DACA recipients, who provided their information to the Department of Homeland Security when applying for the program. Thus, to restrict their possible interactions with the police, they might decrease their participation in the labor market and their labor supply outside home, chilling the effects of DACA. In the same regard, recipients might alter the frequency of their visits to schools, hospitals, or healthcare facilities. On the other hand, expecting the cancellation of the policy might incentivize individuals to reap its last benefits. In this case, forward-looking recipients might choose to increase their working hours, generate more income, and save while they can.

To estimate the effects of DACA and their fluctuation, I employ a difference-in-difference methodology, and exploit a discontinuity in the DACA eligibility criteria pertaining to age at immigration. I utilize data from the American Community Survey (2005-2019) and focus on a wide array of outcomes, including employment, education, and occupation outcomes. My results regarding the effects of DACA between 2012 and 2016 are consistent with the literature. I find that DACA had positive impacts on employment outcomes. At the same time, DACA-eligible individuals seem to substitute schooling for employment. The effects of DACA on employment outcomes mostly disappear after 2017. However, the decrease in schooling is larger after 2017. I find no evidence that DACA significantly affected occupational mobility of eligible individuals. Finally, I present an exhaustive analysis of the effects of DACA across gender, ethnicity, and states' political environments. Results show that eligible individuals benefited from DACA but were more negatively affected after 2017 in Republican states.

This paper adds to two main strands of literature. First, the paper contributes to the literature that studies the impact of immigration reforms. Permanent legalization policies, like the Immigration Reform and Control Act (IRCA) of 1986, have shown significant positive impacts on earnings (Hill, Lofstrom, and Hayes, 2010; Pastor, Scoggins, Tran, and Ortiz, 2010; Barcellos, 2010; and Pan, 2012; Orrenius and Zavodny, 2012; Bratsberg et al, 2002; Lozano and Sorensen, 2011; Kossoudji and Cobb-Clark, 2002; Amuedo-Dorantes, Bansak and Raphael, 2007) and educational attainment (Cortes, 2013) of undocumented immigrants. Unlike IRCA, DACA only provides temporary relief, making it vulnerable and susceptible to risk, uncertainty, and changed expectations. Previous studies have not tackled the role of permanency and expectations in driving the outcomes of immigration policies. Focusing on DACA, I shed light on these aspects and demonstrate how and why temporary policy's outcomes fluctuate. I also explore some institutional factors that drive these outcomes by looking at the differential results across states that advocated for DACA, and those that encouraged its rescission. DACA was not terminated for its existing recipients after 2017 but had an uncertain future with the prospect of a second Trump term. Thus, in this setup, I can attribute the change in outcomes after 2017 to changes in expectations rather than changes in the actual benefits of the policy.

This paper also contributes to a thick literature that studies the effects of DACA on its recipients. Generally, the literature finds positive effects on the economic well-being (Amuedo-Dorantes and Antman, 2016), and labor market outcomes of eligible individuals (Amuedo-Dorantes and Antman, 2017; Pope, 2016). The literature is not as conclusive about the effects of DACA on education outcomes. Kuka et al (2020) and Ballis (2020) find positive effects of DACA on educational investment, school attendance, and completion of eligible students, while Hsin and Ortega (2018) find an increase in university dropout rates and a decrease in full-time enrollment, which is in line with the results of Pope (2016) and Dickson, Gindling and Kitchin (2017). In addition, DACA has led to an increase in health insurance coverage (Guintella and Lonsky, 2020) reduction in stress and anxiety (Hainmueller et al, 2017; Patler, Hamilton, Meagher and Savinar, 2019; Venkataramani et al, 2017), better sleep (Guintella, Lonsky, Mazzonna and Stella, 2021), and a decrease in teenage births (Kuka et al, 2019). On a macroeconomic level, Ortega et al (2019), in a general equilibrium model, find that DACA increased GDP by about $3.5 billion.

This literature paints a good picture about DACA, but it does not investigate the policy's fluctuations after Trump. It relies on data that extends from 2012 to 2016 the latest, missing the challenges that faced DACA between 2017 and 2019. Given the change in perceived risk, there is reason to believe that the effects of DACA varied. Positive effects captured in the literature might only be short-term. Recent studies that look at the impact of uncertainty rely on interviews and focus groups (Nienhusser and Oshio, 2020). Two exceptions are Guintella, Lonsky, Mazzonna and Stella (2021) and Patler, Hamilton, Meagher and Savinar (2019). The former finds that DACA lengthened sleep duration among eligible immigrants, but this effect decreased between 2016 and 2019. The latter finds positive and significant effects of DACA on health outcomes in California, that do not persist between 2015 and 2017. My paper is the first to investigate the longer-term effects of DACA on a wider range of outcomes. Comparing the effects of DACA before and after 2017, I reassert the conclusion of these two studies, showing that uncertainty depressed DACA's benefits on employment.

Finally, focusing on heterogeneity across states and ethnicities is particularly important because state environments are crucial in either accommodating for undocumented immigrants or the opposite (Cebulko and Silver, 2016). For instance, California and Massachusetts have passed multiple legislation to provide undocumented immigrants with driver's license and grant them in-state tuition eligibility. That did not happen in other states, like Arizona or North Carolina, that passed restrictive policies. These environments affect how much benefits can recipients actually derive from the policy. I quantify this fact formally in the heterogeneity analysis and show that the benefits of DACA were not shared equally by all eligible individuals.

On a methodological level, most of the literature (Amuedo-Dorantes and Antman, 2016; Amuedo-Dorantes and Antman, 2017; Antman, 2016; Guintella and Lonsky, 2020; Guintella, Lonsky, Mazzonna and Stella, 2021; Kuka et al, 2019; Kuka et al, 2020; Pope, 2016; Venkataramani et al, 2017) relies on ethnicity and citizenship to determine the legal status of individuals. Specifically, these studies use non-citizenship as a proxy for undocumented and restrict the sample to non-citizens with low levels of education. Thus, the treatment group also includes legal immigrants, green card holders and visa holders, that are not and will not be eligible for DACA, leading to measurement errors and attenuation bias. Instead, I use the residual methodology that is adopted by Borjas (2017) and refined in Borjas and Cassidy (2019) to impute the legal status of individuals. After that, I purely focus on the sample of likely undocumented individuals in my analysis, resulting in more accurate estimates.

The remainder of the paper proceeds as follows: Section 2 provides information about the institutional background surrounding DACA and its rescission. Section 3 gives an overview of the data, and section 4 discusses the identification strategy. Section 5 presents the results, and section 6 elaborates on their heterogeneity. Finally, section 7 concludes.

2 Institutional Background

Immigration is a topic of intense policy debate in American politics. Consecutive administrations have acted to either promote immigration or restrict it. In 1986, the Immigration Reform and Control Act (IRCA) was passed, giving 2.7 million undocumented individuals legal status (Center of Immigration Studies). Some small amnesties were passed by Congress after that in the 1990s, for individuals of specific nationalities[3]. In 2001, the DREAM Act was proposed. However, the bill did not pass, even with a Democratic majority (Arlota, 2018).

[3] In 1994, Congress passed amnesty 245(i) that gave legal status to 587,000 illegal individuals. It was renewed in 1997 and 2000. In 1997, the Congress passed the Nicaraguan Adjustment and Central American Relief Act (NACARA) focusing on undocumented individuals from Central America. Finally, in 1998, the Haitian Refugee Immigration and Fairness Act (HRIFA) was passed, focusing on Haitians (Center of Immigration Studied).

On June 15^{th}, 2012, President Obama passed the Deferred Action of Childhood Arrivals (DACA) through an executive order. The United States Department of Homeland Security's Citizenship and Immigration Services (USCIS) started processing and accepting applications in August 2012, but take-up significantly increased starting 2013. Qualified undocumented immigrants could apply for DACA if they satisfy a series of requirements. Those include: (1) arriving before the age of 16, (2) being under the age of 31 as of June 2012, (3) continuously residing in the US since June 15, 2007, (4) should be in school, graduated, have a certificate of completion from high school or a GED certificate, or is a discharged veteran, (5) should pay a processing fee of $465. Finally, the applicant should not be convicted of a felony or a significant misdemeanor and should be at least 15 years old to request DACA. Applicants should provide proof of records and documents that they meet these criteria (USCIS).

If accepted by the Department of Homeland Security, DACA would provide several benefits for recipients. These include relief from deportation and a legal work authorization. DACA also provides eligible recipients with social security numbers, enabling them to obtain loans, open bank accounts, and build credit history. These benefits are given for two years, subject to renewal. Some states extended the benefits of DACA by allowing recipients to obtain drivers' licenses. New York, California, D.C., Minnesota, Oregon, Washington, Illinois, and Massachusetts, also, made recipients eligible for state-funded Medicaid (Guintella and Lonsky, 2020). Nevertheless, DACA did not grant a path to citizenship.

Multiple states sued to challenge DACA, claiming that the policy took away American jobs and exceeded executive powers. As for President Trump, he did not portray a consistent view. At the beginning of his first term, in 2016, President Trump referred to DACA recipients as "absolutely incredible kids," and claimed that the administration is going "to show great heart" (USA Today, 2018). On September 5^{th}, 2017, the Trump Administration announced the rescission of the program (DHS, 2017). The announcement stated that DACA would be phased out for its recipients within six months, and that no new requests would be granted (Bush, 2017). Fifteen states, including California, Washington, and New York, sued back the Trump Administration in an effort to block DACA's rescission and protect DACA-mented people (REUTERS, 2017). Following that, the federal district court judges of California, New York and D.C. ordered continuing the DACA policy. Thus, the renewal of previously enrolled recipients resumed, but new applications were rejected (DHS, 2017). Individuals who were granted DACA before 2017 were technically able to retain its benefits, as the policy was not altered for them.

President Trump later stated that he would permanently protect DACA recipients conditional on reaching a deal with the Democrats to limit immigration and secure borders. The negotiation period featured Trump announcing his support for a pathway to citizenship for DACA recipients as long as the pillars of his deal were held[4]. No common ground was reached between negotiating parties, so in 2018, President Trump announced that the Democrats "killed" DACA. In 2019, President Trump's tweets referred to DACA recipients as "far from angels" and "hardened criminals" (Vox, 2019). President Trump took the case to the Supreme Court, which ruled in 2020 that the rescission was unwarranted[5], but acknowledged that DHS could properly rescind DACA in the future if done in a legally proper way (National Conference of State Legislatures, 2020). He later promised that he would resubmit on DACA to the Supreme Court (LA Times, 2020).

Figure 1, panels A and B, presents the initial and renewal applications by year, respectively. The trend shows that initial applications and approvals decreased following 2013 and reached their minimum after DACA's rescission. However, renewal applications and renewal approvals remained high between 2017 and 2019. The geographic distribution of DACA applications, documented in Panel C, is basically concentrated in California, Texas, Florida, and New York.

