Policy Impacts under Uncertainty: Evidence from DACA

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Abstract

In 2012, the Deferred Action of Childhood Arrivals (DACA) provided 800,000 undocumented immigrants with temporary work authorization and relief from deportation. However, the policy was significantly challenged by the Trump administration in 2017, creating uncertainty about its permanence and fate. This paper examines how this uncertainty affected the labor market outcomes and occupational choices of eligible undocumented migrants. Using a difference-in-difference methodology, I leverage discontinuities in DACA's eligibility criteria to estimate the policy's impacts between 2012 and 2019. I find positive effects on employment for eligible individuals in the early years after the policy's implementation. The results also indicate an increase in employment in essential and licensed occupations. However, I show that the policy's effects on labor market outcomes fade out in the wake of the 2017 uncertainty. I provide suggestive evidence that this decline is likely driven by fears of cancellation and uncertainty. These findings have important policy implications, as they highlight that challenging temporary policies and generating uncertainty surrounding the status of migrants, even without outright cancellation, can undermine the policies' potential benefits.

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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

In the past two decades, political polarization has become increasingly pronounced in the United States, with Republicans and Democrats holding opposing views on a range of issues, including migration policy (Dugan and Newport 2017). This polarization has resulted in a situation in which policies proposed by one party are often perceived as a threat by the other, resulting in a pattern of overturning policies enacted by previous administrations, irrespective of their effectiveness (Pew Research Center - U.S. Politics & Policy 2014). The Trump administration exemplified this trend, with significant changes made to various policies, such as rolling back the Affordable Care Act, reducing Medicaid funding, and restricting H-1B visas. The Deferred Action for Childhood Arrivals (DACA) program, established during the Obama administration, was also not immune to the political climate of uncertainty, facing the risk of being rescinded during Trump's presidency.

Around 11 million people in the U.S. are undocumented, representing nearly 30% of the foreign-born population in 2008 (Passel and Cohn 2008). Undocumented immigrants face challenges in accessing jobs, welfare benefits, and credit, leading to lower income and educational returns compared to legal immigrants or natives (Rivera-Batiz 1999). While undocumented males have a higher labor supply than the latter two groups, wage gaps increase over time due to occupational barriers (Borjas 2017; Borjas and Cassidy 2019; Hsin and Ortega

[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/.

2018). As a result, various attempts have been made to reform U.S. immigration policy since the 1980s, aiming to improve the lives of undocumented immigrants while simultaneously addressing illegal immigration.

On June 15, 2012, President Obama issued an executive order to pass DACA, which provides undocumented immigrants with work authorization and defers their removal action for two years, subject to renewal, if they satisfy certain requirements (US Citizenship and Immigration Services n.d.). Almost 826,000 individuals have benefited from DACA since its passage (Center for American Progress 2020). The policy primarily focuses on undocumented individuals who arrived in the US before their 16^{th} birthday. However, it does not provide a permanent solution to undocumented immigrants, nor does 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. While DACA recipients were allowed to renew their status and technically receive the policy's benefits thereafter, new applications were not considered. Thus, recipients experienced a great deal of uncertainty regarding their status, and their perceived risk of deportation significantly varied during the 2012-2019 time period.

While policies such as DACA provided temporary benefits to eligible recipients, the uncertainty surrounding the program's future can lead to differential effects, even if the policy itself remains factually unchanged. However, existing literature has yet to explore how varying expectations towards a temporary policy can affect its outcomes. This paper aims to address this gap by examining how variation in risk and uncertainty towards DACA, one of the most significant immigration-related executive actions in recent history, affects its benefits. Specifically, I estimate the effects of DACA on eligible undocumented immigrants and investigate how the policy's outcomes evolved after it was challenged by the Trump administration. I explore whether the effects of DACA persisted or diminished due to changes in expectations towards the policy's permanency.

The uncertainty surrounding DACA's future may have led to two opposing effects on its initial outcomes. First, the risk of policy cancellation could have increased the perceived risk of deportation among DACA recipients, especially as they provided their information to the Department of Homeland Security when applying for the program. Thus, to restrict their interactions with law enforcement, they might decrease their labor market participation and their labor supply outside of their homes, potentially chilling the positive effects of DACA. Alternatively, recipients may have anticipated the policy's cancellation and sought to maximize its benefits. In this case, forward-looking recipients may have increased their working hours, income generation, and savings during the remaining period of DACA's validity. The net effect of these opposing channels is ambiguous and depends on their relative magnitude.

In this paper, I examine the impact of DACA on the employment and occupational mobility of eligible individuals using data from the American Community Survey spanning from 2005 to 2019. I employ a difference-in-difference methodology and leverage discontinuities in the DACA eligibility criteria based on age at immigration. To estimate the fluctuations in the impact of DACA due to the uncertainty ensued by the Trump administration, I compare the effects of the policy on employment and occupational mobility before and after Trump's challenge to the program in 2017.

Methodologically, most of the previous studies examining DACA have relied on ethnicity and citizenship to determine the legal status of individuals.[3] Specifically, these studies use non-citizenship as a proxy for undocumented status and restrict the sample to non-citizens with low levels of education. However, this approach mis-classifies legal immigrants, green card holders, and visa holders as eligible for DACA, even though they are not undocumented, leading to measurement errors and attenuation bias. In contrast, 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. By focusing exclusively on the sample of likely undocumented individuals in my analysis, I provide more accurate estimates.

My findings indicate that DACA had significant and positive effect on employment during the period between 2012 and 2016, which aligns with the previous literature. Specifically, I show that DACA led to a 5.13 percentage point increase in the likelihood of employment and a 4.1 percentage point increase in the likelihood of labor force participation. I find no evidence to suggest that DACA had a significant effect on the income of eligible individuals. Additionally, I find an increase in the likelihood of employment in essential and licensed occupations. Nevertheless, eligible individuals did not experience a significant shift towards higher-paying non-service occupations or occupations involving analytical-intensive tasks. These results indicate that while DACA improved the employment prospects of eligible undocumented individuals, it had limited effects on occupational or income mobility within the sample I focus on.

Importantly, the effects of DACA on employment considerably diminish after Trump challenged the program in 2017. While the effect of the policy on employment and labor force participation remains positive, the estimates are substantially smaller in magnitude and lack

[3] Such studies include Amuedo-Dorantes and Antman 2016, Giuntella and Lonsky 2020, Giuntella et al. 2021, Kuka et al. 2020, Kuka et al. 2019, and Pope 2016

statistical significance. The only exception is the effect of DACA on the number of hours worked by eligible individuals. Between 2012 and 2016, DACA leads to an increase of 1.43 hours worked that is statistically significant at the 1 percent level. However, after 2017, this effect decreases to an increase of 1.3 hours, which is only significant at the 5 percent level. Moreover, the policy had no discernible effects on the income or occupational structure of eligible individuals after 2017.

I provide various checks to ensure the robustness of the results, ruling out changes in reporting or the composition of likely undocumented migrants. Moreover, I explore various factors that may drive the decline in DACA's effects after 2017 on employment and labor force participation. I rule out mechanical effects and factual changes in the policy itself as drivers of these changes in the policy's impacts. Considering that existing DACA recipients were able to renew their status and retain the policy's benefits after 2017, I argue that the decline in outcomes can be attributed to uncertainty and fear leading to chilling effects.

By examining the differential effects of DACA across states with different political environments, I find that eligible individuals experienced significant benefits from the policy in both Democratic and Republican states, but those residing in Republican states were more adversely affected after 2017. Individuals in states with more restrictive policies face more significant repercussions in response to the potential cancellation of DACA, likely due to heightened fear. This can be attributed to the fact that DACA provided additional benefits for these individuals, amplifying the potential impact of its removal. Finally, I utilize Google Trends data to support the notion that changes in search volume related to DACA align with the increase in uncertainty and shifting expectations surrounding the policy after 2017.

This paper makes two key contributions. First, it demonstrates how policies that provide only temporary benefits are affected by uncertainty and expectations towards their permanence. Existing research has highlighted the advantages of both permanent and temporary legalization reforms. For example, studies on the Immigration Reform and Control Act (IRCA) of 1986, a permanent legalization reform in the US, have demonstrated significant positive effects on the earnings of undocumented immigrants (Hill et al. 2010; Pastor et al. 2010; Barcellos 2010; Pan 2012; Orrenius and Zavodny 2012; Bratsberg et al. 2002; Lozano and Sorensen 2011; Kossoudji and Cobb-Clark 2002; Amuedo-Dorantes et al. 2007). Additionally, research by Ibanez et al. 2022 and Urbina et al. 2023 shows that granting temporary legal migratory status to irregular Venezuelan migrants in Colombia through the Permiso Especial de Permanencia program, which includes work permits, led to improvements in various areas such as consumption, entrepreneurship rates, housing conditions, access to healthcare services, and resilience during the COVID-19 pandemic. While this literature shows the benefits of these reforms on their recipients, the literature has not sufficiently addressed the role of permanency and expectations in driving the outcomes of policies that provide only temporary benefits or legal status.

