The Economic Effects of Providing Legal Status to DREAMers

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Abstract

This study quantifies the economic effects of two major immigration policies aimed at legalizing undocumented individuals that entered the United States as children and completed high school: Deferred Action for Childhood Arrivals (DACA) and the DREAM Act. The former offers only temporary legal status to eligible individuals; the latter provides a track to legal permanent residence. Our analysis is based on a general-equilibrium model that allows for shifts in participation between work, college and non-employment. The model is calibrated to account for productivity differences across workers of different skills and documentation status, and a rich pattern of complementarities across different types of workers. We estimate DACA increased GDP by almost 0.02% (about $3.5 billion), or $7,454 per legalized worker. Passing the DREAM Act would increase GDP by around 0.08% (or $15.2 billion), which amounts to an average of $15,371 for each legalized worker. The larger effects of the DREAM Act stem from the expected larger take-up and the increased incentive to attend college among DREAMers with a high school degree. We also find substantial wage increases for individuals obtaining legal status, particularly those that increase their educational attainment. Because of the small size of the DREAMer population, and their skill distribution, legalization entails negligible effects on the wages of US-born workers.

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1 Introduction

It is estimated that 11 to 12 million undocumented immigrants currently live in the United States. Having entered the country without authorization or overstayed their visas, they cannot legally work and live under the threat of deportation. Yet undocumented immigrants are responsible for about 3% of GDP nationwide and close to double that figure in states like California, Texas or Nevada (Edwards and Ortega (2017)).

Whether and how this population should be legally incorporated into the country is a source of great political debate. Similar debates have also taken place in many European countries over the last two decades (Vogel et al. (2011), Orrenius and Zavodny (2016), Devillanova et al. (2018), Fasani (2018)), typically resulting in amnesties before unauthorized populations grow too large. As a result, the unauthorized population in Europe as a whole has rarely amounted to more than a few million individuals.

In this context, the current situation in the United States stands out. The last major legalization process in the United States occurred nearly three decades ago under the 1986 Immigration Reform and Control Act (IRCA), which granted legal permanent residency to over 3 million undocumented immigrants (Kossoudji and Cobb-Clark (2002), Casarico et al. (2018)). In the decades since IRCA's passage, the political climate has shifted rendering a general legalization process politically infeasible. The discussion has moved toward the less ambitious goal of providing legal status to undocumented youth who were brought to the United States as children, commonly known as DREAMers. This population continue to receive wide-spread public support, with some recent polls indicating that 86% of the American public would like to offer them legal residency.[1].

Yet despite continued public support, Congress has failed to pass legislation offering a path to legal status for DREAMers. In 2010, the DREAM Act, bipartisan legislation offering eligible DREAMers pathways to permanent residence, passed the U.S. House of Representatives but failed to pass the U.S. Senate. In response, in June 2012, President Barack Obama enacted the Deferred Action for Childhood Arrivals (DACA) offering undocumented youth who arrived in the country as children reprieve from deportation and renewable 2-year work permits. On September 5, 2017, President Donald Trump rescinded DACA and urged Congress to explore a legislative solution.[2]

[1]Washington Post - ABC News, September 2017. https://www.washingtonpost.com/page/2010-2019/WashingtonPost/2017/09/25/National-Politics/Polling/release_491.xml

[2]To date, two new versions of the DREAM Act have been introduced and await congressional action. In the U.S. Senate, DREAM Act (S.1615) is a bipartisan bill that is co-sponsored by Senate Republicans Lindsey Graham and Jeff Flake and Senate Democrats Chuck Schumer and Dick Durbin. In the U.S. House, DREAM Act (HR.3440) is also a bipartisan bill that is co-sponsored by Republican Ileana

The goal of this paper is to quantify the economic effects of the two most recent immigrant policy reforms aimed at providing legal status to the DREAMer population – DACA and DREAM Act. We report estimates of the effects on GDP, which is a crucial ingredient in the calculation of the net fiscal balance associated to legalizing DREAMers.[3] We also report estimates on the wages of documented and undocumented workers along the education-age distribution, which is informative as to the welfare effects of these policies. Our theoretical framework builds on the work of Borjas (2003), Manacorda et al. (2012), Ottaviano and Peri (2012) and Edwards and Ortega (2017). We develop a general-equilibrium model where production is carried out by means of a multi-level constant-elasticity of substitution production function, which allows for productivity differences across workers of different skills and documentation status, and a rich pattern of complementarities across them.

A novel feature of our framework is that we allow for shifts in participation between work, college and non-employment. This allows us to consider the effects of legalization policy on the college decisions of undocumented youth. Recent empirical studies have argued that DACA led to a substantial increase in the employment rates of DREAMers, driven by shifts from college enrollment into the workforce (Amuedo-Dorantes and Antman (2017) and Hsin and Ortega (2017)) and by shifts from unemployment into employment (Pope (2016)). Our analysis incorporates these effects and discusses the participation effects associated with the DREAM Act as well, which differ in the short and long runs.

To calibrate our model we rely on data from a special extract of the 2012 American Community Survey provided by the Center for Migration Studies (2014), which contains a sophisticated imputation for documentation status (Warren (2014)), in addition to the usual information on employment, skills and wages. Importantly, our 2012 baseline data summarize the economic outcomes of DREAMers immediately prior to DACA.[4] The data show that, on average, undocumented workers earn 19% less than documented workers with the same education and age. This suggests the existence of a large productivity penalty associated with undocumented status.

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[3]A 2017 memo by the Congressional Budget Office estimates that passing the DREAM Act would increase the federal deficit by $2.6B per year over the next ten years. However, their calculation assumes that legalization would have practically no effect on GDP.

[4]This is important because our data do not allow us to distinguish DACA recipients from non-recipients. As a result, data for the period when DACA was already in operation are likely to underestimate the undocumented wage penalty for DREAMers. DACA was approved in June 2012, but very few permits were granted prior to 2013.

