Firm Creation under DACA

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Abstract

Undocumented immigration remains a central issue within US immigration policy debates, yet little is known about how legalization programs affect firm dynamics and labor market composition. In this paper, I study the impact of a particular legalization reform, Deferred Action for Childhood Arrivals (DACA), enacted in 2012, on establishment and employment outcomes. I exploit variation in pre-treatment exposure to the policy in sectors and commuting zones, using a triple-difference estimator. I find that DACA increases establishment entry by 2.4 percent in more exposed sectors and temporarily reduces exit rates, suggesting market expansion and entrepreneurship amongst formerly undocumented workers. The share of native workers rises by 2.1 percentage points, whereas that of ineligible undocumented workers declines by a similar magnitude, demonstrating labor substitution. Heterogeneity estimates across sectoral skill types reveal that these effects are concentrated in low- and medium-skill sectors. These results have important policy implications such that immigrant regularization can enhance firm dynamism and facilitate labor reallocation, without displacing native workers.

Keywords: Immigration Policy, Local Labor Markets, Undocumented Immigrants, DACA.

JEL Codes: J21, J61, J68, L11, L25

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1 Introduction

Tackling undocumented immigration remains a significant policy challenge for many nations, particularly across the Western Hemisphere. The United States, in particular, plays a dominant role in this issue, given that it hosts the largest population of undocumented immigrants in the world. The recent estimates from the Pew Research Center demonstrate that there were approximately 11 million undocumented immigrants residing in the US in 2024, corresponding to 23 percent of the immigrant population and 3.3 percent of the entire US population.[1] The large undocumented immigrant population has prompted the US government to pursue a range of policy responses, including legalization initiatives and deportation programs. One prominent reform aimed at regularizing the status of certain undocumented immigrants is the Deferred Action for Childhood Arrivals (DACA) program, which has also intensified the ongoing debates surrounding US immigration policy.

Enacted in June 2012, DACA provides the eligible recipients with two primary benefits. First, it offers a two-year renewable reprieve from deportation, granting recipients lawful presence in the United States during that period. Second, it confers work authorization through an Employment Authorization Document (EAD), which allows recipients to obtain a Social Security number, acquire a state-issued identification card, open bank accounts, and access other important services. To qualify for DACA, individuals must meet specific requirements related to birth year, year of entry into the country, immigration and citizenship status, and educational attainment.[2] Consequently, DACA has provided relief to approximately 834,000 young undocumented immigrants since its implementation.[3] Prior research has documented the labor market effects of DACA in various settings (Pope, 2016; Amuedo-Dorantes and Antman, 2017; Ortega et al., 2018; Battaglia, 2023; Zaiour, 2023; Kiser and Wilson, 2024). However, the evidence on how the program affects firms remains limited.

In this paper, I study the impact of DACA on establishment entry and exit at the commuting zone and sector levels. The unanticipated announcement of DACA provides a compelling quasi-experimental setting to examine its effects on establishment entry and exit.[4] Apart from the immediate benefits of protection from deportation and access to work authorization, legalization efforts

[1] See https://www.pewresearch.org/short-reads/2024/07/22/what-we-know-about-unauthorized-immigrants-living-in-the-us (accessed on April 18, 2025).

[2] I describe the eligibility criteria for DACA and its associated benefits in detail in Section 2.

[3] See https://www.nilc.org/work/daca (accessed on April 18, 2025).

[4] Although DACA was preceded by a series of unsuccessful legislative efforts, most notably the Development, Relief, and Education for Alien Minors (DREAM) Act, first proposed in 2001 and ultimately rejected by Congress in 2011, it was implemented via executive action without prior public signaling, enhancing its suitability for reliable causal inference. I outline further background and institutional setting in the following section.

may also produce spillover effects, generating broader indirect gains. On the one hand, DACA has been shown to increase educational attainment (Hsin and Ortega, 2018; Kuka et al., 2020; Ballis, 2023) and improve labor market outcomes amongst the undocumented population as discussed above.[5] On the other hand, legalization measures, in general, may induce firm expansion and establishment entry through two potential channels. First, legalization may enhance labor market access for undocumented workers, generating productivity gains for firms and thereby stimulating capital investment (Edwards and Ortega, 2017). Furthermore, legalization policies may increase entrepreneurship amongst formerly undocumented individuals (Bahar et al., 2022).[6] Despite these possibilities, the effect of DACA on US establishment entry and exit remains largely unexplored. Therefore, investigating it becomes an important empirical question.

I utilize data from the American Community Survey (ACS) and Business Dynamics Statistics (BDS) covering the 2008-2019 period and employ a triple-difference estimator by linking individual-level DACA eligibility to commuting zones and sectors through the following procedure. First, I impute the legal status of immigrants using the "residual" method implemented in Borjas (2017), in contrast to previous studies that rely on ethnicity and citizenship along with the Hispanic non-citizen proxy to isolate the legal status.[7] Next, I identify undocumented immigrants likely eligible for DACA based on established eligibility criteria, following the approach used in the literature. I then restrict the sample to the pre-treatment period and construct a threshold based on the distribution of the share of undocumented individuals who would become DACA-eligible in the post-treatment period, measured at the census division and two-digit NAICS sector levels. This step accounts for the potential labor mobility across states and occupations. Finally, I classify sectors in the top quartile of this distribution as "treated," those in the bottom two quartiles as "control," and omit the third quartile to serve as the reference category. I use the identical threshold to assign commuting zones into treatment and control groups.

[5] Orrenius and Zavodny (2015) document the effects of Temporary Protected Status (TPS) on the labor market outcomes of undocumented Salvadorans, and Albert (2021) examines the labor market impacts of both documented and undocumented immigrants in the US. Elias et al. (2022) analyze how granting work permits to undocumented immigrants affects native and immigrant workers in Spain, while Bahar et al. (2021) study the employment effects of a large-scale amnesty program for undocumented Venezuelan workers in Colombia.

[6] Wang (2019) finds that, following the September 11 terrorist attacks, non-citizen Mexican immigrants became increasingly more likely to enter self-employment compared to less-educated Whites. Olney (2013) demonstrates that immigrants have positive effects on the number of establishments at the extensive margin within a city due to an expansion in firm production.

[7] Liu and Song (2020) show that the residual method outperforms the Hispanic non-citizen proxy in identifying undocumented immigrants. In addition, while both methods yield estimates in the same direction for their outcome variables, the effects identified using the residual method are notably larger in magnitude for DACA.

I find that the enactment of DACA positively affects establishment entry in sectors with a high pre-treatment share of DACA-eligible workers. Event study estimates reveal no evidence of pre-trends between treated and control sectors, validating the parallel trends assumption. While the effects on entry rate and the log of exit are statistically insignificant, the exit rate temporarily declines following DACA's implementation, and the log of entry increases several years after. Triple-difference estimates show that establishment entry rises by 2.4 percent in response to the policy, with no significant effects on entry or exit rates. These results are consistent with Brown et al. (2013), who find that employing undocumented workers reduces a firm's hazard of exit, although their context differs in terms of legal status and geographic focus. The potential driving factors behind these effects include improved market access for undocumented workers, which may lead to productivity gains and capital investment (Edwards and Ortega, 2017), as well as increased entrepreneurial activities among undocumented individuals (Wang, 2019; Bahar et al., 2022).

The findings also demonstrate that DACA results in significant changes in employment across legal status and skill groups. In particular, the policy increases the share of native workers and reduces the share of undocumented workers, with the negative effect driven entirely by those ineligible for DACA. However, the impact of DACA on the fraction of eligible workers is statistically insignificant, in contrast to the positive findings in Pope (2016), Amuedo-Dorantes and Antman (2017), Zaiour (2023), and Kiser and Wilson (2024), likely due to differences in treatment assignment and geographic unit of analysis. My findings on native employment align with the positive effects shown in Battaglia (2023), while those on DACA-ineligible immigrants contrast with their estimate of no statistically significant change. Disaggregating by sectoral skill level, I show that these effects are concentrated in low- and medium-skill sectors, where DACA increases the employment share of natives by 2.1 percentage points and decreases that of ineligible immigrants by a similar magnitude.[8] In high-skill sectors, only documented immigrants experience a change in their employment share, which is positive and statistically significant. These findings suggest that labor reallocation is strongest in low- and medium-skill sectors, in which DACA-eligible workers are more concentrated. Furthermore, firms likely substitute away from ineligible undocumented workers towards natives upon the implementation of the policy in these sectors.

My primary contribution is to provide the first empirical evidence on the positive impact of DACA on establishment entry, using a triple-difference identification strategy. To my knowledge, I am the first to study how a policy regularizing undocumented immigrants affects US establishments.

[8] I discuss the assignment of sectors into skill groups in detail in Section 5.

While there is an expanding body of research on how immigration policies, mainly those targeting documented immigrants, affect US firms (Ghosh et al., 2014; Kerr et al., 2015; Khanna et al., 2018; Doran et al., 2022; Mehra and Shen, 2022; Brinatti et al., 2023), I am aware of only one study that broadly examines the effect of undocumented immigrants on US firms. In particular, Brown et al. (2013) find that firms employing undocumented workers are less likely to exit the market.[9] Relative to this literature, my study focuses on a distinct episode of immigration policy, DACA, which regularizes the status of undocumented immigrants, and investigates its effects on establishment entry and exit.