By focusing on DACA, this study sheds light on these aspects and demonstrates that temporary relief, such as that provided through DACA, is vulnerable and prone to risk, uncertainty, and shifting expectations. Despite not being terminated for existing recipients after 2017, DACA faced an uncertain future due to lawsuits filed against the program by the Trump administration and the possibility of a second Trump term. Thus, the changes observed in labor market outcomes after 2017 can be attributed to changes in expectations rather than alterations in the actual benefits of the policy. Indeed, the results indicate that eligible individuals ceased to benefit from the policy after 2017. Relatedly, these findings contribute to existing studies that investigate the impact of waiting times for refugees in Europe before they are granted permission to work.[4] The findings from these studies suggest that prolonging the uncertain status of refugees impedes their ability to fully contribute to the economy. The latter studies focus on refugees in Europe, who eventually attain permanent status but at varying times. In contrast, my paper focuses on the undocumented population in the US, which faces higher deportation risks with the majority having no pathways for long-term legalization.

Second, this paper contributes to a large literature on the effects of DACA. It is among the first to investigate the longer-term effects of the policy on employment and to explore its effects on occupational choice, which is a critical factor in achieving higher income, job security, and professional growth in the long-run. Existing literature extensively investigates the effects of DACA on its recipients, finding positive effects on the economic well-being (Amuedo-Dorantes and Antman 2016), labor market outcomes (Amuedo-Dorantes and Antman 2017; Pope 2016), and geographic and job mobility of eligible individuals (Villanueva and Wilson 2023). However, this literature does not consider the policy's post-Trump fluctuations, as it primarily relies on data ranging from 2012 to 2016, failing to capture the challenges faced by DACA between 2017 and 2019. Given the changing perception of risk, there is reason to believe that the effects of DACA may have varied, and the positive effects reported in the literature could be short-term. Recent studies addressing DACA's uncertainty mostly rely on interviews and focus groups (Patler et al. 2021a). Notable exceptions are Giuntella et al. 2021 and Patler et al. 2019. The former finds that DACA initially increased sleep duration

[4]Notably, studies by Marbach et al. 2018 and Hainmueller et al. 2016 demonstrate the long-lasting effects of employment bans and prolonged asylum decision wait times on the economic integration of refugees in Germany and Switzerland, respectively. Moreover, Phillimore and Cheung 2021 highlight the adverse impact of longer wait times on refugee health.

among eligible immigrants, but this effect decreased between 2016 and 2019. The latter reveals positive and significant effects of DACA on health outcomes in California, which do not persist between 2015 and 2017. By comparing the effects of DACA before and after 2017, my study reaffirms the conclusions of these two studies, demonstrating that uncertainty undermined DACA's employment benefits. In arguing that uncertainty serves as the primary mechanism driving the results, this paper closely aligns with Amuedo-Dorantes and Wang 2023, who demonstrate that the uncertainty surrounding DACA led eligible migrants to marry US citizens in order to secure permanent residence.

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 discusses their robustness. Section 6 provides further insights into the mechanisms driving them. Finally, section 7 concludes.

2 Institutional Background

Immigration is a highly debated policy issue in American politics, with consecutive administrations promoting or restricting it. In 1986, the Immigration Reform and Control Act (IRCA) was passed, granting legal status to 2.7 million undocumented individuals (Center for Immigration Studies). Congress also passed several small amnesties for specific nationalities in the 1990s.[5] Despite a Democratic majority, the DREAM Act, proposed in 2001, failed to pass (Arlota 2018).

On June 15, 2012, President Obama signed an executive order establishing the Deferred Action for Childhood Arrivals (DACA) program. The United States Department of Homeland Security's Citizenship and Immigration Services (USCIS) started processing and accepting applications in August 2012, with increased take-up starting in 2013. Undocumented immigrants who meet certain requirements are eligible to apply for DACA. These requirements include arriving in the US before the age of 16, being under the age of 31 as of June 2012, continuously residing in the US since June 15, 2007, meeting education or military service requirements, paying a processing fee of $465, and having no felony or significant misdemeanor convictions. Applicants must provide evidence to demonstrate their compli-

[5] 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, it passed the Nicaraguan Adjustment and Central American Relief Act (NACARA), which targeted undocumented individuals from Central America. In 1998, the Haitian Refugee Immigration and Fairness Act (HRIFA) was passed, focusing on Haitians (Center for Immigration Studies).

ance with these criteria (US Citizenship and Immigration Services n.d.).

If approved by the Department of Homeland Security, DACA provides several benefits to recipients. These benefits include relief from deportation and a legal work authorization. DACA also grants eligible recipients with social security numbers, enabling them to access loans, open bank accounts, and build credit history. These benefits are initially granted for two years, subject to renewal. In some states, DACA recipients are also eligible to obtain driver's licenses. Moreover, states such as New York, California, D.C., Minnesota, Oregon, Washington, Illinois, and Massachusetts have extended eligibility for state-funded Medicaid to DACA recipients (Giuntella and Lonsky 2020). It is important to note that DACA does not provide a pathway to citizenship.

Several states filed lawsuits 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. In the early stages of his first term in 2016, he referred to DACA recipients as "absolutely incredible kids" and expressed that his administration was going "to show great heart" (Gomez 2018). However, on September 5, 2017, the Trump Administration announced the rescission of the program (Department of Homeland Security 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 the Trump Administration in an effort to block DACA's rescission and protect DACA recipients (Rosenberg 2017). Following this, federal district court judges in California, New York, and D.C. ordered the continuation of the policy. Thus, the renewal of previously enrolled recipients resumed, but new applications were rejected (Department of Homeland Security 2017). Individuals who were granted DACA before 2017 were able to maintain its benefits, as the policy remained unchanged for them.

President Trump initially expressed a willingness to protect DACA recipients, but he made it contingent upon reaching a deal with Democrats to address immigration limitations and border security. The proposal included protecting DREAMers, securing funding for the border wall with Mexico, ending the diversity visa lottery, and decreasing family-based migration. However, negotiations failed to find common ground, and in 2018, President Trump announced that the Democrats "killed" DACA. In 2019, he referred to DACA recipients as "far from angels" and "hardened criminals" on Twitter (Rupar 2019). The Trump Administration's decision to rescind DACA was challenged in court, and in 2020, the Supreme Court ruled that the rescission was unwarranted.[6] However, the Court acknowledged that DHS

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

could properly rescind DACA in the future if done in a legally appropriate way (National Conference of State Legislatures 2020). President Trump later promised to resubmit DACA to the Supreme Court (O'Toole 2020).

Figure 1, panels A and B, display the number of initial and renewal DACA applications by year, respectively. The data reveals a declining trend in both initial applications and approvals, following their peak in 2013, with a notable decrease to a minimum after DACA's rescission. However, renewal applications and approvals remained relatively high from 2017 to 2019. Panel C presents the geographic distribution of DACA applications, showing a concentration primarily in California, Texas, Florida, and New York.

3 Data

I use data from the American Community Survey (ACS) for the period 2005-2019, obtained through IPUMS (Ruggles et al. 2021. The ACS survey provides a representative sample of the US population and does not selectively sample individuals based on their legal status.

My analysis primarily focuses on two sets of outcomes. First, I examine labor market outcomes, which include indicators of employment and labor force participation, as well as hours worked, hourly wages, and annual incomes. Second, I investigate measures of occupational mobility, such as whether an individual worked in an essential sector, a licensed occupation, a service occupation, or a non-service occupation. Essential sectors are those that were deemed crucial during the Covid-19 pandemic by the US Department of Homeland Security. They encompass various fields, including construction, housekeeping, cooking, food preparation, agriculture, medical and health services, and nursing, among others (Svajlenka 2020). Licensed occupations are those that require some form of licensing, such as registered nurses, lawyers, or physicians. Service occupations refer to low-skill services, including housekeeping, cleaning, health services, child care, and personal care. Non-service occupations encompass management, technical, and professional roles. I also examine whether eligible individuals change their job task-intensity following Peri and Sparber 2009, by analyzing whether they moved to occupations with dominant analytical or manual tasks. A detailed description of each variable can be found in the Data Appendix.

3.1 Residual Method

Individual-level surveys do not typically ask whether a foreign-born individual is undocumented. Even if they did, individuals would probably decline to answer or give a false answer. Therefore, researchers have used alternative methods to impute undocumented status. For example, many studies on the effects of DACA use non-citizenship and ethnicity as a proxy for undocumented status. However, this method can be biased, since non-citizens may have legal status through visas or green cards. 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.

To overcome these limitations, I use a modified version of the residual method proposed byBorjas 2017 and Borjas and Cassidy 2019 to impute the undocumented status of individuals. The framework works by estimating the foreign-born population, and then extracting naturalized and legal immigrants from this population, leaving a group of individuals with a high likelihood of being undocumented. A foreign-born individual is considered likely legal or authorized if they meet specific 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 residual group of all non-US born individuals is then considered likely undocumented. This method has been used by the DHS to estimate the undocumented immigrant population.