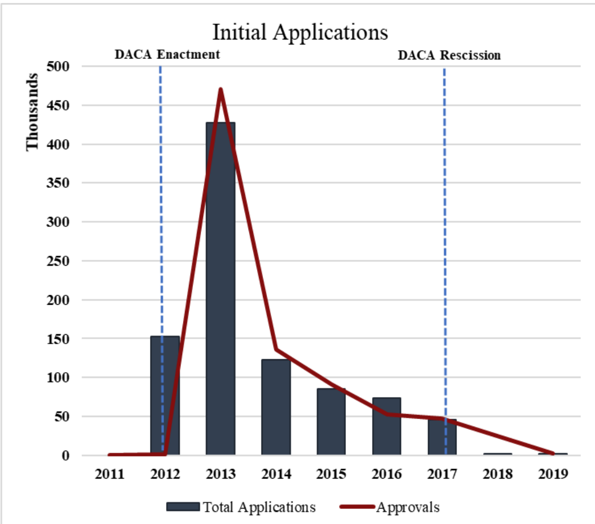
3 Data

I utilize data from the American Community Survey (ACS) for the period 2005-2019[6]. As detailed in Pope (2016), the ACS survey is representative of the US population. The ACS sampling procedure uses the universe of US addresses, so there isn't selection based on legal status into the sample. I look at 2 different sets of outcomes: labor-market and schooling outcomes. Labor market outcomes include occupation variables: whether an individual is working in an essential sector, a licensed occupation, a service occupation, or a non-service occupation. Additionally, to check whether eligible individuals are changing their jobs' task-intensity (following Peri and Sparber, 2009), I look at whether they move to occupations with dominant analytical or manual tasks. I describe in detail the setup of each variable in the Data Appendix.

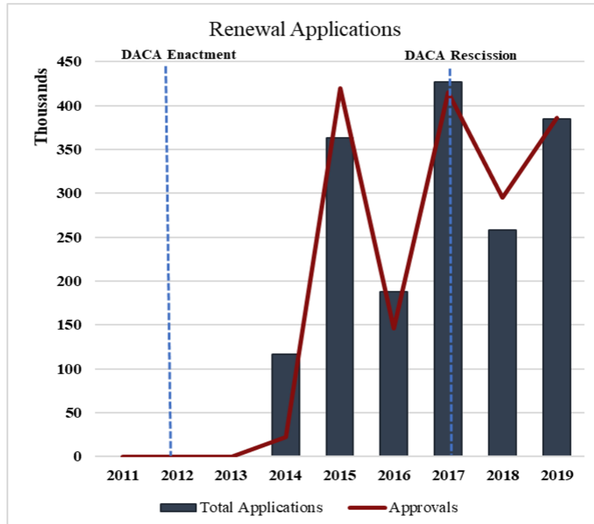
[4]These include: protecting DREAMers, securing funding for the wall at the border with Mexico, ending the diversity visa lottery, and decreasing family-based migration.

[5]The Supreme Court ruled that DACA's rescission was done arbitrarily, violating the Administrative Procedure Act (National Immigration Law Center, 2020).

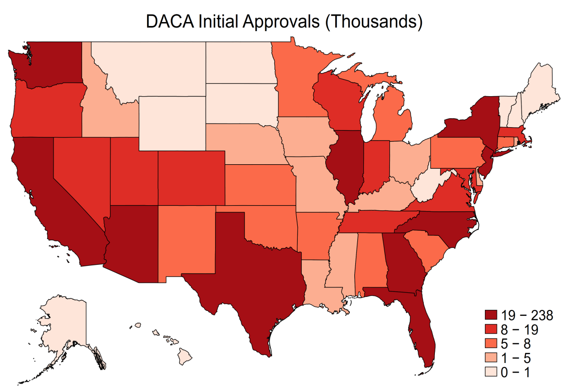
[6]The data was obtained through IPUMS.



((a)) Initial Applications



((b)) Renewal Applications



((c)) Initial Approvals

Figure 1: Number of DACA Initial and Renewal Applications. Panel A shows total initial DACA applications and the number of approved applications from 2011 to 2019. Panel B shows the total renewal DACA applications and the number of approved renewals from 2011 to 2019. Panel C shows geographic distribution of initial DACA applications across states as of the first quarter of 2020. Note that some approved applications may have been received in a previous year.
Source: Department of Homeland Security, U.S. Citizenship and Immigration Services, Performance Report Tool, accessed January 2021.

3.1 Residual Method

Individual-level surveys do not usually ask whether a foreign-born individual has unauthorized status. Even if they did, individuals would probably decline to answer or give a false answer. Thus, multiple methods have been used to impute the undocumented status of individuals relying on alternative information. As previously mentioned, most studies on effects of DACA use non-citizenship and ethnicity as a proxy for undocumented. Given that non-citizens might have visas or green cards, this method might bias the results to zero. In fact, statistics from the Pew Research Forum show that almost 77% of immigrants in the US were legal in 2020 (Budiman, 2020). It has also been shown that Mexican authorized immigrants have the lowest naturalization rates; thus, using the Mexican non-citizen status as a proxy for undocumented might lead to measurement errors. Focusing on Hispanic non-citizens might be misleading as well given that those concentrate in unique states. It might be state environments that are driving the outcomes of the policy, as later shown in the heterogeneity analysis.

Instead of using proxy measures, I use a modified version of the residual method of Borjas (2017), and Borjas and Cassidy (2019) to impute the undocumented status of individuals. This method was initially constructed by Warren and Passel (1987), and since then, has been used by the DHS to count the undocumented immigrant population. The framework works by estimating the foreign-born population, and then extracting naturalized and legal immigrants from this population. The remainder yields the population with a high likelihood of being undocumented. A foreign-born individual is considered legal or authorized if they adhere to any of these conditions: (1) individual arrived before 1980, (2) individual is a citizen, (3) individual receives SS, SSI benefits, or Medicare, (4) individual has veteran status, or works as a federal government employee, in the armed forces, or as a state or local government employee, (5) individual was born in Cuba, (6) individual works in an occupation that includes highly-educated people who are in the US on an H-1B visa, (7) individual has a present legal immigrant or citizen spouse. The remainder group of all non-US born individuals is considered likely undocumented.

Liu and Song (2019) compare the ethnicity proxy to the residual methodology by finding how closely the two match official statistics, and how they differ when estimating the effects of state policies. Their findings show that the residual method surpasses the ethnicity proxy when finding the numbers of undocumented individuals and their geographic variation. However, there are still multiple limitations to this approach. First, it relies on the self-reporting of year of immigration, occupation, and benefits take-up, which suffer from some measurement errors due to recall bias. Second, the DHS argues that undocumented immigrants work actively to avoid being detected and assumes that 10% of unauthorized immigrants are missed (Baker and Rytina, 2013).

3.2 DACA Eligibility Criteria and Undocumented Sample

After imputing the legal status, I determine each individual's DACA eligibility. DACA eligible individuals are undocumented, have lived in the US continuously since 2012, entered the US before the age of 16, immigrated before 2007, are under 31 years old as of June 2012 and meet the education requirements[7]. I do not consider individuals who became eligible for DACA just after 2017 as recipients, since they were not able to apply for DACA, and did not receive its benefits. There isn't a way I can observe actual participation or take-up of DACA. However, USCIS statistics document that almost 67% of DACA-eligible individuals received DACA status (Pope, 2016).

I restrict my sample to include likely undocumented immigrants between the ages of 18 and 30, who entered the US between the ages of 12 and 19, and meet the education requirements, mainly exploiting the variation in the age of immigration. Therefore, the treated group is the sample of likely undocumented individuals who entered the US between the ages of 12 and 16, while the comparison group includes likely undocumented individuals who entered the US between the ages of 16 and 19 and thus, did not receive DACA. This is a more natural comparison group than citizens or those who have legal status.

Given that the ACS includes detailed questions about the year and quarter of birth, years since immigration, and educational attainment, I am able to abide closely to the steps of imputing undocumented status, and then DACA eligibility. Table 1 shows the demographic summary statistics of the sample, using ACS data (2005-2019). By construction, eligible individuals entered the US at an earlier age and thus, have spent more years in the U.S. 63.78% of them are Hispanic, and 21.12% of them live in California. In the appendix, Table A1 presents summary statistics of the outcomes looked at, showing a higher proportion of eligible individuals were working and participating in the labor force.

[7] The individual is currently in school, have graduated from high school, or earned a GED.

Table 1: Summary Statistics

	(1) All Sample	(2) DACA Eligible	(3) DACA Ineligible
Current Age	23.57	24.09	23.43
	(3.552)	(3.124)	(3.651)
Male	56.57	56.40	56.62
	(49.57)	(49.59)	(49.56)
Born in Mexico	35.79	44.24	33.41
	(47.94)	(49.67)	(47.17)
Born in Central/ South America	23.78	26.50	23.01
	(42.57)	(44.13)	(42.09)
Hispanic	53.46	63.78	50.54
	(49.88)	(48.06)	(50.00)
White	12.40	10.21	13.02
	(32.96)	(30.28)	(33.65)
Black	8.991	9.230	8.923
	(28.60)	(28.94)	(28.51)
Asian	23.23	15.36	25.45
	(42.23)	(36.06)	(43.56)
Married	20.84	20.92	20.82
	(40.62)	(40.67)	(40.60)
Age Entered USA	16.46	13.53	17.29
	(2.163)	(1.128)	(1.589)
Years in the United States	7.111	10.56	6.137
	(4.146)	(3.084)	(3.879)
Spanish Primary Language	52.60	62.83	49.71
	(49.93)	(48.33)	(50.00)
Years of Education	12.94	12.90	12.95
	(1.495)	(1.440)	(1.510)
Has high school degree or the equivalent	50.39	52.19	49.88
	(50.00)	(49.95)	(50.00)
Has some college education	37.20	35.99	37.54
	(48.33)	(48.00)	(48.42)
Has a college degree or more	12.41	11.82	12.58
	(32.97)	(32.28)	(33.16)
California	19.86	21.12	19.50
	(39.90)	(40.82)	(39.62)
Texas	11.06	12.80	10.56
	(31.36)	(33.41)	(30.74)
New York	9.359	8.675	9.552
	(29.13)	(28.15)	(29.39)
Observations	100510	20766	79744

Notes: Standard deviations in parentheses. The sample includes likely undocumented individuals ages 18-30, who entered the US between the ages 12-19, and satisfy education requirements. DACA eligibility is decided based on the criteria of Section 3.2. Data is taken from the 2005-2019 waves of the ACS.

4 Identification Strategy

To estimate the causal effects of DACA between 2012 and 2019, I use a difference-in-difference (DiD) model. I utilize some discontinuity elements by restricting the age of immigration of individuals in the sample. The sample constitutes likely undocumented immigrants, and eligibility is determined without information about actual take-up of the policy. Thus, the DiD estimates are giving the intent-to-treat effect. In order to differentiate between the effects of DACA before and after the Trump administration, I split the Post variable into two sub-periods. The main specification is the following:

$$
\begin{aligned}
Y_{it} = \beta_0 + \beta_1 Eligible_i * Post12_t + \beta_2 Eligible_i * Post17_t + \beta_3 Eligible_i + \beta_4 Post12_t \\
+ \beta_5 Post17_t + \beta_6 X_{it} + \beta_7 V_{it} + \theta_t + \gamma_s + \gamma_s t + \epsilon_{it}
\end{aligned} \tag{1}
$$

where Y_{it} is the outcome variable of interest of likely undocumented individual i in year t. $Eligible_i$ is a dummy variable that takes the value one if individual, i, is eligible for DACA, and zero otherwise. That is, the individual meets the following requirements: (i) entered the US before the age of 16, (ii) entered the US before 2007, (iii) should be 31 years old as of June 2012, and (iv) continuously resided in the US since June 15, 2007. Since the sample is restricted to individuals who meet the education requirements, are between 18 and 30, and entered the US between the ages of 12 and 19, the main variation comes from the time of the individual's arrival to the US. Thus, the probability that the treated and the control group have parallel trends before the treatment is higher. There are two coefficients of interest here: β_1 and β_2. The former estimates the causal effect of DACA between the time of its enactment and before it was challenged by the Trump administration in 2017, while the latter estimates the effects of DACA after 2017. Using both, I am comparing the outcomes of eligible individuals to those of ineligible individuals before and after DACA.