Moreover, I contribute to the emerging literature on DACA, which has mainly examined its effects on labor market outcomes for immigrants and natives (Pope, 2016; Amuedo-Dorantes and Antman, 2017; Battaglia, 2023; Zaiour, 2023; Kiser and Wilson, 2024) and human capital (Hsin and Ortega, 2018; Kuka et al., 2020; Ballis, 2023).[10] I extend this literature by investigating the effects of DACA on establishments and labor reallocation across different groups of workers. I find that DACA increases establishment entry and native employment, reduces the employment share of ineligible workers, and has no effect on eligible workers in sectors with a high pre-treatment share of DACA-eligible individuals. To my knowledge, only Garcia-Perez (2019) employs a triple-difference design, though their geographic treatment status is based on the availability of public resources, whereas mine relies on the pre-policy intensity of DACA-eligible undocumented immigrants.[11]

Finally, my results speak to a large strand of literature that studies the labor market effects of undocumented immigrants in the US (Winegarden and Khor, 1991; Rivera-Batiz, 1999; Phillips and Massey, 1999; Chassamboulli and Peri, 2014; Borjas, 2017; Edwards and Ortega, 2017; Borjas and Cassidy, 2019; Albert, 2021; Ortega and Hsin, 2022). In this context, I consider a particular subset of undocumented immigrants eligible for legalization and employment authorization under DACA. I further highlight the importance of such legalization policies, since the results exhibit positive effects on establishments and native employment.

[9]For related studies on the labor market effects of immigration reforms including the amnesty programs, see Kaushal (2006) and Amuedo-Dorantes et al. (2007). For research on the impacts of immigration enforcement and deportation policies on US firms and labor markets, see Orrenius and Zavodny (2009), Clemens et al. (2018), Clemens and Lewis (2022), Long et al. (2022), Abramitzky et al. (2023), East et al. (2023), and Bansak et al. (2024).

[10]For effects on health, see Patler and Pirtle (2018), Getrich et al. (2019), Giuntella and Lonsky (2020), and Giuntella et al. (2021); for crime, see Gunadi (2020) and Pearson (2024); for home-ownership, see Wang et al. (2022); and for intermarriage and living arrangements, see Amuedo-Dorantes and Wang (2023) and Gihleb et al. (2023). Ortega and Connor (2024) analyze the economic impact of eliminating DACA.

[11]Freedman et al. (2018) investigate the impact of the Immigration Reform and Control Act of 1986 (IRCA) on crime using a triple-difference strategy.

The remainder of the paper proceeds as follows. Section 2 provides background and outlines the institutional setting. Section 3 describes the data sources, variable construction, treatment definition, and presents descriptive statistics. Section 4 details the empirical strategy. Section 5 presents the results. Section 6 discusses the findings and concludes.

2 Background and Institutional Setting

Efforts to address shortcomings in federal policy towards young undocumented immigrants predate DACA, which built on a series of earlier, though often unsuccessful, initiatives. Namely, the most notable program was the Development, Relief, and Education for Alien Minors (DREAM) Act. Proposed in 2001, it attempted to set forth a path to legalization for undocumented youth contingent upon the fulfillment of minimum education requirements. Failing to draw ample support, the proposal did not pass Congress following a decade of inaction culminating in the 2011 legislative session. Nevertheless, DACA was enacted via an executive memorandum by President Obama in June 2012.

Due to its sudden announcement and swift implementation, there were minimal anticipation effects amongst potential beneficiaries. This unexpected nature of the announcement suggests that individuals were unlikely to have altered their behavior in expectation of the policy. Furthermore, the timing of the announcement, amidst the 2012 presidential campaign, was perceived by some as an effort to bolster Latino voter support (Amuedo-Dorantes and Antman, 2017).

Recipients of DACA derive two distinct types of benefits from the policy. First, although DACA does not provide the permanent immigration status envisioned in DREAM Act proposals, it offers a two-year reprieve from deportation, allowing eligible individuals to reside lawfully in the United States during that period. Upon expiration, recipients may apply for a renewal, which is granted in two-year increments.

Second, recipients are granted work authorization through an Employment Authorization Document (EAD). This, in turn, enables recipients to apply for a Social Security number, which allows them to obtain a state-issued identification card or driver's license in many states, as well as facilitates access to credit cards, bank accounts, and loans.

The US Citizenship and Immigration Services (USCIS) established the following eligibility requirements: (*i*) an applicant must be under the age of 31 by June 15, 2012, (*ii*) must have arrived in the US before a person's sixteenth birthday, (*iii*) must have continuously resided in the US since

June 15, 2007, and be present while filing an application, and (*iv*) must currently be in school, or have a high school diploma, or have an a general education development (GED) certificate.[12] Additionally, an applicant must be at least 15 years old; however, I do not adopt this restriction in determining eligibility status in this context, since a younger adolescent may age into eligibility over time (Kuka et al., 2020). An applicant must also not have been convicted of a felony or significant misdemeanors. Given the unavailability of data on criminal records, I am unable to incorporate this eligibility criterion. Lastly, there was an application fee of $465, which has progressively increased to $495.

USCIS began accepting DACA applications on August 15, 2012. Between that date and August 31, 2013, USCIS received 588,725 applications, of which 567,563 were accepted and 455,455 were approved.[13] As of September 30, 2024, there are 537,730 active DACA recipients, approximately 54% of whom are female, and about 28% reside in California, 17% in Texas, and 5% in Illinois. Enrollment is highest amongst individuals aged 26 to 30, and approximately 67% of all recipients are reported to be single. The majority of recipients are originally from Mexico, El Salvador, Guatemala, and Honduras, with individuals of Mexican origin comprising roughly 81% of the total.[14]

DACA has been entangled in sustained legal disputes over its legitimacy and future, directly affecting the application process. On September 5, 2017, President Trump issued an executive memorandum rescinding DACA, which immediately halted new applications and renewals. In January 2018, the State of California challenged the rescission, leading to a temporary reinstatement of renewals. On December 4, 2020, the US Supreme Court overturned the rescission, prompting USCIS to resume both new and renewal applications. However, on July 16, 2021, a federal district court in Texas ruled DACA unlawful, limiting the program to renewals only. As of October 2022, USCIS continued to process renewals but remained barred from accepting new applications. On September 13, 2023, the same court reaffirmed its ruling, further intensifying legal uncertainty. Most recently, on January 17, 2025, the US Court of Appeals for the Fifth Circuit upheld parts of that decision, allowing current recipients to retain their status while litigation continues.

[12] This requirement could be waived for an applicant, who was honorably discharged from the Armed Forces or Coast Guard (i.e., an individual with veteran status).

[13] See https://www.uscis.gov/sites/default/files/document/data/daca-13-9-11.pdf (accessed on April 23, 2025).

[14] See https://www.uscis.gov/sites/default/files/document/data/active_daca_recipients_fy2024_q4.xlsx (accessed on April 23, 2025).

3 Data

3.1 Sources

DACA Eligibility. I use microdata from the 2008-2019 American Community Survey (ACS), retrieved from the Integrated Public Use Microdata Series (IPUMS USA: Ruggles et al., 2023) to evaluate the impact of DACA on establishments. While the details on birthplace and citizenship status exist in the ACS, legal status amongst noncitizens is unavailable. Consequently, this poses a challenge to accurately isolating the DACA-eligible population. To overcome this limitation, I proceed in two major steps.

Initially, I impute undocumented status and restrict the sample to only undocumented individuals. This approach differs from the existing literature that attempts to use similar imputation procedures for the DACA-eligible population; nevertheless, it offers two key advantages.[15] First, it helps me focus directly on the subpopulation affected by DACA. This further enhances the internal validity of my estimates, since it reduces noise introduced by including ineligible individuals. I provide detailed explanation on how I generate treatment status in the following subsection. Second, failure to identify the legal status may bias the estimated treatment effects, providing further justification for limiting the sample to those most likely to be affected by the policy. Therefore, I use the algorithm proposed in Borjas (2017) to first impute the legal status, allowing me to estimate DACA's impact more accurately.

This procedure relies on the "residual" method through which a foreign-born person is classified as a legal immigrant if they meet any one of the following conditions. A foreign-born person must (*i*) have arrived in the US before 1980, (*ii*) be a citizen, (*iii*) be a recipient of Social Security benefits, SSI, Medicaid, Medicare, or Military Insurance, (*iv*) be a veteran, or be currently in the Armed Forces, (*v*) work in the government sector, (*vi*) dwell in public housing or receive rental subsidies, or be a spouse of someone who dwells in public housing or receives rental subsidies, (*vii*) be born in Cuba (Cuban immigrants received refugee status before 2017), (*viii*) work in an occupation that requires licensing (e.g., physicians, registered nurses, air traffic controllers, and lawyers), (*ix*) be a spouse of someone who is a legal immigrant or citizen.[16] Since the ACS does not report whether

[15] See Zaiour (2023) for a similar technique, although they do not match individual DACA eligibility to broader units such as commuting zones and sectors, as is done in my study described in the text. Ortega and Connor (2024) introduce a method that probabilistically assigns likely DACA-eligible individuals to recipient status by matching selected target variables using USCIS data. This approach allows for distinguishing between eligible recipients and eligible non-recipients. However, such granularity is not required in my analysis, since the treatment status is defined at broader levels.

[16] Borjas and Cassidy (2019) apply an additional filter to this algorithm by excluding the immigrants who likely hold H-1B visas. They assume that an immigrant is a H-1B visa holder if that immigrant works in certain occupations

a particular household dwells in public housing or receives subsidized rents, I omit condition (vi) from the imputation procedure.

