What is the effect of college in-state tuition policies on the human capital investment of undocumented students?

by

Sebastian Puerta

(Under the Direction of Christopher Cornwell & Joshua Kinsler)

Abstract

This paper studies human capital responses to college in-state tuition policies for undocumented students. Using a sample of young, Hispanic immigrants from the 2000-2018 American Community Survey and 1997-2018 Current Population Survey, I exploit state and time variation in the adoption of these policies to estimate the causal effect of these policies on college enrollment for the affected students. I find in-state tuition policies significantly increased college attendance rates, particularly among young, Mexican immigrants four to five years after policy implementation. I also confirm my findings using 1998-2018 IPEDS data on college enrollment.

Index words: Economics of Education, Labor Economics, Immigration, Policy, Human Capital

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Chapter 1

1.1 Introduction

In 2009, there were an estimated 12 million undocumented immigrants living in the United States. Among undocumented immigrants ages 18-24, 40% did not complete high school, compared to 8% of U.S. born residents, and among those that graduate high school, only half go on to college, compared to 71% of U.S. born residents. [1] Undocumented youth, who account for 1.5% of the population of US minors, particularly suffer as the earnings gap between college educated and non-college educated workers widen. Liquidity constraints, a high opportunity cost of schooling, misperceptions of the returns to education, or uncertainty about duration in the country due to deportation risk may explain the lack of human capital investment among undocumented youth. In this paper, I examine how college in-state tuition policies impact undocumented youths' investments in human capital.

[1] Passel, Jeffrey S. and D'Vera Cohn. "A Portrait of Unauthorized Immigrants in the United States." Pew Research Hispanic Trends Project, 2009.

Undocumented youth are a population of interest for several policy-relevant reasons. First, given the large immigrant population in the U.S., as well as the intense political debates on immigration reform, studying this population may yield insights pertinent to the crafting of future immigration or education policies. Second, the severe under-investment in human capital by undocumented youth is of principal concern as the earnings and health gap between college-educated workers and non-college educated workers increases. Therefore, understanding the effects of these policies is of general concern.

I take advantage of the staggered implementation of college in-state tuition policies (or subsidies) across states and time, beginning with California and Texas in 2001, and, most recently, Maine in 2017 to implement a difference-in-differences design. The subsidies often come with residency requirements. For example, California requires that a student either have gone to school for three years in California or have graduated from a California high school. Maine's tuition subsidy is only available for those who have received temporary protections under federal programs, such as Deferred Action for Childhood Arrivals (DACA).

I navigate the challenge of not being able to directly identify undocumented youth by using information about U.S. citizenship as a proxy and restricting the sample to populations that have a high proportion of undocumented immigrants, namely those of Mexican nationality, consistent with the literature on this or similar topics (Kaushal, 2008, Koohi, 2017, Kuka et al., 2019).

Thus, my difference-in-difference analysis studies the educational investment decisions made by likely undocumented, Hispanic, immigrant youth using the staggered implementation of in-state tuition policies as identifying variation. Using individual-level data from the 2000-2018 American Community Survey (ACS), the 1997-2018 Current Population Survey (CPS), as well as 1998-2018 school-level data from the Integrated Postsecondary Education System (IPEDS) data system, I find support for the common trends assumption: college attendance trends in treated states would have been parallel with trends in untreated states in the counterfactual.

I find that in-state tuition policies have a large effect on likely undocumented youth. Using individual-level data, preferred estimates for Mexicans ages 19-22 imply a 5-10 percentage point (p.p.) increase in college attendance, a 20-40% increase over the pre-treatment mean of 25% in treated states. Results using school-level data from IPEDS are consistent with that of the microdata. Using event-study specifications, I find that the effects take several years to become apparent – often 4 years. This may be due to information frictions among the undocumented community, however, it is also consistent with forward-looking behavior from high school underclassmen.

My results contribute to a literature studying the effects of college in-state tuition policies on likely undocumented students. Kaushal (2008) is the first to attempt to estimate the effects of in-state tuition policies. Using CPS data from 1997 to 2005, a similar difference-in-differences framework, and focusing on Mexican young adults, they find a 2.5 p.p. increase in college enrollment off a base of 8%. Contrary to critics' arguments that educational resources are being channeled away from native students, they also find no adverse effects for the educational outcomes of native students. Chin and Juhn (2010), using the 2001-2005 ACS, along with the 2000 U.S. census and a difference-in-difference design, generally find no significant effects among those that have already graduated high school. They explain that this is likely because the policies have been too recent, and thus the long-run effects from the policies may differ from the short-run effects they present. I confirm that this is the case. However, Kaushal (2008) and Chin and Juhn (2010) use a similar sample period with the former having only three more years before any policies were passed. This could suggest that the ACS and CPS samples have different populations of likely undocumented individuals who responded differently to in-state tuition policies. In light of these differences, I will use both the ACS and CPS in my analysis. Flores (2010), Koohi (2017), and Amuedo-Dorantes and Sparber (2012) find small, significant effects of similar magnitudes to Kaushal (2008) on college attendance using the CPS. Potochnick (2014) similarly finds sizable negative effects on high school dropout rates for likely undocumented youth. Grosz and Hines (2018) specifically analyzes the effects of in-state tuition in Colorado and finds significant effects in overall enrollment, credit hours, and persistence of likely undocumented students. They also show that this was a result of an increase in applications rather than an increase in the acceptance or matriculation rate. In another state-specific study, Monarrez (2016) finds that Texas' in-state tuition policy, the "Texas Dream Act", lead to a five to six percentage point increase in college demand amongst undocumented students – as measured by responses to post-graduation surveys regarding their college plans. They also find slight improvements in test performance among undocumented ninth graders, as well as, however, decreases in graduation and increases in drop out rates. These mixed results are attributed to the complex changes in the institutional environment of Texas public schools, particularly, the enactment of the No Child Left Behind doctrine. Lastly, Conger and Turner (2015) evaluate the effect of the removal of in-state tuition for undocumented students in the City University of New York, New York City's public university system, for a single semester in spring 2002 before in-state rates were restored in the fall. They found that re-enrollment decreased by 8 percent. I contribute to this literature by implementing an event-study design, which many of the early papers lacked, acknowledging the potential for dynamic treatment effects and obtaining more robust results, as well and including a larger sample period to evaluate longer-run effects of the policies. I also further investigate the mechanisms by which we may see positive effects on college attendance by likely undocumented students beyond price effects, namely changes in perceived deportation risk. Additionally, I provide clearer evidence and discussion of the satisfaction of the identification assumptions in my models. Lastly, I tie together much of the previous literature by combining various data sources (ACS, CPS, and IPEDS) to measure the effect of in-state tuition.

I also contribute to a robust literature on Hispanic education trends and immigration policy. Dickson et al. (2017) is unique in that it estimates the effect of in-state tuition policies and Deferred Action for Childhood Arrivals (DACA), a federal deportation amnesty program for immigrant youth, on the college enrollment rates of likely undocumented youth using the CPS, finding results similar to earlier studies (e.g. Kaushal, 2008, Koohi, 2017) on the effects of in-state tuition policies as well as *negative* effects of DACA on college enrollment. Amuedo-Dorantes and Antman (2017) also find negative effects of DACA on college enrollment using the CPS. Hsin and Ortega (2018) finds similar results using administrative data on students attending a large public university. This is likely due to the increasing opportunity cost of college since DACA grants work authorization. Kuka et al. (2019), using the ACS, however, find generally positive yet insignificant effects of DACA on college enrollment. I contribute to this literature by analyzing the effect of a policy that affects perceived deportation risk (much like DACA) – the passage of in-state tuition policies likely signals a decreased likelihood of immigration enforcement for the affected age groups – on college attendance rates for likely undocumented youth.

Moreover, there is a large literature estimating the effects of tuition decreases on college enrollment. (Castleman and Long, 2016) show that the Florida Student Access Grant, a need-based grant, had a postive effect on college enrollment, credit, accumulation, and persistence, particularly at four-year institutions. (Denning, 2017) finds that community college enrollment increased by 5.1 percentage points for each $1,000 decrease in tuition, and (Denning et al., 2019) finds that Pell Grant eligibility affects the enrollment decisions of those on the margin of attending community college. (Bettinger et al., 2019) find long run impacts of California's state-based financial aid, increasing undergraduate and graduate degree completion as well as annual earnings among some sub-groups.(Deming and Dynarski, 2009) review some of the earlier literature on this topic and find that reductions in the cost of higher education increase college entry and persistence. I add to this literature by providing results on the effects on college in-state tuition policies, effectively a decrease in the price of college for undocumented students.

The paper continues as follows. I provide further detail regarding the institutional background and history of in-state tuition policies in Section 1.2. In Section 1.3, I present evidence using survey microdata, namely the 2000-2018 ACS and the 1997-2018 CPS. I then present evidence using college level data from IPEDS in section 1.4. In section 1.5, I discussion potential mechanisms. Lastly, I conclude in section 1.6.

1.2 Institutional Background of In-State Tuition Policies

The Pew Research Center estimates that 10.5 million undocumented immigrants lived in the United States in 2017, down from a peak of 12.2 million in 2007. Nationally, unauthorized immigrants made up 3.3% of the U.S. population in 2016. Unauthorized immigrants account for slightly less than one-in-four foreign-born U.S. residents. Mexicans made up most of the undocumented population during the period of study, but decline to less than half of the population for the first time in 2016. Most other undocumented immigrants come from other Latin American countries. 6.5 million (61%) undocumented immigrants live in only 20 major metropolitan areas, with the largest populations in New York, Los Angeles, Houston and Dallas-Fort Worth. Although there are no precise estimates, data from the American Community Survey suggests that up to 1 million undocumented immigrants are of college going age.

The 1982 *Plyer v. Doe* Supreme Court decision gave all students, regardless of citizenship status, the legal right to obtain a K-12 education. A decade later, the Illegal Immigration Reform and Immigrant Responsibility Act (IIRIRA) of 1996 banned public colleges and universities from allowing undocumented immigrants to pay in-state tuition on the basis of residence, unless all other U.S. citizens (out-of-state students) were eligible for the same benefits. Access to in-state tuition can drastically reduce the price of attending college. In 2017-2018, the average in-state tuition rate for public four(two)-year institutions was $5,865 ($3,321), while the average out-of-state tuition rate was $14,904 ($7,034). The median in-state tuition rate for public four(two)-year institutions was $5,465 ($2,804), while the median out-of-state tuition rate was $14,329 ($6,745).[2]

Since 2001, 24 states (or state Board of Regents) have passed some sort of in-state tuition policy for undocumented immigrants who satisfy certain requirements, with two states, Oklahoma and Wisconsin, rescinding their policies. Proponents of in-state tuition policies argue that the requirements to receive in-state tuition – high school attendance and graduation – are not based on residency, so they are not in conflict with IIRIRA. In agreement with this argument, California' Supreme Court upheld their in-state tuition policy in 2010.[3] Table A.1 outlines enactment dates. States usually stipulate 3 criteria for eligibility: (1) have lived in the state and attended high school for a particular period of time (usually, a two to four year requirement); (2) obtained a high school diploma or GED from the state; and (3) signed an affidavit indicating their intention to file for legal status once they become eligible. Additionally, undocumented students do not qualify for federal aid, and, in most states, they do not qualify for state aid.

The rationale for providing educational assistance to undocumented students usually consists of two arguments. First, the state should not punish children for their parent's actions – bringing their children to this country illegaly. Second, it is likely that the majority of undocumented immigrants will continue to reside in the United States, and that educating them will provide immense positive externalities. However,

[2] Attendance costs from IPEDS
[3] See Martinez vs. Board of Regents of the University of California

despite the mostly bipartisan support for in-state tuition benefits in the states that have enacted this legislation, some states bar undocumented students from receiving in-state tuition benefits, have tried to but failed to pass similar policies, or outright bar undocumented students from attending certain public flagship universities.[4]

It is important to note that in-state tuition policies do not provide amnesty from deportation like DACA or the yet-to-be-passed Development, Relief and Education for Alien Minors (DREAM) Act. The DREAM Act was originally proposed in 2001 to provide a potential path to citizenship to undocumented immigrants who came to the United States as children. Despite the original bi-Partisan support and repeated near successful attempts to pass the act, it has never been signed into law. However, in 2012, President Obama issued DACA, an executive order that gave young undocumented immigrants who meet the requirements of the DREAM Act temporary work authorization and deportation protection for renewable two-year terms. The program has had successful participation and, according to Kuka et al., 2019, is responsible for closing the gap in high school graduation between citizen and non-citizen youth by 40 percent.

1.3 Evidence from Survey Microdata

1.3.1 Research Design

My empirical strategy uses a difference-in-differences approach to identify the causal effect of in-state tuition policies. I estimate the following equation using OLS,

[4] Georgia and Alabama are two notable examples.

$$Y_{ist} = \gamma_s + \gamma_t + \sum_{l=J}^{-2} \beta_l D_{ist}^l + \sum_{l=0}^{K} \beta_l D_{ist}^l + \xi X_i + \nu Q_{st} + \mu_{ist} \tag{1.1}$$

where Y_{ist} is the outcome for individual i living in state s in year t, and J and K are the respective beginning and end of the event-study window. D_{ist}^l is an indicator for being l time periods relative to i's initial treatment ($l = 0$ is the year the in-state tuition policy was passed). I omit period $l = -1$ to avoid multicollinearity, so my reported estimates are relative to that period. γ_s and γ_t are state and time fixed effects which control for time-invariant unobserved state characteristics and state-invariant unobserved time trends, respectfully. I account for fixed individual characteristics by including a vector of controls, X_i, which include indicators for sex, age, race, year of immigration, birth region, English skills, poverty status, and number of family members in the household. I also account for time-varying state characteristics by including Q_{st}, a vector of controls which contains a measure of deportation risk, percent of native population that is college educated, percent of population that is Hispanic, unemployment rate, per-capita personal income, and party of state legislature. I use sampling weights in all regressions. The coefficients β_l for $l \geq 0$ represent the dynamic average treatment effects of in-state tuition policies. I obtain standard errors by clustering at the state level, as is common for difference-in-differences designs with policies adopted at the state level. The identification assumption is that individuals in states with treatment would have had similar trends, namely college attendance, to individuals in states without treatment in the counterfactual.

1.3.2 Data, Sample Selection, and Summary Statistics

I use data from the IPUMS ACS from 2000 to 2018 and the IPUMS CPS from 1997 to 2018 to observe individual's educational decisions and citizenship status. These microdata, however, do not include indicators for undocumented status and solely ask whether a respondent is a citizen or not, making it impossible to distinguish between a permanent resident and an undocumented immigrant for example. I navigate the challenge of not being able to directly identify undocumented youth by following the literature (Kaushal, 2008, Kuka et al., 2019, Koohi, 2017) and instead proxying for undocumented status with the lack of U.S. citizenship and restricting the sample to populations that have a high proportion of undocumented immigrants, namely those of Mexican nationality. I will delve further into the nature of possible measurement error in section 1.3.3.

Crucially, the American Community Survey (ACS), hosted by the Census Bureau collects information on all US households, regardless of legal status. The Census is not permitted to share personal information with other government agencies, and communicates this confidentiality to respondents. The Census also performs outreach to Hispanic organizations and makes the survey available in Spanish. The Current Population Survey, also hosted by the Census Bureau, has similar procedures.