We use the calibrated model to simulate the effects of DACA and the DREAM Act relative to the baseline data. On account of the empirical evidence establishing that illegal status negatively affects the productivity of undocumented workers through its negative effects on health and labor market opportunities (Abrego (2011), Gonzales (2011), Hainmueller et al. (2017), Hall and Greenman (2015)), we assume that gaining legal status increases the productivity of undocumented workers so as to match the level of documented workers with the same age and education level. This assumption is in line with Monras et al. (2017). As a result of a large legalization process in Spain, these authors find that undocumented immigrant workers become close substitutes for similarly skilled natives.

Between its inception and June 2017, almost 800,000 individuals received DACA permits. Based on the actual take-up of the program, our analysis estimates that DACA increased GDP by 0.018% (about $3.5 billion), or $7,454 on average per employed DACA recipient. Our analysis also shows that the wages of DACA recipients increased by around 12%, and that native wages were practically unaffected. The latter is driven by the fact that DACA-recipients are a very small share of the workforce and, in addition, because of the high-school-degree requirement, their skill distribution is very similar to that of natives in the same age group.

Turning now to the analysis of the DREAM Act, our data imply that there were 1.65 million undocumented that arrived in the country as children and had completed high school (by 2012) and therefore were eligible for legal status.[5] It is important to note that the overall number of eligible individuals could be as high as 2.93 million if the DREAMers that do not yet have a high school degree obtain one. Our simulations suggest that the DREAM Act would increase GDP by 0.08% (i.e. $15.2 billion annually), which amounts to $15,371 per legalized worker. The reasons for the larger effects, compared to DACA, are the expected larger take-up rate and the increase in educational attainment among DREAMers with a high school degree that decide to obtain some college education in order to qualify for the DREAM Act. However, the positive effects on GDP will take several years to materialize. The reason is that, initially, the positive productivity effect of legalization on GDP will be offset by a negative participation effect driven by the return to college of a subset of DREAMers in the workforce. After a few years, these individuals rejoin the workforce with their enhanced skills, resulting in a

[5] We have restricted our sample to individuals older than 17 in year 2012. We also note that we do not have data on criminal records. As a result, some of these individuals may not satisfy the eligibility condition requiring a clean criminal record.

substantial increase in GDP. Further, our analysis implies that the wages of most of the DREAMers that obtain legal status will increase by at least 15%, although those that decide to obtain some college education will experience an average 52% increase in wages. At the same time, we find that the DREAM Act will have very minimal effects on the wages of natives workers, ranging between 0.4% reductions and 0.4% increases.

The rest of the paper is organized as follows. Section 2 contains the literature review. Section 3 describes our data and Section 4 presents our theoretical framework. Section 5 describes the calibration of the model. Our findings are presented in Section 6 (regarding DACA) and Section 7 (regarding the DREAM Act). Section 8 summarizes our conclusions.

2 Literature Review

A large body of literature has analyzed the labor market effects of immigration. However, the literature on the effects of legalization or the wage penalty associated with unauthorized status, is much smaller, and is almost exclusively reduced-form, which is an important limitation in terms of simulating the effects of actual policies. In the context of the United States, several studies have documented substantial wage gaps between similarly skilled documented and undocumented workers. For instance, Hall et al. (2010) estimated a 17 percent wage disparity between documented and undocumented male Mexicans using the Survey of Income and Program Participation. This estimate is highly consistent with the conclusions of studies quantifying the wage effects of obtaining legal status. Two studies that focus on the 1986 IRCA amnesty estimate the wage penalty for being unauthorized to be around 15% (Kossoudji and Cobb-Clark (2002) and Lozano and Sorensen (2011)). Lynch and Oakford (2013) estimated that gaining legal status *and* citizenship would allow unauthorized immigrants to earn 25% more within five years. Orrenius and Zavodny (2015) provide additional evidence of the existence of a wage penalty associated with undocumented status. This study shows that the introduction of E-Verify, a program that allows employers to verify the legal status of employees, led to a reduction on the wages of undocumented workers. Only one study (Lofstrom et al. (2013)) found no evidence of improved employment outcomes following legalization, although this was only the case among the least-skilled immigrants.

In the recent years, many researchers have turned to the analysis of legalization using European data (Orrenius and Zavodny (2016)). Devillanova et al. (2018) focus on the analysis of the effects of the prospect of legal status on employment rates using data for

Italy. This issue is important because often times a requirement to become eligible for legalization is having been employed in the country for a period of time. Also analyzing the Italian experience, Fasani (2018) analyzes the effects of legalization on crime. Monras et al. (2017) focus on Spain's 2004 amnesty, which legalized 0.6 million individuals. Their main finding is that legalization led to a net increase in tax revenue of about 4,000 euros per legalized individual. All these studies consider the whole undocumented population, without considering the educational choices of younger unauthorized individuals.

Some recent studies have developed structural frameworks that are useful to analyze the effects of legalization (as well as the effects of deportation). Edwards and Ortega (2017) emphasize the importance of skill and productivity differences across documented and undocumented workers, and calibrate their model using detailed micro-data (Center for Migration Studies (2014)). Chassambouli and Peri (2015) analyze the effects of undocumented migration in frictional labor markets, focusing on the effects on vacancies and unemployment. Machado (2017) builds a related framework that emphasizes intergenerational aspects and allows for estimation of the fiscal effects of legalization.

While the existence of documented-undocumented wage gaps has been clearly established, what is less understood is the nature of these gaps. Several authors have provided evidence of detrimental effects of illegality on the labor market opportunities and health of undocumented workers, which point to the existence of an *undocumented productivity penalty*. For example, illegal status has been shown to increase the risk of depression and anxiety among undocumented youth (Abrego (2011), Gonzales (2011), Hainmueller et al. (2017)). Other studies have shown how lack of legal work options confine educated undocumented youth into jobs that are not commensurate with their skills (Gonzales (2011), Gleeson and Gonzales (2012), Cho (2017)). In addition, Hall and Greenman (2015) find that unauthorized workers are more likely to work in jobs that are physically strenuous and hazardous and receive no compensating differential for working in dangerous work environments.