Afterwards, I continue with identifying individuals eligible for DACA. For this purpose, I follow the literature and use information on birth year, birth quarter, immigration and citizenship status, year of immigration, and education to identify likely DACA-eligible individuals. As mentioned above, the only difference in my approach is that I focus on the universe of undocumented immigrants rather than all immigrants (foreign-born persons). Since age of arrival is not reported in the survey, I take the difference between year of immigration and birth year to assign age of arrival. To determine whether an undocumented immigrant meets the requirement of "under 31 by June 2012" corresponding to the timing of the policy, I utilize birth year and birth quarter variables provided in the survey. Using the school attendance (i.e., currently in school) and detailed educational attainment variables, I can determine whether an individual meets the education requirement. Together, these conditions constitute whether individuals are DACA-eligible, which I use to isolate the "treated" commuting zones and sectors in the subsection below. I define the comparison group, DACA-ineligible individuals, as those who do not meet the eligibility criteria outlined above.

It should be highlighted that I limit the sample to individuals aged 6 to 35 for two primary reasons. First, setting the lower age limit at 6 allows for the observation of individuals as they age into potential eligibility over time. The upper age limit of 35 ensures that the sample consists of young working-age individuals. Notably, the literature reports that the average age of DACA-eligible individuals falls within the twenties, which is comparable to statistics reported in the subsequent subsection.[17] Second, individuals within this age range are most likely to enter the labor market and engage in entrepreneurial activities.

Establishments and Employment. The data on establishments for the 2008-2019 period come from the Business Dynamics Statistics (BDS) dataset, which is produced by the Census Bureau and offers annual insights into business dynamics across the US. It encompasses measures such as

(such as those in "high-tech"), has resided in the US for up to six years, and is a college graduate. In my analysis, this filter is not necessary to adopt, since I restrict the sample to a subpopulation of undocumented immigrants (i.e., DACA-eligible individuals). Moreover, only approximately 1.5% and 3% of DACA-eligible individuals have educational attainment equivalent to a college degree and higher in the pre- and post-treatment periods, respectively. Thus, not filtering out potential H-1B visa holders is unlikely to meaningfully affect the treatment status of commuting zones or sectors.

[17] It is important to note that average ages can vary depending on the sampling time frames. For instance, Pope (2016) reports an average age of 24 for the 2005–2014 period. In contrast, my analysis separates data into pre- and post-treatment periods, which may lead to slight discrepancies compared to existing studies.

establishment openings and closings, firm startups and shutdowns, and job creation and destruction, categorized by firm size, age, industry and sector, as well as geographic location (Haltiwanger et al., 2009). In my analysis, I focus on establishment entry and exit along with their corresponding rates. The BDS defines an establishment entry as an establishment with positive employment in the current year and zero employment in the prior year, whereas it defines an establishment exit as an establishment with zero employment in the current year and positive employment in the prior year. The establishment entry or exit rate is calculated by dividing the number of establishment entries or exits in year t by the average number of establishments with positive employment in years t and $t-1$. This approach accounts for year-to-year scope changes and ensures consistency in measuring establishment dynamics.

I obtain the employment data for the 2008-2019 from two distinct sources. First, I use the ACS to generate employment variables by nativity alongside immigrant and legal statuses. Second, I utilize the data provided by the Quarterly Census of Employment and Wages to examine the impact of DACA on employer-reported records as opposed to self-reported employment by households in the ACS. Since these sources along with the BDS do not produce the data at the commuting zone level, I crosswalk counties and Public Use Microdata Areas (PUMAs) to commuting zones using the crosswalk file generated in Autor and Dorn (2013).[18]

3.2 Treatment Status by Commuting Zone and Sector

The triple-difference estimator extends the difference-in-differences (DiD) approach by incorporating variation across three dimensions, which commonly are time, treatment status, and a third characteristic such as a specific group, to measure the causal effect of an intervention. In my examination, I designate commuting zones as the second dimension and sectors as the third. Yet, assigning treatment status in my analysis presents a significant challenge because DACA eligibility is determined at the individual level. As a result, this complicates the process of aggregating and aligning these eligibility criteria with broader units such as commuting zones or sectors. To this end, I undertake the following steps to accurately map individual DACA eligibility to these larger units as a complex but essential aspect of the analysis.

The most intuitive approach to assigning treatment status to commuting zones or sectors would be to rely on the magnitudes of the shares of DACA-eligible undocumented immigrant workers in those units. This would rest on a strong assumption that DACA-eligible immigrants do not

[18]For additional details, see David Dorn's website. Specifically, I use crosswalk files [E5] through [E8] to match (PUMAs) to commuting zones, and then link commuting zones to states and census divisions.

move across regions or industries.[19] Heterogeneity in how states implement DACA, including differing levels of restrictiveness, adds another layer of complexity by potentially encouraging labor mobility across state lines.[20] To circumvent these issues, I use a method that accounts for potential mobility of DACA-eligible population and proceed as follows. First, I restrict the sample to the pre-treatment period and compute the share of undocumented workers, who would likely become eligible for DACA upon its enactment, at the census division and two-digit NAICS sector levels.[21] Next, I construct a threshold criterion based on the distribution of the share of DACA-eligible workers. I classify the sectors in the top quartile as "treated," while I designate those within the bottom two quartiles as "control" sectors. As the reference category, I omit the sectors in the third quartile. I apply the same threshold criterion to classify commuting zones into treatment and control groups.[22] Table 1 reports the shares of DACA-eligible undocumented workers by treatment status in commuting zones and five largest sectors within census divisions during the pre-treatment period. Figure 1 displays the density plot of the shares of those workers by commuting zone, and Figure 2 maps them by treatment status in the pre-DACA period.

3.3 Summary Statistics and Descriptive Analysis

Tables 2 and 3 present summary statistics for DACA-eligible and ineligible individuals aged 6–35 during the pre- and post-treatment periods, respectively. Specifically, these tables report weighted means (using ACS-provided sample weights) and standard deviations for the employment, education, age, and English-speaking ability variables.

Between the pre- and post-treatment periods, both labor force participation and employment rates have increased amongst DACA-eligible males and females. In contrast, these economic indicators have declined amongst the DACA-ineligible population. The share of eligible individuals with a high school degree has risen substantially, while the shares with some college education and a college degree have increased more modestly. Amongst the ineligible population, the shares of individuals with some college education, a college degree, and education beyond college have increased slightly. A notable observation is the gender gap in high school attainment: in both groups,

[19] Kiser and Wilson (2024) demonstrate that DACA induced geographic and job mobility amongst young immigrants.

[20] Garcia-Perez (2019) documents that DACA-eligible workers experience improved employment and educational outcomes in "accommodating areas" (i.e., states such as California, New York, Massachusetts, and Minnesota) that provide supportive public resources.

[21] There are nine census divisions and twenty sectors at the two-digit NAICS level.

[22] Tolbert and Sizer (1996) were the first to systematically define commuting zones (CZs) as local labor market areas based on commuter flows. These geographic units were later popularized in empirical labor economics by Autor et al. (2013) and have since become a standard framework for analyzing localized economic effects.

the share of males with a high school degree exceeds that of females. However, there do not seem to be notable gender differences in educational attainment for the other categories. The average ages of eligible individuals are around 17 and 22 in the pre- and post-DACA periods, respectively, while it is around 27 for eligible individuals in both periods. English-speaking proficiency among eligible individuals has remained virtually unchanged over time, whereas ineligible individuals have experienced a notable improvement. Nevertheless, eligible individuals consistently exhibit stronger English-speaking skills than their ineligible counterparts across both periods.

Table 4 reports summary statistics for establishments, including means and standard deviations for the pre- and post-DACA periods. All outcome variables, entry and exit rates, and the logs of entry and exit, are lower in the post-treatment period compared to the pre-treatment period. One can observe the most marked decline in the exit rate, which has decreased by approximately 1.2 percentage points, whereas the difference in means for the entry rate is around 0.37 percentage points.

4 Empirical Strategy

I employ the triple-difference design to estimate the causal effects of DACA on the outcome variables. To this end, let Z be an indicator equal to 1 for commuting zones that had a relatively high share of DACA-eligible undocumented workers during the pre-period (i.e, 2008-2011). These "treated" commuting zones are identified based on a threshold, whereby those falling in the top quartile of the distribution of the share of DACA-eligible undocumented immigrant workers are classified as treated. Let S_d denote an indicator equal to 1 for sectors within a census division d that employed a markedly high share of DACA-eligible undocumented immigrant workers during the pre-period. The treatment status for these sectors is in line with the threshold identical to that of commuting zones. Let $\mathbf{1}(\tau_t \geq 2012)$ represent an indicator equal to 1 for years $t \geq 2012$ corresponding to the enactment of DACA.

Therefore, the term $Z \times S_d \times \mathbf{1}(\tau_t \geq 2012)$ is an indicator equal to 1 for sectors in census divisions that employed a substantially larger share of undocumented immigrant workers, located in commuting zones with a sizable share of those workers in the pre-period, who would become eligible for DACA after its enactment in 2012. This interaction estimates the average effect of DACA on sectors affected by the policy, effectively yielding the following triple-difference estimator:

$$Y_{s,z,t} = \beta[Z \times S_d \times \mathbf{1}(\tau_t \geq 2012)] + \lambda_{s,z} + \gamma_{s,t} + \theta_{z,t} + \varepsilon_{s,z,t}, \tag{1}$$

where, $Y_{s,z,t}$ is an outcome (*i.e.*, the establishment entry and exit rates as well as the log of employment of a certain group of workers disaggregated by nativity and legal statuses) of sector s in commuting zone z in year t regressed on the main variable of interest, $[Z \times S_d \times \mathbf{1}(\tau_t \geq 2012)]$, and a set of fixed effects. These fixed effects include (i) sector $\times$ commuting zone fixed effects, $\lambda_{s,z}$, which account for time-invariant characteristics correlated with the outcomes and interaction term; (ii) sector $\times$ year fixed effects to control for time-varying shocks specific to treated sectors; and (iii) commuting zone $\times$ year fixed effects to absorb time-varying shocks common across treated commuting zones. The error term, $\varepsilon_{s,z,t}$, captures all unobserved sector $\times$ commuting zone shocks to outcomes, which are assumed to be uncorrelated with the main variable of interest.