To construct my final analysis sample, I exclude native born residents of the U.S and focus primarily on foreign-born Hispanics ages 19-22, typical college going ages. Proxying for undocumented status, I further restrict my sample to noncitizen Mexicans. My final sample contains 248,901 and 183,201 observations in the ACS and CPS, respectively.

Tables A.2 and A.3 (ACS and CPS, respectively) and Figures A.1-A.2 contain descriptive statistics of the sample. Treated states, on average, have a higher percentage of Hispanic immigrants that are noncitizens than untreated states, however there are a few years in the CPS data where this is not true. In both data sets I observe a upward trend in the percentage of noncitizens until about 2008, followed by a downward trend until 2018. This is consistent with analysis of U.S. Census Bureau Data.[5] Figures A.2 show trends in the college education rates of noncitizens in the U.S. over time. College attendance increases throughout the sample period in both treated and untreated states. However, treated states pre-treatment have a small gap in the college-going rates of Hispanic immigrant noncitizens compared to untreated states, but the gap grows in favor of treated noncitizens over time. This gives some descriptive evidence of a treatment effect.

1.3.3 Measurement Error

I overcome the challenge of not measuring undocumented status by instead proxying for non-citizenship combined with Mexican nationality. My measure for undocumented status, lack of citizenship, includes those with lawful permanent residency, i.e. green cards, who already qualify for in-state tuition. However, this measurement error likely biases estimates downwards since those with lawful permanent residency are not truly affected by the policy – they experience no price change – yet they are in my analysis sample. So, assuming that there are no positive differential college attendance trends for lawful permanent residents, conditional on my controls, estimates significantly different from zero are a lower bound of the effect of the policy.

Furthermore, the response rate in 2016 for a census tract with a 25.5 to 100 percent likely noncitizen share was 92 percent, compared to 97 percent for low noncitizen share census tracts (Brown et. al 2018) So, the sample in this paper contains proportionally more citizens than it should. As a result, the noncitizens

[5] See Pascal and Cohn. 2018 "U.S. Unauthorized Immigrant Total Dips to Lowest Level in a Decade". Pew Research Center.

that are my sample are partially selected. Any interaction with the government could invoke fear of deportation for undocumented individuals, so it may be that these individuals have less perceived deportation risk than those that did not respond to the survey. However, those that were too afraid to respond to a government survey, may also be weary of declaring undocumented status to public universities to attain in-state tuition. Thus, the estimate of the effect of college in-state tuition policy would be a local average treatment effect among those with the lowest perceived deportation risk. It is unclear how this effect would differ among those with higher deportation risk, and thus those that may not have responded to the survey in the first place.

Additionally, according to Brown et al. (2018), 4.7 percent of 2016 ACS Hispanic respondents who are noncitizens according to confidential census administrative data state that they are citizens in the survey, so my estimates will be slightly less precise. It was likely that these discrepancies were the result of misunderstanding the question (Brown et al. (2018). If, however, those that responded incorrectly did so as a result of perceived deportation risk, this would again imply that my treatment effect estimate is a local average treatment effect among those with lower perceived deportation risk.

To dissuade any doubts about bias, I control for things that could relate to perceived deportation risk – the controls that Brown et al. (2018) found to be significantly related to survey non-response – namely English skills in addition to the number of relatives in household and the deportation rate for a state in any given year.

1.3.4 Results

I present estimates of the effect of in-state tuition policy in Figures A.3 - A.6 calculated using an indicator for college attendance as the outcome and using multiple combinations of controls, or lack thereof.

Figure A.3. shows evidence of the positive effects of in-state tuition policies without using controls beyond state and year fixed effects by plotting the coefficients and corresponding confidence intervals of equation (1.1) estimated using OLS. 19-22 year old Mexican immigrants see a 5-8 p.p increase in college attendance, a 20-40% increase off a base of 25%, five years post-treatment. There are significant pre-trends however in one period of the ACS sample. To investigate whether these significant pre-trends were the result of limited data pre-treatment (in the case of California and Texas who enacted their policies in 2001), I reproduce these results separately dropping California or Texas. A similar pattern of results is visble in Figure A.7 without California but the significant pre-treatment trends in Panel (a) disappear. However, the significant pre-trends persist when I drop Texas from the analysis.

Figure A.4 re-estimates equation (1.1) but with the inclusion of state controls. A similar pattern is visible but with tighter confidence intervals. The inclusion of linear and quadratic state time trends in Figures A.5 and A.6 bear similar patterns and conclusions: after about five years there seems to be a statistically and economically significant increase in the college attendance rates of suspected undocumented immigrants. This pattern could arise from information frictions among the undocumented community or an initial hesitance to reveal one's status to a public institution.

These estimates are much larger than most found in past literature (Kaushal, 2008,Koohi, 2017,Chin and Juhn, 2010), but are however consistent with the effects found in Monarrez, 2016, who should using Texas educational administrative data that in-state tuition policies increased college demand by five to six percentage points among likely undocumented students.

Other work that studies the effects of changes in tuition on college attendance finds similar results. Dynarski, 2003, using the elimination of the Social Security student benefit program as identifying variation, finds that a $1,000 grant aid increases the probability of attending college by 3.6 p.p.. Some work, like Seftor and Turner, 2002, however, finds contrary results. They find negligible effects of Pell Grant eligibility on college attendance. Because my sample likely resembles Pell Grant eligible students due to the low household income of undocumented families, my results oppose that of Seftor and Turner, 2002. This may, however, be due to the immense decrease in price in my setting.

1.3.5 Evidence of Identifying Assumptions

Identification relies on the assumption that in-state tuition policies did not coincide with other policies or compositional changes that affected my sample in similar ways. This is tested by measuring whether predicted schooling based on observable characteristics was constant around the timing on in-state tuition policies. To test this, I first regress college attendance on observable individual and state characteristics: poverty, number of family members in household, English skill[6], state deportation risk, percent of state population that is Hispanic, state per-capita income, state unemployment rate, and the party of the legislature. Using the estimates from this regression, I create predicted values of college attendance for each individual in my sample. I then test if these predicted values vary around the adoption of the policy. The results of this process are shown in Figure A.8. Although there appears to be an upward trend towards the end of the sample, the coefficients are generally insignificant especially, most importantly, around 5 years after treatment when I begin to see effects using my event-study specification.

One can do a similar process to see if the treatment predicts any changes in the controls as shown in Figures A.9 and A.10. In favor of the identifying assumption, the coefficients are generally not significantly different from zero. Hence, any effects of in-state tuition policies reflect behavior changes, not compositional changes.

[6]The CPS, however, does not contain a measure of English skill, thus this control is not included in the specification when using CPS data.

Additionally, as a further robustness test, I estimated whether in-state tuition policies had any effect on *citizen* Mexican immigrant's college attendance rates. Figure A.11 shows the results of a placebo test checking whether there are any significant effects of in-state tuition policies on *citizen* Mexican immigrants. Consistent with intuition, the figure confirms there are no significant effects among this sub-sample.

I do, however, observe statistically significant pre-treatment effects (pre-trends) for one period when using the ACS data, in addition to a trend in the point estimates. This significance disappears when California is dropped from the analysis in Figure A.7. The same does not occur when I drop Texas from the analysis, which happened to receive policy treatment in the same year as and is the most similar state to California in my analysis. It is unclear why there are no similar significant pre-trends present using the CPS data. Since the CPS contains about 15,000 fewer observations in the final analysis sample, it may be the case that there are pre-trends in the CPS data, but I do not have enough power to measure them. It is also unclear whether there is something inherent in California itself which leads to significant pre-trends and no significant pre-trends when dropping it from the analysis. It may be that dropping it simply reduces my power to measure significant pre-trends. It is somewhat comforting, however, that the pre-treatment coefficients themselves flatten when I drop California from the analysis. However, the lack of pre-trends may also be because I have more years of pre-trend data for California and Texas, the two earliest adopters. Nevertheless, I observe a similar post-treatment pattern of affects regardless of significant pre-trends or the exclusion of California. And fortunately, results in Section 1.4 ease some doubts pertaining to the satisfaction of the identification assumptions in order to make causal claims about the effect of in-state tuition policies.

One may also be concerned about families with undocumented children moving to states with in-state tuition policies biasing the results. This would cause selection bias and tend to overstate estimated treatment effects. This is, however, likely not the case. Every state with in-state tuition policies have a residency requirement with most requiring that students have lived in the state for three or more years. One may imagine a scenario where a family moves while their children is still young enough to potentially benefit from the policy. Driving while undocumented, however, bears significant risks since most states prohibit undocumented immigrants from acquiring driver's licenses and it is illegal to drive without a license. Furthermore, in some states, e.g. Texas, local law enforcement agencies often have partnerships with Immigration's and Custom's Enforcement or U.S. Custom's and Border Protection which deport those detained by local agencies. Some states, often the same states that have in-state tuition policies, e.g. California and New York, eventually adopted laws allowing undocumented residents to obtain driver's licences but the difference between the years of adoption are large: 13 years in the case of California. So, it is unlikely that undocumented families bore such large risk to move from a state where they likely do not have driver's licenses to another state where they also will likely not have driver's licenses. This population is already so risk-averse that they are less likely to open the door to a census worker, so it is difficult to see a scenario where they face such large risk in order to benefit from this policy.

1.4 Evidence from College-level Data

1.4.1 Research Design

I again estimate the effect of college in-state tuition policies by taking advantage of cross-state variation in the timing of policy adoption between 2001 and 2018. I estimate using OLS the following event-study/generalized difference-in-differences equation at the college level

$$Y_{cst} = \gamma_s + \gamma_t + \sum_{l=J}^{-2} \beta_l D^l_{cst} + \sum_{l=0}^{K} \beta_l D^l_{cst} + \eta Z_{ct} + \nu Q_{st} + \mu_{cst} \tag{1.2}$$

where Y_{cst} is the outcome for college or university c in state s in year t, and J and K are the respective beginning and end of the event-study window. D^l_{cst} is an indicator for being l time periods relative to c's initial treatment ($l = 0$ is the year the in-state tuition policy was passed). I omit period $l = -1$ to avoid multicollinearity. γ_s and γ_t are state and time fixed effects which control for time-invariant unobserved state characteristics and state-invariant unobserved time trends, respectively. I account for time-varying college characteristics by controlling for Z_c and time-varying state characteristics by controlling for Q_{st}. Z_c is a vector of controls which includes type of institution (two-year of four-year), ranking, and the total amount of white students enrolled. Q_s is a vector of controls which contains a measure of deportation risk, percent of native population that is college educated, percent of population that is Hispanic, unemployment rate, per-capita personal income, and party of state legislature. The coefficients β_l for $l \geq 0$ represent the dynamic average treatment effects of in-state tuition policies. I obtain standard errors by clustering at the college level. The identification assumption is that colleges in states with treatment would have had similar trends, namely enrollment of nonresident students, to colleges in states without treatment in the counterfactual.

1.4.2 Data, Sample Selection, and Summary Statistics

I use data from the Integrated Postsecondary Education Data System (IPEDS) hosted by the National Center for Education Statistics to observe enrollment and tuition information at the college-year level.

I follow Chetty et al., 2020 in constructing my sample of college-year observations. I first exclude colleges that have on average fewer than 100 students across 1998-2018, the years for which I have data, all college-year observations that have fewer than 50 students, and colleges that have missing data for more than half of the sample period. Lastly, I include only 2- and 4-year public colleges in my sample since these institutions are the ones affected by in-state tuition policies. There are 75,051 college-year observations and 3850 unique colleges in the final sample. I focus on the enrollment of nonresident students, which according to IPEDS, are students whom are not citizens nor nationals of the United States who are here on a temporary basis and do not have the right to remain indefinitely. Therefore, this measure likely includes undocumented youth in addition to those on visas. Assuming that the measurement error is independent of the treatment and controls, there will be no consequences for the bias or consistency of my estimators.

In Tables A.4-A.5 along with Figures A.12 - A.13, I present descriptive statistics on in-state and out-of-state tuition as well as the enrollment of nonresident students. Table A.4. displays sample means for the analysis sample. Column (1) corresponds to all colleges in my sample. Column (2) corresponds to colleges in untreated states. Columns (3) and (4) correspond to colleges in treated states pre- and post-treatment, respectively. Four-year colleges form 60% of the sample and public colleges form about 47% of the sample. Average In-state and out-of-state tuition are relatively similar between treated and untreated states pre-treatment, however tuition rises slightly in treated states post-treatment. Additionally, the number of nonresident students in a college on average is similar in treated and untreated states pre-treatment, but rises considerably in treated states post-treatment. The number of Hispanic students enrolled on average bears a similar trend that is not mirrored in the number of White students enrolled on average. Figure A.12 shows the trend in the average number of nonresident students in colleges in treated and non-treated states. There is an overall upward trend in the data, and there is a gap between treated and untreated states that grows throughout the sample period. Table A.5. provides information about tuition for the colleges in my analysis sample. Columns (1) and (2) show the minimum and maximum, respectively, average tuition difference between in-state and out-of-state tuition within a state in a year. Column (3) shows the mean tuition difference across the entire sample difference. Overall, most states have an average tuition-difference between in-state and out-of-state tuition of between $2,000 and $4,000. Figure A.13 shows the percent difference between average in-state and out-of-state tuition across three states: New Mexico, California, New York.

1.4.3 Results

I present estimates of the effect of in-state tuition policy on nonresident student enrollment in Figures A.14 - A.17.

Figure A.14 shows the estimated effects in public and private colleges using a specification that includes log(enrolled nonresident students) as the outcome and controls for college and states characteristics as well as state linear time trends. In this figure, there is relatively clear evidence for the satisfaction of the identification assumption. Beginning one year after treatment, I estimate positive and significant treatment effects that grow until about five years after treatment before diminishing, consistent with the pattern visible in the microdata. At its peak, the effect is estimated to be a 20% increase in the enrollment of non-resident students, a sizable and economically significant result. Similar results are visible when I exclude California. I see no effect on enrollment in private colleges which were not affected by in-state tuition policies.

In Figure A.15, I further decompose the results by gender, finding slightly stronger effects for female nonresident enrollment. This is consistent with much of the literature finding larger effects of education policies/interventions among females (Deming and Dynarski, 2009).

In Figure A.16, I compare results by type of college – four-year and two-year. Although, I see some results among four-year colleges, the considerably large significant pre-trends make it difficult to interpret these results as anything other than suggestive. When looking at two-year colleges, however, I see much stronger results with no significant pre-trends that suggest many nonresident student enrolled in two-year institutions following the passage of in-state tuition policies. These results suggest that in-state tuition policies increased the enrollment of nonresident students by up to 40% at two-year colleges.

Lastly, in Figure A.17, I present results using levels (number of nonresident students enrolled) and proportions (proportion of total enrolled that are nonresident). Panel (a) shows strong results with no significant pre-trends when using levels. It implies that in-state tuition policies increased the enrollment of nonresident students by up to 100 students. The results in Panel (b) are less conclusive due to strong pre-trends, however, they bear a consistent pattern. I also found that the policies had ample effects on in-state tuition, especially for two-year colleges, for most of the sample period in Figures A.18 and A.19. This could explain why the treatment effect eventually subsides are reaching a peak about seven years after policy enactment.