Our study is also related to a series of recent empirical studies analyzing the effects of DACA on the labor market outcomes and college participation of DREAMers. Pope (2016) and Amuedo-Dorantes and Antman (2017) use data from the ACS and CPS, respectively. Both studies find positive effects of DACA on employment, but disagree on the effects on schooling. Amuedo-Dorantes and Antman (2017) find that DACA reduces college enrollment among probable DACA eligible students, whereas Pope (2016) fails to find evidence of an effect on schooling decisions. Hsin and Ortega (2017) use administrative data on students attending a large public university to estimate the effect of

DACA on undocumented students' educational outcomes. Their data are unique because they accurately identify legal status. They find that DACA led to a large increase in dropout rates among undocumented college students enrolled at 4-year colleges (though not among those attending community college), providing additional confirmation for the findings in Amuedo-Dorantes and Antman (2017).

In a recent study, Kuka et al. (2018) study the effects of DACA on teenagers' human capital investments. They find large increases in high-school graduation rates, along with a reduction in teenage pregnancy and increased college attendance (for women).

3 Data

3.1 Sources

Our data is based on the special extract of the American Community Survey (ACS) for the year 2012 provided by the Center for Migration Studies (2014), which contains a sophisticated individual-level measure of *imputed undocumented status* (Warren (2014)).[6] The methodology is based on the so-called *residual method*. The starting point is the non-citizen population that arrived in the United States after 1981, because those arrived earlier were able to obtain legal status under the 1986 IRCA law. The first, and main, step is to apply *logical edits*. This entails using the micro-data to identify individuals who are likely to be documented. Specifically, the key variables employed are occupation, citizenship status of immediate relatives, country of birth, receipt of public benefits, and age at entry.[7] Clearly, while occupation is only useful for employed respondents, the other logical edits apply equally to all individuals regardless of employment status. As a result, the quality of legal status in the CMS imputation for those who are not employed is probably roughly on par with those of the employed. To further narrow the set of likely undocumented individuals, individual observations are then re-weighted to match aggregate estimates on the presence of foreign-born for 145 origin countries that yield independent totals for each U.S. state and for the total undocumented resident

[6] First developed by Passel and Clark (1998), the method has continued to evolve in Baker and Rytina (2013), Warren and Warren (2013), and Passel and Cohn (2015).

[7] Workers with certain occupations that require licensing or background checks, such as legal professions, police and fire, some medical professions, are assumed to be authorized, as well as individuals in government or in the military. Anecdotal evidence shows that there are some unauthorized workers in the military. Nevertheless the size of this group is very small.

population.[8]

Existing estimates of the characteristics of the imputed unauthorized population obtained from the Census, the ACS and the CPS tend to be largely consistent with each other (Warren (2014), Borjas (2016), Pastor and Scoggins (2016)). Nevertheless, the broader validity of the imputation is still being analyzed. Assessments remain constrained by lack of large representative surveys that ask legal status.[9]

3.2 Sample definitions and summary statistics

We restrict to the population age 17-70 in the 2012 ACS. We distinguish between documented individuals, defined as those that were born in the United States or born abroad but deemed as likely authorized on the basis of the imputation, and likely unauthorized foreign-born individuals. Among the likely undocumented population we will concentrate on DREAMers, defined as individuals that arrived in the country before the age of 18 and have obtained a high school diploma (or similar).

We classify individuals as employed, in college, or doing neither of those activities. More specifically, we consider individuals as enrolled in college if they have a high school degree and report that are currently enrolled in school. An individual is considered employed if he stated so in the ACS survey. Last, we define individuals as *non-employed* if they are not employed and not enrolled in school. Table 1 provides a summary of the data. Column 1 shows that our data accounts for 232.4 million individuals (age 17-70). Among these, 61% were employed, 11% in college, and 28% doing neither of these two activities. Column 2 reports on the documented population, which amounts to 222 million individuals. Column 3 reports on 10.4 million (likely) undocumented individuals. Their employment rate is 68%, 7 percentage points higher than for the documented population, and their college enrollment rate is 6%, 5 percentage points lower than for the documented population. Column 4 restricts the sample to (likely) unauthorized individuals that arrived in the United States at age 17 or younger, which amounts to 2.93 million individuals. About 1.76 million of these are currently employed and the employment and college attendance rates are essentially the same as for the documented population. In column 5 we further restrict to the 1.65 million undocu-

[8] The method also makes adjustments for under-enumeration in the survey on the basis of time of arrival.

[9] The Survey of Income and Program Participation (SIPP), also a Census product, directly asks respondents about legal status but is roughly one sixth the size of the ACS. See Van Hook et al. (2015) for a comparison of results based on the SIPP and the ACS.

mented individuals with at least a high school diploma (or similar), which corresponds to our main population of interest. The data show an employment rate of 60% (or about 0.99 million employed individuals) and a college attendance rate of 22%. The last column also imposes the condition of being 32 years old or younger in year 2012, which was required in order to qualify for DACA. In our data there are 1.42 million potentially DACA-eligible individuals. The table also reports the mean hourly wages of full-time workers for each column. On average documented workers earn close to $21 while undocumented workers earn roughly 5 dollars less. Naturally, the bulk of the gap is explained by the lower average education and experience of undocumented workers, but not entirely.

It is also interesting to examine the relative size of these groups. In year 2012, undocumented individuals made up for 4.5% of the population, but almost 5% of employment. Undocumented individuals that arrived in the United States prior to age 18 accounted for about 1.25% of both the population and employment. When we further restrict to undocumented individuals that arrived as children and have a high school diploma (or similar), we find that this group accounts for 0.7% of the population and of employment. Because DREAMers are such a small fraction of the population, the effects of gaining legal status on overall GDP will necessarily be relatively small.