It is worth noting that all first- and second-order interaction terms attributed to a triple-difference estimator are indirectly included in equation (1). Specifically, sector $\times$ commuting zone fixed effects, $\lambda_{s,z}$, capture the time-invariant sector s and commuting zone z covariates, and the set of sector $\times$ year fixed effects absorbs the time covariates. The coefficient of interest, β, returns the average effect of DACA on sectors that employed a relatively high share of DACA-eligible undocumented immigrant workers in treated commuting zones relative to those that employed a low share of workers with identical profiles in control commuting zones during the pre-treatment period. The robust standard errors are clustered at the state level in all specifications.[23]

The identifying assumption is that the relative outcome of sectors with a history of employing a notably high share of DACA-eligible undocumented immigrant workers and those employing a low share of the same workers in treated commuting zones would have trended similarly to the relative outcome of the comparable sectors in control commuting zones in the absence of treatment.[24] This further requires that there be no other contemporaneous factors inducing a difference in differential trends between the outcomes of treated and control sectors located in their respective commuting zones. To empirically assess the plausibility of this assumption, I estimate the following event-study

[23] See Hoynes et al. (2015) for suggesting the state-level clustering in a DiD setting with a federal policy. Olden and Møen (2022) address the over-rejection problem stemming from having few treated clusters within the frameworks of *i.i.d.* standard errors, robust standard errors, and those clustered by state. With 50 state-level clusters, 30 of which contain treated commuting zones, and sufficient statistical power, my specification is unlikely to suffer from over-rejection. Conley and Taber (2011) show that the asymptotic properties can be applied to the treated and untreated clusters, requiring a sufficiently large number of each group for reliable inference. Thus, in this context, the robust standard errors clustered at the state level provide valid inference (I will also carry a second method with permutation tests). See Cameron and Miller (2015) for a comprehensive practical guideline that identifies related issues and offers solutions.

[24] Olden and Møen (2022) illustrate that although a triple-difference design is constructed from two difference-in-differences, it does not require two parallel trends assumptions. Instead, the identifying assumption relies on the relative outcome of two groups in the treatment unit trending similarly to that of the same groups in the control unit.

specification:

$$Y_{s,z,t} = \sum_{\substack{m \neq 2011 \\ m=2008}}^{2019} \beta_m [Z \times S_d \times \mathbf{1}(\tau_t = m)] + \lambda_{s,z} + \gamma_{s,t} + \theta_{z,t} + \varepsilon_{s,z,t}. \tag{2}$$

Equation (2) modifies the triple-difference estimator such that it allows the effects to dynamically vary over time, rather than imposing the assumption that the treatment effect is immediate and permanent. The estimated coefficients of interest, $\hat{\beta}_m$ (for m $\in$ [2008,2019], omitting 2011 as a reference year corresponding to one period prior to the enactment of DACA), represent the differential time path of the outcomes of the treated sectors in the pre- and post-DACA periods.

5 Results

5.1 Establishment Entry and Exit

I begin by examining how the enactment of DACA affected establishments. As such, I analyze the dynamic impact of DACA on the logs of establishment entry and exit, as well as on establishment entry and exit rates, by estimating equation (2). The event studies, displayed in Figure 3, show no evidence of pre-existing trends between treated and control sectors prior to 2012, supporting the parallel trends assumption. While the effects on entry rate and the log of exit are statistically insignificant, the exit rate temporarily declines in the years immediately following the enactment of DACA, with the effect dissipating after a few years. Furthermore, the log of establishment entry increases several years after the implementation of the policy.

Table 5 presents the triple-difference estimates obtained from equation (1). Consistent with the event study results reported above, the table demonstrates that DACA leads to a 2.4 percent increase in establishment entry in sectors that employed a considerably high share of eligible workers in the pre-treatment period. The impacts on both entry and exit rates in those sectors are statistically insignificant, although the effect on entry rate is positive, and the effect on exit rate is negative. The coefficient of the log of exit is statistically insignificant and close to zero.

Taken together, these findings suggest that the implementation of DACA positively affects establishment entry. One potential explanation is that legalization improves market access for undocumented workers, thereby allowing firms to benefit from productivity gains, which may then induce capital investment (Edwards and Ortega, 2017). Another likely channel is an increase in entrepreneurial activities amongst undocumented individuals (Wang, 2019; Bahar et al., 2022).[25] Although not directly comparable, Brown et al. (2013) find that a firm's hazard of exit declines by 19 percent in response to employing undocumented workers in the state of Georgia. They attribute this to an increase in the number of firms adopting similar labor strategies, an expansion in the firm's market reach, and greater labor intensity in production.[26]

5.2 Employment

The existing literature has primarily studied the labor market effects of DACA on immigrants (Pope, 2016; Amuedo-Dorantes and Antman, 2017; Ortega et al., 2018; Zaiour, 2023; Kiser and Wilson, 2024) and native workers (Battaglia, 2023) in different contexts. In this subsection, I extend the analysis by exploring how various groups of workers responded to the enactment of DACA, employing a different treatment assignment approach as outlined in Section 3. The outcome variables are employment shares, defined as the number of workers in each category within a commuting zone and sector, relative to the total number of workers in that commuting zone and sector.

Baseline Analysis. Table 6 reports the employment estimates across nativity, legal status, and DACA eligibility. The effect on the share of native workers is positive, whereas the impact on the share of immigrant workers is negative and statistically significant. Further disaggregation by legal status and DACA eligibility reveals that the adverse impact is entirely driven by DACA-ineligible undocumented workers. In particular, the enactment of DACA reduces the employment of DACA-ineligible workers by 1.6 percentage points in sectors that previously employed a notably greater share of eligible workers. In contrast, the effects of DACA on total employment share and the share of documented immigrant workers are positive but statistically insignificant. Similarly, the coefficient estimate for the share of DACA-eligible workers is negative but not statistically significant. The event study plots in Figure 4 illustrate the dynamic effects of these estimated coefficients. In line with the regression results, the figure shows an immediate and persistent fall in the employment share of undocumented workers, accompanied by a more gradual yet sustained decrease among DACA-ineligible immigrants and a corresponding increase in the share of natives. The estimated coefficients for the remaining groups, however, are imprecise and not statistically distinguishable from zero.

[25] As a potential channel, I will look at self-employment amongst DACA-eligible individuals as a proxy for entrepreneurship.

[26] As another potential channel, I will look at capital investment (probably proxied by GDP) after DACA's implementation.

On the whole, my findings demonstrate that, in sectors with a substantially higher pre-treatment share of DACA-eligible workers, this group does not exhibit any significant change in their employment share following the policy's implementation. This contrasts with the positive results documented in Pope (2016), Amuedo-Dorantes and Antman (2017), Zaiour (2023), and Kiser and Wilson (2024). However, native workers experience an increase in their employment share, suggesting labor reallocation, while DACA-ineligible workers face a decrease in their employment share in the post-treatment period. My findings for native workers align with the positive effects shown in Battaglia (2023), whereas the results for DACA-ineligible workers contrast with their estimates, which indicate no significant change. These differences in findings are likely attributable to the different treatment assignment method employed in my study, as well as the use of commuting zones to define local labor markets, in contrast to the alternative geographic units used in the aforementioned literature.

Sectoral Skill Analysis. Prior literature has illustrated the wedge between work and education (Hsin and Ortega, 2018) amongst undocumented students, along with the positive effect of DACA on human capital accumulation of eligible population (Kuka et al., 2020; Ballis, 2023). If eligible individuals invest in their education and delay labor market entry, as suggested in these studies, then one would expect differential effects of the policy across sectors with different skill requirements. To empirically test this hypothesis, I estimate the impact of DACA on different groups of workers employed in sectors categorized by skill levels. This also unmasks important heterogeneity in labor reallocation across skill cells that has not been previously explored in the literature.

Central to this exercise is the allocation of sectors into skill groups. To do so, I classify sectors based on the average years of education of workers in each sector. Specifically, I define sectors with a mean education level equivalent to a high school degree as low-skill, those corresponding to some college as medium-skill, and those with an average education level equivalent to a college degree as high-skill.[27] Table 7 presents the regression results of this exercise for low- and medium-skill sectors in Panel A and for high-skill sectors in Panel B.[28] Consistent with the baseline results, the estimates in Panel A show that DACA positively affects the employment share of native workers, while it adversely impacts the share of DACA-ineligible workers in low- and medium-skill sectors. Moreover, the magnitude of these effects is substantially larger in this subsample. Specifically, the implementation of DACA increases the employment fraction of natives by 2.1 percentage points,

[27]For a similar classification scheme, see Hotchkiss and Quispe-Agnoli (2013).

[28]Due to the small number of observations in low-skill sectors, estimating regressions for this group separately is not feasible.

while it decreases that of DACA-ineligible immigrants by a comparable magnitude. The estimates in Panel B demonstrate that DACA has a statistically significant effect only on the employment share of documented immigrants employed in high-skill sectors, and that the impact is positive. In particular, the share of documented workers rises by 1.1 percentage points following the implementation of the policy. The event study plots depicting the dynamic effects in Figures 5 and 6 are consistent with the corresponding regression estimates reported above.