$Post12_t$ is a dummy variable that takes the value 1 if the survey year is between 2013 and 2016, inclusive. I use 2013 as the first year of the treatment because DHS started accepting applications in August 2012, but the take-up significantly increased after that in 2013. If there are any effects of DACA, they would show in 2013. $Post17_t$ is another dummy variable that takes the value 1 if the survey year is between 2017 and 2019, inclusive. X_{it} is a vector of control variables, including race, Hispanic ethnicity, sex, years of education, marital status, and state-level unemployment rates[8]. V_{it} includes a set of fixed effects: individual's age, and age at immigration to the US. Year and state fixed effects and state-specific time trends are also added[9]. Finally, the standard errors are clustered at the state-year level.

The validity of my identification strategy relies on the parallel trends assumption. That is, the treatment and comparison group would have exhibited similar trends in the outcomes if DACA had not been enacted. To test this assumption, I utilize an Event-Study approach, where I replace the Post variables with indicator variables for each survey year and estimate dynamic treatment effects. I omit the interaction with survey year 2012. Specifically, I estimate equation (2). I graphically plot the estimated coefficients over time and present the results in section 9. I confirm the absence of pretrends for most of the outcomes of interest, implying no treatment effect in the pre-period.

$$Y_{it} = \beta_0 + \sum_{t=-8}^{7} \beta_1 Eligible_i * Year_t + \beta_2 Eligible_i + \beta_3 X_{it} + \beta_4 V_{it} + \theta_t + \gamma_s + \gamma_s t + \epsilon_{it} \quad (2)$$

5 Results and Discussion

5.1 Difference-in-Difference Effects

Table 2 and Table 3 report the results of equation (1) on employment, education, and occupation outcomes respectively. Consistent with the literature, findings of Table 2 show that between DACA's enactment in 2012 and 2016, the likelihood of working significantly increased for DACA-eligible individuals by 5.13 percentage points. This estimate is larger in magnitude than that of Pope (2016), using a similar sample. This provides evidence that using non-citizenship as a proxy for undocumented status attenuates the results. The increase in working is driven by a 4.11 percentage points increase in the likelihood of participating in the labor force, and a 1.65 percentage points reduction in unemployment of eligible individuals. Although hours worked of eligible individuals significantly increase by 1.44 hours between 2012 and 2016, there is no effect of DACA on income. The likelihood of self-employment is not affected as well.

[8]**Source:** Local Area Unemployment Statistics. Bureau of Labor Statistics (BLS).

[9]The results are not sensitive to the inclusion of state-specific time trends. Appendix tables Table A2 and Table A3 present the baseline results without controlling for state time trends. Estimates are close but slightly larger in magnitude than those of the main results presented in section 5.

The last two columns of Table 2 show the effect of DACA on education. The results show that eligible individuals experience a 2.39 percentage points reduction in the probability of attending school before 2017. There is no evidence that DACA changed the likelihood of obtaining the GED.

After 2017, the effect of DACA on employment outcomes of eligible individuals fades out, supporting the "chilling effect" mechanism. One exception is the hours worked variable which shows a persistent but smaller increase of 1.35 hours ($p < 0.05$) for eligible individuals. Interestingly, the decrease in schooling of eligible individuals persists and gets larger after 2017 (2.7 percentage points). The effect of DACA on schooling can be explained from two directions, over-investment and risk. The first pertains to the fact that eligible individuals were over-investing in education before they received DACA. After 2017, since the fate of DACA was uncertain, individuals who stayed in school might have left at a higher rate to reap the last benefits of DACA by working and generating income. If so, we would have seen a significant increase in working or entering the labor force after 2017. On the other hand, by rescinding DACA, the Trump administration increased the deportation risk, also increasing school completion risk. Athreya and Eberly (2021) theoretically explain that even if the college premium is high, students focus on the completion risk when deciding their educational investment. Their paper does not discuss undocumented immigrants or risk of deportation, but their results are relevant in explaining the further reduction in schooling of DACA eligible individuals after 2017. Looking at these effects by gender in Table 4, I find that the reduction in schooling is larger for males than the whole sample after 2017. This might confirm the completion risk theory, since the risk of deportation (and thus, that of school completion) is higher for males (Kuka et al, 2020) than females.

Table 2: Difference-in-Difference Effects on Employment & Education Outcomes

	(1) Working	(2) In the Labor Force	(3) Hours Worked	(4) Unemployed	(5) Self-employed	(6) Worked last year	(7) Log Personal Income	(8) In School	(9) GED
Elig*Post12	0.0513***	0.0411***	1.436***	-0.0165**	-0.00674	0.0408***	0.0122	-0.0239***	0.00169
	(0.010)	(0.011)	(0.426)	(0.008)	(0.005)	(0.011)	(0.025)	(0.009)	(0.004)
Elig*Post17	0.0231	0.00815	1.350**	-0.00961	0.00647	0.0188	-0.000638	-0.0270**	0.00451
	(0.015)	(0.014)	(0.603)	(0.009)	(0.011)	(0.014)	(0.036)	(0.013)	(0.007)
Eligible	-0.00904	-0.00708	-0.204	0.00420	-0.00185	-0.00955	-0.0480**	-0.00372	0.0110***
	(0.009)	(0.010)	(0.355)	(0.007)	(0.005)	(0.009)	(0.024)	(0.008)	(0.004)
Mean Y	0.616	0.673	25.70	0.0840	0.0530	0.699	9.479	0.363	0.0301
Observations	100510	100510	100510	62788	73172	100510	70725	100510	77877
R-squared	0.192	0.203	0.261	0.0319	0.0166	0.179	0.252	0.465	0.0408

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the difference-in-differences estimates of Equation (1) on employment and education outcomes. Year and state fixed effects and state-specific time trends are added. Standard errors are clustered at the state-year level. Estimates in all columns are derived from a sample of likely undocumented individuals ages 18-30, who entered the US between the ages 12-19, and satisfy education requirements. Data is taken from the 2005-2019 waves of the ACS.

To examine whether DACA led to a shift in occupations, I further restrict the sample to employed individuals, comparing the employed DACA-eligible group to the employed ineligible group. Results of Table 3 show that DACA has not substantially affected the occupational mobility of eligible individuals. An exception is column 2, which shows that employment in licensed occupations increased between 2012 and 2016 by almost 1 percentage point. That might be because DACA provided individuals with SSNs, allowing them to apply for occupational licenses. I find no evidence that eligible individuals shifted to or away from service, non-service, or essential occupations after the policy. Finally, I also do not find any change in the work schedules or task intensity of eligible individuals.

The absence of effects of DACA on occupations might have two explanations. The first is that DACA had moderate effects on employment and did not change the composition of jobs pursued by individuals. The policy might have not had enough time to push individuals to better occupations, so it only provided a short-term push to jobs. The second might pertain to the sample used in the analysis, as it is restricted to individuals between the ages of 18 and 30. That might mask the variation in occupational mobility that might have been experienced by older individuals. Broadly, my findings confirm interviews documented in Patler et al (2020). The authors assert that recipients did not necessarily move to better jobs, but rather took jobs that fit their interests and lifestyles, providing pathways for future mobility.

Table 3: Difference-in-Difference Effects on Occupation Outcomes

	(1) Essential	(2) Licensed Occupation	(3) Service Occupation	(4) Non-Service Occupation	(5) Manual-Intensive	(6) Analytical-Intensive
Elig*Post12	0.00110	0.00990*	0.00337	-0.0103	0.0154	-0.0148
	(0.010)	(0.005)	(0.012)	(0.009)	(0.011)	(0.011)
Elig*Post17	0.00343	0.0129	0.00357	-0.0242	0.0108	-0.0222
	(0.015)	(0.008)	(0.014)	(0.015)	(0.016)	(0.016)
Eligible	-0.000480	-0.00224	-0.00254	0.0112	-0.0163	0.0162*
	(0.009)	(0.004)	(0.011)	(0.007)	(0.011)	(0.009)
Mean Y	0.798	0.0447	0.264	0.181	0.251	0.249
Observations	57209	57209	57209	57209	57143	57143
R-squared	0.0455	0.0866	0.0681	0.310	0.0685	0.273

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the difference-in-differences estimates of Equation (1) on occupation outcomes. Year and state fixed effects and state-specific time trends are added. Standard errors are clustered at the state-year level. Estimates in all columns are derived from a sample of likely undocumented individuals ages 18-30, entered the US between the ages 12-19, satisfy education requirements and who are employed. Data is taken from the 2005-2019 waves of the ACS.

5.2 Event-Studies

Figure 2-Figure 10 present the dynamic employment effects of DACA graphically. Reassuringly, there are no pretrends for the majority of employment outcomes before 2012 between the treatment and the comparison groups. A major exception is the 'in school' outcome variable (Figure 9), that does not exhibit the same level of clean pretrends. Two minor exceptions include 'in the labor force' (Figure 3) and 'unemployed' (Figure 5), which show only one estimate as slightly significant in 2006 and 2008 respectively.

In unpacking the results, the event-study analysis shows that the estimates of the effects of DACA on working increase to reach a maximum in 2016 and then decrease and become insignificant starting 2017. A similar pattern can be seen with the estimates of in the labor force, hours worked and worked last year, but these effects are mostly not significant. There is no evidence that DACA had a significant impact on income or self-employment in any year.

Analyzing occupation outcomes (Figure 11-Figure 16), there are no preexisting trends between the treated and comparison groups before 2012. In addition, there does not seem to be any effect of DACA or Trump on eligible individuals' occupational mobility.

5.3 Mechanism using Google Search Data

It can be concluded from the results above that DACA's outcomes faded out after the Trump administration challenged the program in 2017. I argue that this decrease in the benefits of DACA is due to uncertainty and change in expectations towards the policy, rather than a factual change in the policy itself. To provide secondary evidence of this mechanism, I resort to Google Search Query data, referred to as Google Trends (GT) data. GT data has been increasingly used to measure social attitudes and perceptions (Stephens-Davidowitz, 2014; Stephens-Davidowitz, 2013b; Baker and Fradkin, 2017). I obtain monthly data of searches done in the U.S. between June 01, 2012 and December 31, 2019 for the topic "Deferred Action for Childhood Arrivals," and for the related queries "daca deportation," "daca trump news," and "daca news today"[10]. The variation in the search activity containing these queries basically reflects individuals' awareness of DACA's situation and their inquiring of any change in news.

A Google Search index measures the search intensity by topic or term (x) over a time

[10]Data source: Google Trends (https://www.google.com/trends), accessed August 25, 2021.

period (t) in a geographical area (g) by analyzing web queries according to equation (3) below. The index is then adjusted to reflect the relative search rate. That is, in the area where the search rate was maximum during time period t, the index takes a value 100. Other values are computed relative to the maximum search rate.

$$\text{GT Index}_g = \left(\frac{\#\ \text{Searches (topic x)}}{\text{Total}\ \#\ \text{Searches}}\right)_{g,t} \tag{3}$$

Figure A1, in the Appendix, plots the trend in the GT indices for the 4 search queries specified above. The four graphs move together and spike to a maximum of 100 in September 2017, when President Trump announced the recession of DACA. The indices are almost zero in the months before September 2016, indicating very low search activity. The values start to increase in September 2016. After September 2017, the graph shows another jump that is smaller relative to the previous one. The intense search activity after September 2017 indicates that individuals were aware and worried of news related to DACA and Trump. Thus, in the absence of a change in the actual benefits of DACA and in the renewals of the DACA status (Figure 1), this search behavior supports that uncertainty and change in expectations towards the policy along with a fear of deportation are the mechanisms through which the benefits of DACA faded out.