1.5 Potential Mechanisms

In-state tuition policies clearly affect the college attendance of likely undocumented students, but the mechanisms, beyond that of simply decreasing the price, are unclear.

Although it is possible that the population of likely undocumented students may have such large elasticities of demand that our measured effects (5-10 p.p using microdata and 20% using IPEDS data) are feasible in a standard model of economic rationality and decision making, there may be more at play.

In order to evaluate the extent to which solely the tuition price change is causing the increase in noncitizen college attendance, I will exploit the variation in the price decrease (out-of-state tuition minus in-state tuition) noncitizen students receive across colleges. I estimate the following equation using OLS,

$$Y_{cst} = \gamma_s + \gamma_t + \sum_{l=J}^{-2} \beta_l (D^l_{cst} \times P_{ct}) + \sum_{l=0}^{K} \beta_l (D^l_{cst} \times P_{ct}) + \eta Z_{ct} + \nu Q_{st} + \mu_{cst} \tag{1.3}$$

where P_{ct} is the log of the difference between out-of-state and in-state tuition and everything else is defined identically to equation (1.2).

Figure A.20 plots the coefficients of interest , β_l, when estimating equation (1.3) using OLS. The pre-trends are mostly insignificant, and the effect on nonresident enrollment steadily rises over time after the passage of the policy. At its height seven years after initial treatment, the estimates imply that a 10% increase in the difference between out-of-state and in-state tuition (price decrease) is associated with a 0.7% increase in nonresident enrollment. The price reduction on average in treated states pre-treatment was $2,684 or about 18%.[7] The results from Figure A.20 would then imply a 1.26% increase in nonresident enrollment. This is vastly different from the estimated 40% increase in nonresident enrollment we see in Figure A.16 Panel (b). So, it seems that the tuition decrease is likely not the only channel through which in-state tuition policies are affecting nonresident college enrollment. I also estimate of version of equation (1.3) using microdata (ACS and CPS) and present the coefficients of interest in Figure A.21, which shows even smaller results than Figure A.20.

[7] Calculated using statistics present in Table A.4

The passage of in-state tuition policies in a state may also signal a certain sympathy with the plight of undocumented students, a recognition of the need to better educate all residents of a state, documented or undocumented, or more. In addition to signaling commitment to education or more, a state's passage of in-state tuition policy laws may signal a decreased likelihood of immigration enforcement since the benefits of an increasingly educated populace requires those educated to stay within the state. It would be against the state's incentives to deport its educated residents. Therefore, the perceived deportation risk of undocumented students (or even documented students as well since many live in "mix" status families), may decrease. This decrease would permit more interaction with public institutions, including national surveys like the ACS or CPS as well as public colleges of universities. If such a theory were to hold true, then my sample composition could be changing due to policy treatment , which would violate exogeneity assumptions, however I do not find that this is the case in Figures A.9 and A.10. This theory may also explain the large estimated effects.

I test this theory in Figures A.15, A. 24, and A.25. Males face a far higher deportation risk than females, accounting for nearly 90 percent of all deportations, hence one would expect to see larger treatment effects for males. However, as Figures A.15 and A.25 show, the opposite is the case. Additionally, in Figure A.24, I estimate equation (1.1) separately for the subset of observations that have above and below the median number of family members in their household – three. Intuitively, the more undocumented family members in the house, the larger the perceived deportation risk. Thus, we expect to see larger effects among those with more family members in their household as these individuals likely have more perceived deportation risk. Figure A.24 Panels (a) and (c) confirms this, showing that estimates of the treatment effect are generally smaller and insignificant for those in homes with below the median number of family members in the household. Panels (b) and (d) show larger and significant effects on the contrary.

However, it is difficult to say whether this result is because of perceived deportation risk or because those in above median family member households are more likely to be undocumented and thus have the policy bind as there is a strong positive correlation between family size and noncitizenship. Another possible explanation could be that the income effect of the price decrease would be larger in a larger family.

In Figures A.22 and A.23, I investigate the effect of treatment on high school completion and employment which may reveal information about the mechanisms. In these figures, I estimate equation (1.1) using high school completion and working as the outcomes and including state controls and state linear time trends. I do not find any results significantly different from zero. Thus, it seems that the policy treatment does not induce Mexican, noncitizen high school students to graduate at higher rates. This runs contrary to what one may expect since the continuation value of completing high school has increased due to a higher probability of attending and completing college. A partial explanation for why I observe effects for college attendance but not high school graduation could be that the marginal college student is different from the marginal high school student. Even though the policy treatment decreases the price of college, it is not enough to overcome the marginal high school student's low probability of completing college. So there is not a significant enough increase in the continuation value of completing high school. For example, the marginal high school student moderately adjusts the continuation value of completing high school as a result of the policy treatment since it is now cheaper to attend college. However, this adjustment is not large enough to compensate for their already low probability of completing college. Perhaps if the price decrease was even larger, I would estimate a significant effect on high school graduation. [8] The policy does not seem to draw Mexican youth out of the labor force either.

[8]See Heckman et al. (2018) for more on models of human capital investment that include continuation values.

1.6 Conclusion

In this paper, I measure the response of likely undocumented youth to the adoption of in-state tuition policies by several states. Using the variation in the adoption timing in a difference-in-differences design, I estimate that in-state tuition policy increased the college attendance of undocumented youth. In microdata, the policy increased college attendance by 5-10 p.p. among Mexican immigrants ages 19-22. These results have substantial policy implications. In-state tuition policies increase the education status of undocumented immigrants in a time when immigration policy is at the center of the public debate.

Appendix A

Table A.1: Legislative History of In-state Tuition Policies for Undocumented Students

State	BillNumber	Requirements	StateFinancialAid	YearEnacted
Texas	HB 1403 (2005 revised version: SB 1528)	3 years	Yes	2001
California	AB 540 (2011 revised version: AB 131)	3 years	Yes, effective 1/1/2013	2001
Utah	HB 144	3 years	No	2002
Illinois	HB 60 (2011 revised version: SB 2185)	3 years	No	2003
Kentucky	KRS 164.020(8)	Graduated from Kentucky HS	No	2003
New York	SB 7784	2 years	No	2002
Oklahoma	SB 596	2 years	Yes	2003
Washington	HB 1079	Complete full senior year of high school & lived in state for 3 years prior to diploma	Yes	2003
Kansas	HB 2145	3 years	Yes	2004
New Mexico	SB 582	1 year	Yes	2005
Nebraska	LB 239	3 years	No	2006
Wisconsin	A75 (revoked in 2011)	3 years	No	2009
Maryland	SB 167/ H470	3 years	No	2011
Rhode Island	Residency Policy S-5.0	3 years	No	2011
Colorado	SB 33	3 years	No	2013
Hawaii	Board of Regents	3 years	No	2013
Michigan	Board of Regents	Attend Michigan middle school for 2 years and a Michigan high school for at least 3 years	No	2013
Minnesota	Senate File 1236	3 years	Yes	2013
New Jersey	SB 2479	3 years	No	2013
Oregon	HB 2787	3 years	No	2013
Connecticut	HB 6390	4 years	No	2011
Virginia	Attorney General Letter	DACA	No	2014
Florida	HB 851	3 years	No	2014
Maine	UMS Board of Trustees	DACA	No	2017

Notes: This table shows the legislative history of in-state tuition policies. The first column contains the name of the state that adopted an in-state tuition policy. The second column contains the name of the legislation or law that enacted in-state tuition policy. The third column states the requirements for undocumented students to be eligible for in-state tuition. Most states require that students live within the state for at least three years. The fourth column includes whether a state offers financial aid to undocumented students. The final columns presents the year the in-state tuition policy was enacted.

Table A.2: ACS Descriptive Statistics

			Treated States	
	All	Untreated States	Pre-Treatment	Post-Treatment
Years in US	9.107	8.897	8.121	9.476
	(0.0196)	(0.0272)	(0.1292)	(0.0258)
Age	20.604	20.598	20.605	20.610
	(0.0033)	(0.0045)	(0.0229)	(0.0043)
Number of Family Members in Household	2.902	2.742	3.203	3.032
	(0.0052)	(0.0064)	(0.0416)	(0.0068)
Noncitizen	0.675	0.635	0.756	0.706
Speaks English	0.174	0.214	0.134	0.136
Mexican	0.332	0.225	0.434	0.433
High DACA Take-up	0.481	0.399	0.573	0.556
Female	0.457	0.456	0.437	0.460
Employed	0.562	0.575	0.593	0.544
In School	0.467	0.481	0.373	0.466
HS Grad or above	0.753	0.773	0.624	0.749
College or above	0.448	0.461	0.338	0.449
Observations	249,901	125,441	4,270	120,190

Notes: This table includes descriptive statistics of the population of Hispanic immigrants ages 19-22 in the ACS from 2000 to 2018 calculated using survey weights. The first column includes this entire sample. The second column includes those that live in untreated states. The third column includes those that lived in treated states pre-treatment. The final columns includes that that live in treated states post-treatment. Non-citizens includes permanent residents, i.e. those with green cards.

Table A.3: CPS Descriptive Statistics

			Treated States	
	All	Untreated States	Pre-Treatment	Post-Treatment
Years in US	10.374	9.471	9.278	11.561
	(0.1485)	(0.2220)	(0.1950)	(0.2726)
Age	20.621	20.631	20.586	20.641
	(0.0028)	(0.0058)	(0.0049)	(0.0043)
Number of Family Members in Household	2.854	2.678	2.825	2.957
	(0.0040)	(0.0080)	(0.0065)	(0.0064)
Noncitizen	0.702	0.680	0.723	0.697
Mexican	0.240	0.263	0.064	0.351
Female	0.461	0.460	0.455	0.467
Employed	0.552	0.568	0.583	0.522
In School	0.395	0.363	0.377	0.422
HS Grad or above	0.727	0.719	0.697	0.752
College or above	0.427	0.398	0.402	0.457
Observations	183,201	49,409	61,876	71,916

Notes: This table includes descriptive statistics of the population of Hispanic immigrants ages 19-22 in the CPS from 1997 to 2018 calculated using survey weights. The first column includes this entire sample. The second column includes those that live in untreated states. The third column includes those that lived in treated states pre-treatment. The final columns includes that that live in treated states post-treatment. Non-citizens includes permanent residents, i.e. those with green cards.

Table A.4: IPEDS Descriptive Statistics

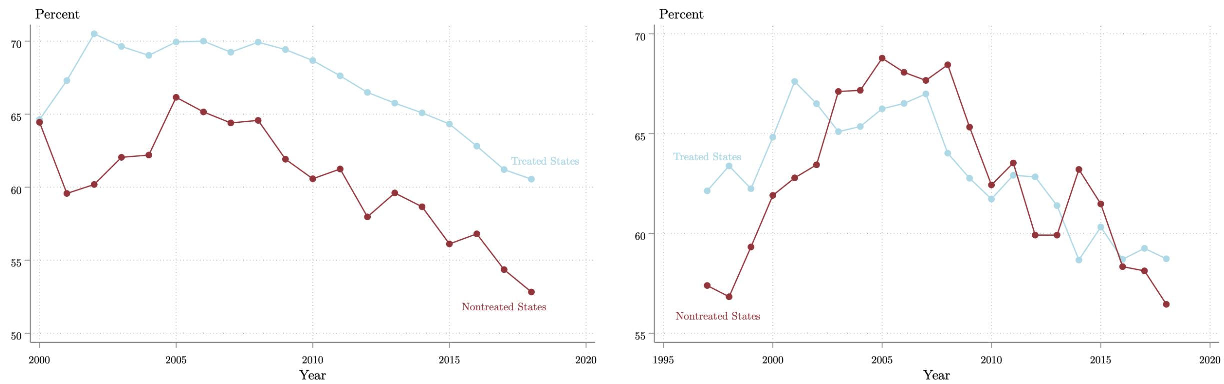
			Treated States	
	All	Untreated States	Pre-Treatment	Post-Treatment
Two-Year College	0.40	0.39	0.41	0.39
Four-Year College	0.60	0.61	0.59	0.61
Public	0.46	0.44	0.47	0.47
Private	0.37	0.39	0.35	0.36
For Profit	0.17	0.17	0.19	0.17
In-State Tuition	12860	12757	11881	13665
Out-of-State Tuition	15582	15389	14565	16545
Number of Students	5714	4581	4834	7846
Nonresidents	214	158	190	314
Hispanics	781	359	594	1540
Whites	2932	2662	3291	3094
Observations	75,051	35,395	15,988	23,668

Notes: This table includes descriptive statistics of my sample of colleges and universities from 1998 to 2018. The first column includes this entire sample, and the second column includes colleges in untreated states. The third column includes colleges in treated states pre-treatment, the final column includes colleges in treated states post-treatment. Nonresidents includes permanent residents, i.e. those with green cards.

Table A.5: Min. and Max. Difference between In- and Out-of-State Tuition: 1998-2018

	(1) Min. Tuition Diff.	(2) Max. Tuition Diff.	(3) Mean Tuition Diff.
Alabama	1833	4071	2825
Alaska	2653	9287	5729
Arizona	1780	5310	3402
Arkansas	1800	2444	2172
California	2935	4823	3687
Colorado	3869	6217	4607
Connecticut	2338	5766	4241
Delaware	2907	5199	3790
D.C.	221	676	472
Florida	2354	3598	2805
Georgia	2473	3579	3122
Hawaii	3791	5594	4587
Idaho	3078	6645	4427
Illinois	1470	1849	1598
Indiana	1567	3520	2577
Iowa	884	1269	1063
Kansas	1520	2426	1763
Kentucky	1732	5333	3277
Louisiana	1219	3666	2196
Maine	2926	4275	3794
Maryland	2314	4586	3469
Massachusets	1871	2826	2193
Michigan	1511	3130	2310
Minnesota	626	2307	1245
Mississippi	1983	2981	2404
Missouri	947	1964	1383
Montana	3038	5656	4711
Nebraska	878	2027	1535
Nevada	3513	6284	4482
New Hampshire	2374	5284	4058
New Jersey	1442	2986	2329
New Mexico	2133	3546	2879
New York	1034	2328	1745
North Carolina	4580	5113	4846
North Dakota	2092	3357	2810
Ohio	1987	2943	2448
Oklahoma	1446	5130	3361
Oregon	2458	4869	3591
Pennsylvania	1390	2239	1838
Rhode Island	1774	3426	2742
South Carolina	2456	4248	3295
South Dakota	505	2145	1186
Tennesse	1834	4380	2969
Texas	1813	3773	2738
Utah	2582	4329	3442
Vermont	2213	4717	3651
Virginia	3255	4679	3916
Washington	2812	4469	3466
West Virginia	1329	3737	2746
Wisconsin	2420	8688	5211
Wyoming	3244	5234	4230

Notes: This table includes descriptive statistics on tuition at U.S. college and universities from 1998 to 2018 calculated using data from IPEDS (Integrated Postsecondary Education Data System). Each column contains a measure of tuition difference, the difference between in-state and out-of-state tuition at a college or university. I first calculate the tuition difference for each college or university in my sample. I then average this differences by state and year. Column one (two) is the minimum (maximum) value of the year in which a state has the smallest (largest) tuition difference. Column three is the average tuition difference throughout the sample period.