Overall, these results have several implications. First, DACA-eligible workers are highly concentrated in low- and medium-skill sectors due to their educational attainment, confirm the results on human capital accumulation in the literature. This indicates the labor reallocation is the strongest in these sectors following the enactment of DACA. Furthermore, native workers employed in low- and medium-skill sectors are more substitutable with undocumented immigrants ineligible for DACA in these sectors. Legalizing a subset of undocumented workers through DACA may have induced firms to substitute away from ineligible undocumented immigrants towards natives in these sectors. Finally, since high-skill sectors require a college degree and prior work experience, which most DACA recipients may not meet, their penetration is low. Thus, the policy has minimal a measurable impact in these sectors.

6 Discussion and Conclusion

Addressing undocumented immigration has remained at the forefront of US immigration policy debates in recent years, prompting policymakers to pursue various reforms. In this paper, I study the impact of a particular episode of such reforms, the implementation of Deferred Action for Childhood Arrivals (DACA) in 2012, on establishments. My identification strategy employs a triple-difference estimator, leveraging variation in treatment intensity in sectors and commuting zones based on their pre-treatment shares of undocumented individuals eligible for DACA.

I find that DACA increases establishment entry by 2.4 percent in sectors that employed a substantially higher share of undocumented workers eligible for DACA in the pre-treatment period. While effects on establishment exit are statistically insignificant, event study results display a temporary decline in exit rate following the policy. These effects may potentially be driven by improved market access for formerly undocumented workers, increased firm-level capital investment, and greater entrepreneurial activities amongst previously undocumented immigrants. Moreover, DACA raises native employment, reduces that of ineligible undocumented immigrants, and has no effect on eligible workers, with effects concentrated in low- and medium-skill sectors. In particular, the fraction of native employment rises by 2.1 percentage points, while that of ineligible immigrant employment declines by a similar margin. The findings suggest that firms may have substituted ineligible undocumented workers with native workers in response to the policy.

These results have several important policy implications. First, legalization programs such as DACA can enhance firm dynamism by encouraging establishment entry, particularly in low- and medium-skill sectors that heavily rely on undocumented labor. Second, the increase in native employment alongside a decline in ineligible immigrant employment indicates that such policies may facilitate labor market reallocation rather than intensifying competition, potentially improving overall efficiency. Finally, targeted regularization efforts could be used as tools for local economic development by stimulating entrepreneurship and expanding labor supply in sectors with limited access to formal labor markets.

I aim to expand this analysis in the following ways. First, incorporating firm-level financial data from sources like Compustat would help me examine mechanisms such as capital investment and productivity. Second, using a continuous measure of DACA exposure rather than a binary indicator would allow for more flexible estimation of treatment intensity. Third, exploring spillover effects across neighboring commuting zones could reveal broader general equilibrium impacts.

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Table 1: THE SHARES OF DACA-ELIGIBLE UNDOCUMENTED WORKERS BY TREATMENT STATUS IN THE PRE-TREATMENT PERIOD

	Control	Treated	Omitted
	(1)	(2)	(3)
Panel A: Commuting Zones			
Employment (%)	0.10	1.05	0.39
	(0.08)	(0.52)	(0.09)
Panel B: Top-Five Sectors within Census Divisions			
Employment (%)	0.08	0.63	0.32
	(0.03)	(0.30)	(0.07)

Notes: This table reports means and standard deviations (in parentheses) for the employment share of DACA-eligible individuals during the pre-treatment period (2008–2011), separately for commuting zones (Panel A) and for the top five two-digit NAICS sectors within each of the nine census divisions (Panel B). Using data from the American Community Survey (ACS), I impute the legal status based on the residual method described in Borjas (2017). DACA eligibility is determined following standard criteria established in the literature, as outlined in the text. Treatment status is assigned based on the distribution of undocumented workers likely to become DACA-eligible, with sectors in the top quartile defined as "treated," those in the bottom two quartiles as "control," and the third quartile as "omitted." The top-five treated sectors include "Arts, Entertainment, and Recreation," "Educational Services," "Finance and Insurance," "Real Estate and Rental and Leasing," and "Transportation and Warehousing." Control sectors include "Accommodation and Food Services," "Administrative and Support and Waste Management and Remediation Services," "Construction," "Manufacturing," and "Professional, Scientific, and Technical Services." Omitted sectors include "Health Care and Social Assistance," "Other Services (except Public Administration)," "Professional, Scientific, and Technical Services," "Retail Trade," and "Wholesale Trade." The assignment of commuting zones into the treatment status follows a similar procedure.

Table 2: Summary Statistics for the Pre-DACA Period (2008-2011)

	DACA-Eligible		DACA-Ineligible	
	Male	Female	Male	Female
Labor Force (%)	31.97	20.85	47.76	23.59
	(0.19)	(0.21)	(1.81)	(0.51)
Employment (%)	50.81	32.52	61.82	28.65
	(1.53)	(0.88)	(1.25)	(0.50)
Unemployment (%)	9.72	6.96	5.09	4.46
	(1.46)	(0.82)	(1.08)	(0.68)
Less than High School (%)	28.55	26.48	26.85	17.57
	(2.82)	(3.08)	(0.56)	(0.32)
High-School Graduates (%)	19.12	14.13	15.29	11.32
	(2.56)	(1.61)	(0.22)	(0.10)
Some College (%)	5.13	5.14	6.81	6.15
	(0.80)	(0.70)	(0.48)	(0.46)
College Graduates (%)	0.60	0.69	4.57	5.19
	(0.16)	(0.13)	(0.17)	(0.13)
More than College (%)	0.09	0.10	3.24	3.03
	(0.02)	(0.02)	(0.04)	(0.07)
Average Age	17.45	16.94	27.60	27.74
	(5.61)	(5.51)	(5.34)	(5.46)
Speaks English Well (%)	42.31	37.98	25.99	19.77
	(1.08)	(0.39)	(0.85)	(1.09)
N	26,106	22,724	80,779	61,555

Notes: This table reports means, standard deviations (in parentheses), and the number of observations for employment, education, and demographic variables amongst undocumented male and female immigrants aged 6–35, categorized by DACA eligibility status during the pre-treatment period (2008–2011). Using data from the American Community Survey (ACS), I impute legal status based on the residual method described in Borjas (2017). DACA eligibility is determined following standard criteria established in the literature, as outlined in the text. All share variables are expressed as percentages and calculated relative to the total number of undocumented individuals within each eligibility group.

Table 3: Summary Statistics for the Post-DACA Period (2012-2019)

	DACA-Eligible		DACA-Ineligible	
	Male	Female	Male	Female
Labor Force (%)	37.43	25.21	41.38	23.36
	(3.02)	(2.42)	(1.59)	(0.98)
Employment (%)	54.19	35.44	60.99	32.67
	(2.49)	(2.12)	(1.18)	(2.29)
Unemployment (%)	5.55	4.83	2.94	3.45
	(2.45)	(1.70)	(0.76)	(0.72)
Less than High School (%)	15.78	14.59	22.45	15.76
	(5.05)	(4.90)	(1.84)	(0.86)
High-School Graduates (%)	29.84	21.97	13.79	10.68
	(4.70)	(3.62)	(0.50)	(0.28)
Some College (%)	7.40	7.50	8.23	7.21
	(0.60)	(0.79)	(0.30)	(0.27)
College Graduates (%)	1.16	1.21	5.90	6.65
	(0.33)	(0.20)	(0.81)	(0.72)
More than College (%)	0.30	0.27	4.78	4.56
	(0.12)	(0.12)	(0.71)	(0.75)
Average Age	21.95	21.26	26.59	26.42
	(6.15)	(6.14)	(6.69)	(6.96)
Speaks English Well (%)	43.43	37.47	30.85	25.97
	(0.71)	(1.15)	(1.42)	(2.38)
N	31,855	26,648	133,803	108,853

Notes: This table reports means, standard deviations (in parentheses), and the number of observations for employment, education, and demographic variables amongst undocumented male and female immigrants aged 6 to 35, categorized by the DACA eligibility status during the post-treatment period (2012–2019). Using data from the American Community Survey (ACS), I impute the legal status based on the residual method described in Borjas (2017). DACA eligibility is determined following standard criteria established in the literature, as outlined in the text. All share variables are expressed as percentages and calculated relative to the total number of undocumented individuals within each eligibility group.

Table 4: Summary Statistics for Establishments

	Pre-DACA	Post-DACA
	(1)	(2)
Establishment Entry Rate	5.69	5.32
	(7.25)	(7.12)
Establishment Exit Rate	6.18	4.95
	(7.38)	(6.24)
Log of Establishment Entry	1.63	1.56
	(1.86)	(1.87)
Log of Establishment Exit	1.68	1.54
	(1.89)	(1.83)
N	37,021	74,783

Notes: This table reports means, standard deviations (in parentheses), and the number of observations for the outcome variables, using data from the Business Dynamics Statistics (BDS) covering the 2008–2019 period. Establishment entry and exit rates are expressed as percentages, whereas the establishment entry and exit variables are in logs. According to BDS, an establishment entry is defined as having positive employment in the current year and zero employment in the previous year, while an establishment exit is defined as having zero employment in the current year and positive employment in the prior year. Entry and exit rates are calculated as the number of entries or exits in year t, divided by the average number of establishments with positive employment in years t and $t-1$.