Importantly, our analysis will distinguish between workers by education and age, besides legal status. Specifically, we define 5 age groups: (1) 17-26, (2) 27-36, (3) 37-46, (4) 47-56, and (5) 57-70. We also define 4 groups on the basis of completed education (in year 2012): (1) high school dropouts, (2) individuals with a high school diploma or GED, (3) individuals with some college (i.e. at least one year of college or an associate's degree), and (4) individuals with a bachelor's degree (and possibly higher degrees as well). On the basis of our definition, there are no high-school dropout DREAMers.

We collapse the individual-level data (using the appropriate sample weights) by education, age, and documentation status. The results are summarized in Table 2. The table reports the shares of the column totals. Columns 1-3 refer to the documented population, which can be broken down into 135 million employed individuals, 24 million attending college, and 63 million doing neither of those two activities. Note that by definition, individuals currently enrolled in college cannot be high school dropouts. Turning to DREAMers (columns 4-6), we find that 0.99, 0.37 and 0.29 million individuals were, respectively, employed, enrolled in college or doing neither of those two. We also note that under our definition there are no DREAMers in age groups 4 (age 47-56) and 5 (age 57-70).

4 Theoretical framework

Production takes place by means of a constant-returns Cobb-Douglas production function combining capital and labor. We assume that employers have access to a capital rental market at a fixed rental rate $\overline{R}$. As a result, the capital stock is proportional to labor, which results in a linear relationship between output and labor: $Y = BL$, where we will refer to B as total labor productivity. Below we describe the labor aggregate in detail. To close the model, we simply impose market clearing conditions on the output market and on all the skill-specific labor markets.

4.1 The labor aggregate

Let us now describe in detail the labor aggregate L. We allow workers to differ in education ($e = 1, ..., E$), age ($a = 1, ..., A$), and documentation status (Doc, $Undoc$). In total the number of labor types is given by $2 \times E \times A$. In our preferred specification we will focus on four education groups ($E = 4$) and five age groups ($A = 5$).

We aggregate all these types of workers by means of a multi-nested constant-elasticity of substitution (CES) aggregator, as in Borjas (2003), Manacorda et al. (2012) and Ottaviano and Peri (2012). To construct the labor aggregate we need data on the number of workers by education, age, and documentation status. We denote the vector of data by $\mathbf{V}$. In addition we need values for an array of worker productivity terms $\Theta = \{\theta\}$, one for each worker type, and elasticities of substitution across worker types $\Sigma = \{\sigma\}$. It is helpful to employ the following compact notation to make explicit the inputs needed to compute the labor aggregates $L(V; \Theta, \Sigma)$.

Specifically, the labor aggregate is given by three levels of CES aggregation, with potentially different elasticities of substitution. To maximize comparability with previous studies, we choose the following nesting structure:

$$L_{e,a} = \theta_{e,a}^{Doc} L_{e,a}^{Doc} + L_{e,a}^{Undoc}, \text{ for } e = 1, 2, ..., E \text{ and } a = 1, s, ..., A, \tag{1}$$

$$L_e = C(L_{e,a=1}, ..., L_{e,a=A} | \theta_{e,a}, \sigma_a), \text{ for } e = 1, 2, ..., E, \tag{2}$$

$$L = C(L_{e=1}, ..., L_{e=E} | \theta_e, \sigma_e) \tag{3}$$

In a general form, the CES aggregator across M inputs is defined by

$$C(x_1, x_2, ..., x_M | \theta, \sigma) = \left(\theta_1 x_1^{\sigma/(\sigma-1)} + \theta_2 x_2^{\sigma/(\sigma-1)} + ... + \theta_M x_M^{\sigma/(\sigma-1)} \right)^{\frac{\sigma-1}{\sigma}}. \tag{4}$$

Implicitly, the equation for $L_{e,a}$ assumes that within an education-age group, documented and undocumented workers are perfect substitutes (as in Borjas (2003)), despite evidence to the contrary (Manacorda et al. (2012), Ottaviano and Peri (2012)). This choice is made to keep the framework as simple as possible and has virtually no effect on the estimated GDP effects (as shown in Edwards and Ortega (2017)). However, it will tend to exaggerate the effects of changes in the size and skill composition of the immigrant population on natives. Thus our analysis of wage effects should be interpreted as providing upper bounds for the effects on native wages.[10]

The documented-undocumented relative productivity parameters $\{\theta_{e,a}^{Doc}\}$ will play a crucial role in our analysis. In essence, when we simulate the effects of legalization we endow undocumented workers with the productivity of documented workers with the same age and level of education. Thus if these relative productivity parameters are larger than one, legalization will entail an increase in the labor aggregate $L_{e,a}$, as well as in the overall amount of labor L. The increase in labor will then trigger an investment response in the same direction in order to bring the capital-labor ratio and the marginal product of capital back to their initial level.

4.2 Exploitation of undocumented workers

There is plenty of evidence suggesting that the performance of undocumented workers in the labor market is diminished by their lack of legal status. Clear evidence of this is the over-qualification phenomenon (Gonzales (2011), Gleeson and Gonzales (2012), Cho (2017)), which is probably more widespread among undocumented workers than for immigrants in general. The typical example of over-qualification is when a highly educated immigrant, e.g. with a college degree, ends up employed in a low-skill occupation. These occupations are characterized by low productivity and, hence, pay low wages. Individuals in this situation will display very low wages given their education levels, which will translate into large documented-undocumented productivity gaps. More specific to the DREAMer population, there is also evidence that the threat of deportation creates anxiety and depression, which are likely to negatively affect the productivity of these workers (Abrego (2011), Gonzales (2011), Hainmueller et al. (2017)). Last, undocumented workers are probably subject to a substantial degree of mismatch in their

[10] On the contrary, the effects on the wages of legal immigrants will tend to be underestimated. We also note that we allow for different productivity (and therefore wage) levels between documented and documented workers within education-age cells in order to accommodate this important feature of the data.

workplaces, reflecting the fact that they cannot obtain a driver's license and are barred from many jobs because of E-Verify or licensing requirements. As a result, they often end up in jobs that are a poor match for their skills, which results in a very low return to their levels of experience and education.