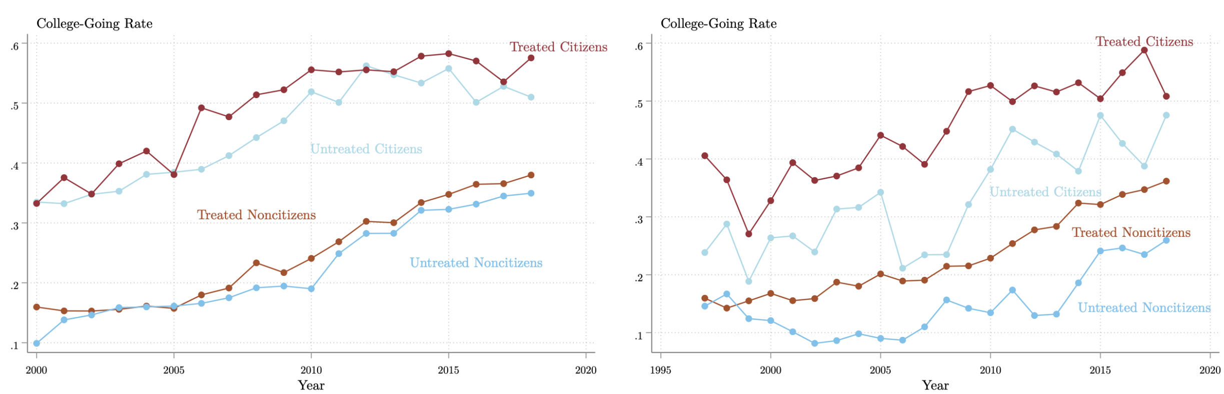


(a) ACS Data

(b) CPS Data

Figure A.1: Percent of Hispanic Immigrants that are Noncitizens in Treated and Untreated States

Notes: Panel (a) corresponds to 2000-2018 ACS data and panel (b) corresponds to 1997-2018 CPS data. This figure shows the number of immigrant Hispanic noncitizens and citizens ages 19-22. To construct these figures, the number of non-citizens and citizens were counted in each state and year, then these counts were further averaged by treatment status. Sampling weights were used to construct both graphs.

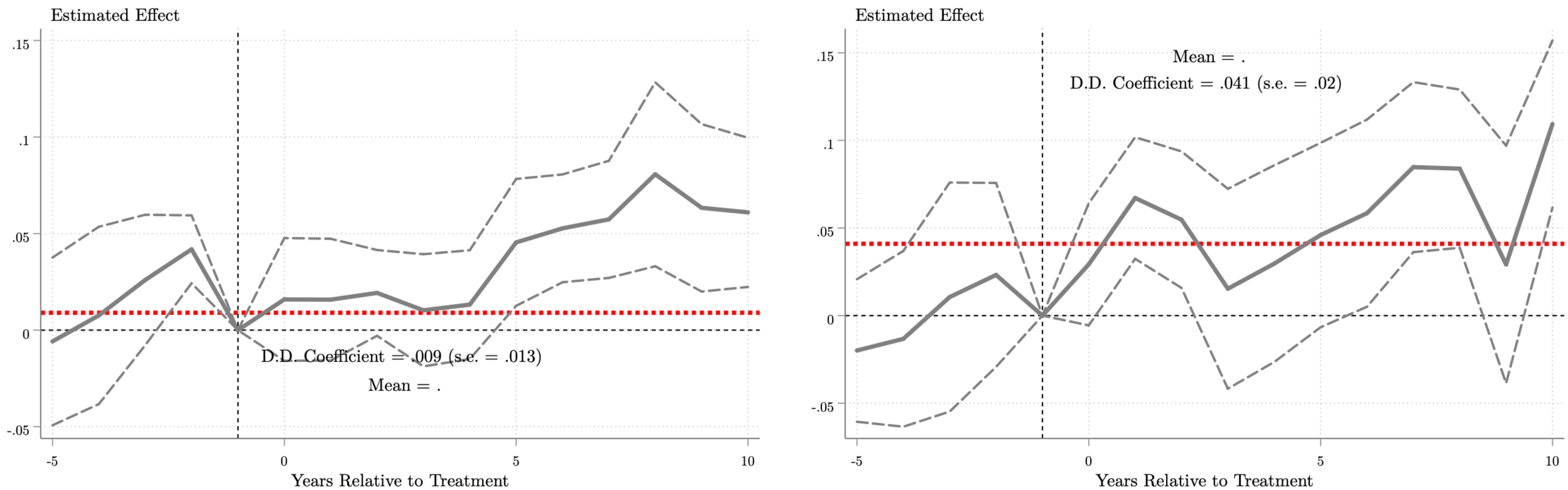


(a) ACS Data

(b) CPS Data

Figure A.2: College-going rate of Foreign-Born Hispanic Immigrant Noncitizens and Citizens in Treated and Untreated States

Notes: Panel (a) corresponds to 2000-2018 ACS data and panel (b) corresponds to 1997-2018 CPS data. The figure shows the college-going rate of immigrant Hispanic noncitizens and citizens ages 19-22 in treated and untreated states. Sampling weights were used to construct both graphs.

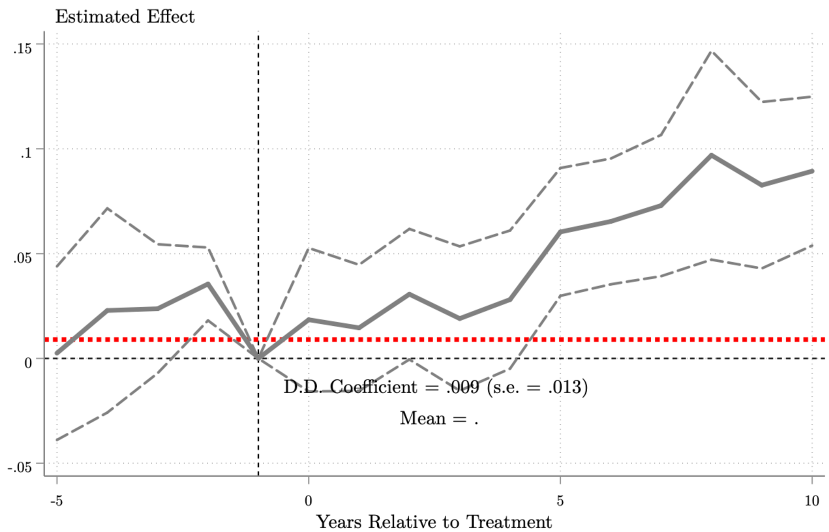


(a) ACS Data

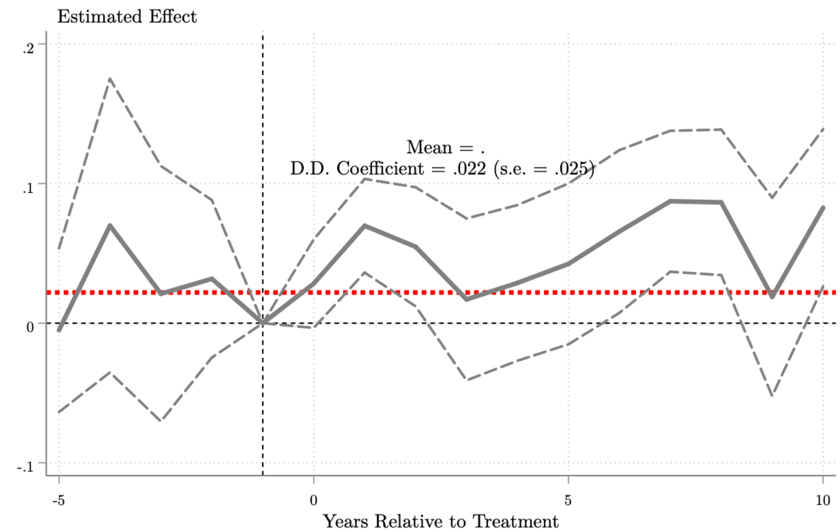
(b) CPS Data

Figure A.3: Effect on College-Going: No Controls

Notes: Panel (a) corresponds to 2000-2018 ACS data and panel (b) corresponds to 1997-2018 CPS data. The graphs plot the coefficients of interest and the corresponding confidence intervals from equation (1.1) estimated using OLS on the subsample of Mexican, immigrant, noncitizens ages 19-22 with college attendance as the outcome. This specification includes no controls (other than state, year, and year-of-immigration fixed effects. Also displayed is the standard difference-in-differences coefficient and corresponding standard error estimated using OLS and the pre-treatment mean in treated states. Sampling weights were used to construct both graphs.



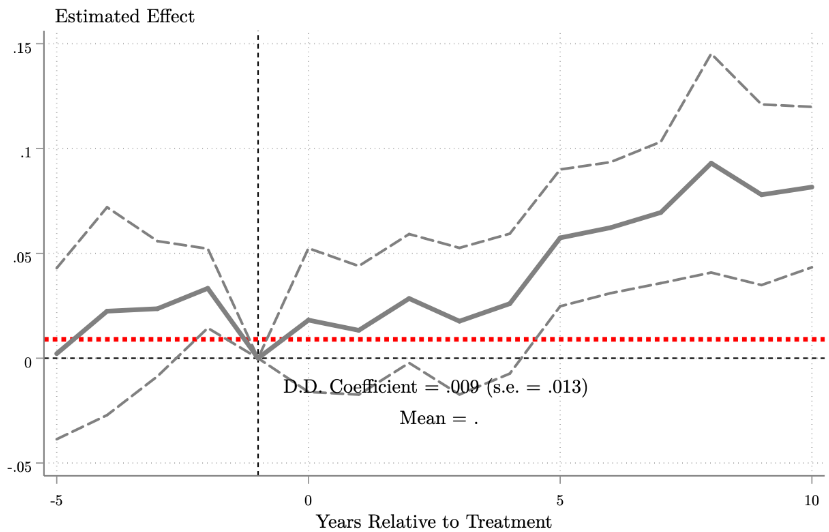
(a) ACS Data



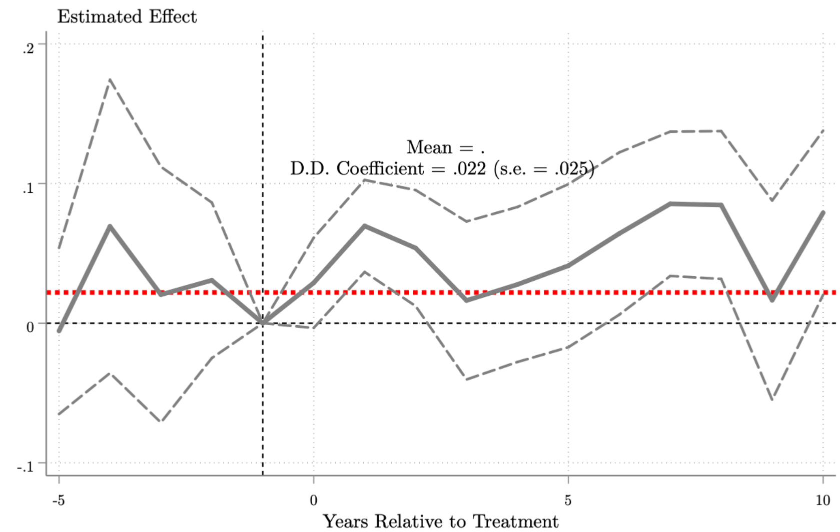
(b) CPS Data

Figure A.4: Effect on College-Going: State and Individual Controls

Notes: Panel (a) corresponds to 2000-2018 ACS data and panel (b) corresponds to 1997-2018 CPS data. The graphs plot the coefficients of interest and the corresponding confidence intervals from equation (1.1) estimated using OLS on the subsample of Mexican, immigrant, noncitizens ages 19-22 with college attendance as the outcome. This specification includes controls for time-varying state characteristics such as deportation risk, college-going rate among Foreign-Born Hispanic citizens, percent of population that is Hispanic, unemployment rate, proportion of Hispanic youth with children, per-capita income, and political party of legislature. It also includes individual controls for race, age, sex, year of immigration, poverty status, English skills, and number of family members in the household. Also displayed is the standard difference-in-differences coefficient and corresponding standard error estimated using OLS and the pre-treatment mean in treated states. Sampling weights were used to construct both graphs.



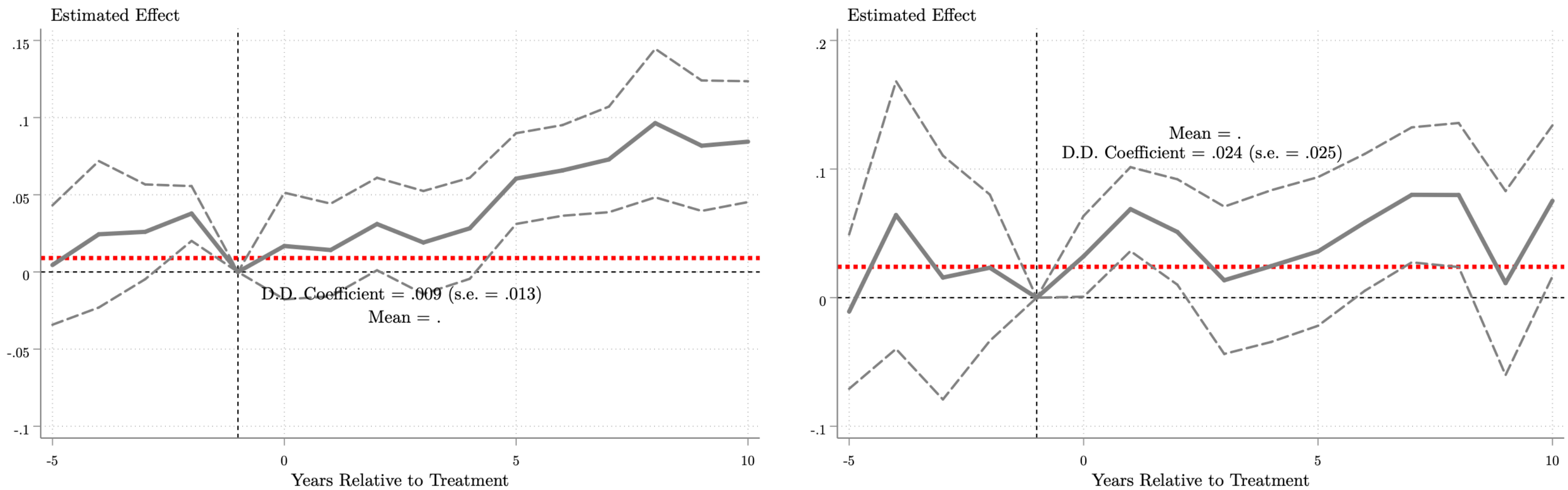
(a) ACS Data



(b) CPS Data

Figure A.5: Effect on College-Going: State Controls and Linear State Time Trends

Notes: Panel (a) corresponds to 2000-2018 ACS data and panel (b) corresponds to 1997-2018 CPS data. The graphs plot the coefficients of interest and the corresponding confidence intervals from equation (1.1) estimated using OLS on the subsample of Mexican, immigrant, noncitizens ages 19-22 with college attendance as the outcome. This specification includes linear state time trends and controls for time-varying state characteristics such as deportation risk, college-going rate among Foreign-Born Hispanic citizens, percent of population that is Hispanic, unemployment rate, proportion of Hispanic youth with children, per-capita income, and political party of legislature. It also includes individual controls for race, age, sex, year of immigration, poverty status, English skills, and number of family members in the household. Also displayed is the standard difference-in-differences coefficient and corresponding standard error estimated using OLS and the pre-treatment mean in treated states. Sampling weights were used to construct both graphs.