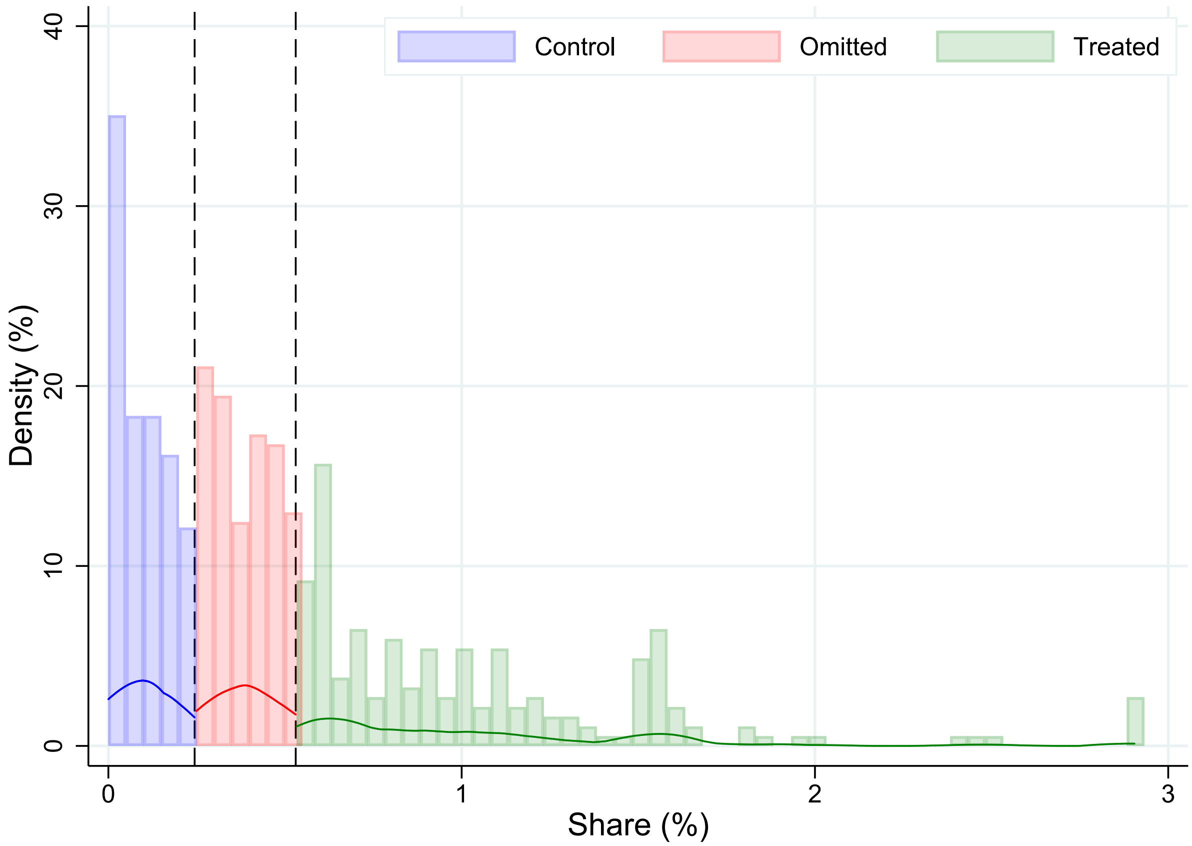
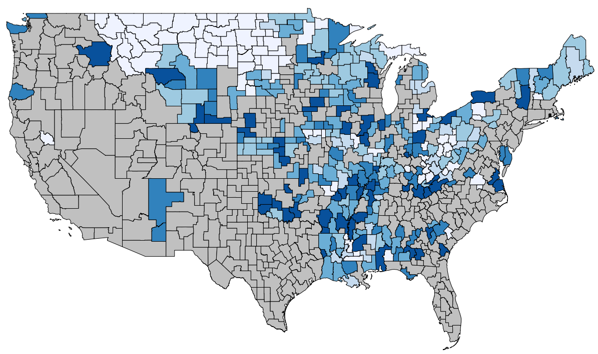
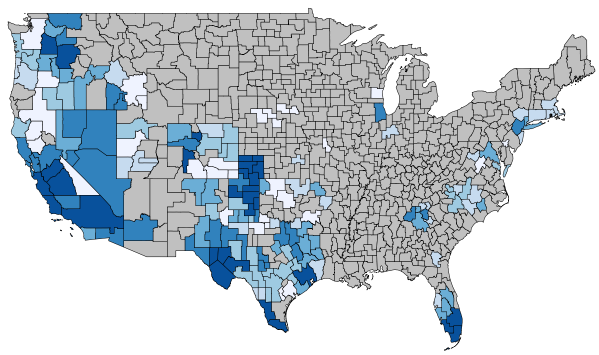


Figure 1: The Density Plot of DACA-Eligible Immigrant Workers by Treatment Status of Commuting Zones in the Pre-Treatment Period

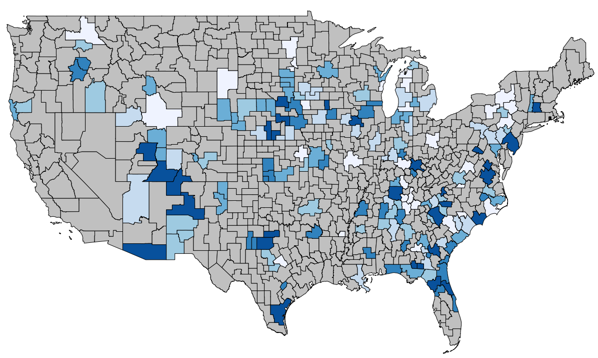
Notes: This figure displays the distribution of the employment share of DACA-eligible individuals during the pre-treatment period (2008–2011) by commuting zone. Treatment status is assigned based on the distribution of undocumented workers likely to become DACA-eligible, with commuting zones in the top quartile defined as "treated," those in the bottom two quartiles as "control," and the third quartile as "omitted."



(A) Control



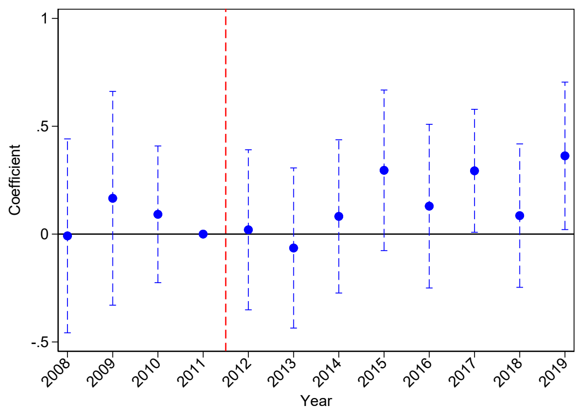
(B) Treated



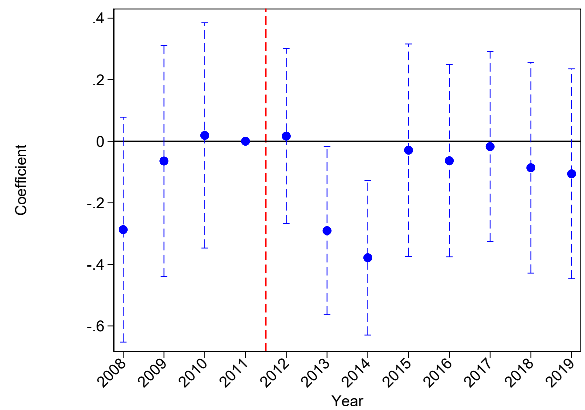
(C) Omitted

Figure 2: The Distributions of DACA-Eligible Immigrant Workers by Treatment Status of Commuting Zones in the Pre-Treatment Period

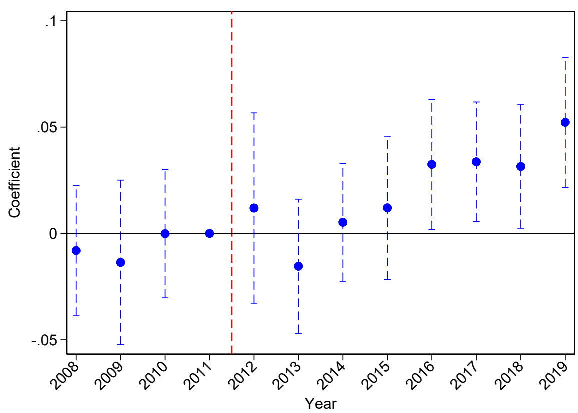
Notes: This map illustrates the distribution of the employment share of DACA-eligible individuals during the pre-treatment period (2008–2011) by commuting zone. Treatment status is assigned based on the distribution of undocumented workers likely to become DACA-eligible, with commuting zones in the top quartile defined as "treated," those in the bottom two quartiles as "control," and the third quartile as "omitted." Darker colors indicate higher concentrations.



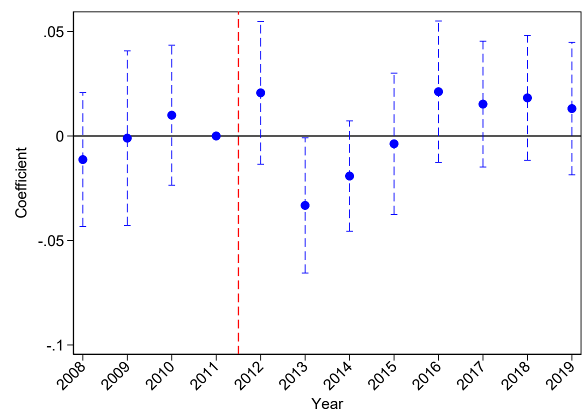
(A) Entry Rate



(B) Exit Rate



(C) Entry



(D) Exit

Figure 3: The Impact of DACA on the Establishment Entry and Exit Rates and the Logs of Establishment Entry and Exit

Notes: This figure displays event study coefficient estimates based on equation (2). The independent variable is the interaction between year and DACA treatment indicators at the commuting zone and sector levels. The dependent variables, estimated in separate regressions, include establishment entry and exit rates, as well as the logs of establishment entry and exit. Dashed blue lines represent 95% confidence intervals, and the vertical red dashed line marks the enactment of DACA, with the year 2011 serving as the omitted category. All specifications include sector-by-commuting zone, sector-by-year, and commuting zone-by-year fixed effects, and standard errors clustered at the state level.