However, this method still has some limitations. It relies on the self-reporting of year of immigration, occupation, and benefits take-up, which may suffer from some measurement errors due to recall bias. Additionally, the DHS assumes that 10% of unauthorized immigrants are missed due to their active efforts to avoid detection (Baker and Rytina 2014). Liu and Song 2020 compare the ethnicity proxy and residual methodology and find that the residual method was superior in estimating the numbers of undocumented individuals and their geographic variation.[7]

[7] Spence et al. 2020 suggest caution when using the residual method. However, in their "logical approach" that mimics the residual method I use, they omit the criterion that eliminates individuals if they are citizens

3.2 DACA Eligibility Criteria and Undocumented Sample

After imputing the legal status of each individual, I determine their eligibility for DACA. To be eligible, an individual must be undocumented, have continuously resided in the US since 2012, entered the US before turning 16, immigrated prior to 2007, be under 31 years old as of June 2012, and meet the education requirements, which include being currently enrolled in school, having graduated from high school, or having earned a GED. I do not consider individuals who only became eligible for DACA after 2017 as recipients, as they were unable to apply for DACA and did not receive its benefits. Actual participation or take-up of DACA is not observable, but USCIS statistics indicate that almost 67% of DACA-eligible individuals received DACA status (Pope 2016).

Since the ACS includes detailed questions about birth year and quarter, years since immigration, and educational attainment, I am able to closely abide to the steps of imputing undocumented status and DACA eligibility. I limit 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 met the education requirements. This allows me to exploit the variation in the age at 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 comparison group is more appropriate than citizens or individuals with legal status.

I present the demographic summary statistics for the sample, using ACS data from 2005-2019 in Table 1. Column (1) provides the summary statistics for the full sample, while columns (2) and (3) report these statistics for the DACA eligible and ineligible populations, respectively.

Both the eligible and the ineligible populations exhibit similarities in terms of average age, proportion of males, and marital status. Almost 64% of eligible individuals are Hispanic, compared to only 50.5% of the ineligible population. A large proportion of the eligible population is concentrated in California (21.12%), Texas (12.8%), and New York (8.6%). This geographic distribution is also similar for the ineligible population and the broader likely undocumented population. In terms of educational profiles, nearly half of the sample holds a high school degree or its equivalent, and this proportion is similar consistent across the three groups. Given the requirements for DACA eligibility, eligible individuals entered

and then compare their results to a survey question that indicates legal status. In my approach, I incorporate the citizen criterion.

the US at a younger age, with an average age of entry at 13 years old, compared to 17 for the ineligible individuals. Consequently, eligible individuals have also spent more years in the US.

In the appendix, Table A1 similarly presents summary statistics of the outcomes of this sample. Overall, the likely undocumented population in the sample has a high employment rate (62%) and labor force participation rate (67%). On average, eligible individuals have a higher proportion of employment and labor force participation compared to the ineligible individuals throughout the analyzed time period. Approximately 35% of the employed likely undocumented individuals work in essential occupations, while 26.3% of them work in service occupations. Licensed occupations constitute only a minority of their employment (4.4%).

4 Identification Strategy

To estimate the causal effects of DACA between 2012 and 2019, I use the difference-in-difference (DiD) approach, utilizing discontinuity elements by restricting the age of immigration of individuals in the sample. The analysis focuses on a group of likely undocumented immigrants, and eligibility is determined without information about actual take-up of the policy. Therefore, the DiD estimates provide the intent-to-treat effect. To differentiate between the effects of DACA before and after the Trump administration, I divide the Post variable into two sub-periods. One sub-period captures the effect of the policy during the Obama administration, while the other sub-period captures the effects of the policy during the Trump administration. Specifically, I estimate the following specification:

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

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 have been 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, ensuring that the treated and control groups are comparable prior to the passage of the policy.

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, as 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, educational attainment, 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. Finally, the standard errors are clustered at the state-year level.

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 compare the outcomes of eligible individuals to those of ineligible individuals before and after DACA.

The validity of my identification strategy relies on the parallel trends assumption. That is, the treatment and comparison groups 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. Additionally, I include the same individual-level controls and fixed effects (state, year, age, and age at migration) as in Equation 1. Specifically, I estimate Equation 2, and I graphically plot the estimated coefficients over time. I present the results in section 5, where I confirm the absence of pre-trends, implying no treatment effect in the pre-period.

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

In addition to the importance of this approach for validating the identification strategy, it is particularly crucial in the context of this paper to examine the dynamic effects of the policy over time. The event-study results are especially valuable as they allow for the observation of how the effects of the policy vary over time and whether they start to decline after 2017,

[8] **Source** of state-level unemployment rates: Local Area Unemployment Statistics. Bureau of Labor Statistics (BLS).

if at all. Overall, this analysis provides insights into the temporal dynamics of the policy's impacts.

5 Results and Discussion

5.1 Event-Study Results

I present the dynamic effects of DACA on employment outcomes in Figure 2, panels (a) to (e), and on occupation outcomes in Figure 3, panels (a) to (f), using graphical representations. These estimates are derived from Equation 2, and each estimate reflects the impact of DACA in a specific survey year, with the exception of 2012 which is omitted.

All panels of Figure 2 indicate the absence of pre-existing trends between the treatment and comparison groups prior to 2012. The estimates before 2012 are mostly close to zero and not statistically significant at conventional levels. This finding is reassuring, as it suggests that both groups would likely have continued on the same trajectory in the absence of DACA, supporting the parallel trends assumption. Second, panel (a) of the effect of DACA on the likelihood of working reveals that the effect increases after 2012, reaching its peak in 2016 (with an almost 6 percentage point increase for the eligible group compared to the ineligible group), and subsequently declines. From 2017 onwards, the effect becomes statistically insignificant, ultimately returning to zero by 2019.

A similar pattern can be observed in the estimates of the effect of DACA on the likelihood of labor force participation (panel b) and hours worked (panel c), although the effects on the latter tend to be less significant compared to the former two. There is no evidence to suggest that DACA had an impact on the hourly wage or annual income of eligible individuals either before or after the implementation of the policy.

The dynamic effects of DACA on occupation outcomes for individuals of the sample are presented in Figure 3, where each estimate reflects the likelihood of begin employed in the specified sector. Panels (b) to (f) demonstrate parallel trends in the pre-period. As an exception, panel (a) reveals that some estimates of the effect of DACA on the likelihood of working in an essential occupation are statistically significant in certain years prior to 2012, although these significant estimates do not show a discernible trend. All other variables exhibit no pre-existing trends between the treated and comparison groups before 2012. Additionally, there does not appear to be any significant effect of DACA or the Trump administration on eligible individuals' occupational mobility.

5.2 Difference-in-Difference Effects

I report the main results on the effects of DACA on employment and occupation outcomes in Table 2 and Table 3, respectively. The first row of each table presents the effects of the policy on the eligible population between 2013 and 2016. The second row reports the effects of the policy between 2017 and 2019. As previously mentioned, all specifications include individual-level demographic controls, year, state, age, and age at migration fixed effects as well as state-specific time trends.[9]

The findings of Table 2 show that between DACA's enactment in 2012 and 2016, the likelihood of eligible individuals working increased by 5.13 percentage points, that is statistically significant at the 1 percent level. This estimate is larger in magnitude than that of Pope 2016, who used a similar identification strategy but proxied for undocumented status using non-citizenship, suggesting that using non-citizenship as a proxy for undocumented status may attenuate the results. The increase in working is primarily driven by a 4.1 percentage point increase in the likelihood of participating in the labor force among eligible individuals. While there is a significant increase of 1.44 hours worked by eligible individuals between 2012 and 2016, there is no evidence of DACA's impact on annual income or hourly wage.

After 2017, the effect of DACA on employment outcomes of eligible individuals fades out, providing evidence for the "chilling effect" mechanism. Specifically the impact of DACA on the likelihood of employment decreases to a 2.3 percentage point increase that is not significant at the conventional levels. The impact of DACA on participating in the labor force also decreases to almost 0.8 percentage point increase that is not significant. Additionally, there are no changes in the effects of DACA on hourly wage or annual income. An exception is the effect of DACA on hours worked of eligible individuals, which shows a persistent but smaller increase of 1.35 hours ($p < 0.05$) for eligible individuals, that is only significant at the 5 percent level.

Next, I examine the effect of DACA on the occupational choice and mobility of eligible individuals. Specifically, I investigate whether the policy had any effect on employment in specific occupations. Each outcome in this analysis indicates whether an individual is employed in a particular sector.[10] Table 3 presents the results. Between 2012 and 2016, the results reveal that the policy leads to a 2.4 percentage point increase in the likelihood

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

[10] Since I have observed changes in employment, I do not condition the analysis on employment when analyzing changes in the composition of occupations to avoid selection.

of employment in essential occupations or sectors for eligible individuals. These sectors encompass a wide range of fields in which undocumented migrants constitute a significant proportion of the workforce, such as construction, housekeeping, or health services. Furthermore, Column (2) demonstrates a 1 percentage point increase in the likelihood of being employed in licensed occupations, which is substantial compared to the mean of 2.7 percent. This effect is attributed to DACA providing individuals with Social Security Numbers (SSNs), thereby enabling them to apply for occupational licenses. Both of these effects are statistically significant at the 1 percent level.