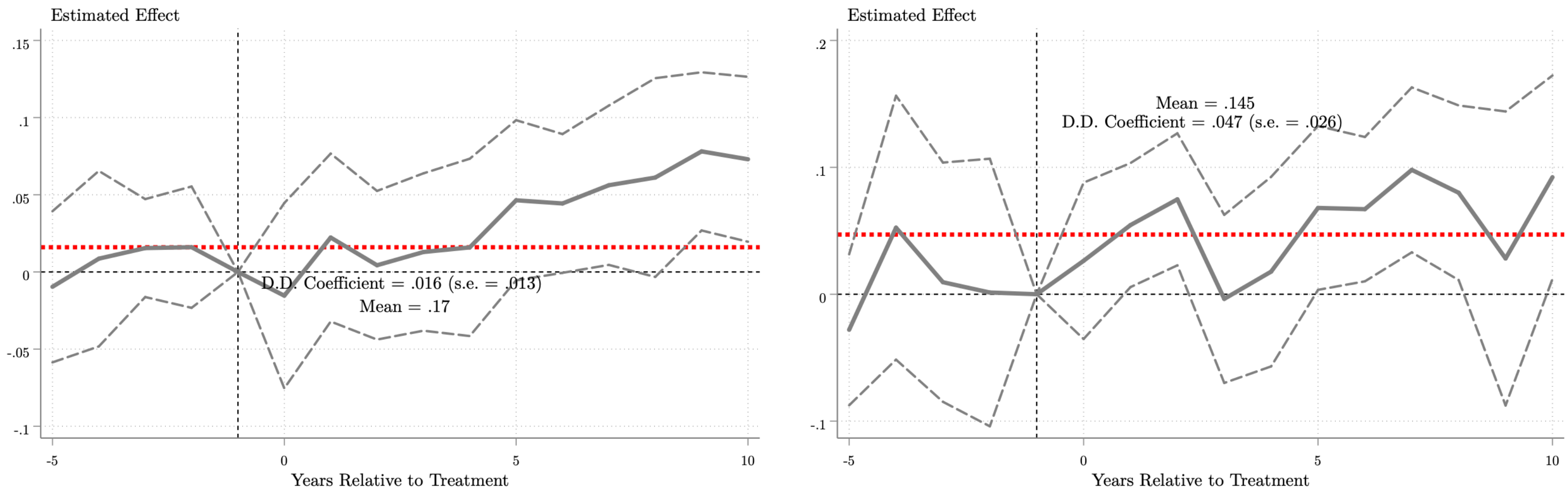


(a) ACS Data

(b) CPS Data

Figure A.6: Effect on College-Going: State Controls and Quadratic State Time Trends

Notes: Panel (a) corresponds to 2000-2018 ACS data and panel (b) corresponds to 1997-2018 CPS data. The graphs plot the coefficients of interest and the corresponding confidence intervals from equation (1) estimated using OLS on the subsample of Mexican, immigrant, noncitizens ages 19-22 with college attendance as the outcome. This specification includes linear state time trends and controls for time-varying state characteristics such as deportation risk, college-going rate among Foreign-Born Hispanic citizens, percent of population that is Hispanic, unemployment rate, proportion of Hispanic youth with children, per-capita income, and political party of legislature. It also includes individual controls for race, age, sex, year of immigration, poverty status, English skills, and number of family members in the household. Also displayed is the standard difference-in-differences coefficient and corresponding standard error estimated using OLS and the pre-treatment mean in treated states. Sampling weights were used to construct both graphs.

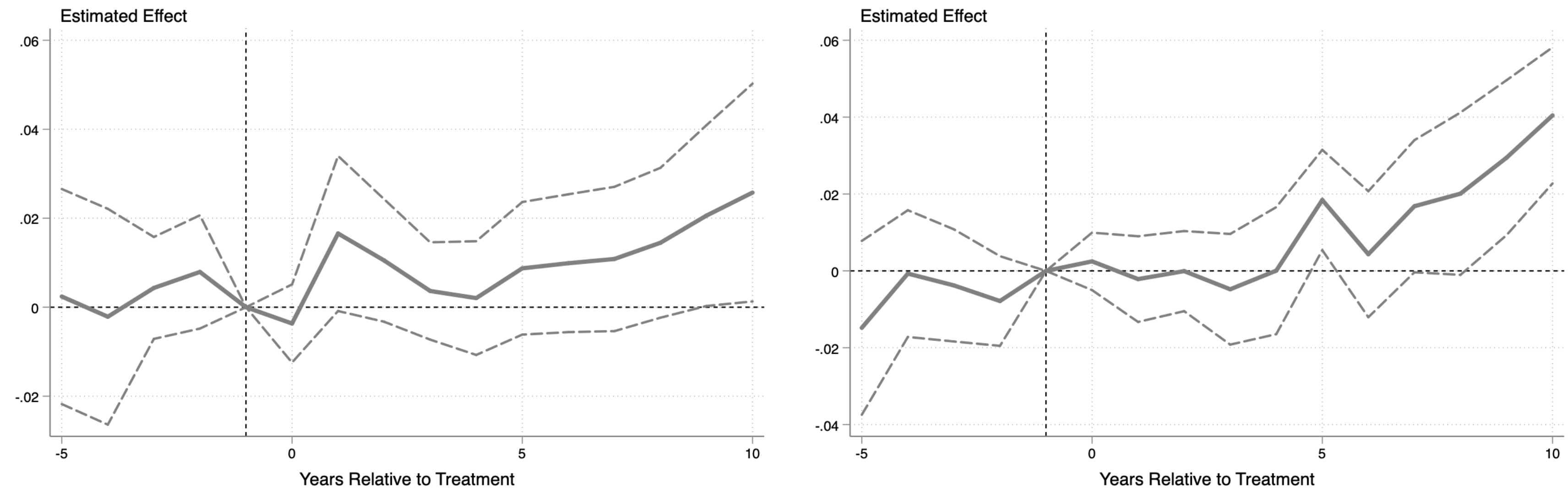


(a) ACS Data

(b) CPS Data

Figure A.7: Effect on College-Going: State Controls, Linear State Time Trends, and Excluding California

Notes: Panel (a) corresponds to 2000-2018 ACS data and panel (b) corresponds to 1997-2018 CPS data. The graphs plot the coefficients of interest and the corresponding confidence intervals from equation (1.1) estimated using OLS on the subsample of Mexican, immigrant, noncitizens ages 19-22 with college attendance as the outcome. This specification includes linear state time trends and controls for time-varying state characteristics such as deportation risk, college-going rate among Foreign-Born Hispanic citizens, percent of population that is Hispanic, unemployment rate, proportion of Hispanic youth with children, per-capita income, and political party of legislature. It also includes individual controls for race, age, sex, year of immigration, poverty status, English skills, and number of family members in the household. Also displayed is the standard difference-in-differences coefficient and corresponding standard error estimated using OLS and the pre-treatment mean in treated states. Sampling weights were used to construct both graphs.

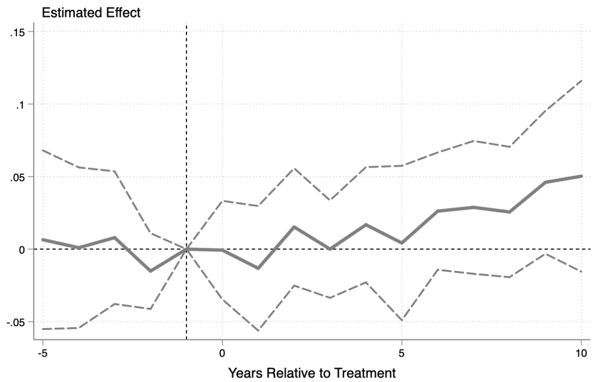


(a) ACS Data

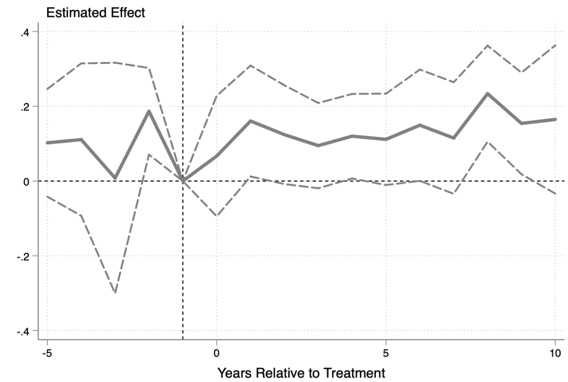
(b) CPS Data

Figure A.8: Event-Study Estimates of the Effect of Policy on *Predicted College Attendance* Based on Observable Characteristics

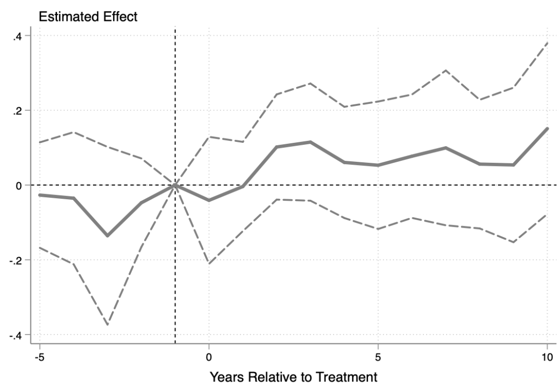
Notes: Panel (a) corresponds to 2000-2018 ACS data and panel (b) corresponds to 1997-2018 CPS data. This figure plots predicted college attendance based on observable characteristics. I regress college attendance on the state and linear controls used in previous tables to obtain values for predicted college attendance. I then regress these predicted values on the event-time variables to measure whether predicted schooling was constant around the timing of policy adoption. Sampling weights were used to construct both graphs.



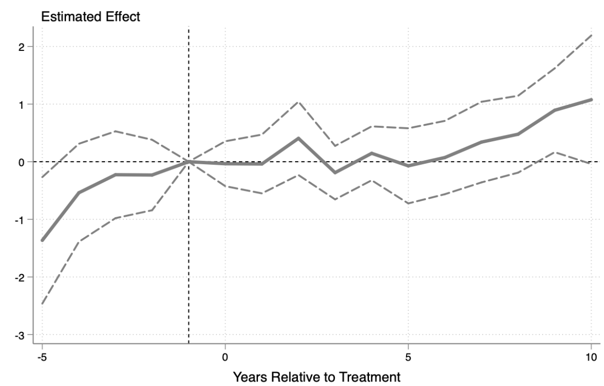
(a) Prob(Mexican)



(b) Number of Persons in a Household



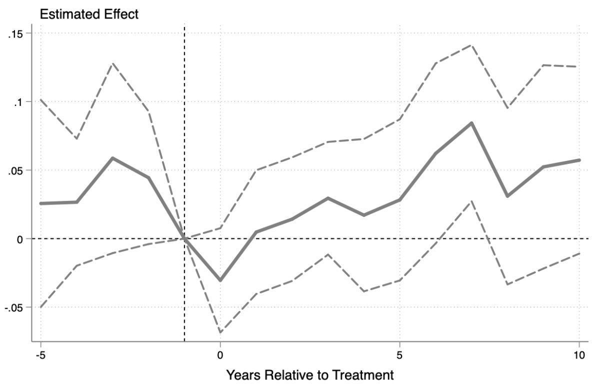
(c) English Speaking Ability



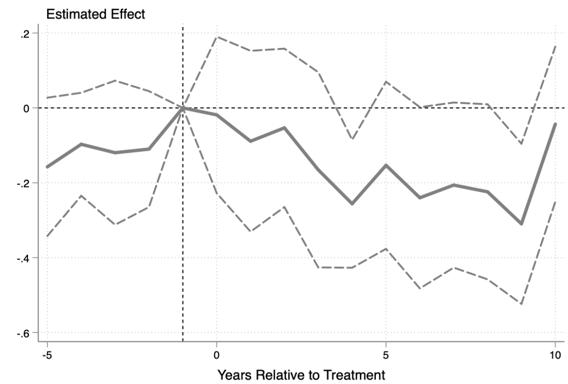
(d) Year of Immigration

Figure A.9: Evidence of Identifying Assumptions: Does the Treatment Predict the Controls in the ACS?

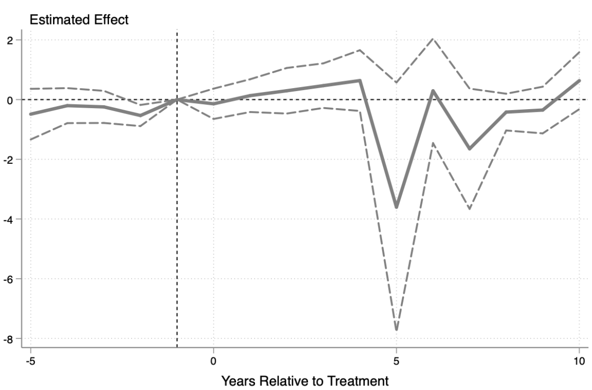
Notes: Panel (a) shows the effect of the treatment on the probability of being Mexican. Panel (b) shows the effect of the treatment on the number of persons in a household. Panel (c) shows the effect of treatment on English Speaking ability. Panel (d) shows the effect of treatment on the year of immigration. Data: 2000-2018 ACS. Sampling weights were used to construct both graphs.



(a) Prob(Mexican)



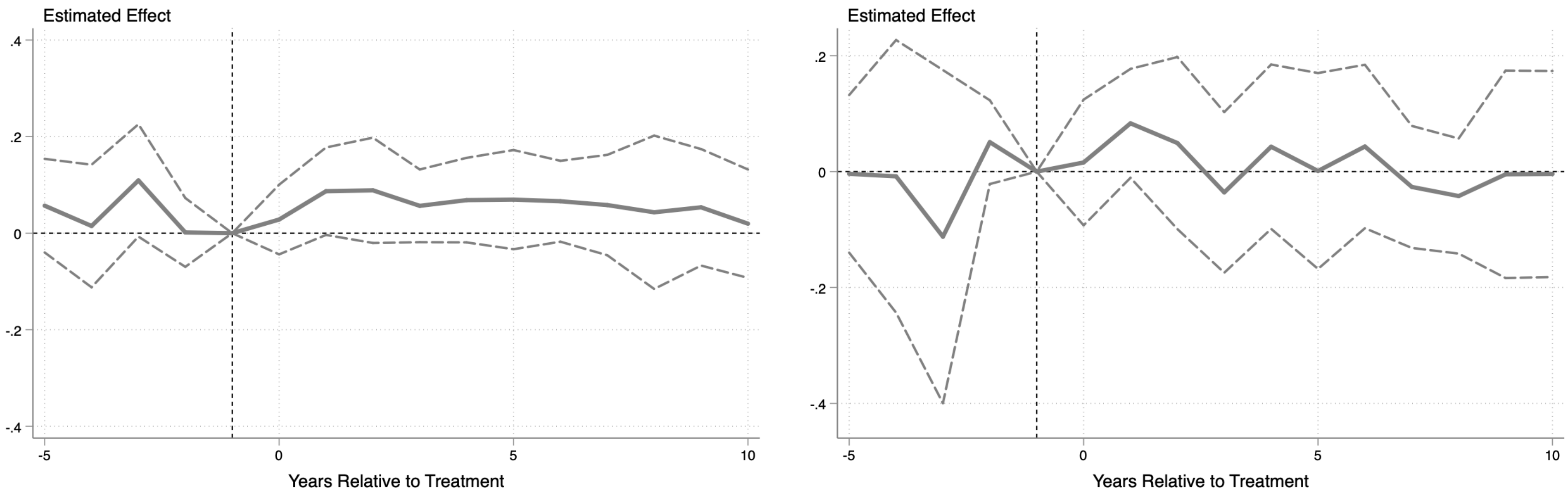
(b) Number of Persons in a Household



(c) Year of Immigration

Figure A.10: Evidence of Identifying Assumptions: Does the Treatment Predict the Controls in the CPS?