It is also possible that documented-undocumented wage gaps reflect other factors besides productivity gaps. Some studies (Hotchkiss and Quispe-Agnoli (2009), Brown et al. (2013) and Hirsch and Jahn (2015)) suggest that undocumented workers are often not paid their full marginal product. Clearly, their bargaining power is diminished by their lack of legal status, and employers can appropriate a larger part of the surplus generated by the employer-employee match. If exploitation of this type is present and we ignore it, observed wages will *underestimate* the productivity of undocumented workers relative to legal immigrants and natives with the same education and experience. This will result in upwardly biased productivity gaps between documented and undocumented immigrant workers, and will lead to upwardly biased estimates of the gains from legalization.

In order to allow documented-undocumented relative wages to reflect both productivity differences and exploitation, we assume that unauthorized workers are 'taxed' at a rate $\tau_{e,a}$ by employers.[11] The net income of undocumented workers in education age group (e, a) is then given by

$$w_{e,a}^{Undoc} = (1 - \tau_{e,a}) MPL_{e,a}^{Undoc}, \tag{5}$$

where MPL stands for the marginal product of labor of that education-age group.

Because of perfect substitution between documented and undocumented immigrants, their relative wage (within an education-experience cell) will be given by

$$\frac{w_{e,a}^{Doc}}{w_{e,a}^{Undoc}} = \frac{\theta_{e,a}^{Doc}}{1 - \tau_{e,a}}. \tag{6}$$

As we shall see below, the data show substantial wage gaps between documented and undocumented workers in the same education-age category. Because the degree of exploitation is not known, we will need to make an identifying assumption in order to back out the relative productivity terms from the data on relative wages. In our main specification we will choose the more standard approach of ignoring exploitation and assume that relative productivity equals relative wages, but we will also analyze the alternative scenario where there are no productivity differences between documented

[11] For consistency with the rest of the model, we assume that the proceeds of this tax are distributed in a lump-sum manner to all documented workers.

and undocumented workers with the same observable skills, $\{\theta_{e,a}^{Doc} = 1\}$, and all wage gaps are explained on the basis of exploitation taxes $\{\tau_{e,a}\}$.[12]

5 Calibration

We need to assign values to the parameters of the model: $\{B, \Theta, \Sigma, \tau\}$. In our calibration we will consider $E = 4$ levels of education and $A = 5$ age groups. We first consider the following values for the elasticities of substitution. Because workers are increasingly more similar in terms of observable skills as we move up the CES layers, it makes sense to consider elasticities of substitution that (weakly) increase as we move from level 1 to level 2: $\sigma_e \leq \sigma_a$. We adopt fairly standard values for these elasticities: $(\sigma_e, \sigma_a) = (3, 6)$. These values are fairly uncontroversial (Card and Lemieux (2001), Goldin and Katz (2008)).

Next, we turn to the calibration of the productivities by type of labor. For now we take the stance that documented-undocumented wage gaps (within education-age groups) are the reflection of productivity differences. As discussed earlier, it is well established empirically that lack of legal status negatively affects labor market opportunities and health, with detrimental effects on worker productivity. We follow a sequential process to calibrate productivity terms Θ and to compute the CES aggregates at each level. The process relies crucially on data on relative wages and employment. We use average hourly wages for full-time workers as our measure of income, but measure employment including workers regardless of their usual hours worked.

We begin with level 3, which aggregates documented and undocumented workers in the same age and completed education groups. Under the assumption of no exploitation ($\tau_{e,a} = 0$ for all e, a), Equation (6) becomes

$$\frac{w_{e,a}^{Doc}}{w_{e,a}^{Undoc}} = \frac{\theta_{e,a}^{Doc}}{1}. \tag{7}$$

Thus, documented-undocumented relative wages identify the relative productivity terms. It is then straightforward to compute, for each cell (e, a), the CES labor aggregate $L_{e,a}$.

Next, we turn to level 2. For each education level e, given the value of σ_a and data

[12] Ortega and Hsin (2018) analyze the sources of the wage gaps between documented and undocumented workers in the United States. Employing a novel identification strategy, they find that the bulk of the wage gap is explained by the reduction in labor productivity associated to lack of legal status, with a small role for employer exploitation. They conclude that the diminished productivity is largely due to occupational barriers that are specific to undocumented workers.

on wages and the values for $L_{e,a}$ computed in the previous step, we can easily obtain $\theta_{e,a}$ from

$$\frac{w_{e,a}}{w_{e,1}} = \left(\frac{\theta_{e,a}}{1}\right)\left(\frac{L_{e,a}}{L_{e,1}}\right)^{-1/\sigma_a}, \text{ for } a = 2, ..., A, \tag{8}$$

where we have normalized $\theta_{e,1} = 1$. Next, we compute aggregate L_e for each e using

$$L_e = C(L_{e,1}, ..., L_{e,A}|\boldsymbol{\theta_{e,a}}, \sigma_a), \text{ for } a = 2, ..., A.^{13} \tag{9}$$

Finally, level 1 relates the relative wages between the two education groups. For each cell e, we obtain $\boldsymbol{\theta_e} = (1, \theta_2, \theta_3, \theta_4)$ from

$$\frac{w_e}{w_1} = \left(\frac{\theta_e}{1}\right)\left(\frac{L_e}{L_1}\right)^{-1/\sigma_e}, \tag{10}$$

and compute L using

$$L = C(L_1, ..., L_4|\boldsymbol{\theta_e}, \sigma_e). \tag{11}$$

At this point it is helpful to examine the values that we obtain for these parameters, which are collected in Table 3. Column 1 reports the values for the relative productivity terms (under the assumption of no exploitation). The weighted average of the column is 1.22, indicating that documented workers earn about 22% more than undocumented workers with the same observable skills. Under our assumption of no exploitation, this translates into a sizable productivity gap. We also note that there is a great deal of heterogeneity in the size of the undocumented productivity penalty across skill groups. Consider, for instance, age group 2 (27-36 year-olds). The documented-undocumented relative productivity terms for this age group are 1.18, 1.26, 1.34 and 1, for education levels 1 (high school dropouts), 2 (high school graduates), 3 (an associate's degree or some college), and 4 (college graduates or higher), respectively. These figures show that the highest gaps are for workers with a high school degree and some college education, and the gap is non-existing for college graduates.