Furthermore, the findings reveal a 1.5 percentage point increase in the likelihood of employment in service occupations (column 3), encompassing roles such as housekeeping, cleaning, and health services, as well as a 1.8 percentage point increase in the likelihood of working in occupations involving manual-intensive tasks (column 5). However, these effects are marginally significant at the 10 percent level. There is no evidence to suggest that eligible individuals shifted towards non-service occupations after the policy implementation.

Overall, these results indicate that the policy had a positive impact on eligible immigrants by directing them towards licensed occupations and essential sectors. Nevertheless, there is no evidence to indicate that eligible migrants moved towards occupations requiring analytical skills, which could offer greater potential for earnings growth. While these findings demonstrate a beneficial and significant impact of the policy, two possible explanations could account for these moderate effects. First, DACA may have had only moderate effects on employment, not substantially changing the types of jobs pursued by undocumented individuals. It's possible that the policy did not provide sufficient time for individuals to transition to better occupations, and thus only provided a short-term boost to employment. Second, the age range of the sample (18 to 30 years old) might have masked variations in occupational mobility experienced by older individuals. Overall, these findings align with the interviews conducted by Patler et al. 2021b, who suggest that DACA recipients did not necessarily move to better jobs but rather found jobs that fit their interests and lifestyles, potentially leading to future mobility.

After 2017, there is no apparent effect of the policy on the likelihood of employment in any specific industry, further confirming the observed chilling effects on employment. Specifically, the estimates regarding the likelihood of employment in any of the specified sectors are close to zero and lack statistical significance at conventional levels.

5.3 Robustness

In this section, I perform multiple checks to ensure the robustness of the results on labor market and occupation outcomes.

As previously mentioned, the main analysis is conducted on a sample of likely undocumented individuals aged 18 to 30 and who entered the US between the ages of 12 and 19. A major concern in this case is the potential for compositional changes arising from two sources. First, in my analysis, I rely on repeated cross-sectional data in a difference-in-difference framework. It is possible that the composition or the characteristics of the treated group change over time, and these demographic changes drive the results rather than the actual policy. To address this concern, I estimate the effect of DACA on observable characteristics of individuals in the sample, and check whether there are any significant shifts in the demographic characteristics directly associated with the implementation and rescission of DACA. In particular, I estimate the event-study specification of Equation 2 without demographic controls, where the outcomes are the demographic characteristics themselves.

Table A4 presents the results, showing that out of 26 coefficients, only four are statistically significant at the 1 percent level. Specifically, the coefficients on age and on years spent in the US are significant and positive. However, the latter effects are mechanical and a result of the sample construction. 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 to 2012 only, 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.[11]

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, or do not respond at all. To address this issue, I run the analysis separately for those who had an in-person interview. Table A5 and Table A6 present the results of the analysis using this sample. Unlike the findings from the overall sample, the estimates for the likelihood of employment and hours worked are statistically significant after 2017 in this analysis. However, the magnitude of the effect is still smaller than that observed between 2012 and 2016, thus preserving the main conclusions. The results of the effect of

[11]Figure A1 shows the yearly trend in average age of the eligible or the treated (in red) and comparison (in black) groups. The figure shows that while the average of the latter is slightly decreasing but almost constant, that of the eligible group is on an upward trend. For this reason, the addition of age fixed effects in the main specification, controlling for this change in ages, is essential.

DACA on occupations are consistent with the main findings.

One potential 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 capture a decrease in response after 2017, as individuals become hesitant to provide information about their employment. I test for such changes by estimating equation (1) using the quality flags in the ACS, following Pope 2016. In this analysis, each outcome variable is a dummy variable that takes the value one if the variable was not answered by the individual 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 A7 of the Appendix presents the results. From 2012 to 2016, the analysis shows no significant effect of DACA on survey-item response rates. After 2017, the results show that there is a 1.91 percentage points increase in the likelihood of imputing the occupation variable. This estimate is significant at the 10% level only. 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. The likelihood of imputing other variables after 2017 is not significant. 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 and only marginally significant.

This analysis not only provides comfort that the response rate is not responsible for driving the results, but it also indicates that this specific channel is unlikely to have influenced the findings. In other words, it is unlikely that eligible individuals stopped responding to the survey or specific questions of interest after 2017 due to apprehension about being identified and deported. Consequently, any decrease in the benefits of DACA observed after 2017 cannot be solely attributed to a decline in the response rate.

6 Mechanisms

All the aforementioned results demonstrate that DACA had substantial and statistically significant positive effects on the eligible population between 2012 and 2016, especially on employment and labor force participation. However, these effects diminish considerably after

September 2017. In this section, I explore the factors that could be contributing to the fading out of DACA's effects after 2017.

6.1 Ruling Out Factors

A first possible scenario is that eligible individuals stopped taking up the policy after the uncertainty that ensued. Thus, they may not have fully realized the benefits or advantages it offered. However, as previously mentioned, Figure 1 shows that although initial applications and approvals decline to almost zero after 2017, the number of renewal applications and approvals remain relatively high. This trend signals that the take-up of the policy by individuals who were already eligible for DACA before 2017 did not substantially change.

Second, considering that renewal applications remained relatively high, it might be that the positive effects of DACA are broadly driven by young individuals who age into the policy. In this case, DACA would primarily benefit a new cohort that enters the program, but its effects naturally fade out over a relatively short period of time, to be replaced by those of a new entering cohort. Since no new cohorts were allowed to enroll in DACA after the September 2017, we can only estimate the effects of DACA on older cohorts who may have experienced a natural decline in outcomes, rather than one caused by the policy's uncertainty after 2017.

Given that the minimum age to apply for DACA is 15, some individuals became eligible beginning 2012, while other age into the policy between 2013 and 2016. In order to check whether DACA's effects fade out for older cohorts after 2 to 4 years of taking up the policy, I restrict my sample to individuals who, based on the age requirement only, became eligible for DACA starting 2012. I restrict the sample to those who were at least 15 years old in 2012 and thus were eligible from the beginning. This sample includes individuals who are between the ages 18 and 30. If the effects of DACA naturally fade out for older cohorts, we would see a decrease in the benefits starting 2014, the year when the first cohort was required to renew their status. Nevertheless, the results on labor market outcomes, as presented in Table A8, are consistent with the main results.[12] I do not find a sharp drop in the benefits of DACA in this sample until 2017. Consequently, I can conclude that the benefits of DACA did not naturally fade out for cohorts who became eligible for the policy starting in 2012. Instead, it appears that the benefits were affected after 2017, indicating that external factors

[12]The event study analysis using this approach yields figures that display an identical trend to the main results. Specifically, there is an increase in employment and labor force participation, peaking in 2016, and diminishing from 2017 onwards. To maintain conciseness, I have not included these figures here, but they are available upon request.

contributed to the decline.

6.2 Uncertainty and Risk

In the previous subsection, I have addressed and ruled out potential factors that could be driving the decline in the benefits of DACA after 2017. In the following discussion, I propose that the diminishing advantages of DACA could be attributed to the uncertainty and evolving expectations surrounding the policy, rather than a factual change in the policy itself. However, directly testing this mechanism is challenging, as the baseline expectations of DACA recipients and their evolution over time are not directly observable.

Nevertheless, surveys conducted by Wong et al. 2018 provide insights into the concerns of DACA recipients. In their 2018 and 2019 questionnaires, respondents were asked about their fears of detention in a facility and deportation from the US. The results indicate that approximately 22% of respondents answered "about once a day" to the first question in 2018, with this percentage increasing to 25% in 2019. Regarding the second question, 25% of respondents answered "about once a day" in 2018, rising to 27.3% in 2019. Although these samples may not be highly representative due to their small sizes (ranging from 1,050 to 1,105 individuals), they offer suggestive evidence of the fears experienced by DACA recipients after 2017.

Additionally, supporting the liminal legality theory, Patler et al. 2019 present quotes from in-depth interviews conducted with individuals who attended at least one DACA informational session in Los Angeles County between 2012 and 2014 (DLS). These interviews shed light on how DACA recipients did not feel completely safe or secure about their immigration status in 2018. One participant expressed their thoughts as follows: "DACA has been wonderful in the benefits that it has provided, allowing me to work, study, and drive with less fear. I had hoped it would provide a transition to a more permanent solution [for my legal status], but that doesn't seem to be the case, especially with the current president and government. The fear of DACA being taken away is constantly on my mind." My results provide evidence supporting the liminal legality theory, which states that transitioning from more to less legally vulnerable states (akin to the deal DACA provided) has fluctuating effects over time.

Based on these anecdotes, there is reason to believe that uncertainty and expectations play a significant role in this context. I present suggestive evidence supporting this mechanism.

First, I conduct heterogeneity analysis by the ethnicity of individuals, specifically focusing on Hispanic individuals. This analysis is motivated by the fact that Hispanic individuals comprise a significant proportion of those who have been deported, making them more likely to experience the fear of deportation and uncertainty regarding their legal status (East et al. 2022). Consequently, if the fear of deportation and uncertainty are the driving factors behind the observed results, we would expect to observe a notable decrease in the effects of DACA for this particular population.