5.4 Robustness

5.4.1 Multiple Hypothesis Testing

Several studies have shed light on the problems of simultaneous inference when the analysis covers a large number of outcomes, as the probability of at least one false rejection increases. To correct for that, I apply 3 different types of multiple inference adjustments. First, I calculate p-values using Bonferroni's correction method. Second, I compute sharpened false discovery rates (FDR), q-values, using Anderson's (2008) procedure. Finally, I compute randomization inference p-values based on Young (2019, 2021). The latter runs a joint test of the null hypothesis that there isn't a treatment that has any effect.

The computed p-values are presented in Table A4 and Table A5. Using the sharpened q-values, the estimate of the likelihood of being unemployed is significant at 10% rather than 5% after 2012. In addition, the estimates of the likelihood of attending school is significant at 5% rather than 1% level. These estimates are not significant using Bonferroni's method. As for the occupation outcomes, the estimate of licensed occupations is significant at 10% level when looking at sharpened q-values and non-significant using Bonferroni's method. Finally, I reject the null of complete irrelevance that reflects no effect of any treatment using Young p-values ($p < 0.01$).

5.4.2 Compositional Changes

One major concern when working with repeated cross-sectional data in a difference-in-difference framework is compositional changes. That is, the composition or the characteristics of the treated group change over time, and these demographic changes drive the results rather than the actual policies. To check that, I estimate the effect of DACA on observable characteristics. Following Pope (2016), I use the Event-Study specification, without controls or fixed effects. Table A6 presents the results. As expected, the coefficients on years spent in the US and the age of entry to the US are significant because of how the sample is constructed. Similarly, the coefficients on age are significant and positive, a result of the sample construction as well. Since the sample includes individuals who are between 18 and 30 years old, the requirement of being 31 years old by June 2012 is binding in survey years 2005 - 2012, making the average age of the treated group low in this time period. However, in the following survey years, this requirement becomes less binding given that the majority the sample satisfies it, increasing the average age of the treated group. Figure A2 shows the trend in average age for the treated and comparison groups. For this reason, the addition of age fixed effects in the main specification, controlling for this change in ages, is essential.

Another concern is that the sample of individuals who are inclined to answer the ACS survey is different that those who are not. Although responding to the ACS is required by law, some individuals do not respond to the survey until they are randomly chosen to be contacted in person. I run the analysis separately for those who had an in-person interview. Table A7 and Table A8 present the results of the analysis using this sample. Unlike the overall sample, the estimates of the likelihood of working and having worked last year are significant after 2017. However, they are smaller in magnitude than those between 2012 and 2016. Thus, the conclusions do not change regarding the effectiveness of DACA and the decrease in its benefits after 2017.

5.4.3 Change in Response Rates

One threat to the validity of the results is the change in the likelihood of completing the ACS survey after receiving DACA status. It is possible that individuals' hesitancy to honestly respond changes after they become eligible for DACA, as they are granted relief from deportation. In this case, the estimates would be capturing an increase in honest response about employment between 2012 and 2016. Similarly, the estimates would be capturing a decrease in response after 2017, as individuals become hesitant to answer about their employment. I test for such changes by estimating equation (1) using the quality flags in the ACS, following Pope (2016). In this case, each outcome variable is a dummy variable that takes the value one if the variable was not answered but rather imputed by ACS, and zero otherwise. If there's an effect of Trump on eligible individuals' response rate, that would show as a significant increase in the likelihood of imputing outcome variables.

Table A9 of the Appendix presents the results. Between 2012 and 2016, there was no effect of DACA on survey-item response. After 2017, the results show that there is a 1.91 percentage points increase in the likelihood of imputing the occupation variable and a 1.96 percentage point increase in the likelihood of imputing the self-employed variable. These estimates are significant at the 10% level. In addition, there is a 3.1 percentage points increase in the likelihood of imputing the hours worked variable, that is significant at the 5% level. All in all, these findings show that the DACA eligible individuals did not change their survey response behavior between 2012 and 2016. After 2017, there is a slight change in this behavior, but it is not large in magnitude or highly significant.

6 Heterogeneity

In this section, I look at the differential effects of DACA on labor-market and education outcomes across ethnicity, states, and their political environments. I show that benefits of DACA are not shared equally among all eligible individuals, but rather widely vary with the place of residence and ethnicity.

6.1 By Gender

Table 4 shows that the employment effects of DACA were larger for females than males after 2012. After 2017, the effects of DACA persist but slightly decrease for males and disappear for females. Column (3) shows that the estimate on the hours worked outcome is significant and larger after 2017 than after 2012 for males.

6.2 By Ethnicity and Mexican Origin

Panel A of Table 5 looks at the sample of likely undocumented individuals of Hispanic ethnicity. Results show that DACA had significant and positive effects on employment outcomes of Hispanic eligible individuals, that are larger in magnitude than the estimates of the whole sample (panel A). This group experienced an increase in the likelihood of working and participating in the labor force by 5.2 percentage points and 4.13 percentage points, respectively. After 2017, the benefits of DACA persist with smaller magnitudes, but hours worked increase more than the previous period. The likelihood of being in school decreases by 6.37 percentage points, a sharper dip than that between 2012 and 2016 (3.03 percentage points). As for the non-Hispanic eligible individuals, results show that there are smaller positive effects of DACA on the likelihood of working (3.68 percentage points); these effects do not persist after 2017 (panel B).

Focusing specifically on individuals of Mexican origin, results of Table 6 show the effects of DACA after 2017 are persistent, significant, and positive. Column (1), panel A, documents that the likelihood of working increases from 4.32 to 5 percentage points for eligible individuals after 2017. This might be due to the fact that the Hispanic community, including those of Mexican origin, are larger than other communities of the DACA-eligible population, with more established networks.

6.3 By Political Environments

To analyze the results in terms of different political environments, I look at the effects of DACA in Democratic versus Republican states. Generally, Democratic states have provided a safety net for unauthorized individuals; some of them, like California, have sued the Trump administration to halt DACA's rescission. On the contrary, Republican states have acted to restrict undocumented individuals. Table 7 shows the effect of DACA in these two different environments. Panel B documents a highly significant increase in the likelihood of working and being in the labor force after 2012 for eligible individuals in Republican states. In addition, column (4) shows a significant decrease in unemployment and the likelihood of attending school, which is larger in magnitude than those seen in Democratic states. After

2017, the results of DACA persist in Democratic states, but disappear in Republican ones. Given that DACA technically gave more security and benefits to individuals in Republican states as they were not as protected on the state-level, it seems plausible that the results of DACA in these states were sizeable after 2012, but non-significant after 2017.

Finally, Table 8 shows the impacts of DACA by Hispanic ethnicity across political environments. The findings of panels C and D imply that the non-Hispanic eligible individuals did not benefit much from DACA, but were hurt more in Republican states after 2017, although the negative estimates are not significant. As for Hispanic eligible individuals, they do not derive any benefits of DACA after 2017 in Republican states, or retain some of the positive increases in employment in Democratic states. These results confirm that the effects of temporary policies, like DACA, are very volatile and are affected by state-level institutions and environments.

All in all, not all eligible populations were able to equally benefit from DACA. Other institutional environments and network effects were at play in who benefits from DACA and how much.

7 Conclusion

In this paper, I examine the fluctuations in the effects of the Deferred Action of Childhood Arrivals (DACA) after the Trump administration actively worked on rescinding the program in 2017. I focus on two aspects, uncertainty and risk, as vital factors that drive the outcomes of a temporary immigration policy. Looking at the sample of likely undocumented individuals and utilizing a difference-in-difference methodology, I find that DACA indeed had positive and significant effects on labor market outcomes between 2012 and 2016. However, the effects of DACA on employment fade out after 2017. Eligible individuals' investment in education decreases after DACA's enactment, and more so after 2017. These results imply chilling effects induced by the uncertainty of the continuation of the policy. Taken together, my results show that the change in perceived risk altered the employment and education decisions of eligible individuals. Looking at the heterogeneous effects of DACA across political environments and ethnicities, I find that the fluctuations in DACA's outcomes widely varied.

This study holds important policy ramifications. To begin with, any cost-benefit analysis of DACA, or other temporary policies, should take into account that the policy's outcomes are volatile and are affected by other factors, that are not controlled by its recipients. For instance, in 2020, the Supreme Court asserted that DACA can be rescinded if the right legal actions were taken. This implies that DACA might face future challenges, further depressing the outcomes of the policy. In this case, the policy's benefits might be underestimated, biasing any conclusion about the policy's advantages.

On the other hand, the Biden administration seems focused on improving the well-being of undocumented immigrants, especially after a large proportion of them proved their essential role in the economy during the Covid-19 pandemic[11]. Thus, understanding the impacts of DACA and the factors that drive them is crucial before passing the next immigration legislation. Given that temporary policies can be volatile, it is important to find a policy that focuses on a permanent legalization strategy in order to help undocumented immigrants totally integrate in the economy in the long-term.

[11] On March 18^{th}, 2021, President Biden gave a statement, praising the House of Representatives for passing the American Dream and Promise Act of 2021. Source: https://www.whitehouse.gov/briefing-room/statements-releases/2021/03/18/statement-by-president-biden-on-the-american-dream-and-promise-act-of-2021/.

8 Heterogeneity Analysis Tables

Table 4: Difference-in-Difference Effects by Gender

	(1) Working	(2) In the Labor Force	(3) Hours Worked	(4) Unemployed	(5) Self-employed	(6) Worked last year	(7) Log Total Personal Income	(8) In School	(9) GED
Panel A: Female									
Elig*Post12	0.0501***	0.0506***	1.847***	-0.00398	0.00188	0.0553***	-0.0153	-0.0259*	0.00376
	(0.016)	(0.016)	(0.569)	(0.013)	(0.009)	(0.016)	(0.041)	(0.014)	(0.006)
Elig*Post17	0.0213	0.00452	1.418	-0.00737	0.0130	0.0226	-0.0296	-0.0101	-0.000793
	(0.023)	(0.021)	(0.864)	(0.013)	(0.016)	(0.022)	(0.065)	(0.019)	(0.010)
Eligible	-0.00506	-0.0123	0.275	-0.00923	-0.00604	-0.00885	0.00582	-0.0152	0.00932**
	(0.012)	(0.013)	(0.482)	(0.011)	(0.007)	(0.013)	(0.036)	(0.010)	(0.004)
Observations	45486	45486	45486	25007	30511	45486	28673	45486	35265
R-squared	0.117	0.121	0.154	0.0335	0.0241	0.109	0.236	0.454	0.0453
Panel B: Male									
Elig*Post12	0.0477***	0.0290**	0.926*	-0.0241***	-0.0122*	0.0250**	0.0260	-0.0210*	0.000815
	(0.012)	(0.012)	(0.532)	(0.009)	(0.007)	(0.011)	(0.031)	(0.011)	(0.006)
Elig*Post17	0.0281*	0.0145	1.519**	-0.0104	0.00164	0.0204	0.0115	-0.0392**	0.00892
	(0.017)	(0.014)	(0.692)	(0.011)	(0.013)	(0.014)	(0.045)	(0.016)	(0.009)
Eligible	-0.00918	-0.000285	-0.456	0.0116	0.00109	-0.00785	-0.0841***	0.00568	0.0125**
	(0.011)	(0.012)	(0.453)	(0.008)	(0.007)	(0.010)	(0.030)	(0.012)	(0.006)
Observations	55024	55024	55024	37781	42661	55024	42052	55024	42612
R-squared	0.285	0.310	0.336	0.0378	0.0174	0.278	0.240	0.475	0.0422

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the difference-in-differences estimates of Equation (1) on employment and education outcomes by gender. Year and state fixed effects and state-specific time trends are added. Standard errors are clustered at the state-year level. Estimates in all columns are derived from a sample of likely undocumented individuals ages 18-30, who entered the US between the ages 12-19, and satisfy education requirements. Data is taken from the 2005-2019 waves of the ACS.