Table 5: The Effect of DACA on the Establishment Entry and Exit Rates and the Logs of Establishment Entry and Exit

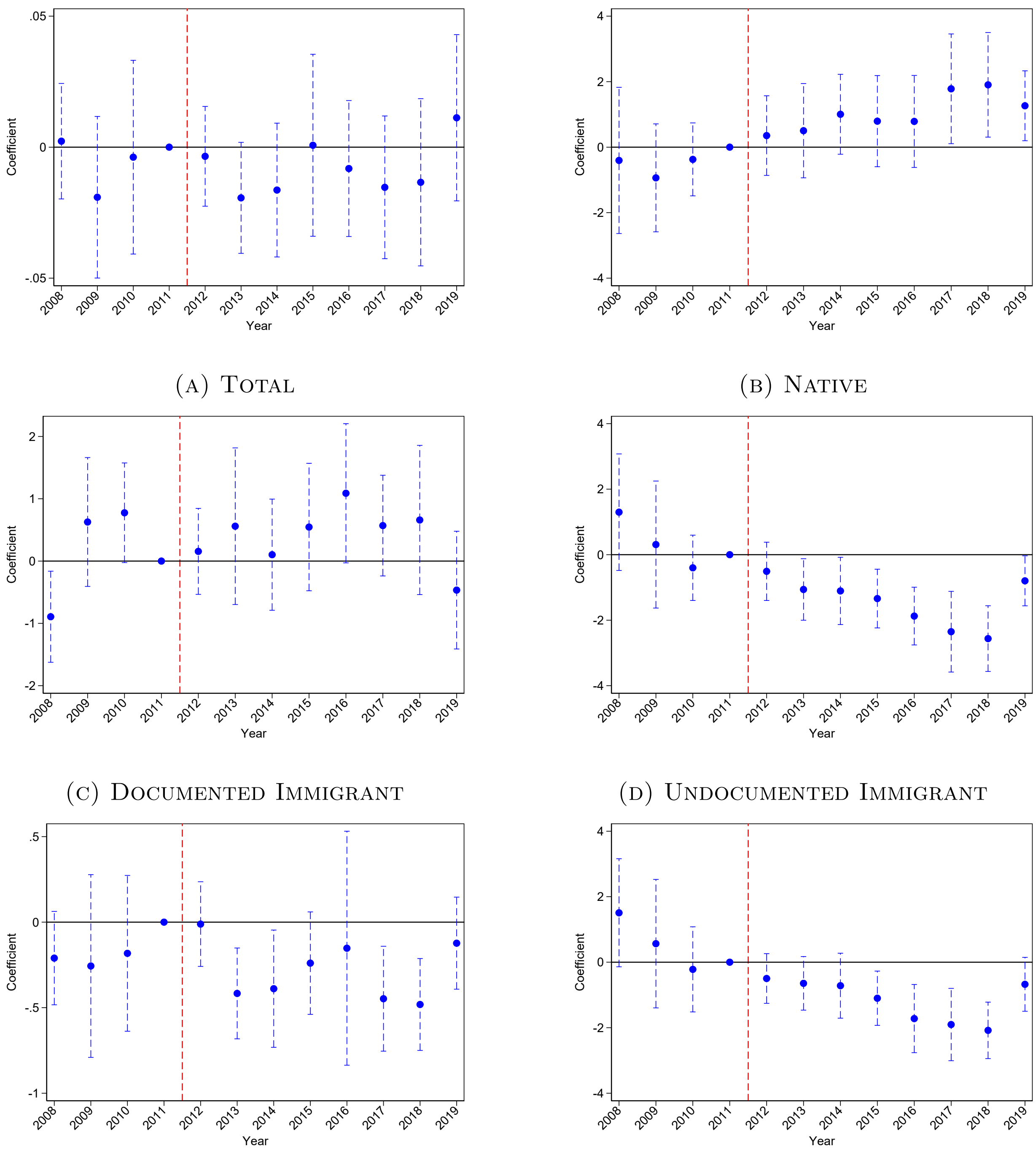
	Entry Rate	Exit Rate	Entry	Exit
	(1)	(2)	(3)	(4)
$CZ \times Sector_d \times Post$	0.112	-0.066	0.024**	0.004
	(0.119)	(0.111)	(0.010)	(0.011)
R^2	0.502	0.543	0.946	0.944
N	111,660	111,660	111,660	111,660
Mean	5.452	5.366	1.588	1.591
CZ-Time FE	Yes	Yes	Yes	Yes
Sector-Time FE	Yes	Yes	Yes	Yes
CZ-Sector FE	Yes	Yes	Yes	Yes

Notes: This table presents the regression results of the effects of DACA on establishment outcomes. The independent variable is the interaction between year and DACA treatment indicators at the commuting zone and sector levels. The dependent variables, estimated in separate regressions, include establishment entry and exit rates, as well as the logs of establishment entry and exit. All regressions include commuting zone-by-time, sector-by-time, and commuting zone-by-sector fixed effects. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: The Effect of DACA on Employment Shares

	All	Native	Immigrant	Doc.	Undoc.	DACA-El.	DACA-In.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$CZ \times Sector_d \times Post$	0.217	1.476***	-1.476***	0.275	-1.751***	-0.120	-1.631***
	(0.689)	(0.448)	(0.448)	(0.371)	(0.533)	(0.149)	(0.488)
R^2	0.258	0.492	0.492	0.371	0.414	0.207	0.390
N	119,581	119,581	119,581	119,581	119,581	119,581	119,581
Mean	19.443	94.552	5.448	2.992	2.456	0.418	2.038
CZ-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CZ-Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the regression results of the effects of DACA on establishment outcomes. The independent variable is the interaction between year and DACA treatment indicators at the commuting zone and sector levels. The dependent variables, estimated in separate regressions, include the shares of various groups of workers. The legal status is imputed based on the residual method described in Borjas (2017). DACA eligibility is determined following standard criteria established in the literature, as outlined in the text. All regressions include commuting zone-by-time, sector-by-time, and commuting zone-by-sector fixed effects. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.



(A) Total

(B) Native

(C) Documented Immigrant

(D) Undocumented Immigrant

(E) DACA-Eligible

(F) DACA-Ineligible

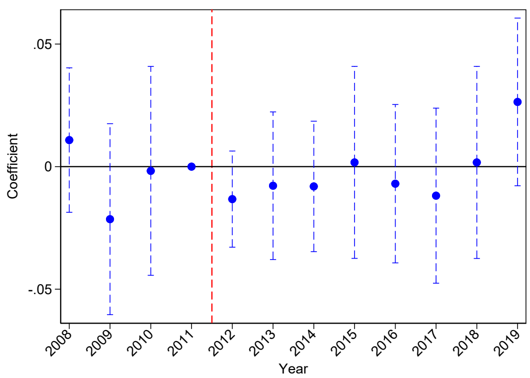
Figure 4: The Impact of DACA on Various Groups of Workers

Notes: This figure displays event study coefficient estimates based on equation (2). The independent variable is the interaction between year and DACA treatment indicators at the commuting zone and sector levels. The dependent variables, estimated in separate regressions, include the shares of various groups of workers. The legal status is imputed based on the residual method described in Borjas (2017). DACA eligibility is determined following standard criteria established in the literature, as outlined in the text. Dashed blue lines represent 95% confidence intervals, and the vertical red dashed line marks the enactment of DACA, with the year 2011 serving as the omitted category. All specifications include sector-by-commuting zone, sector-by-year, and commuting zone-by-year fixed effects, and standard errors clustered at the state level.

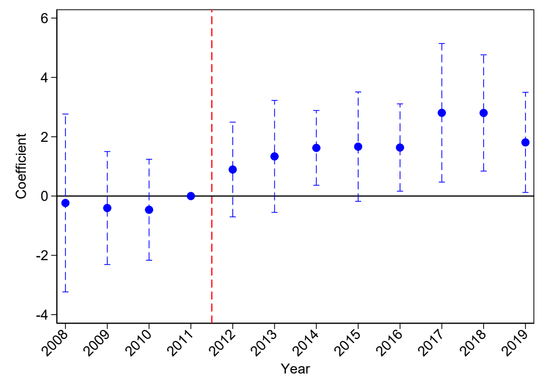
Table 7: The Effect of DACA on Employment Shares by Sectoral Skill Type

	All	Native	Immigrant	Doc.	Undoc.	DACA-El.	DACA-In.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Low and Medium Skill Types							
$CZ \times Sector_d \times Post$	0.948	2.095***	-2.095***	0.100	-2.195***	-0.069	-2.125***
	(0.674)	(0.522)	(0.522)	(0.425)	(0.624)	(0.152)	(0.598)
R^2	0.298	0.504	0.504	0.365	0.422	0.216	0.400
N	99,388	99,388	99,388	99,388	99,388	99,388	99,388
Mean	19.110	94.486	5.514	2.754	2.761	0.480	2.281
Panel B: High Skill Type							
$CZ \times Sector_d \times Post$	1.881	-0.831	0.831	1.077**	-0.246	-0.344	0.098
	(2.025)	(0.692)	(0.692)	(0.528)	(0.529)	(0.206)	(0.378)
R^2	0.339	0.730	0.730	0.726	0.586	0.508	0.579
N	19,445	19,445	19,445	19,445	19,445	19,445	19,445
Mean	21.263	94.863	5.137	4.184	0.953	0.112	0.841
CZ-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CZ-Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