The results are presented in Table 4. Panel A shows the results on Hispanic individuals, comparing Hispanic eligible individuals to Hispanic non-eligible individuals, while panel B focuses on non-Hispanic individuals. The findings reveal that DACA had significant and positive effects on the employment outcomes of eligible Hispanic individuals, that are larger in magnitude than the estimates of the whole sample (panel A). This group experienced a 5.2 percentage point increase in the likelihood of being employed and a 4.13 percentage point increase in labor force participation, despite these outcomes already having relatively high sample means. However, after 2017, the benefits of DACA diminished in magnitude and significance, decreasing by 3 percentage points. Regarding non-Hispanic eligible individuals, the results indicate smaller positive effects of DACA on the likelihood of employment (3.68 percentage points), but these effects do not persist after 2017 (Panel B).

Second, I examine the differential effects of DACA by the political environments of the states in which individuals reside. Democratic states have generally offered a safety net for unauthorized individuals, with some, such as California, even taking legal action against the Trump administration to block the rescission of DACA. In contrast, Republican states have implemented measures to restrict undocumented individuals. If the stringent state environments intensify the uncertainty surrounding DACA, I anticipate that the effects of DACA will continue to be observed in Democratic states after 2017, while diminishing or disappearing in Republican states.

Table 5 shows the effect of DACA in Democratic states (panel A) compared to Republican states (panel B). In Democratic states, the effects of DACA are both highly significant and substantial in magnitude, with nearly a 6 percentage point increase in employment and a 5 percentage point increase in labor force participation. Although the effects decrease in magnitude after 2017, they remain significant and noteworthy. Panel B documents a significant and large increase in the likelihood of employment and labor force participation after 2012 for eligible individuals residing in Republican states as well. However, these effects disappear after 2017 in Republican states, becoming close to zero and not significant. Considering that DACA provided more security and benefits to individuals in Republican states, where they were less protected at the state level, it is plausible that the results of DACA in these states were considerable after 2012 but became non-significant after 2017, potentially due to heightened anxiety among undocumented individuals about the consequences of losing DACA in these environments.

Finally, 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 2013; Stephens-Davidowitz 2014; 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."[13] The variation in the search activity associated with these queries basically reflects individuals' awareness of DACA's situation and their interest in seeking information about any news developments.

Google Search Index measures the search intensity for a particular topic or term (x) over a time 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 A2, in the Appendix, plots the trend in the GT indices for the four search queries specified above. The graphs for all four queries display a similar pattern, reaching a peak of 100 in September 2017, coinciding with President Trump's announcement of the rescission of DACA.

Prior to September 2016, the indices remain close to zero, indicating minimal search activity. Starting from September 2016, the values begin to rise steadily. After September 2017, there is a smaller jump compared to the previous one, but the graph demonstrates a significant surge in search activity, reaching a maximum. This intense search behavior after September 2017 suggests that individuals were aware and concerned about news regarding DACA and Trump. Furthermore, I narrow down the data to focus on states with the highest proportion of undocumented and DACAmented individuals, particularly California and Texas. The trends observed in these two locations are remarkably similar, with a clear spike to 100 in September 2017. However, there is a slightly more pronounced increase starting from the beginning of 2017 in these states. This search behavior supports the

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

notion that uncertainty and changing expectations regarding the policy are the mechanisms through which the benefits of DACA gradually faded away.

All in all, the findings presented here offer suggestive evidence that the diminishing benefits of DACA and the significant decline observed in 2017 may be linked to factors such as uncertainty, changing expectations, and fears of deportation triggered by the recession of the policy implemented by the Trump administration.

7 Conclusion

In this paper, I examine the effects of the Deferred Action of Childhood Arrivals (DACA) and its fluctuations following the Trump administration efforts to rescind the program in 2017. Specifically, I examine the role of uncertainty and risk as influential factors that shape the outcomes of a temporary immigration policy. Using a difference-in-difference methodology and focusing on a sample of likely undocumented individuals, I find that DACA initially had positive and statistically significant effects on labor market outcomes between 2012 and 2016. However, the positive effects on employment fade out after 2017, particularly in Republican states where the policy had more benefits for undocumented migrants. These findings suggest that uncertainty surrounding the continuation of DACA induces chilling effects and dampens the policy's outcomes.

This study has important policy ramifications. To begin with, any cost-benefit analysis of DACA, or similar temporary policies, should consider the volatility of their outcomes, which are influenced by factors beyond the control of the policy's recipients. For example, the Supreme Court's ruling in 2020 indicated that DACA could be rescinded under specific legal actions. This implies that DACA might face future challenges, further undermining its outcomes. Consequently, any assessment of the policy's benefits may underestimate its true advantages and introduce biases into policy conclusions.

On the other hand, the Biden administration has demonstrated a focus on improving the well-being of undocumented immigrants, especially given their essential role in the economy during the Covid-19 pandemic.[14] TTherefore, it is crucial to understand the impacts of DACA and the underlying drivers before enacting future immigration legislation. Recognizing the volatility of temporary policies, policymakers should consider adopting a strategy

[14]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/.

that prioritizes the full integration of undocumented immigrants into the economy over the long term.

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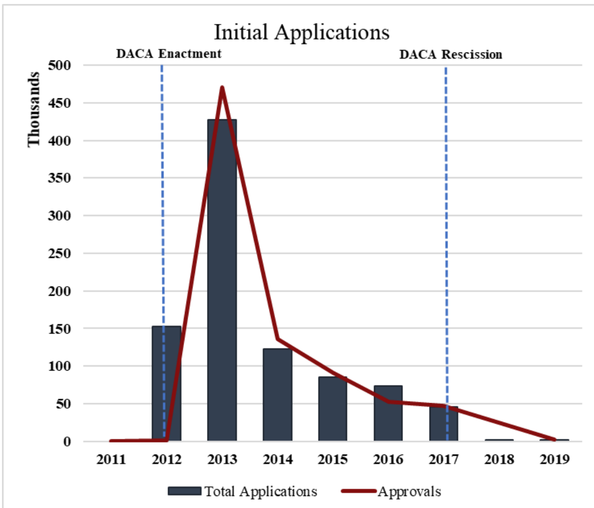
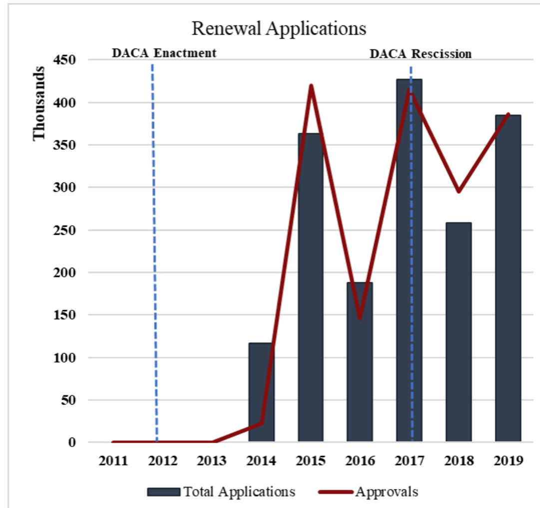
Figures and Tables

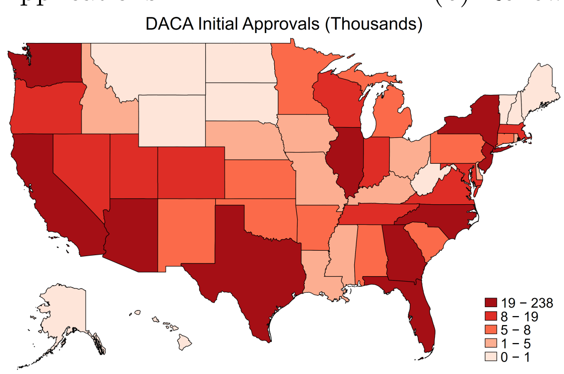
Figure 1: Number of DACA Initial and Renewal Applications



(a) Initial Applications



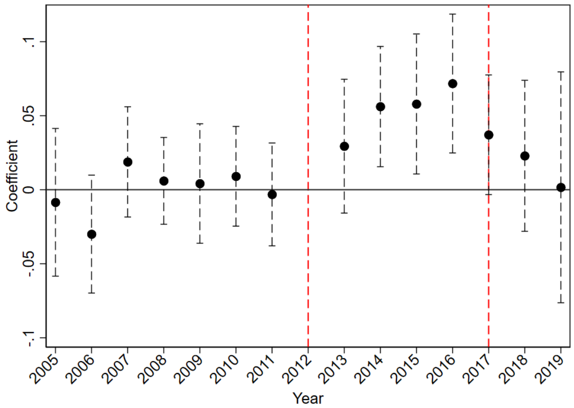
(b) Renewal Applications



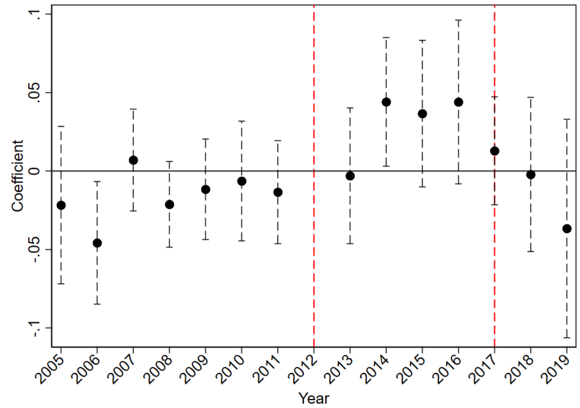
(c) Initial Approvals

Notes: 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.