Table 5: Difference-in-Difference Effects by Hispanic Ethnicity

	(1) Working	(2) In the Labor Force	(3) Hours Worked	(4) Unemployed	(5) Self-employed	(6) Worked last year	(7) Log Total Personal Income	(8) In School	(9) GED
Panel A: Hispanic									
Elig*Post12	0.0520***	0.0413***	1.288***	-0.0173**	-0.0109	0.0345***	0.0260	-0.0303***	0.00186
	(0.011)	(0.011)	(0.488)	(0.009)	(0.007)	(0.011)	(0.025)	(0.010)	(0.006)
Elig*Post17	0.0354**	0.0249*	2.172***	-0.0120	0.00999	0.0371**	0.0461	-0.0637***	0.000594
	(0.017)	(0.014)	(0.784)	(0.010)	(0.014)	(0.015)	(0.037)	(0.011)	(0.010)
Eligible	-0.00954	-0.00527	-0.348	0.00571	-0.000589	-0.0127	-0.0285	-0.00106	0.0120**
	(0.011)	(0.010)	(0.422)	(0.008)	(0.007)	(0.011)	(0.024)	(0.009)	(0.006)
Observations	47907	47907	47907	36115	39683	47907	37885	47907	34627
R-squared	0.154	0.157	0.215	0.0280	0.0157	0.168	0.180	0.264	0.0330
Panel B: Non-Hispanic									
Elig*Post12	0.0368**	0.0254	1.037	-0.0171	0.00222	0.0384**	-0.0395	-0.00841	-0.00302
	(0.018)	(0.016)	(0.726)	(0.016)	(0.008)	(0.017)	(0.050)	(0.013)	(0.005)
Elig*Post17	0.0118	-0.00831	0.173	-0.0108	0.00204	0.000938	-0.0609	-0.00512	0.00577
	(0.026)	(0.022)	(0.891)	(0.018)	(0.013)	(0.022)	(0.064)	(0.022)	(0.009)
Eligible	-0.00789	-0.00410	-0.118	0.00409	-0.00634	-0.00729	-0.0782*	-0.0157	0.00794*
	(0.013)	(0.013)	(0.495)	(0.012)	(0.007)	(0.012)	(0.042)	(0.012)	(0.004)
Observations	52603	52603	52603	26673	33489	52603	32840	52603	43250
R-squared	0.207	0.220	0.283	0.0464	0.0286	0.183	0.328	0.387	0.0558

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the difference-in-differences estimates of Equation (1) on employment and education outcomes by Hispanic ethnicity. Year and state fixed effects and state-specific time trends are added. Standard errors are clustered at the state-year level. Estimates in all columns are derived from a sample of likely undocumented individuals ages 18-30, who entered the US between the ages 12-19, and satisfy education requirements. Data is taken from the 2005-2019 waves of the ACS.

Table 6: Difference-in-Difference Effects by Mexican Origin

	(1) Working	(2) In the Labor Force	(3) Hours Worked	(4) Unemployed	(5) Self-employed	(6) Worked last year	(7) Log Total Personal Income	(8) In School	(9) GED
Panel A: Mexican									
Elig*Post12	0.0432***	0.0367***	0.982*	-0.0122	-0.0140*	0.0276**	0.0373	-0.0230*	0.00556
	(0.013)	(0.013)	(0.593)	(0.010)	(0.008)	(0.013)	(0.029)	(0.012)	(0.008)
Elig*Post17	0.0500**	0.0437**	2.821**	-0.0102	0.00952	0.0465**	0.0597	-0.0608***	-0.000614
	(0.024)	(0.020)	(1.104)	(0.013)	(0.017)	(0.021)	(0.054)	(0.013)	(0.010)
Eligible	-0.00398	0.000256	0.0248	0.00518	-0.00851	0.00409	-0.0677**	-0.0108	0.00815
	(0.012)	(0.010)	(0.491)	(0.010)	(0.009)	(0.012)	(0.027)	(0.010)	(0.008)
Observations	31834	31834	31834	24138	26513	31834	25190	31834	22193
R-squared	0.189	0.195	0.249	0.0316	0.0170	0.209	0.171	0.209	0.0334
Panel B: Non-Mexican									
Elig*Post12	0.0443***	0.0302**	1.210**	-0.0197*	-0.00124	0.0391***	-0.0348	-0.0168	-0.00418
	(0.015)	(0.014)	(0.562)	(0.010)	(0.007)	(0.014)	(0.036)	(0.012)	(0.005)
Elig*Post17	-0.00373	-0.0224	-0.138	-0.00838	0.00670	-0.00174	-0.0700	-0.00396	0.00843
	(0.018)	(0.017)	(0.672)	(0.012)	(0.013)	(0.017)	(0.048)	(0.017)	(0.009)
Eligible	-0.0110	-0.00726	-0.399	0.00635	0.000425	-0.0174*	-0.0354	-0.000792	0.0117***
	(0.011)	(0.011)	(0.413)	(0.009)	(0.006)	(0.010)	(0.032)	(0.010)	(0.004)
Observations	68676	68676	68676	38650	46659	68676	45535	68676	55684
R-squared	0.207	0.220	0.279	0.0376	0.0254	0.186	0.299	0.419	0.0496

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the difference-in-differences estimates of Equation (1) on employment and education outcomes by Mexican Origin. Year and state fixed effects and state-specific time trends are added. Standard errors are clustered at the state-year level. Estimates in all columns are derived from a sample of likely undocumented individuals ages 18-30, who entered the US between the ages 12-19, and satisfy education requirements. Data is taken from the 2005-2019 waves of the ACS.

Table 7: Difference-in-Difference Effects by Political Party

	(1) Working	(2) In the Labor Force	(3) Hours Worked	(4) Unemployed	(5) Self-employed	(6) Worked last year	(7) Log Total Personal Income	(8) In School	(9) GED
Panel A: Democratic States									
Elig*Post12	0.0539***	0.0489***	1.637***	-0.0122	-0.0129*	0.0552***	-0.0221	-0.0195*	0.00589
	(0.016)	(0.016)	(0.568)	(0.009)	(0.007)	(0.015)	(0.031)	(0.011)	(0.005)
Elig*Post17	0.0345*	0.0251	1.972**	-0.00734	-0.00577	0.0430**	-0.0147	-0.0392**	0.00456
	(0.021)	(0.018)	(0.764)	(0.012)	(0.013)	(0.017)	(0.050)	(0.018)	(0.010)
Eligible	0.000747	0.00499	0.0694	0.00567	0.00313	0.000861	-0.0476	-0.0109	0.00587
	(0.012)	(0.013)	(0.445)	(0.009)	(0.006)	(0.011)	(0.032)	(0.012)	(0.005)
Observations	56641	56641	56641	35921	41502	56641	40286	56641	43277
R-squared	0.194	0.207	0.262	0.0308	0.0150	0.186	0.244	0.445	0.0430
Panel B: Republican States									
Elig*Post12	0.0465***	0.0304**	1.098*	-0.0205*	0.000161	0.0228	0.0480	-0.0281**	-0.00330
	(0.014)	(0.015)	(0.650)	(0.012)	(0.008)	(0.014)	(0.037)	(0.014)	(0.007)
Elig*Post17	0.00894	-0.0110	0.602	-0.0108	0.0200	-0.00841	0.0132	-0.0147	0.00391
	(0.020)	(0.019)	(0.914)	(0.013)	(0.016)	(0.019)	(0.053)	(0.018)	(0.009)
Eligible	-0.0212*	-0.0224	-0.544	0.00192	-0.0101	-0.0228*	-0.0464	0.00572	0.0173***
	(0.013)	(0.014)	(0.535)	(0.011)	(0.007)	(0.014)	(0.037)	(0.011)	(0.006)
Observations	43869	43869	43869	26867	31670	43869	30439	43869	34600
R-squared	0.193	0.200	0.263	0.0356	0.0215	0.172	0.259	0.493	0.0394

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the difference-in-differences estimates of Equation (1) on labor market outcomes by political environments of states where individuals reside. A state is considered Democrat or Republican based on the results of the 2016 Presidential election (source: www.nytimes.com/elections/2016/results/president). Year and state fixed effects and state-specific time trends are added. Standard errors are clustered at the state-year level. Estimates in all columns are derived from a sample of likely undocumented individuals ages 18-30, who entered the US between the ages 12-19, and satisfy education requirements. Data is taken from the 2005-2019 waves of the ACS.

Table 8: Difference-in-Difference Effects by Hispanic Ethnicity and by Political Party

	(1) Working	(2) In the Labor Force	(3) Hours Worked	(4) Unemployed	(5) Self-employed	(6) Worked last year	(7) Log Total Personal Income	(8) In School	(9) GED
Panel A: Hispanic in Democratic States									
Elig*Post12	0.0523***	0.0457***	1.782***	-0.0118	-0.0207**	0.0507***	0.00200	-0.0228*	0.00683
	(0.014)	(0.014)	(0.593)	(0.011)	(0.009)	(0.014)	(0.034)	(0.013)	(0.009)
Elig*Post17	0.0399	0.0237	2.445**	-0.0182	-0.00494	0.0522**	0.0390	-0.0692***	-0.00103
	(0.025)	(0.020)	(1.142)	(0.014)	(0.017)	(0.020)	(0.051)	(0.016)	(0.016)
Eligible	0.000806	0.00745	-0.253	0.00693	0.0111	0.000925	-0.0700**	0.000484	0.00191
	(0.015)	(0.013)	(0.567)	(0.011)	(0.008)	(0.014)	(0.028)	(0.012)	(0.008)
Observations	25053	25053	25053	19469	21178	25053	20305	25053	17725
R-squared	0.144	0.145	0.201	0.0278	0.0126	0.156	0.177	0.248	0.0339
Panel B: Hispanic in Republican States									
Elig*Post12	0.0499***	0.0351**	0.675	-0.0221*	-0.000478	0.0160	0.0466	-0.0369**	-0.00311
	(0.017)	(0.017)	(0.774)	(0.013)	(0.011)	(0.016)	(0.037)	(0.014)	(0.009)
Elig*Post17	0.0267	0.0207	1.716	-0.00556	0.0259	0.0194	0.0445	-0.0554***	0.00100
	(0.024)	(0.020)	(1.075)	(0.014)	(0.021)	(0.021)	(0.055)	(0.015)	(0.011)
Eligible	-0.0243	-0.0218	-0.523	0.00562	-0.0188*	-0.0316**	0.0314	-0.00443	0.0229***
	(0.015)	(0.015)	(0.629)	(0.012)	(0.010)	(0.014)	(0.043)	(0.013)	(0.008)
Observations	22854	22854	22854	16646	18505	22854	17580	22854	16902
R-squared	0.166	0.168	0.230	0.0313	0.0195	0.181	0.185	0.284	0.0340
Panel C: Non-Hispanic in Democratic States									
Elig*Post12	0.0459*	0.0440**	1.005	-0.0117	-0.00128	0.0526**	-0.0768	-0.0111	0.00215
	(0.025)	(0.022)	(0.992)	(0.019)	(0.010)	(0.025)	(0.060)	(0.016)	(0.006)
Elig*Post17	0.0224	0.0213	0.890	0.00489	-0.00463	0.0251	-0.0874	-0.0224	0.00761
	(0.037)	(0.028)	(1.004)	(0.026)	(0.018)	(0.027)	(0.083)	(0.026)	(0.009)
Eligible	-0.00576	0.000192	0.178	0.00668	-0.00952	-0.00558	-0.0345	-0.0224	0.00873*
	(0.016)	(0.016)	(0.600)	(0.015)	(0.009)	(0.015)	(0.053)	(0.015)	(0.005)
Observations	31588	31588	31588	16452	20324	31588	19981	31588	25552
R-squared	0.207	0.220	0.281	0.0422	0.0297	0.189	0.314	0.372	0.0594
Panel D: Non-Hispanic in Republican States									
Elig*Post12	0.0203	-0.00454	0.879	-0.0253	0.00631	0.0158	0.0139	-0.000401	-0.00993
	(0.026)	(0.025)	(1.059)	(0.026)	(0.011)	(0.024)	(0.083)	(0.023)	(0.009)
Elig*Post17	-0.00339	-0.0498	-0.777	-0.0357	0.0107	-0.0338	0.00185	0.0211	0.00265
	(0.034)	(0.035)	(1.544)	(0.023)	(0.019)	(0.033)	(0.099)	(0.040)	(0.017)
Eligible	-0.00629	-0.00595	-0.369	-0.000841	0.000396	-0.00566	-0.142**	-0.00823	0.00692
	(0.020)	(0.022)	(0.790)	(0.019)	(0.011)	(0.021)	(0.067)	(0.019)	(0.007)
Observations	21015	21015	21015	10221	13165	21015	12859	21015	17698
R-squared	0.209	0.222	0.289	0.0573	0.0342	0.180	0.333	0.407	0.0543