Notes: Panel (a) shows the effect of the treatment on the probability of being Mexican. Panel (b) shows the effect of the treatment on the number of persons in a household. Panel (c) shows the effect of treatment on the year of immigration. Data: 1997-2018 CPS. Sampling weights were used to construct both graphs.



(a) ACS Data

(b) CPS Data

Figure A.11: Effect on College-Going for Mexican-born U.S.*Citizens*

Notes: Panel (a) corresponds to 2000-2018 ACS data and panel (b) corresponds to 1997-2018 CPS data. The graphs plot the coefficients of interest and the corresponding confidence intervals from equation (1.1) estimated using OLS on the subsample of Mexican, immigrant, citizens ages 19-22 with college attendance as the outcome. This specification includes linear state time trends and controls for time-varying state characteristics such as deportation risk, college-going rate among Foreign-Born Hispanic citizens, percent of population that is Hispanic, unemployment rate, proportion of Hispanic youth with children, per-capita income, and political party of legislature. It also includes individual controls for poverty, English skills, and number of family members in the household. Sampling weights were used to construct both graphs.

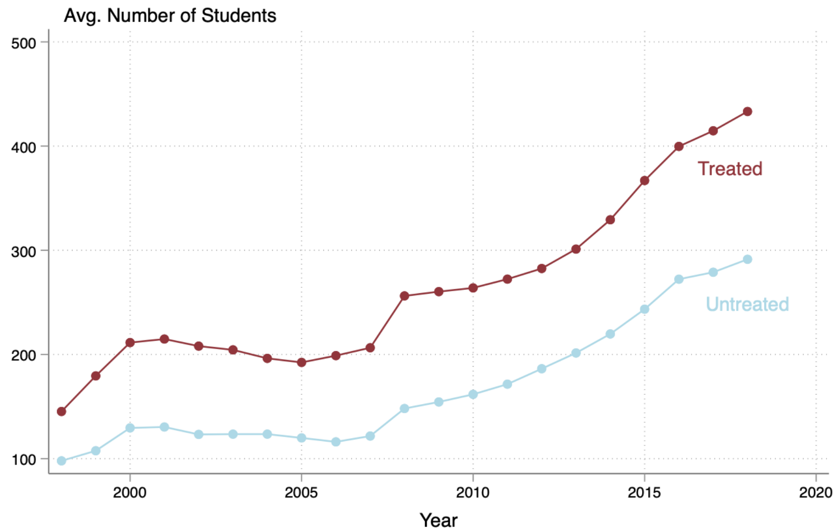


Figure A.12: Number of Nonresident Students on Average in Treated and Untreated States

Notes: This figure shows the average number of nonresident students in colleges and universities across treated and untreated states. Data: IPEDS.

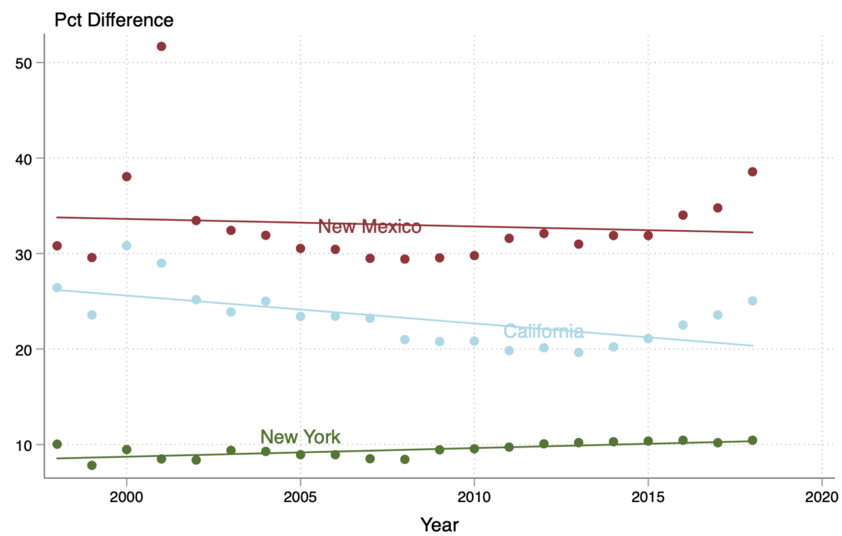
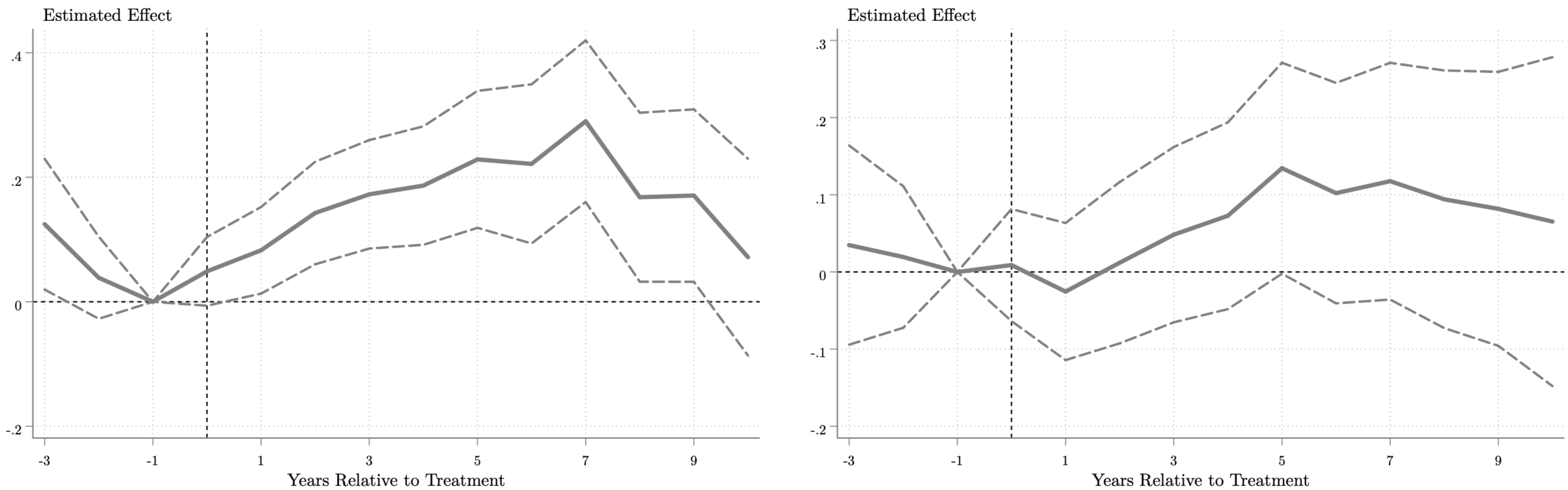


Figure A.13: Difference between In-State and Out-of-State Tuition Across Multiple States

Notes: This figure shows the average difference between in- and out-of-state tuition in three states: New Mexico, California, and New York. Data: IPEDS.

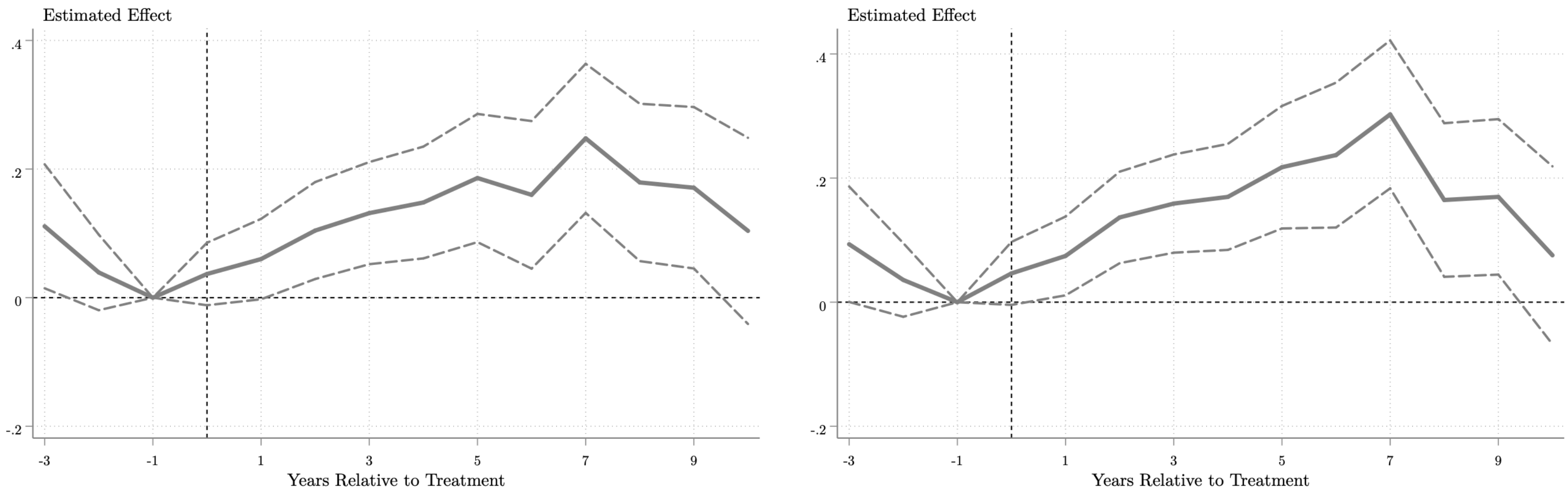


(a) Public Colleges

(b) Private Colleges

Figure A.14: Effect on Nonresident Enrollment: State Controls and State Linear Time Trends

Notes: This figure plots the coefficients and corresponding confidence intervals of equation (1.2) estimated using OLS on the subsample of public or private colleges with log(Enrolled Nonresident Students) as the outcome. Data: IPEDS. The data is at the college-year level. This specification includes linear state-year time trends and college-level controls such as institution type, ranking, and the amount of white students. It also includes state-level controls such as deportation risk, college-going rate among Foreign-Born Hispanic citizens, percent of population that is Hispanic, unemployment rate, proportion of Hispanic youth with children, per-capita income, and political party of legislature.

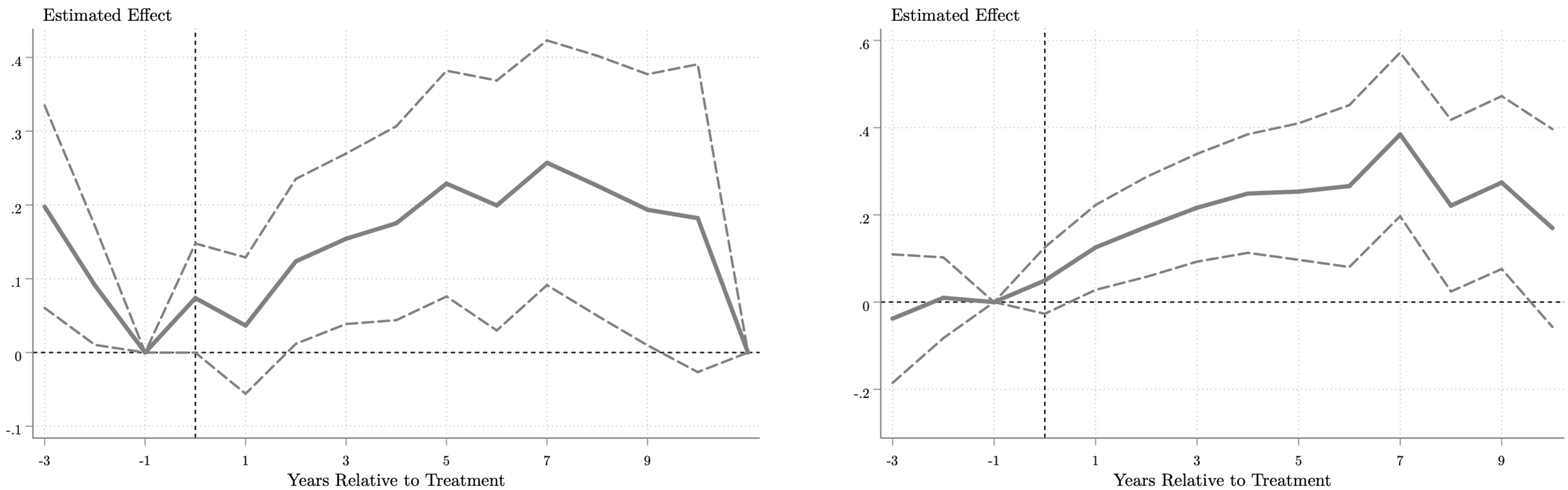


(a) Nonresident Males

(b) Nonresident Females

Figure A.15: Effect on Nonresident Enrollment: State Controls and State Linear Time Trends

Notes: This figure plots the coefficients and corresponding confidence intervals of equation (1.2) estimated using OLS on the subsample of public colleges with log(Enrolled Nonresident Male Students) log(Enrolled Nonresident Female Students) as the outcome. Data: IPEDS. The data is at the college-year level. This specification includes linear state-year time trends and college-level controls such as institution type, ranking, end the amount of white students. It also includes state-level controls such as deportation risk, college-going rate among Foreign-Born Hispanic citizens, percent of population that is Hispanic, unemployment rate, proportion of Hispanic youth with children, per-capita income, and political party of legislature.