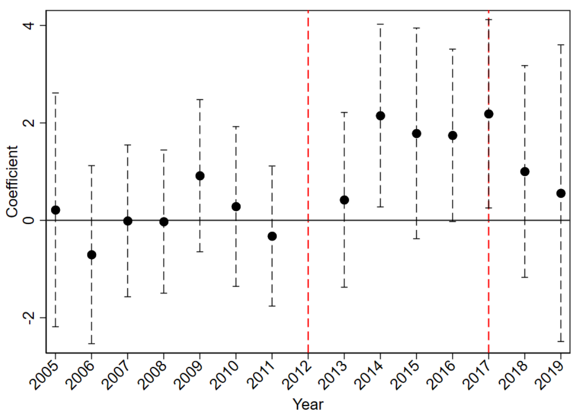
Figure 2: Event-study Analysis of Employment Outcomes



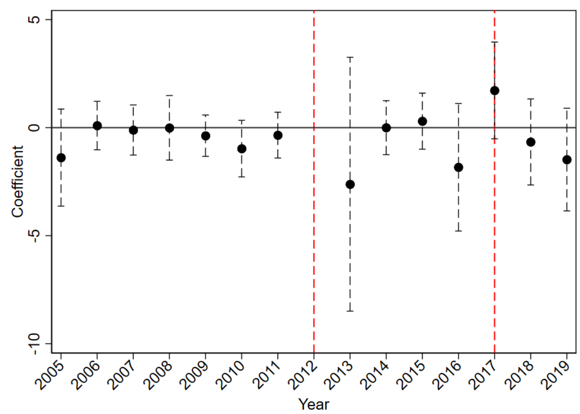
(a) Working



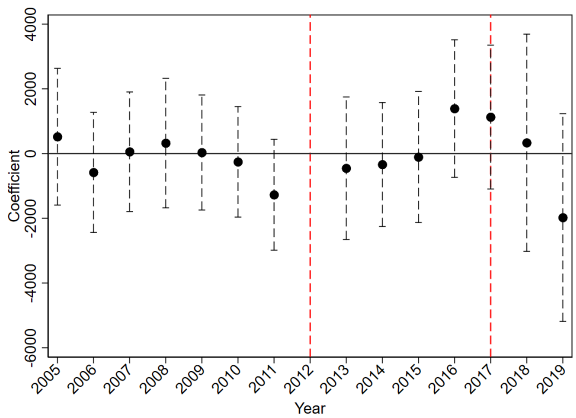
(b) In Labor Force



(c) Hours Worked



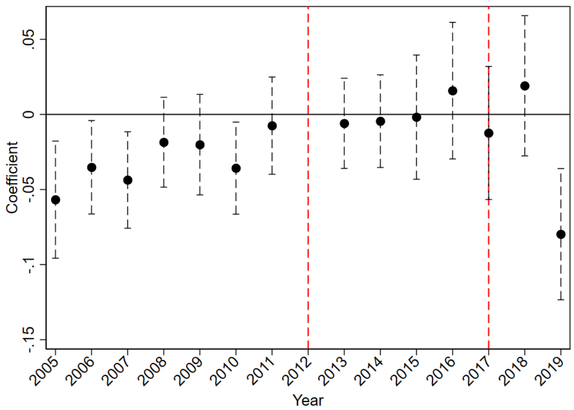
(d) Hourly Wage



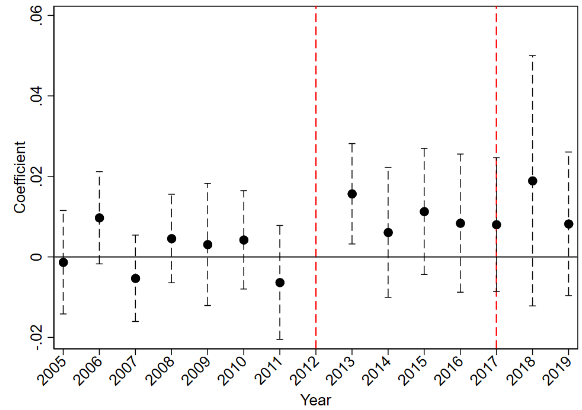
(e) Annual Income

Notes: These figures show the estimated coefficients and the 95 percent confidence intervals from event study regressions of Equation 2. Age, age at migration, 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. Hourly wages and annual incomes include zeros. The estimate of survey year 2012 is excluded.

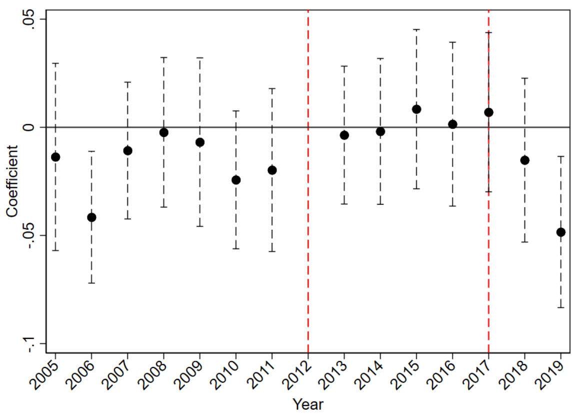
Figure 3: Event-study Analysis of Occupation Outcomes



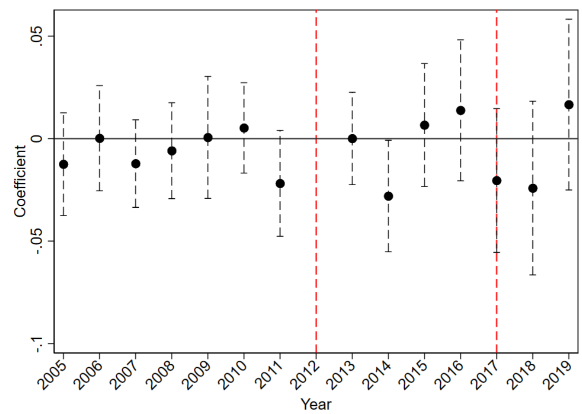
(a) Essential



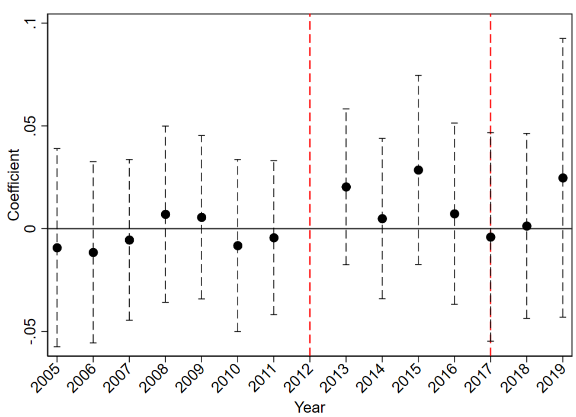
(b) Licensed Occupation



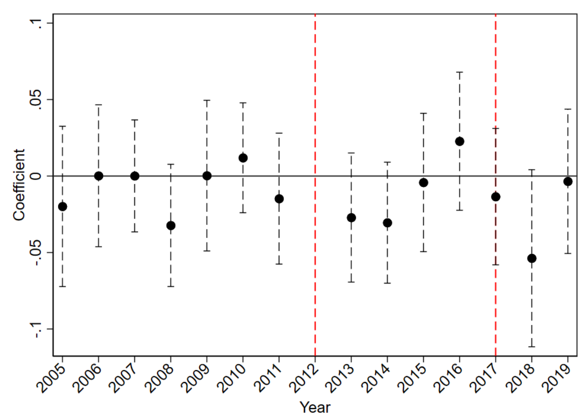
(c) Service Occupation



(d) Non-Service Occupation



(e) Manual-Intensive Tasks



(f) Analytical-Intensive Tasks

Notes: These figures show the estimated coefficients and the 95 percent confidence intervals from event study regressions of Equation 2. Age, age at migration, year and state fixed effects and state-specific time trends are added. Standard errors are clustered at the state-year level. Each outcome is an indicator of employment in a specific sector. 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. The estimate of survey year 2012 is excluded.

Table 1: Summary Statistics

	(1) All Sample	(2) DACA Eligible	(3) DACA Ineligible
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)
Poor English	25.94	18.17	28.13
	(43.83)	(38.56)	(44.96)
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

Standard deviations in parentheses

Notes: This table presents the summary statistics of the sample used in the analysis. 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.