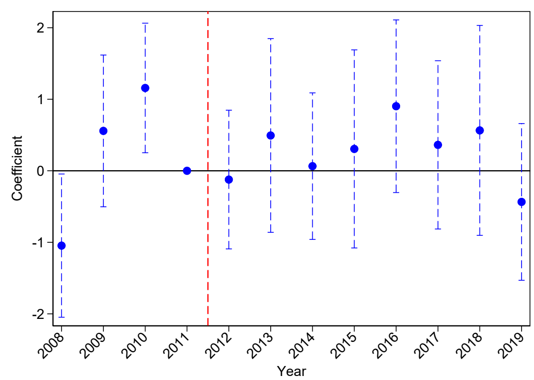
Notes: This table presents the regression results of the effects of DACA on establishment outcomes. The independent variable is the interaction between year and DACA treatment indicators at the commuting zone and sector levels. The dependent variables, estimated in separate regressions, include the shares of various groups of workers employed in sectors of different skill types. The legal status is imputed based on the residual method described in Borjas (2017). DACA eligibility is determined following standard criteria established in the literature, as outlined in the text. Sectoral skill levels are defined based on the average years of education of workers employed in each sector. All regressions include commuting zone-by-time, sector-by-time, and commuting zone-by-sector fixed effects. Standard errors are clustered by state for all specifications, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.



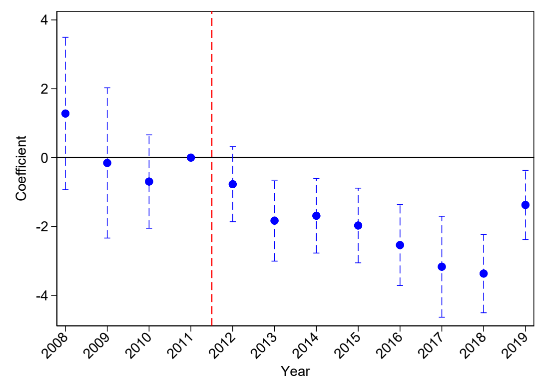
(A) Total



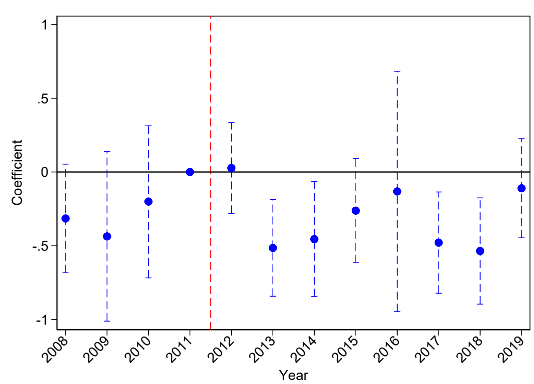
(B) Native



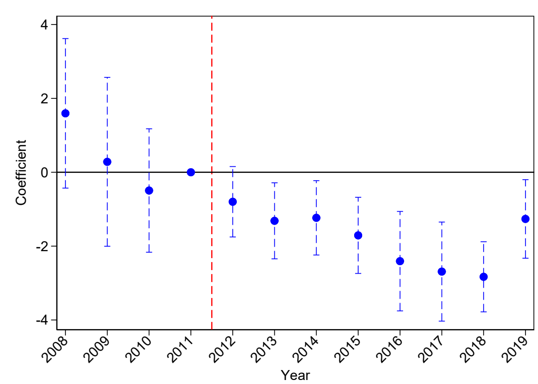
(C) Documented Immigrant



(D) Undocumented Immigrant



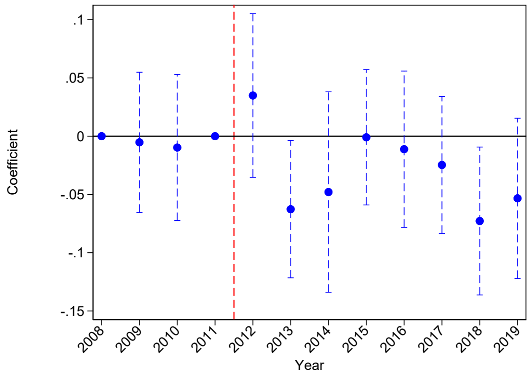
(E) DACA-Eligible



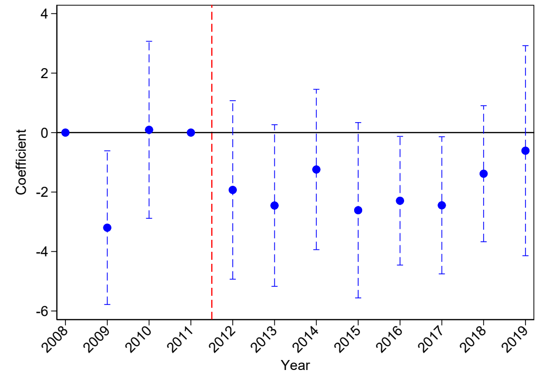
(F) DACA-Ineligible

Figure 5: The Impact of DACA on Various Groups of Workers Employed in Low- and Medium-Skill Sectors

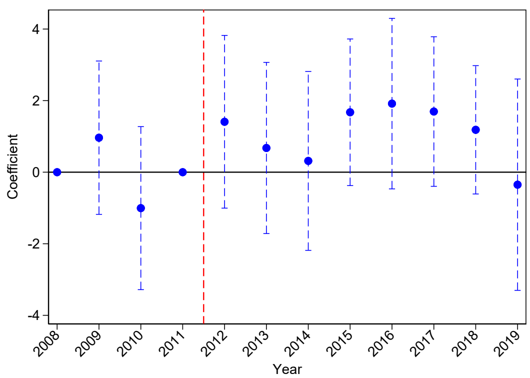
Notes: This figure displays event study coefficient estimates based on equation (2). The independent variable is the interaction between year and DACA treatment indicators at the commuting zone and sector levels. The dependent variables, estimated in separate regressions, include the shares of various groups of workers employed in low- and medium-skill sectors. The legal status is imputed based on the residual method described in Borjas (2017). DACA eligibility is determined following standard criteria established in the literature, as outlined in the text. Sectoral skill levels are defined based on the average years of education of workers employed in each sector. Dashed blue lines represent 95% confidence intervals, and the vertical red dashed line marks the enactment of DACA, with the year 2011 serving as the omitted category. All specifications include sector-by-commuting zone, sector-by-year, and commuting zone-by-year fixed effects, and standard errors clustered at the state level.



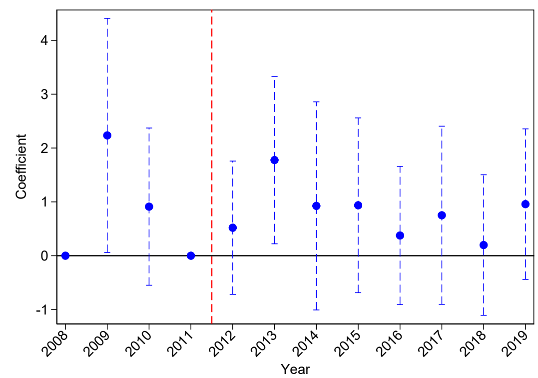
(A) Total



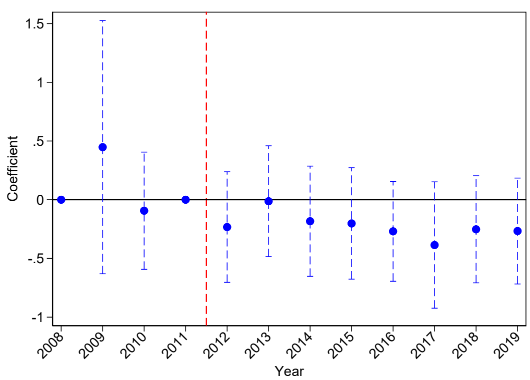
(B) Native



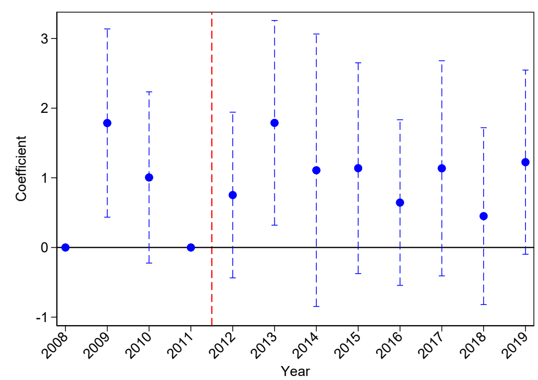
(C) Documented Immigrant



(D) Undocumented Immigrant



(E) DACA-Eligible



(F) DACA-Ineligible

Figure 6: The Impact of DACA on Various Groups of Workers Employed in High-Skill Sectors

Notes: This figure displays event study coefficient estimates based on equation (2). The independent variable is the interaction between year and DACA treatment indicators at the commuting zone and sector levels. The dependent variables, estimated in separate regressions, include the shares of various groups of workers employed in high-skill sectors. The legal status is imputed based on the residual method described in Borjas (2017). DACA eligibility is determined following standard criteria established in the literature, as outlined in the text. Sectoral skill levels are defined based on the average years of education of workers employed in each sector. Dashed blue lines represent 95% confidence intervals, and the vertical red dashed line marks the enactment of DACA, with the year 2011 serving as the omitted category. All specifications include sector-by-commuting zone, sector-by-year, and commuting zone-by-year fixed effects, and standard errors clustered at the state level.