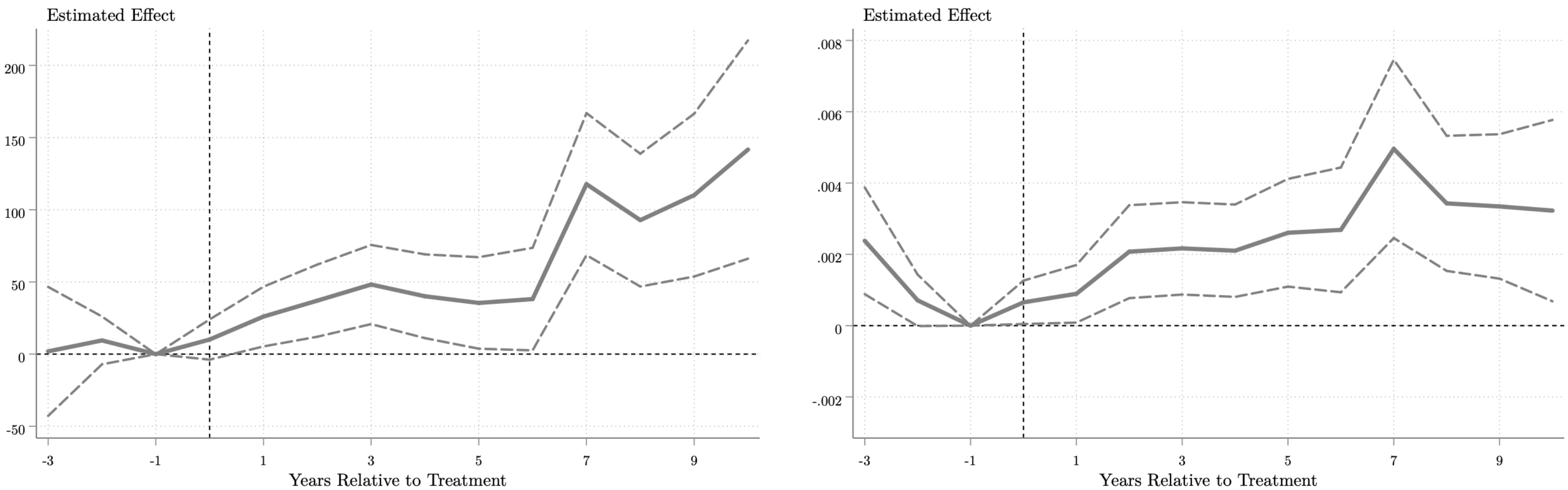


(a) Four Year Colleges

(b) Two Year Colleges

Figure A.16: Effect on Nonresident Enrollment: State Controls and State Linear Time Trends

Notes: This figure plots the coefficients and corresponding confidence intervals of equation (1.2) estimated using OLS on the subsample of public four- or two-year colleges with log(Enrolled Nonresident Students) as the outcome. Data: IPEDS. The data is at the college-year level. This specification includes linear state-year time trends and college-level controls such as institution type, ranking, end the amount of white students. It also includes state-level controls such as deportation risk, college-going rate among Foreign-Born Hispanic citizens, percent of population that is Hispanic, unemployment rate, proportion of Hispanic youth with children, per-capita income, and political party of legislature.

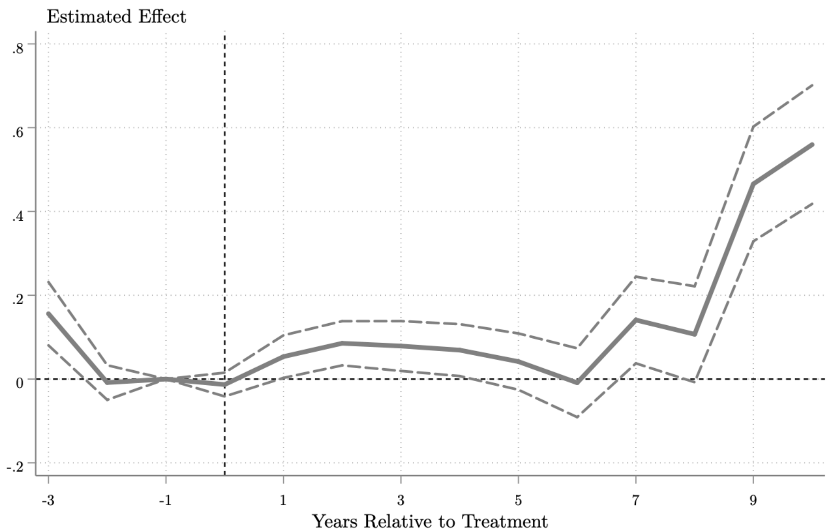


(a) Level

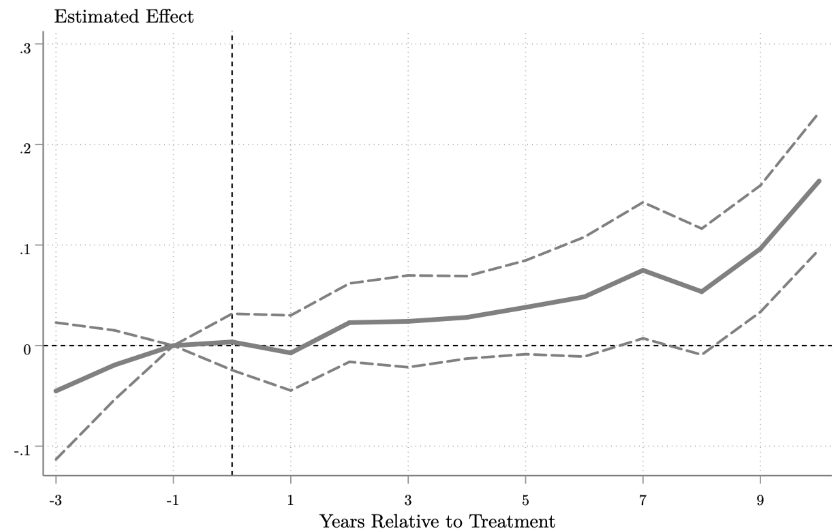
(b) Proportion Nonresident

Figure A.17: Effect on Nonresident Enrollment: State Controls and State Linear Time Trends

Notes: This figure plots the coefficients and corresponding confidence intervals of equation (1.2) estimated using OLS on the subsample of public colleges with levels and proportion of nonresident students as the outcome. Data: IPEDS. The data is at the college-year level. This specification includes linear state-year time trends and college-level controls such as institution type, ranking, and the amount of white students. It also includes state-level controls such as deportation risk, college-going rate among Foreign-Born Hispanic citizens, percent of population that is Hispanic, unemployment rate, proportion of Hispanic youth with children, per-capita income, and political party of legislature.



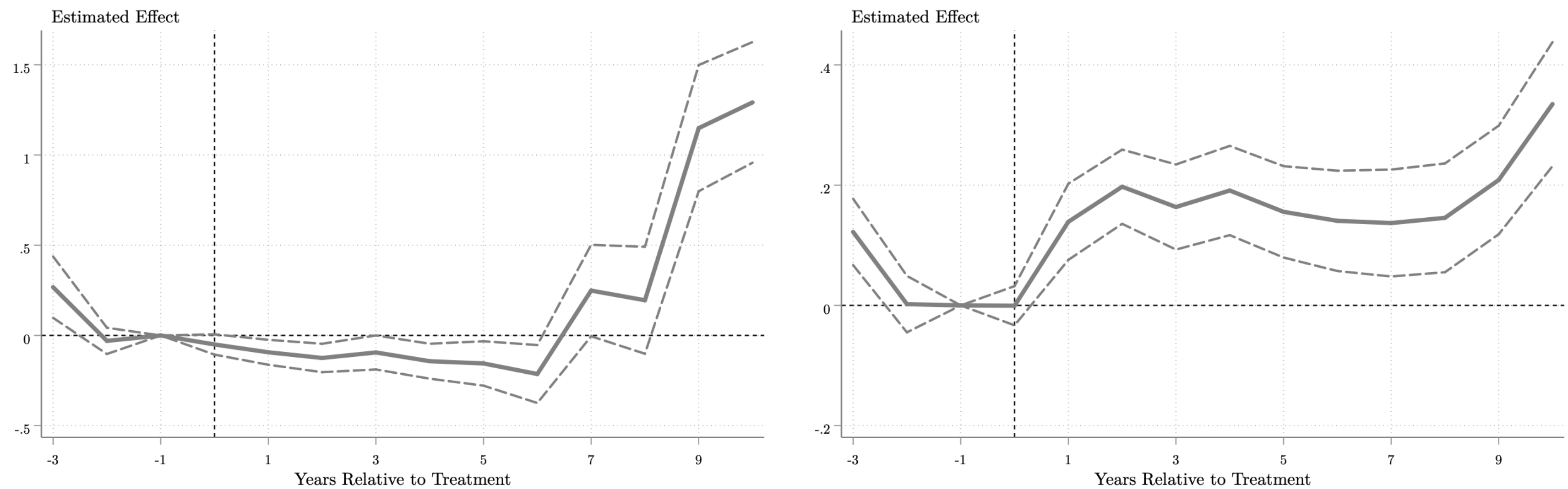
(a) In-State Tuition



(b) Out-of-State Tuition

Figure A.18: Effect on Tuition: State Controls and State Linear Time Trends

Notes: This figure plots the coefficients and corresponding confidence intervals of equation (1.2) estimated using OLS on the subsample of public colleges with log(in-state) or log(out-of-state) tuition as the outcome. Tuition is in 2018 dollars, converted using the CPI-U. Data: IPEDS. The data is at the college-year level. This specification includes linear state-year time trends and college-level controls such as institution type, ranking, and the amount of white students. It also includes state-level controls such as deportation risk, college-going rate among Foreign-Born Hispanic citizens, percent of population that is Hispanic, unemployment rate, proportion of Hispanic youth with children, per-capita income, and political party of legislature.



(a) Four Year Colleges

(b) Two Year Colleges

Figure A.19: Effect on In-State Tuition: State Controls and State Linear Time Trends

Notes: This figure plots the coefficients and corresponding confidence intervals of equation (1.2) estimated using OLS on the subsample of public colleges with log(in-state) tuition as the outcome. Tuition is in 2018 dollars, converted using the CPI-U. Data: IPEDS. The data is at the college-year level. This specification includes linear state-year time trends and college-level controls such as institution type, ranking, the amount of white students, and the difference between in-state and out-of-state tuition. It also includes state-level controls such as deportation risk, college-going rate among Foreign-Born Hispanic citizens, percent of population that is Hispanic, unemployment rate, proportion of Hispanic youth with children, per-capita income, and political party of legislature.

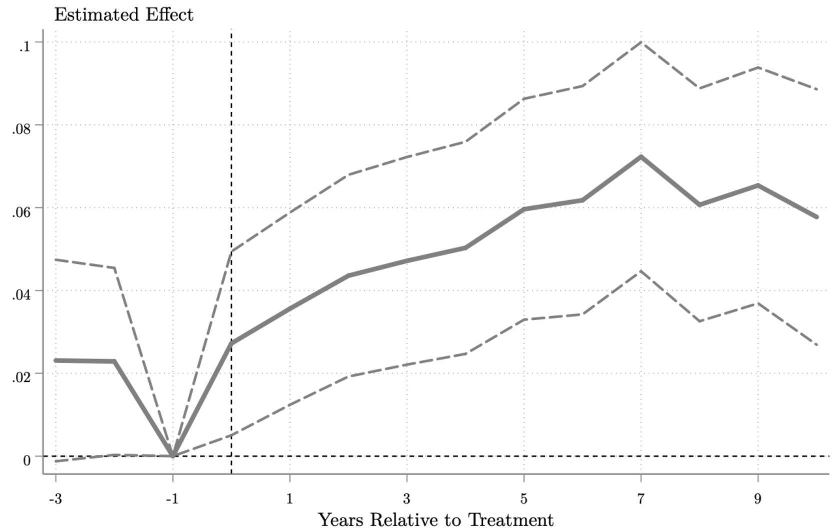
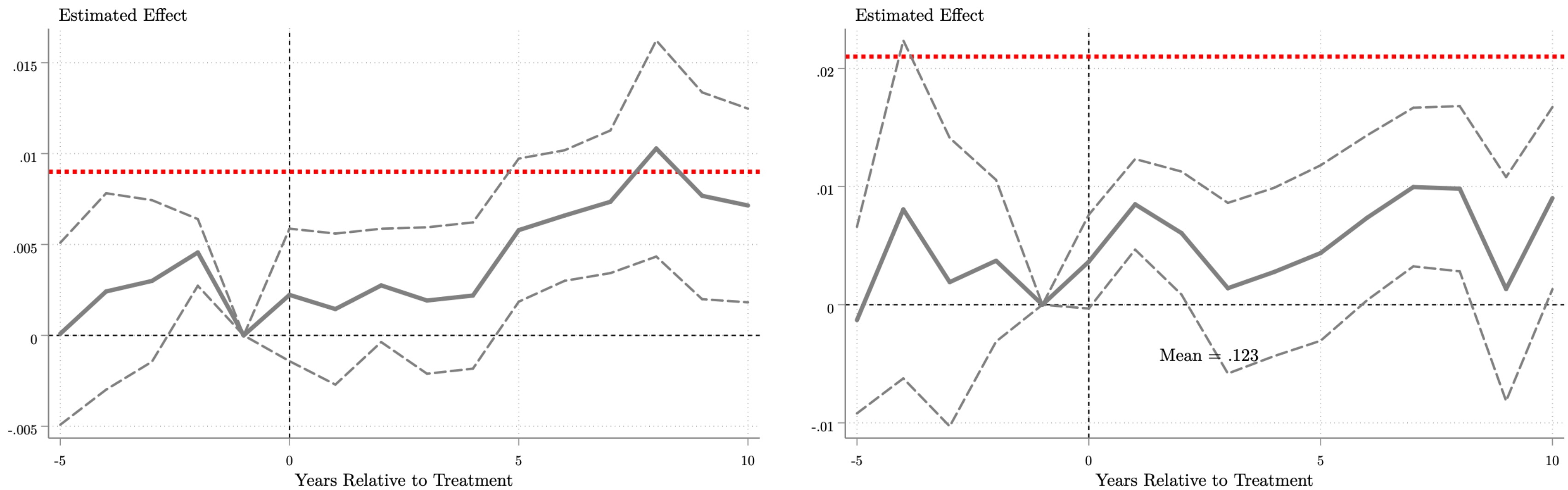


Figure A.20: Dosage Effect on Nonresident Enrollment: College & State Controls & Linear Time Trends

Notes: This figure plots the coefficients and corresponding confidence intervals of equation (1.3) estimated using OLS on the subsample of public colleges with log(Enrolled Nonresident Students) as the outcome. Data: IPEDS. The data is at the college-year level. This specification includes linear state-year time trends and college-level controls such as institution type, ranking, the amount of white students, and the difference between in-state and out-of-state tuition. It also includes state-level controls such as deportation risk, college-going rate among Foreign-Born Hispanic citizens, percent of population that is Hispanic, unemployment rate, proportion of Hispanic youth with children, per-capita income, and political party of legislature.