Last, we calibrate the term for total aggregate productivity to match GDP in year 2012 by setting $B^{LR} = GDP/L$.

[13] $\boldsymbol{\theta_{e,a}}$ denotes the vector of relative productivity terms across experience groups with education e.

6 The effects of temporary legal status: DACA

Deferred Action for Childhood Arrivals (DACA) was launched by President Obama in June 2012. Our baseline data is for year 2012, which can be considered the latest pre-DACA period.[14] Thus, we can interpret our baseline values for the wages of DREAMers as reflecting their wages while working lacking legal status. On the basis of the key eligibility requirements for DACA, our population of interest are likely undocumented individuals that arrived in the United States prior to their 16th birthday, were younger than 32 years old in 2012, and had a high school diploma (or GED) in that year.[15] According to our data, this population contains 1.4 million individuals, which is fairly close to the 1.3 million estimated by the Migration Policy Institute (2016).[16]

6.1 The DACA counterfactual

As of June 2017, slightly less than 800,000 individuals have been granted DACA permits. This amounts to a take-up rate slightly above 0.5. In order to take this into account, we denote by ϕ the DACA take-up rate.[17] Lacking evidence against it, for now we assume that the take-up rate is the same across education and age groups within the DREAMer population.

Based on the existing empirical evidence, it appears that DACA had two effects. First, DACA recipients were given work permits presumably allowing them to access the labor market under the same conditions as documented workers. In the model, we will assume that DACA recipients become indistinguishable from documented workers with the same age and education in terms of productivity. Because DREAMers graduated from a U.S. high school, this assumption seems highly plausible. Quantitatively, the key terms in determining the resulting productivity boost are the relative documented-undocumented productivity terms, $\theta_{e,a}^{Doc}$. Second, there is evidence that DACA triggered a participation effect that led to an increase in employment. According

[14]Even though DACA was rolled out in 2012, the number of work permits issued was very low until 2013. Only 1,684 applications were approved by the end of 2012 according to the USCIS.

[15]There were a number of additional eligibility requirements that cannot be measured using our data, such as having a clean criminal record.

[16]See https://www.migrationpolicy.org/programs/data-hub/deferred-action-childhood-arrivals-daca-profiles.

[17]Several reasons explain the low participation in the DACA program. First, the application is a lengthy process and undocumented youth may be concerned about disclosing personal information to immigration authorities, including home address, financial information and bio-metric data. Moreover, DACA grants temporary protection from deportation for eligible youth but offers no protection for parents or siblings who are not eligible. Thus, applying to the program means not only incurring personal risk but also exposing family members.

to Pope (2016) the additional workers transitioned from unemployment and according to Amuedo-Dorantes and Antman (2017) and Hsin and Ortega (2017), they dropped out of college in order to work. This participation effect will magnify the effect of DACA on GDP beyond the productivity boost, at least in the short run.[18]

To introduce the participation effect into our model, let δ_c be the fraction of DACA recipients that were in college and decided to drop out of school in order to work.[19] Thus the number of college students that receive DACA and dropped out before graduation to join the workforce is given by $\delta_c(\Sigma_e \Sigma_a \phi C_{e,a}^{Dream})$, where $C_{e,a}^{Dream} \leq C_{e,a}^{Undoc}$ is the number of undocumented individuals of age a and education e that are enrolled in college and arrived in the country as children.[20] Likewise, we let δ_N be the fraction of DACA recipients that were initially non-employed and started working when they received a DACA permit. This results in an increase in employment equal to $\delta_N(\Sigma_a \Sigma_e \phi N_{e,a}^{Dream})$.

We denote the baseline population in the 2012 data by:

$$\mathbf{V} = \{L_{e,a}^{Doc}, C_{e,a}^{Doc}, N_{e,a}^{Doc}, L_{e,a}^{Undoc}, C_{e,a}^{Undoc}, N_{e,a}^{Undoc}\}.$$

The counterfactual undocumented population under DACA is therefore: for each (e, a),

$$\begin{aligned}
\widehat{L}_{e,a}^{Undoc} &= L_{e,a}^{Undoc} - \phi L_{e,a}^{Dream} \\
\widehat{C}_{e,a}^{Undoc} &= C_{e,a}^{Undoc} - \phi C_{e,a}^{Dream} \\
\widehat{N}_{e,a}^{Undoc} &= N_{e,a}^{Undoc} - \phi N_{e,a}^{Dream}.
\end{aligned}$$

Turning now to the documented population, for each (e, a),

$$\begin{aligned}
\widehat{L}_{e,a}^{Doc} &= L_{e,a}^{Doc} + \phi \left(L_{e,a}^{Dream} + \delta_c C_{e,a}^{Dream} + \delta_n N_{e,a}^{Dream} \right) \\
\widehat{C}_{e,a}^{Doc} &= C_{e,a}^{Doc} + \phi(1 - \delta_c) C_{e,a}^{Dream} \\
\widehat{N}_{e,a}^{Doc} &= N_{e,a}^{Doc} + \phi(1 - \delta_n) N_{e,a}^{Dream}.
\end{aligned}$$

Note that the overall population is the same in the counterfactual and baseline scenarios. However, there may be an increase in the overall amount of *labor* because of the differential productivity between documented and undocumented workers. A bit

[18]The long run effects will depend on whether these individuals eventually return to college and graduate. As of now we have no empirical evidence regarding whether or not this is the case.