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the difference-in-differences estimates of Equation (1) on labor market outcomes by Hispanic ethnicity across political environments of states. Year and state fixed effects and state-specific time trends are added. Standard errors are clustered at the state-year level. Estimates in all columns are derived from a sample of likely undocumented individuals ages 18-30, who entered the US between the ages 12-19, and satisfy education requirements. Data is taken from the 2005-2019 waves of the ACS.

9 Event-Study Figures

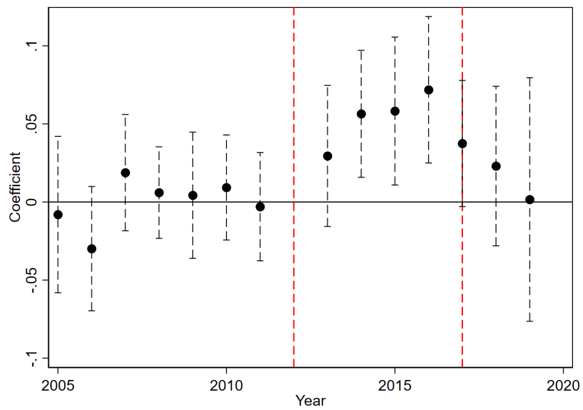


Figure 2: Working

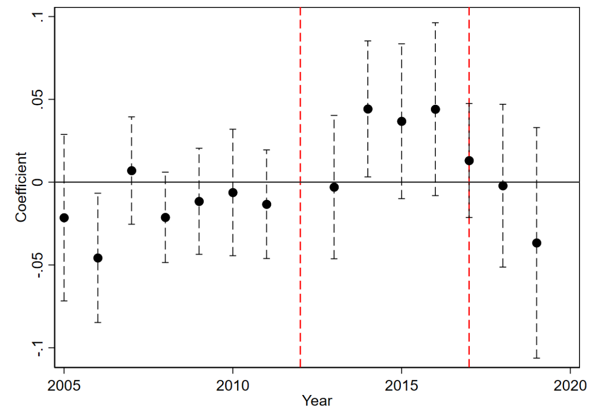


Figure 3: In the Labor Force

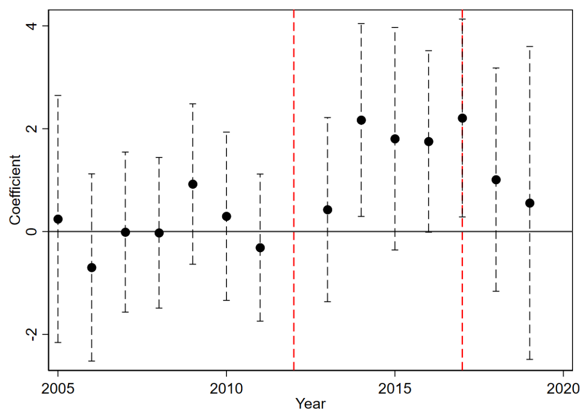


Figure 4: Hours Worked

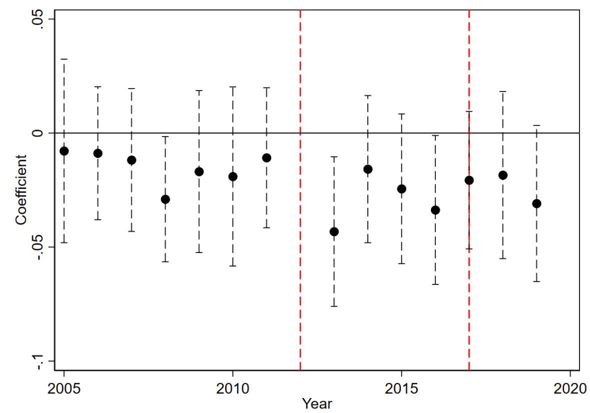


Figure 5: Unemployed

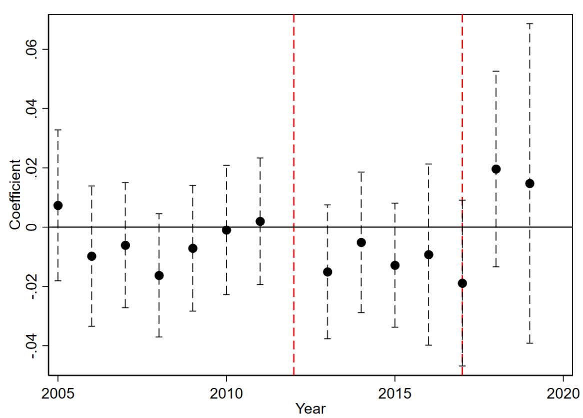


Figure 6: Self-Employed

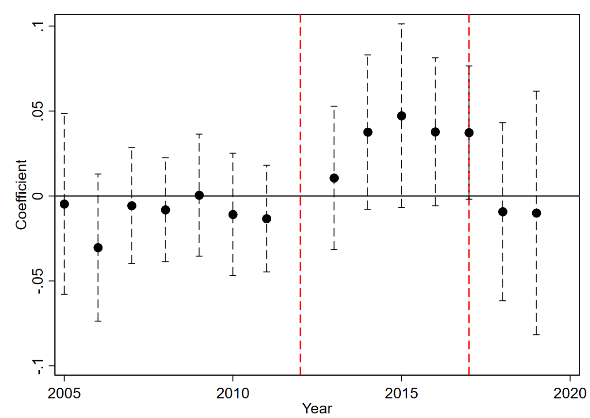


Figure 7: Worked Last Year

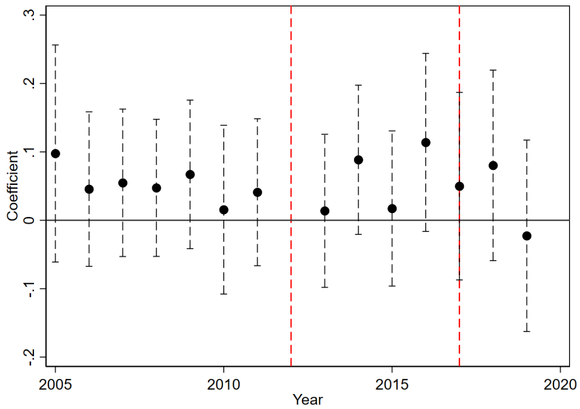


Figure 8: Log of Total Income

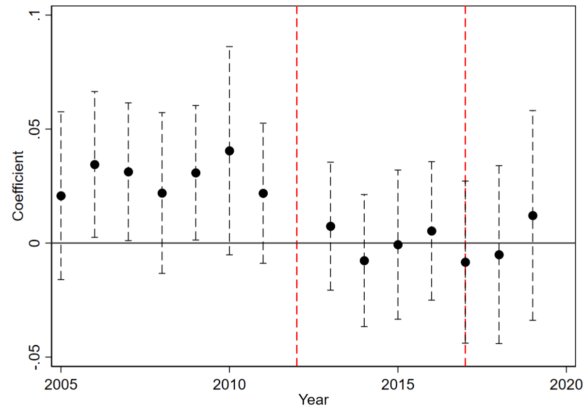


Figure 9: In School

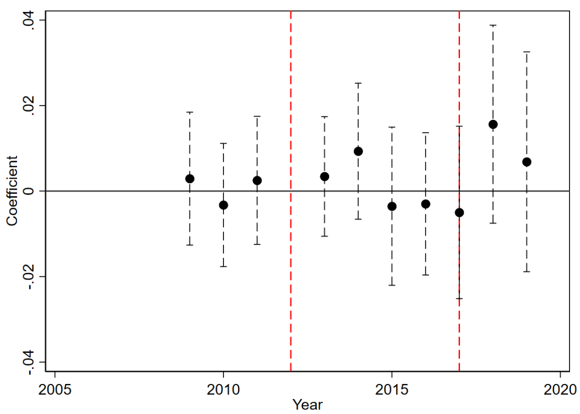


Figure 10: GED

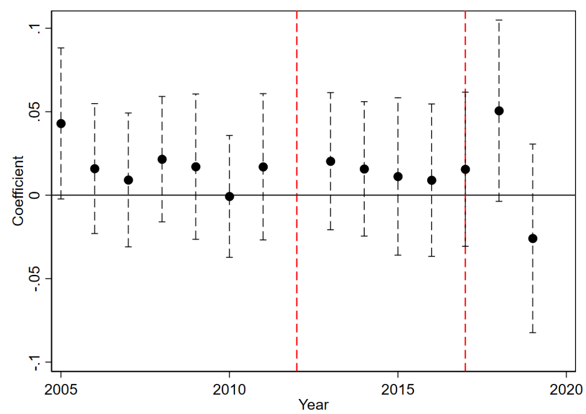


Figure 11: Essential

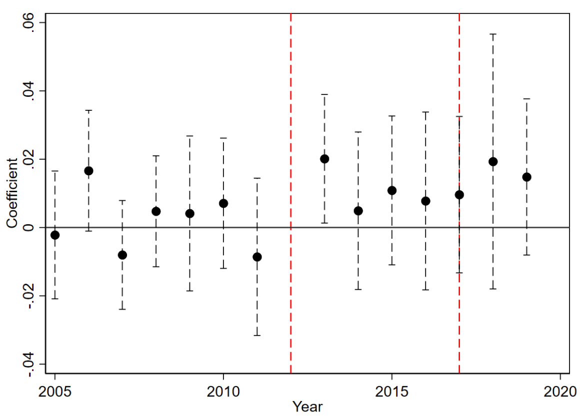


Figure 12: Licensed Occupation

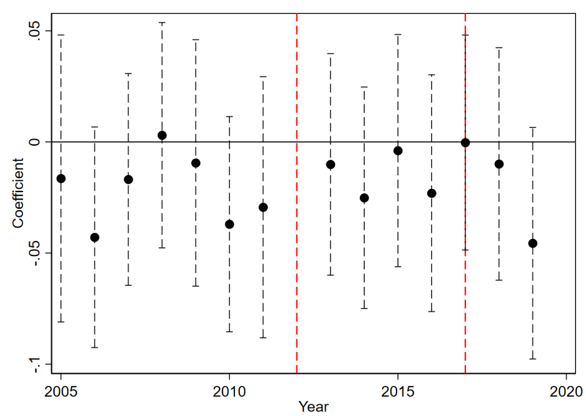


Figure 13: Service Occupation

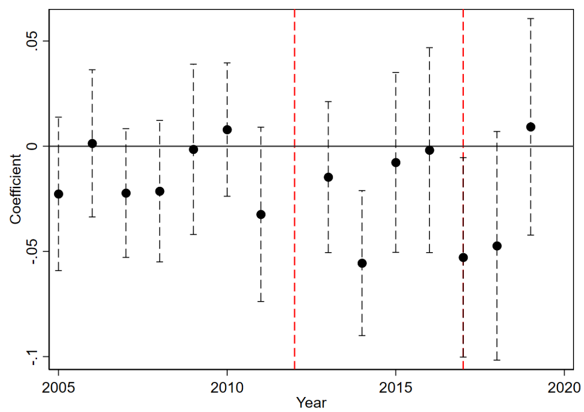


Figure 14: Non-Service Occupation

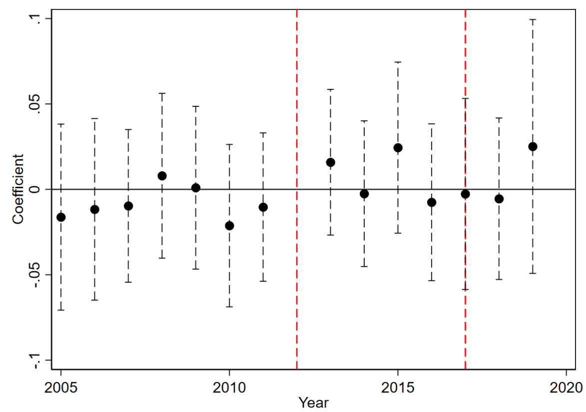


Figure 15: Manual-Intensive Tasks

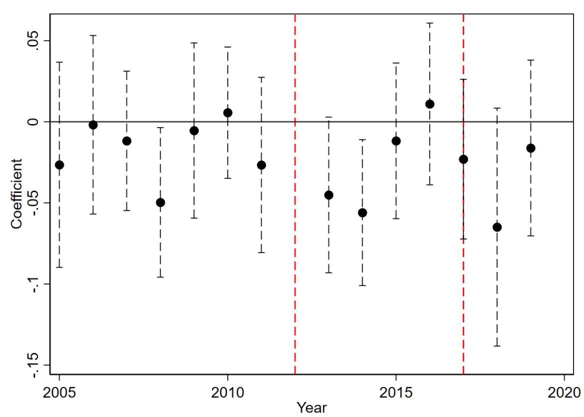


Figure 16: Analytical-Intensive Tasks

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A Appendix

A.1 Tables and Figures

Table A1: Summary Statistics of Outcome Variables.

	(1) All Sample	(2) DACA Eligible	(3) DACA Ineligible
Working	61.63	69.62	59.38
	(48.63)	(45.99)	(49.11)
In the Labor Force	67.29	76.37	64.72
	(46.92)	(42.48)	(47.78)
Hours Worked	25.70	28.86	24.81
	(19.75)	(18.41)	(20.02)
Unemployed	8.404	8.842	8.258
	(27.75)	(28.39)	(27.52)
Self-employed	5.304	5.216	5.333
	(22.41)	(22.24)	(22.47)
Worked last year	69.88	77.60	67.70
	(45.88)	(41.70)	(46.76)
Log Total Personal Income	9.479	9.573	9.450
	(1.219)	(1.110)	(1.249)
Essential	59.24	65.06	57.59
	(49.14)	(47.68)	(49.42)
Licensed Occupation	3.470	3.446	3.477
	(18.30)	(18.24)	(18.32)
Service Occupation	19.93	21.07	19.61
	(39.95)	(40.78)	(39.70)
Non-Service Occupation	13.71	14.54	13.48
	(34.40)	(35.25)	(34.15)
Manual-Intensive	19.17	20.30	18.85
	(39.37)	(40.23)	(39.11)
Analytical-Intensive	43.81	38.33	45.35
	(49.62)	(48.62)	(49.78)
In School	36.30	28.07	38.63
	(48.09)	(44.93)	(48.69)
GED	2.284	3.199	2.026
	(14.94)	(17.60)	(14.09)
Observations	100510	20766	79744

Standard deviations in parentheses. Sample is using ACS data (2005-2019).

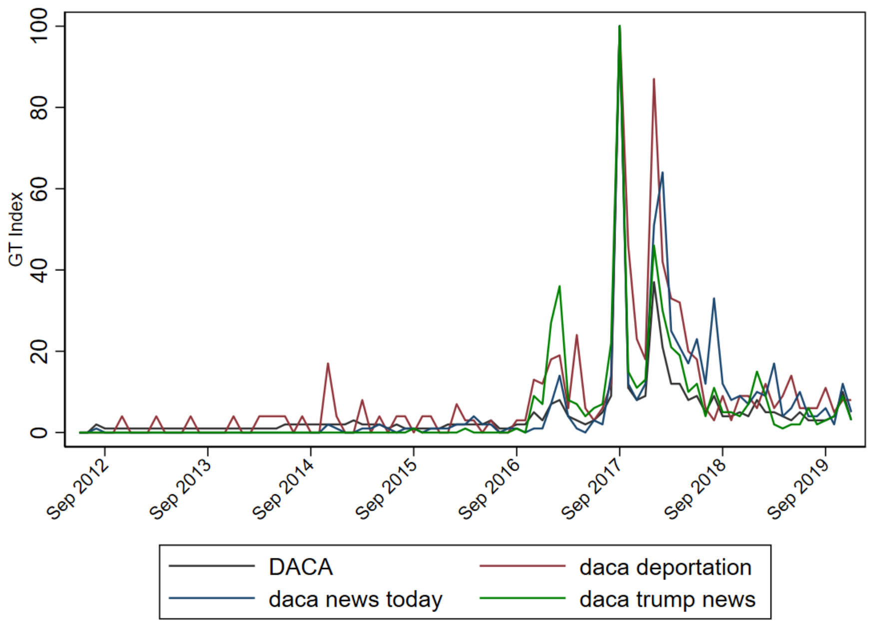

Figure A1: Temporal Variation in Google Trends Indices

Table A2: Sensitivity of Employment Effects to State-time Trends

	(1) Working	(2) In the Labor Force	(3) Hours Worked	(4) Unemployed	(5) Self-employed	(6) Worked last year	(7) Log Total Personal Income	(8) In School	(9) GED