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

	(1) Working	(2) In Labor Force	(3) Hours Worked	(4) Hourly Wage	(5) Annual Income
Elig*Post12	0.0513***	0.0410***	1.431***	-0.726	224.1
	(0.010)	(0.011)	(0.425)	(0.858)	(438.357)
Elig*Post17	0.0230	0.00812	1.347**	0.475	295.5
	(0.015)	(0.013)	(0.603)	(0.689)	(739.579)
Eligible	-0.00890	-0.00699	-0.196	0.319	396.3
	(0.009)	(0.010)	(0.354)	(0.303)	(363.157)
Mean Y	0.616	0.673	25.70	9.726	14551.0
Observations	100510	100510	100510	100510	100510
R-squared	0.192	0.203	0.261	0.00782	0.218

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 outcomes. Age, age at migration, 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 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	0.0247***	0.00982***	0.0155*	0.00253	0.0186*	-0.00651
	(0.009)	(0.004)	(0.009)	(0.007)	(0.010)	(0.010)
Elig*Post17	0.00615	0.0110	0.000580	-0.00696	0.00797	-0.0192
	(0.015)	(0.007)	(0.011)	(0.011)	(0.015)	(0.013)
Eligible	0.000767	-0.00127	-0.00424	0.00894*	-0.0152	0.0138*
	(0.008)	(0.003)	(0.007)	(0.005)	(0.009)	(0.007)
Mean Y	0.212	0.0276	0.163	0.112	0.207	0.204
Observations	100510	100510	100510	100510	73094	73094
R-squared	0.0359	0.0592	0.0374	0.216	0.0621	0.217

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. Each outcome is an indicator of employment in a specific sector. Age, age at migration, 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. Data is taken from the 2005-2019 waves of the ACS.

Table 4: Difference-in-Difference Effects by Hispanic Ethnicity

	(1) Working	(2) In Labor Force	(3) Hours Worked	(4) Hourly Wage	(5) Annual Income
Panel A: Hispanic					
Elig*Post12	0.0520***	0.0413***	1.288***	-0.0858	262.9
	(0.011)	(0.011)	(0.488)	(0.561)	(491.529)
Elig*Post17	0.0354**	0.0249*	2.172***	0.470	871.9
	(0.017)	(0.014)	(0.784)	(0.601)	(758.556)
Eligible	-0.00954	-0.00527	-0.348	0.256	208.2
	(0.011)	(0.010)	(0.422)	(0.363)	(330.189)
Mean Y	0.726	0.782	30.61	9.401	15342.5
Observations	47907	47907	47907	47907	47907
R-squared	0.154	0.157	0.215	0.0116	0.186
Panel B: Non-Hispanic					
Elig*Post12	0.0366**	0.0252	1.022	-1.952	-850.7
	(0.018)	(0.016)	(0.726)	(1.659)	(809.621)
Elig*Post17	0.0115	-0.00848	0.152	0.709	-564.7
	(0.026)	(0.022)	(0.888)	(1.251)	(1501.774)
Eligible	-0.00764	-0.00395	-0.101	0.299	77.68
	(0.013)	(0.013)	(0.494)	(0.512)	(612.317)
Mean Y	0.490	0.547	20.07	10.10	13641.8
Observations	52603	52603	52603	52603	52603
R-squared	0.207	0.220	0.283	0.00837	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 employment outcomes by Hispanic ethnicity. Age, age at migration, 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. Data is taken from the 2005-2019 waves of the ACS.

Table 5: Difference-in-Difference Effects by Political Party

	(1) Working	(2) In Labor Force	(3) Hours Worked	(4) Hourly Wage	(5) Annual Income
Panel A: Democratic States					
Elig*Post12	0.0539***	0.0490***	1.635***	-1.668	-578.1
	(0.016)	(0.016)	(0.568)	(1.568)	(667.876)
Elig*Post17	0.0345*	0.0251	1.974**	1.366	994.6
	(0.021)	(0.018)	(0.766)	(0.996)	(1018.957)
Eligible	0.000805	0.00499	0.0730	0.560	680.9
	(0.012)	(0.013)	(0.445)	(0.374)	(540.357)
Mean Y	0.626	0.683	26.03	10.59	16010.1
Observations	56641	56641	56641	56641	56641
R-squared	0.194	0.207	0.262	0.00675	0.216
Panel B: Republican States					
Elig*Post12	0.0463***	0.0302**	1.087*	0.303	1162.2**
	(0.014)	(0.015)	(0.649)	(0.533)	(486.019)
Elig*Post17	0.00870	-0.0112	0.588	-0.332	-137.7
	(0.020)	(0.019)	(0.914)	(0.703)	(891.008)
Eligible	-0.0209	-0.0221	-0.526	0.0971	257.7
	(0.013)	(0.014)	(0.534)	(0.493)	(434.964)
Mean Y	0.604	0.660	25.30	8.652	12734.1
Observations	43869	43869	43869	43869	43869
R-squared	0.193	0.200	0.263	0.0133	0.227

Standard errors in parentheses

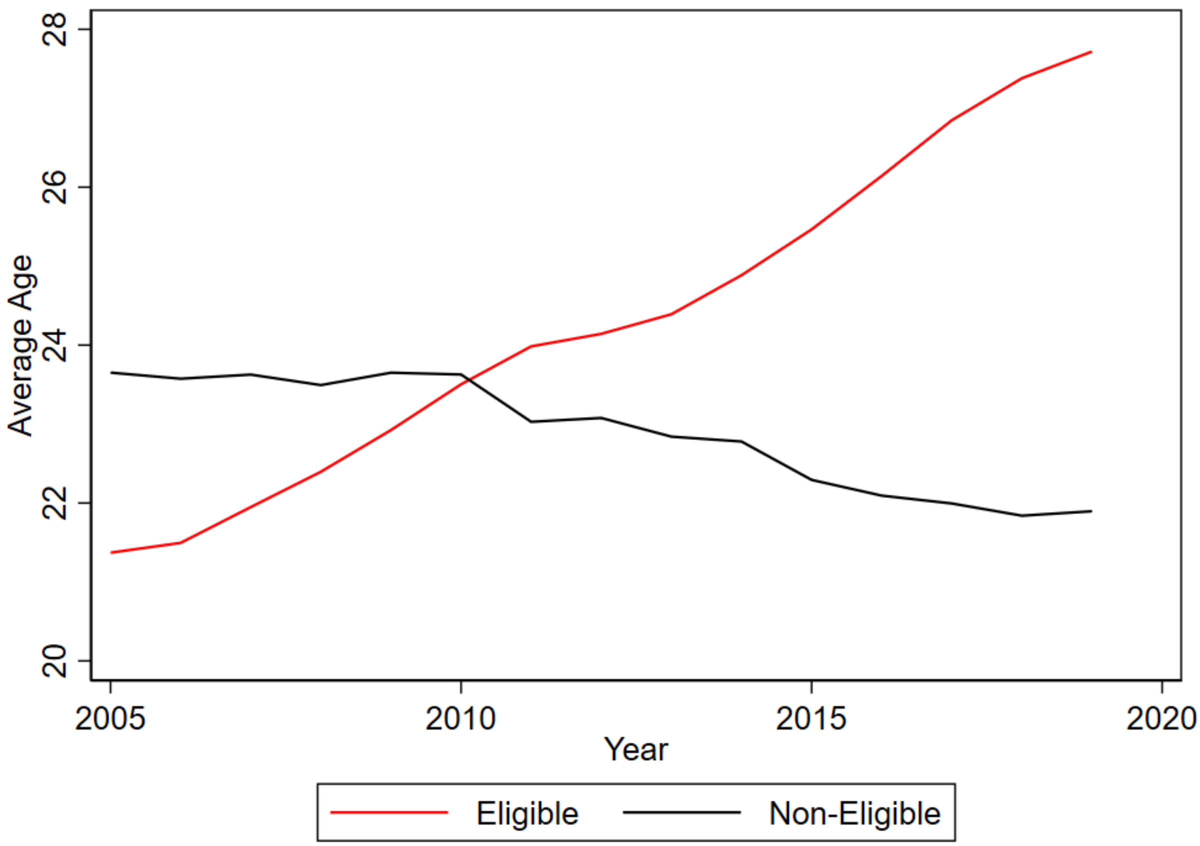
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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`). Age, age at migration, 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. Data is taken from the 2005-2019 waves of the ACS.

A Appendix

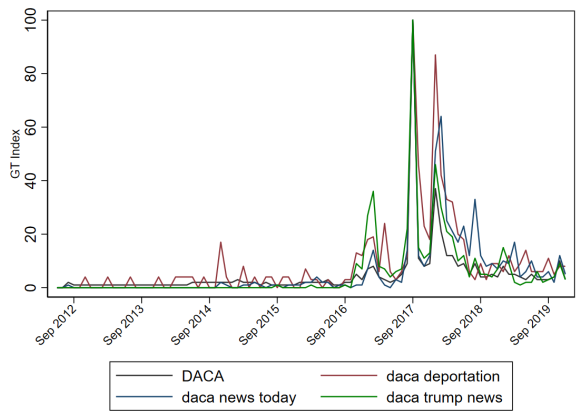
A.1 Figures and Tables

Figure A1: Trend in Average Age by Eligible Group

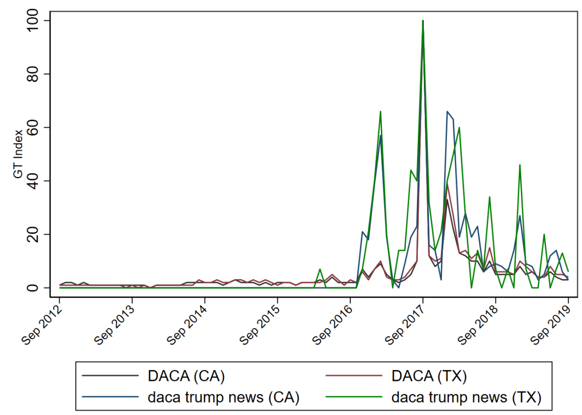


Notes: This figure illustrates the average age of a sample comprising likely undocumented individuals aged 18-30 who entered the US between the ages of 12-19 for each survey year. The red line represents the average age of individuals eligible for DACA in the sample, while the black line represents the average age of individuals who are not eligible in the sample.