[19]Note that δ_c is *not* the fraction of DREAMers in college, but only the fraction of that group that decided to drop out of college upon receiving temporary legalization.

[20]$C_{e,a}^{Undoc}$ refers to all undocumented individuals enrolled in college (with the corresponding education and age), and $C_{e,a}^{Dream}$ refers only to those that arrived as children.

of algebra delivers the key expression summarizing the effects of DACA on the labor aggregates: for each (e,a), the increase in labor is given by

$$\widehat{L}_{e,a} - L_{e,a} = \phi \left[\left(\theta^{Doc}_{e,a} - 1 \right) L^{Dream}_{e,a} + \theta^{Doc}_{e,a} \left(\delta_c C^{Dream}_{e,a} + \delta_N N^{Dream}_{e,a} \right) \right]. \tag{12}$$

The first term is the productivity boost associated with legalization. The second term is the participation boost because of DREAMers that were initially in college or non-employed and decided to seek employment because of DACA. Aggregation over age and education groups will deliver the overall increase in L. Clearly, the documented-undocumented relative productivity terms,$\{\theta^{Doc}_{e,a}\}$, will play a key role in determining the economic effects of DACA. To the extent that these coefficients are larger than one, temporary legalization through DACA will lead to a net increase in the overall amount of labor. Moreover, because of the linear relationship between labor and output, the percent change in labor will translate into an equal percent change in output. Thus

$$G = \left(\frac{\widetilde{Y}}{Y_0} \right) = \left(\frac{\widetilde{L}_1}{L_0} \right), \tag{13}$$

and we shall calculate dollar amounts for the effect of DACA on GDP using

$$\widetilde{Y} - Y_0 = \left(\frac{\widetilde{Y}}{Y_0} - 1 \right) Y_0 = (G-1)\, Y_0. \tag{14}$$

6.2 Parameters regarding the effects of DACA

Parameter ϕ stands for the DACA take-up rate. According to USCIS, between its inception in 2012 and 2017 (September 30), 798,980 individuals received protection through DACA. We will set ϕ equal to the ratio between the actual number of DACA applications approved (not counting renewals) and the number of DACA eligible individuals according to our dataset (1.42 million as shown in the last column of Table 1). This results in a value of $\phi = 0.56$.

Parameter δ^C is the probability that a DACA recipient who was in college decides to drop out and join the labor market. Hsin and Ortega (2017) estimate that the college dropout rates for DREAMers in college increased by 4 percentage points when DACA was implemented (reaching 7 percentage points in senior colleges). Their data does not identify DACA recipients and therefore they interpret their estimate as an intent-to-treat effect. Therefore their estimates corresponds more closely to $\phi\delta^C = 0.04$.

Given the value for ϕ, we therefore pick $\delta^C = 0.07$. Using CPS data, Amuedo-Dorantes and Antman (2017) also found evidence that DACA reduced college attendance among DACA-eligible college students. Their estimates are somewhat larger than those of Hsin and Ortega (2017), but their identification of unauthorized individuals in the data is less accurate, so we base our calibration on the more conservative estimates.

Parameter δ_N is the probability that a DACA recipient who was non-employed, defined as not working and not enrolled in college, successfully seeks employment. According to Pope (2016), DACA increased the probability of employment for DACA-eligible individuals by 4 to 5 percentage points. His estimates suggest that the increase in employment was fueled by an increase in labor force participation and a decrease in unemployment. As before, a conservative interpretation of his estimates implies that $\phi\delta^N = 0.04$ and therefore the probability that an actual DACA recipient who was previously non-employed obtains employment is around $\delta^N = 0.07$. However, it is important to keep in mind that we need to avoid duplicating the increase in employment triggered by DACA (by maintaining $\delta^N + \delta^C = 0.07$). The studies above largely agree on the increase in employment generated by DACA, but disagree on whether the newly employed individuals originated from college or from non-employment. Thus we will consider the two scenarios separately. The top panel of Table 4 summarizes the DACA-specific parameters.

6.3 Results

As explained above, our calibrated model matches several relevant moments about the U.S. economy in year 2012. Specifically, we match overall GDP and the structure of wages and employment in terms of education, age and documentation status. Now we turn to the results of our simulation. In terms of outcomes, we first quantify the effects of DACA on GDP and later turn to the effects on the wage structure, emphasizing the effects on the wages of the individuals gaining temporary legalization through the DACA program.

6.3.1 Effects of DACA on GDP

It is helpful to consider first the productivity effect, which is the first part of the expression in Equation (12). At the education-age level, this term only depends on the take-up rate in the program (ϕ) and the documented-undocumented relative productivity term ($\theta_{e,a}^{Doc}$). To isolate this effect we shut down the participation channels ($\delta_c = \delta_N = 0$) when simulating the scenario where DACA permits are distributed in the numbers observed in the data. The results are presented in the first column of Table 5. In this first scenario, the increase in GDP due to DACA amounts to 0.0144%, which amounts to a $2.8 billion annually, or $6,217 per DACA recipient in the workforce.[21] While this figure is small relative to the U.S. GDP, it is important to keep in mind that DACA recipients are only about 0.3% of the U.S. population.