Elig*Post12	0.0519***	0.0418***	1.460***	-0.0164**	-0.00668	0.0411***	0.0153	-0.0252***	0.00175
	(0.010)	(0.011)	(0.426)	(0.008)	(0.005)	(0.011)	(0.025)	(0.009)	(0.004)
Elig*Post17	0.0268*	0.0122	1.479**	-0.00999	0.00707	0.0211	0.00149	-0.0310**	0.00521
	(0.015)	(0.013)	(0.600)	(0.009)	(0.011)	(0.014)	(0.036)	(0.013)	(0.007)
Eligible	-0.00999	-0.00796	-0.230	0.00468	-0.00201	-0.0104	-0.0455*	-0.00300	0.0108***
	(0.009)	(0.010)	(0.358)	(0.007)	(0.005)	(0.009)	(0.024)	(0.008)	(0.004)
Observations	100510	100510	100510	62788	73172	100510	70725	100510	77877
R-squared	0.191	0.202	0.259	0.0304	0.0157	0.177	0.250	0.464	0.0397

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the difference-in-differences estimates of Equation (1) on employment and education outcomes. Year and state fixed effects **without controlling for state-specific time trends**. Standard errors are clustered at the state-year level. Estimates in all columns are derived from a sample of likely undocumented individuals ages 18-30, who entered the US between the ages 12-19, and satisfy education requirements. Data is taken from the 2005-2019 waves of the ACS.

Table A3: Sensitivity of Occupation Effects to State-time Trends

	(1) Essential	(2) Licensed Occupation	(3) Service Occupation	(4) Non-Service Occupation	(5) Manual-Intensive	(6) Analytical-Intensive
Elig*Post12	-0.0000530	0.0103**	0.00464	-0.0106	0.0155	-0.0151
	(0.010)	(0.005)	(0.012)	(0.009)	(0.011)	(0.011)
Elig*Post17	0.00164	0.0126	0.00514	-0.0245*	0.0113	-0.0227
	(0.015)	(0.008)	(0.014)	(0.015)	(0.016)	(0.016)
Eligible	-0.000911	-0.00216	-0.00187	0.0108	-0.0158	0.0157*
	(0.009)	(0.004)	(0.011)	(0.007)	(0.011)	(0.009)
Observations	57209	57209	57209	57209	57143	57143
R-squared	0.0437	0.0851	0.0658	0.309	0.0670	0.272

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the difference-in-differences estimates of Equation (1) on occupation outcomes. Year and state fixed effects **without controlling for state-specific time trends**. Standard errors are clustered at the state-year level. Estimates in all columns are derived from a sample of likely undocumented individuals ages 18-30, who entered the US between the ages 12-19, and satisfy education requirements. Data is taken from the 2005-2019 waves of the ACS.

Table A4: Multiple Hypothesis Testing of Employment Outcomes

		(1) Working	(2) In Labor Force	(3) Hours Worked	(4) Unemployed	(5) Self-employed	(6) Worked Last year	(7) Log Personal Income	(8) In School	(9) GED	All
Elig*Post12	p-value	1.20E-06	0.00020034	0.00078575	0.03030131	0.18664717	0.00019951	0.62060668	0.007148	0.350293	
	sharpened q-value	0.001	0.002	0.003	0.059	0.205	0.002	0.44	0.021	0.309	
	Bonferroni	2.15E-05	0.00360612	0.0141435	1	1	0.00359118	1	0.128663	1	
Elig*Post17	p-value	0.1178068	0.54654151	0.02537568	0.26880747	0.54213865	0.18185476	0.98592403	0.034151	0.274518	
	sharpened q-value	0.151	0.44	0.059	0.268	0.44	0.205	0.614	0.059	0.268	
	Bonferroni	1	1	1	1	1	1	1	0.614711	1	
	Young Westfall-Young Joint Test	0.00091	2.50E-05	0.00114	0.00077	0.00167	0.00013	0.00169	0.99932	0.99939	0.0003

Notes: This table shows the p-values calculated through Anderson's (2008) procedure, Bonferroni's method, and Young's method (2019, 2021).