Figure A2: Temporal Variation in Google Trends Indices



(a) United States



(b) California and Texas

Notes: These figures show the Google search volume of the terms "Deferred Action for Childhood Arrivals," and for the related queries "daca deportation," "daca trump news," and "daca news today.". In panel (a), the time series portrays the search volume in the US, while in panel (b), the time series portray the search volume in California and Texas. The vertical axes of both panels depict the search interest measured by Google. It is important to note that Google calculates the search volume or interest level relative to the highest point on the chart. A value of 100 represents the peak popularity of the term.

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)
usual hours worked per week	25.70	28.86	24.81
	(19.75)	(18.41)	(20.02)
Worked last year	69.88	77.60	67.70
	(45.88)	(41.70)	(46.76)
Annual Income	14551.0	16237.2	14074.9
	(22126.8)	(19182.7)	(22867.2)
Hourly wage	9.726	9.840	9.693
	(56.75)	(12.94)	(63.89)
Essential	34.45	33.59	34.74
	(47.52)	(47.23)	(47.61)
Licensed Occupation	4.473	4.334	4.519
	(20.67)	(20.36)	(20.77)
Service Occupation	26.37	25.20	26.76
	(44.06)	(43.42)	(44.27)
Non-Service Occupation	18.13	18.15	18.12
	(38.53)	(38.55)	(38.52)
Manual-Intensive	25.11	23.83	25.54
	(43.37)	(42.60)	(43.61)
Analytical-Intensive	24.94	26.65	24.38
	(43.27)	(44.21)	(42.94)
Observations	57209	13944	43265

Standard deviations in parentheses

Notes: This table presents the summary statistics of the outcomes considered in the analysis. The sample includes likely undocumented individuals ages 18-30, who entered the US between the ages 12-19, and satisfy education requirements. To calculate the summary statistics of occupation outcomes, the sample is narrowed down to include only those who are employed. DACA eligibility is decided based on the criteria of Section 3.2. Data is taken from the 2005-2019 waves of the ACS.

Table A2: Difference-in-Difference Effects on Employment without Controlling for State Time Trends

	(1) Working	(2) In Labor Force	(3) Hours Worked	(4) Hourly Wage	(5) Annual Income
Elig*Post12	0.0518***	0.0417***	1.456***	-0.751	245.3
	(0.010)	(0.011)	(0.425)	(0.857)	(438.919)
Elig*Post17	0.0268*	0.0122	1.477**	0.282	351.0
	(0.014)	(0.013)	(0.600)	(0.694)	(741.302)
Eligible	-0.00985	-0.00788	-0.221	0.335	416.9
	(0.009)	(0.010)	(0.357)	(0.299)	(364.555)
Observations	100510	100510	100510	100510	100510
R-squared	0.191	0.202	0.259	0.00736	0.217

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 outcomes. Age, age at migration, year and state fixed effects are added 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: Difference-in-Difference Effects on Occupations without Controlling for State Time Trends

	(1) Essential	(2) Licensed Occupation	(3) Service Occupation	(4) Non-Service Occupation	(5) Manual-Intensive	(6) Analytical-Intensive
Elig*Post12	0.0311***	0.0100**	0.0170*	0.00150	0.0126	-0.0119
	(0.009)	(0.004)	(0.009)	(0.007)	(0.010)	(0.010)
Elig*Post17	0.0142	0.0125*	0.00000353	-0.00673	0.0198	-0.0222
	(0.016)	(0.007)	(0.012)	(0.012)	(0.015)	(0.014)
Eligible	-0.00439	-0.00364	-0.00983	0.00707	-0.0190*	0.0166**
	(0.008)	(0.003)	(0.008)	(0.005)	(0.010)	(0.008)
Observations	100510	100510	100510	100510	73094	73094
R-squared	0.0280	0.0623	0.0390	0.224	0.0653	0.244

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. Each outcome is an indicator of employment in a specific sector. Age, age at migration, year and state fixed effects are added 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: Change in Observable Characteristics between 2012 and 2019

	(1) Age	(2) Male	(3) Hispanic	(4) White	(5) Black	(6) Asian	(7) Born in Central/ South 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 individual-level controls are included. Only 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 A5: Difference-in-Difference Effects on Employment Outcomes using In Person Interview Sample

	(1) Working	(2) In Labor Force	(3) Hours Worked	(4) Hourly Wage	(5) Annual Income
Elig*Post12	0.0598***	0.0457***	1.980***	0.0104	979.5*
	(0.012)	(0.013)	(0.521)	(0.471)	(505.162)
Elig*Post17	0.0388**	0.0270	2.384***	1.040	2031.4**
	(0.018)	(0.017)	(0.855)	(0.785)	(1014.073)
Eligible	-0.0195*	-0.0173	-0.679	0.366	-237.5
	(0.011)	(0.012)	(0.457)	(0.303)	(412.475)
Observations	50700	50700	50700	50700	50700
R-squared	0.187	0.197	0.245	0.0253	0.197

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 outcomes, using the sample of individuals who strictly took the in-person interview for the ACS. Age, age at migration, 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 A6: Difference-in-Difference Effects on Occupation Outcomes 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	0.0279**	0.0141***	0.00640	0.0143	0.00814	0.00658
	(0.012)	(0.005)	(0.012)	(0.009)	(0.013)	(0.012)
Elig*Post17	0.0232	0.0191**	-0.000985	0.0171	0.0149	-0.00912
	(0.020)	(0.009)	(0.017)	(0.017)	(0.022)	(0.018)
Eligible	-0.0102	-0.00535*	-0.0121	-0.000796	-0.0213*	0.00694
	(0.011)	(0.003)	(0.010)	(0.006)	(0.012)	(0.009)
Observations	50700	50700	50700	50700	39424	39424
R-squared	0.0334	0.0688	0.0416	0.191	0.0609	0.218

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, using the sample of individuals who strictly took the in-person interview for the ACS. Age, age at migration, year and state fixed effects and state-specific time trends are added. Standard errors are clustered at the state-year level. Each outcome is an indicator of employment in a specific sector. 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 A7: Difference-in-Difference Effects on Survey-item Response

	(1) Employment Status	(2) Occupation	(3) Total Income	(4) Hours Worked	(5) Education
Elig*Post12	-0.00513	0.0100	0.0162	0.00855	0.00666
	(0.006)	(0.008)	(0.010)	(0.007)	(0.008)
Elig*Post17	0.00996	0.0192*	0.0259	0.0310**	0.0179
	(0.011)	(0.011)	(0.016)	(0.012)	(0.014)
Eligible	-0.00303	-0.00139	0.00111	-0.00478	-0.00712
	(0.004)	(0.005)	(0.006)	(0.005)	(0.005)
Observations	100510	100510	100510	100510	100510
R-squared	0.0313	0.0170	0.521	0.0161	0.0403

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. Age, age at migration, 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 A8: Difference-in-Difference Effects on a non-Aging Sample

	(1) Working	(2) In Labor Force	(3) Hours Worked	(4) Hourly Wage	(5) Annual Income
Elig*Post12	0.0520***	0.0416***	1.466***	-0.726	374.4
	(0.010)	(0.011)	(0.426)	(0.855)	(436.670)
Elig*Post17	0.0114	-0.00400	0.999	-0.00923	-722.0
	(0.015)	(0.013)	(0.611)	(0.701)	(772.742)
Eligible	-0.000620	-0.00124	-0.0662	0.493	600.9
	(0.009)	(0.010)	(0.369)	(0.309)	(393.101)
Mean Y	0.632	0.689	26.42	9.890	15083.5
Observations	93383	93383	93383	93383	93383
R-squared	0.181	0.189	0.247	0.00773	0.213

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 outcomes. Age, age at migration, 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. Additionally, the sample is restricted to those who were at least 15 years old in 2012. Data is taken from the 2005-2019 waves of the ACS.

A.2 Data Appendix

Employment Variables:

- Working: This variable is a dummy variable that equals 1 if the individual is currently employed. It is defined through the variable empstat.
- In the labor force: This variable is a dummy variable that equals 1 if the individual is currently participating in the labor force.
- Hours Worked: This variable reports the total number of hours worked per week usually by the respondent during the previous 12 months.
- Total personal income: The variable reports the total pre-tax personal income from all sources for the previous 12 months.
- Hourly wage: The variable is calculated by dividing the total personal income by the total number of hours worked per year (hours worked per week multiplied by weeks worked per year).

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. 2019, 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.