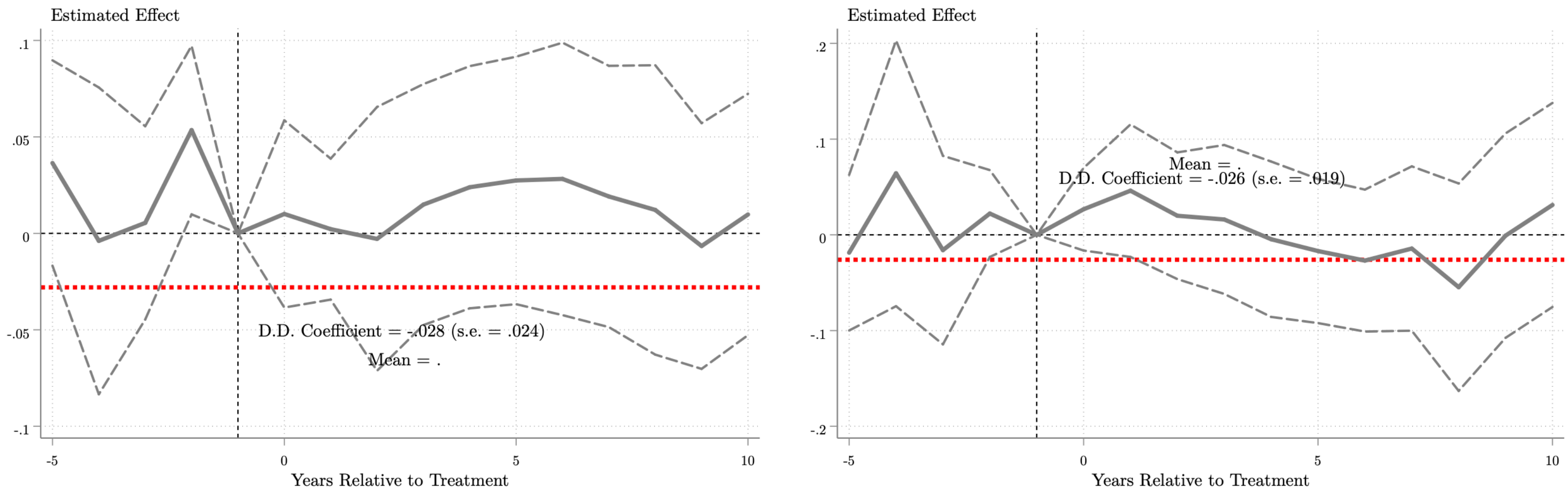


(a) ACS Data

(b) CPS Data

Figure A.21: Dosage Effect on Tuition: State Controls & State Linear Time Trends

Notes: Panel (a) corresponds to 2000-2018 ACS data and panel (b) corresponds to 1997-2018 CPS data. The graphs plot the coefficients of interest and the corresponding confidence intervals from an equation similar to equation (1.3), – modified for use with microdata – estimated using OLS on the subsample of Mexican, immigrant, noncitizens ages 19-22 with college attendance as the outcome. This specification includes linear state time trends and controls for time-varying state characteristics such as deportation risk, college-going rate among Foreign-Born Hispanic citizens, percent of population that is Hispanic, unemployment rate, proportion of Hispanic youth with children, per-capita income, and political party of legislature. It also includes individual controls for race, age, sex, year of immigration, poverty status, English skills, and number of family members in the household. Also displayed is the standard difference-in-differences coefficient and corresponding standard error estimated using OLS and the pre-treatment mean in treated states. Sampling weights were used to construct both graphs.

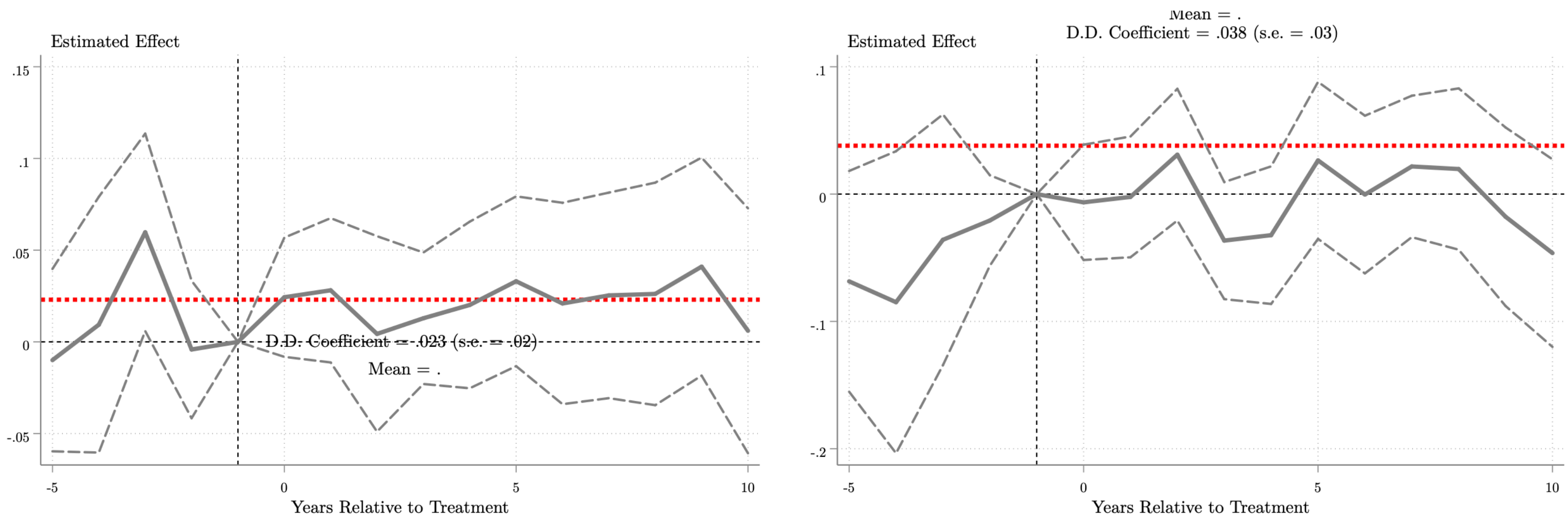


(a) ACS Data

(b) CPS Data

Figure A.22: Effect on High School Graduation: State Controls and State Linear Time Trends

Notes: Panel (a) corresponds to 2000-2018 ACS data and panel (b) corresponds to 1997-2018 CPS data. The graphs plot the estimated coefficients and corresponding confidence intervals from equation (1.1) estimated using OLS on the subsample of Mexican, immigrant, noncitizens ages 19-22 with high school graduation as the outcome. This specification includes state linear time trends and controls for time-varying state characteristics such as deportation risk, college-going rate among Foreign-Born Hispanic citizens, percent of population that is Hispanic, unemployment rate, proportion of Hispanic youth with children, per-capita income, and political party of legislature. It also includes individual controls for poverty, English skills, and number of family members in the household.

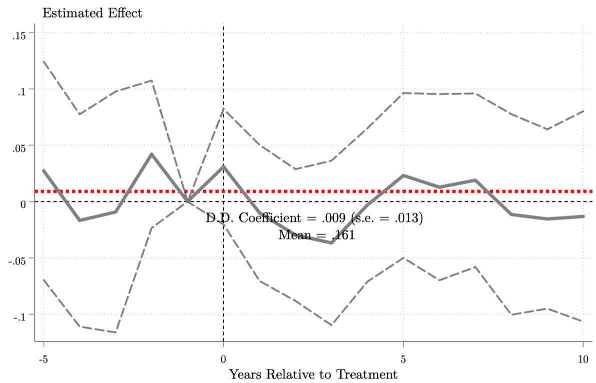


(a) ACS Data

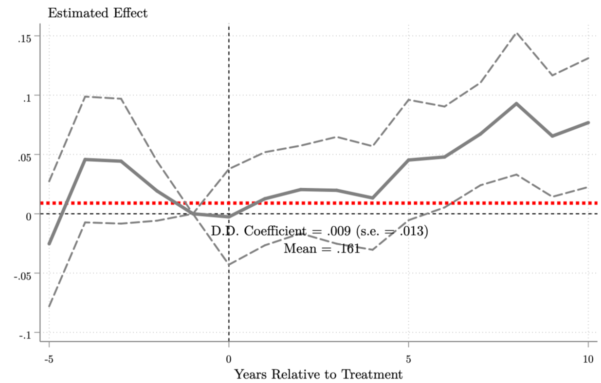
(b) CPS Data

Figure A.23: Effect on Working: State Controls and State Linear Time Trends

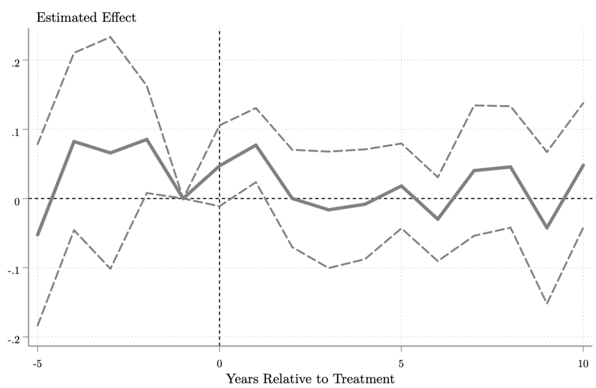
Notes: Panel (a) corresponds to 2000-2018 ACS data and panel (b) corresponds to 1997-2018 CPS data. The graphs plot the estimated coefficients and corresponding confidence intervals from equation (1.1) estimated using OLS on the subsample of Mexican, immigrant, noncitizens ages 19-22 with working as the outcome. This specification includes state linear time trends and controls for time-varying state characteristics such as deportation risk, college-going rate among Foreign-Born Hispanic citizens, percent of population that is Hispanic, unemployment rate, proportion of Hispanic youth with children, per-capita income, and political party of legislature. It also includes individual controls for poverty, English skills, and number of family members in the household.



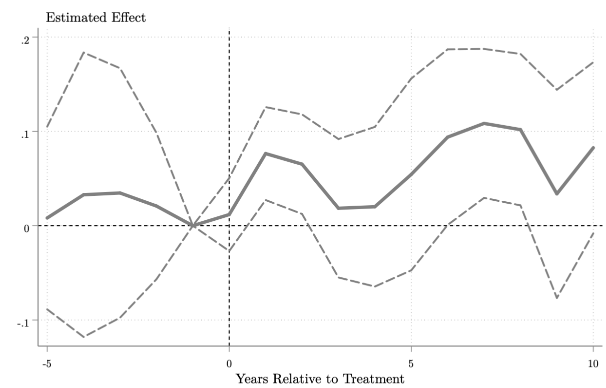
(a) ACS: Below Median Family Size



(b) ACS: Above Median Family Size



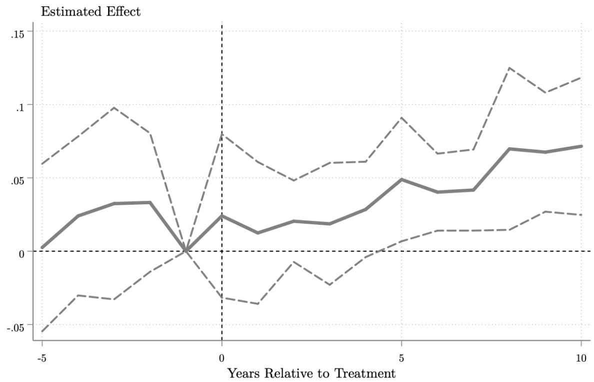
(c) CPS: Below Median Family Size



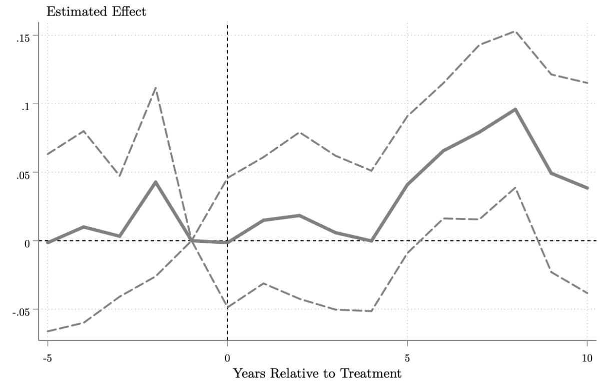
(d) CPS: Above Median Family Size

Figure A.24: Effect on College Attendance by Family Size

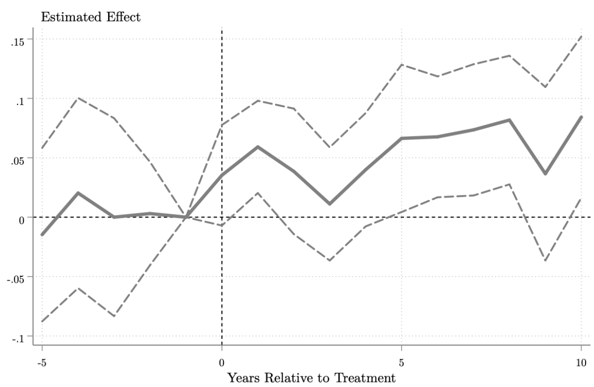
Notes: Panel (a), using ACS data, plots the estimated coefficients and corresponding confidence intervals from equation (1.1) estimated using OLS on the subsample of Mexican, immigrant, noncitizens ages 19-22 who live in below median sized families in their household with college attendance as the outcome. Panel (b), using ACS data, plots the estimated coefficients and corresponding confidence intervals from equation (1.1) estimated using OLS on the subsample of Mexican, immigrant, noncitizens ages 19-22 who live in above median sized families in their household with college attendance as the outcome. Panel (c), using CPS data, plots the estimated coefficients and corresponding confidence intervals from equation (1.1) estimated using OLS on the subsample of Mexican, immigrant, noncitizens ages 19-22 who live in below median sized families in their household with college attendance as the outcome. shows the effect of treatment on English Speaking ability. Panel (d), using CPS data, plots the estimated coefficients and corresponding confidence intervals from equation (1.1) estimated using OLS on the subsample of Mexican, immigrant, noncitizens ages 19-22 who live in above median sized families in their household with college attendance as the outcome. Sampling weights were used to construct both graphs.



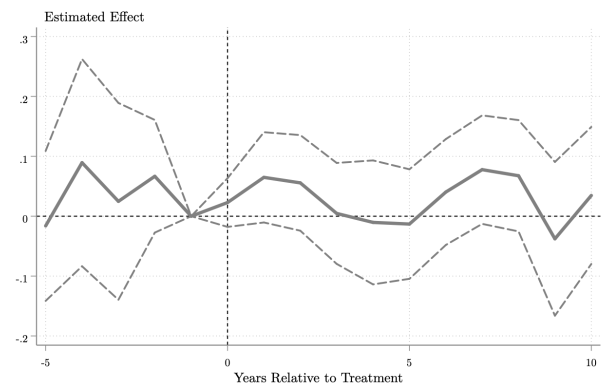
(a) ACS: Male



(b) ACS: Female



(c) CPS: Male



(d) CPS: Female

Figure A.25: Effect on College Attendance by Gender

Notes: Panel (a), using ACS data, plots the estimated coefficients and corresponding confidence intervals from equation (1.1) estimated using OLS on the subsample of Mexican, immigrant, male, noncitizens ages 19-22 with college attendance as the outcome. Panel (b), using CPS data, plots the estimated coefficients and corresponding confidence intervals from equation (1.1) estimated using OLS on the subsample of Mexican, immigrant, female, noncitizens ages 19-22 with college attendance as the outcome. Panel (c), using CPS data, plots the estimated coefficients and corresponding confidence intervals from equation (1.1) estimated using OLS on the subsample of Mexican, immigrant, male, noncitizens ages 19-22 with college attendance as the outcome. Panel (d), using CPS data, plots the estimated coefficients and corresponding confidence intervals from equation (1.1) estimated using OLS on the subsample of Mexican, immigrant, female, noncitizens ages 19-22 with college attendance as the outcome. Sampling weights were used to construct both graphs.

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