Table A5: Multiple Hypothesis Testing of Occupation Outcomes

		(1) Essential	(2) Licensed Occupation	(3) Service Occupation	(4) Non-service Occupation	(5) Manual-Intensive	(6) Analytical-Intensive	All
Elig*Post12	p-value	0.9130878	0.05632952	0.7820045	0.27151113	0.15710878	0.18911855	
	sharpened q-value	0.841	0.609	0.817	0.609	0.609	0.609	
	Bonferroni	1	0.67595424	1	1	1	2.2694226	
Elig*Post17	p-value	0.8240195	0.11903316	0.79825911	0.10914075	0.50709944	0.16781156	
	sharpened q-value	0.817	0.609	0.817	0.609	0.614	0.609	
	Bonferroni	1	1.42839792	1	1	1	2.01373872	
	Young Westfall-Young Joint Test	0.0118	0.00081	0.001	3.80E-05	0.0006	0.0009	0.00081

Notes: This table shows the p-values calculated through Anderson's (2008) procedure, Bonferroni's method, and Young's method (2019, 2021).

Table A6: Change in Observable Characteristics between 2012 and 2019

	(1) Age	(2) Male	(3) Hispanic	(4) White	(5) Black	(6) Asian	(7) Born in Latin America	(8) Born in Mexico	(9) HS Degree	(10) Some College Education	(11) College Degree	(12) Years in the United States	(13) Age Entered USA
Eligible*2013	0.243*	-0.00934	0.0162	-0.00197	-0.0106	-0.00434	0.0330	-0.0219	-0.0236	0.00885	0.0148	0.246**	-0.00256
	(0.126)	(0.020)	(0.018)	(0.012)	(0.014)	(0.017)	(0.027)	(0.024)	(0.020)	(0.020)	(0.011)	(0.120)	(0.050)
Eligible*2017	2.732***	0.00399	0.0333	-0.0240**	-0.00245	-0.0187	0.0349	0.0124	-0.0217	-0.0481**	0.0698***	2.882***	-0.150***
	(0.145)	(0.026)	(0.024)	(0.012)	(0.021)	(0.018)	(0.024)	(0.029)	(0.030)	(0.024)	(0.026)	(0.156)	(0.056)
Eligible	0.782***	0.0104	0.121***	-0.0359***	0.00650	-0.0814***	0.0239	0.102***	0.0143	-0.00414	-0.0102	4.475***	-3.693***
	(0.098)	(0.018)	(0.014)	(0.008)	(0.010)	(0.015)	(0.015)	(0.020)	(0.017)	(0.016)	(0.008)	(0.097)	(0.042)
Observations	100510	100510	100510	100510	100510	100510	100510	100510	100510	100510	100510	100510	100510
R-squared	0.0755	0.00240	0.0901	0.0301	0.0549	0.0592	0.159	0.154	0.0197	0.0131	0.0144	0.252	0.522

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the effect of DACA eligibility on observable characteristics. No controls are added. Standard errors are clustered at the state-year level. Estimates in all columns are derived from a sample of likely undocumented individuals ages 18-30, who entered the US between the ages 12-19, and satisfy education requirements. Data is taken from the 2005-2019 waves of the ACS.

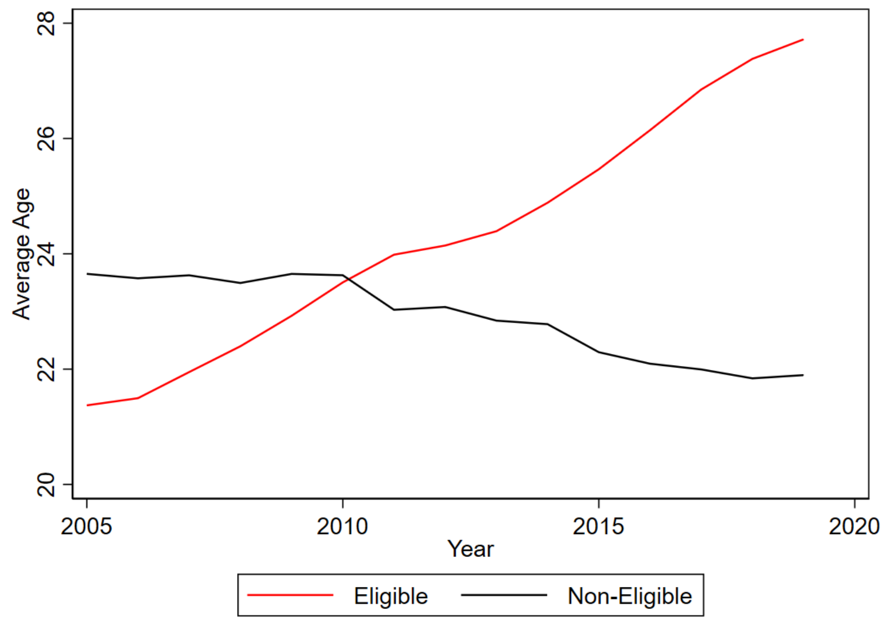

Figure A2: Trend in Average Age by Eligible Group

Table A7: Difference-in-Difference Employment Effects using In-Person Interview Sample

	(1) Working	(2) In the Labor Force	(3) Hours Worked	(4) Unemployed	(5) Self-employed	(6) Worked last year	(7) Log Personal Income	(8) In School	(9) GED
Elig*Post12	0.0599***	0.0458***	1.984***	-0.0223***	-0.0113*	0.0492***	0.0515*	-0.0336***	-0.00161
	(0.012)	(0.013)	(0.522)	(0.008)	(0.007)	(0.012)	(0.030)	(0.011)	(0.006)
Elig*Post17	0.0388**	0.0270	2.382***	-0.00953	0.0132	0.0427**	0.0157	-0.0417***	0.00185
	(0.018)	(0.017)	(0.855)	(0.010)	(0.014)	(0.018)	(0.043)	(0.016)	(0.009)
Eligible	-0.0195*	-0.0173	-0.681	0.00584	-0.00386	-0.0182	-0.0401	0.00229	0.00908*
	(0.011)	(0.012)	(0.457)	(0.008)	(0.006)	(0.011)	(0.025)	(0.010)	(0.005)
Observations	50700	50700	50700	37049	39479	50700	38767	50700	35653
R-squared	0.187	0.197	0.245	0.0351	0.0190	0.198	0.194	0.430	0.0343

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the difference-in-differences estimates of Equation (1) on employment and education outcomes. Year and state fixed effects and state-specific time trends are added. Standard errors are clustered at the state-year level. Estimates in all columns are derived from a sample of likely undocumented individuals ages 18-30, who entered the US between the ages 12-19, and satisfy education requirements. In addition, the sample is restricted to individuals who took an in-person interview. Data is taken from the 2005-2019 waves of the ACS.

Table A8: Difference-in-Difference Occupation Effects using In-Person Interview Sample

	(1) Essential	(2) Licensed Occupation	(3) Service Occupation	(4) Non-Service Occupation	(5) Manual-Intensive	(6) Analytical-Intensive
Elig*Post12	-0.00181	0.0135**	-0.0125	0.00227	0.0110	0.00234
	(0.012)	(0.006)	(0.015)	(0.011)	(0.014)	(0.013)
Elig*Post17	-0.00989	0.0154	0.00251	-0.0103	0.00829	-0.0184
	(0.021)	(0.010)	(0.019)	(0.019)	(0.023)	(0.020)
Eligible	-0.00562	-0.00496	-0.00681	0.000600	-0.0196	0.00364
	(0.010)	(0.004)	(0.013)	(0.008)	(0.014)	(0.010)
Observations	33902	33902	33902	33902	33853	33853
R-squared	0.0438	0.0911	0.0690	0.257	0.0590	0.230

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the difference-in-differences estimates of Equation (1) on occupation outcomes. Year and state fixed effects and state-specific time trends are added. Standard errors are clustered at the state-year level. Estimates in all columns are derived from a sample of likely undocumented individuals ages 18-30, who entered the US between the ages 12-19, satisfy education requirements, and who are employed. In addition, the sample is restricted to individuals who took an in-person interview. Data is taken from the 2005-2019 waves of the ACS.

Table A9: Difference-in-Difference Effects on Survey-item Response

	(1) Employment Status	(2) Occupation	(3) Total Income	(4) Hours Worked	(5) Worked in Past year	(6) Self-employed	(7) School	(8) GED
Elig*Post12	-0.00516	0.0100	0.0162	0.00853	-0.00110	0.00587	-0.00409	0.00246
	(0.006)	(0.008)	(0.010)	(0.007)	(0.006)	(0.006)	(0.005)	(0.008)
Elig*Post17	0.00994	0.0191*	0.0259	0.0310**	0.0102	0.0196*	0.00736	0.0135
	(0.011)	(0.011)	(0.016)	(0.012)	(0.011)	(0.012)	(0.009)	(0.014)
Eligible	-0.00297	-0.00133	0.00115	-0.00474	0.00487	0.00230	-0.00114	-0.00799
	(0.004)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)	(0.007)
Observations	100510	100510	100510	100510	100510	100510	100510	77877
R-squared	0.0313	0.0171	0.521	0.0161	0.0261	0.0165	0.0146	0.0407

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table shows the difference-in-differences estimates of Equation (1). The outcome variables are dummy variables that take the value 1 if the variable was imputed by ACS. Year and state fixed effects and state-specific time trends are added. Standard errors are clustered at the state-year level. Estimates in all columns are derived from a sample of likely undocumented individuals ages 18-30, who entered the US between the ages 12-19, and satisfy education requirements. Data is taken from the 2005-2019 waves of the ACS.

A.2 Data Appendix

Employment Variables:

- Working: Dummy equals 1 if the individual is employed. It is defined through empstat.
- In the labor force: Dummy equals 1 if the individual is in the labor force.
- Total personal income: Total pre-tax personal income from all sources for the previous year (past 12 months).
- Worked in the last year: Dummy equals 1 if the individual worked for profit, pay, or as an unpaid family during the previous year.
- Unemployed: Dummy equals 1 if the individual is not working but is in the labor force.
- Self-employed: Dummy equals 1 if the individual is self-employed.

Occupation Variables:

- Essential: Dummy equals 1 if an individual is working in an essential industry or occupation.
- Licensed: Dummy equals 1 if the occupation needs a license.
- Service occupation: low-skill services that includes housekeeping, cleaning, laundry, building and grounds cleaning and maintenance occupations, all protective service, food preparation and service occupations, health service occupations (dental ass., health/nursing aides), personal appearance occupations, recreation and hospitality occupations, child care workers, and personal care and service occupations.
- Non-service occupation: management/professional/technical/financial sales/public security occupations.
- Manual-Intensive and Analytical-Intensive: Tasks related to each occupation are based on the O*NET version 17.0 database. Using the variable occsoc and following Borjas and Cassidy (2019), I merge each occupation with its characteristics for years 2010-2016. I focus on two tasks: analytical and manual. As specified in Imai et al. (2018), analytical characteristics include "inductive reasoning, deductive reasoning, mathematical reasoning, and information ordering". Manual characteristics include "physical activities, strength and stamina". These characteristics are grouped together following Borjas and Cassidy (2019) to form two task requirements foe every occupation code: analytical and manual. Each task requirement is then standardized to have a zero mean and a standard deviation of one. Then, I use occ1990 codes to merge the task requirements with all of the ACS samples I am using. Finally, I generate a variable, "task." Task = analytical requirement - manual requirement.

I create two dummy variables: analytical-intensive and manual-intensive. Analytical-intensive dummy takes the value 1 if the task variable has a value that is higher than the 75^{th} percentile. Manual-intensive dummy takes the value 1 if the task variable has a value that is lower than the 25^{th} percentile.

Education Variables:

- In school: Dummy equals 1 if the individual is in school. That includes nursery or preschool, kindergarten, elementary school, home school, and schooling which leads to a high school diploma or a college degree.
- GED: Dummy equals 1 if individual has a GED or a similar credential (only available for years>=2008).