Scenario 2 is our preferred scenario. In this case we allow for a participation effect driven by DREAMers that were initially enrolled in college but decided to drop out in order to work when they received DACA, where the intensity of this effect is based on the estimates by Amuedo-Dorantes and Antman (2017) and Hsin and Ortega (2017). In this case the effect is about 25% higher than in scenario 1, amounting to a 0.0178% increase in GDP corresponding to $3.5 billion in the aggregate and $7,454 per employed DACA recipient. In scenario 3 we consider the alternative participation effect based on the estimates by Pope (2016), where the inflow of DREAMers into employment originates in individuals that were previously non-employed. The results imply a slightly smaller GDP gain than in scenario 2, with a GDP increase of 0.0170%, amounting to $7,181 per employed DACA recipient. It is also worth noting that this increase in GDP is solely due to the effects of legalization. A full assessment of the economic contribution of undocumented workers to the economy needs to take into account the value added of these workers prior to receiving DACA (as in Edwards and Ortega (2017)). We will return to this point in the next section.

Scenario 4 estimates the potential gains from DACA, in the case that all 1.42 million eligible individuals received protection under the program. In this case the GDP increase could have reached almost 0.03% of GDP. Last, scenario 5 considers an alternative calibration where we assume that the wage gaps between similarly skilled documented and undocumented workers are exclusively due to exploitation. In this case, the calibration entails $\theta_{e,a}^{Doc} = 1$ and we are effectively turning off the productivity effect and are left exclusively with the participation effect. In this case (scenario 5), DACA would have led to a meager 0.0032% increase in GDP. Clearly, the assumption of full exploitation as an explanation of the relative wage gaps between documented and undocumented workers is very extreme, given the extensive empirical evidence in support of the detrimental productivity effects of undocumented status.[22]

[21] Keep in mind that some DACA recipients are in college or non-employed.

[22] If we had accurate estimates of the degree of exploitation we would be able to separately calibrate the exploitation tax and the relative productivity terms. However, the existing empirical literature does not offer an estimate of the extent of exploitation for undocumented workers.

6.3.2 Wage effects of DACA

We now turn to the wage effects of DACA. Before discussing the details, it is important to keep in mind that DACA beneficiaries are a very small share of the U.S. population and, as a result, their impact on the wages of natives is bound to be very small. Naturally, the effect on the wages of the DREAMers obtaining legal status will be much larger.

The wage effects of our simulation are reported in Table 6. We begin with column 1, which reports the percent change in wages relative to baseline for workers that did not change documentation status, that is, for documented workers or undocumented workers that did not receive DACA permits. Because we assumed that documented and undocumented workers with the same observable skills are perfect substitutes, these two groups experience the same percent change in their wages. Column 1 shows that the wage effects of DACA are negligible. To a large extent this is due to the change in the relative skill supplies of DACA is very small given the small size of the group of DACA recipients relative to overall employment. The largest effects entail a 0.04% reduction in the wages of high school graduates (age group 2) and a 0.02 percent reduction in the wages of workers with some college (age groups 1 and 2). Column 3 aggregates these figures by education group, weighting each age-education group by their age shares by education (from column 2). The resulting figures show 0.01% drops in the wages of high-school graduates and individuals with some college, and practically zero effects on the wages of workers at the top and bottom of the education distribution.

Column 4 reports the percent changes in the wages of the DACA recipients, which on the basis of the eligibility criteria consisted only of DREAMers with at least a high school diploma in age groups 1 and 2. These individuals experienced a substantial productivity increase. The figures in the table show sizable increases for all age-education groups containing legalized individuals, reaching up to 31%. However, there is a great deal of heterogeneity in the size of the wage growth across education-age groups of legalized individuals. The largest increases pertain to individuals in age group 2 (27-36 year olds) with a high school degree or some college. Column 6 provides the corresponding age-weighted averages by education level. The average DACA recipient with a high school degree experienced a 12.43% increase in wages. Likewise, individuals with some college experienced average wage increases of 11.73%. In contrast, we do not find evidence of significant wage growth for the average DACA recipient with a college degree. The reason is that the documented-undocumented relative productivity for this group turned out to be essentially 1 in our calibration (see Table 3). Thus legalization did not improve their labor market outcomes.

7 The effects of permanent legalization

7.1 The DREAM Act counterfactual

According to the 2017 Senate version of the DREAM Act, obtaining permanent residence is a two-stage process.[23] The first stage provides eligible individuals with *conditional status*, that is, reprieve from deportation and a work permit. The key requirements for conditional status that can be measured using our data are: (i) having arrived in the country at age 17 or younger and (ii) having graduated from high school or obtained a GED.[24] The second stage of the process imposes additional requirements in order to obtain legal permanent residence. Eligible individuals must satisfy one of the following criteria by the end of the conditional status period (besides maintaining a clean criminal record): (i) obtaining an associate's degree or at least 2 years of college education toward a bachelor's degree; (ii) 2 years of military service; (iii) or 3 years of continuous employment.

On the basis of the 2014 ACS, the Migration Policy Institute estimates that 1.8 million individuals are eligible for conditional status in year 2017, out of an overall 3.3 million individuals that arrived in the country illegally as children. In comparison, our estimates based on the 2012 ACS for these figures are 1.4 million – undocumented that arrived by the age of 17 and currently hold a high school diploma – and 2.9 million, respectively (Table 1). Our main estimates of the economic effects of the DREAM Act will be based on the 1.4 million individuals already eligible for conditional status.

Individuals that obtain *conditional status* will benefit from relief from deportation and a work permit, much like was the case for DACA recipients. In terms of the model we will simply consider them as having the same productivity as documented workers with the same age and education. This is exactly the productivity boost considered earlier, potentially differing only in the take-up rate ψ. Unlike in the case of DACA, we believe that the take-up rate for the DREAM Act will be practically universal among eligible individuals since there is no fear from deportation ($\psi = 1$). We also believe that, unlike DACA, conditional status is unlikely to induce DREAMer college students to drop out. The reason is that their planning horizon remains unchanged and the returns

[23] The current version of the House bill has similar requirements, though a little more restrictive.

[24] Like for DACA, a clean criminal record is also a requirement to obtain conditional status.

to a college degree will increase thanks to the permanent legal status.

In fact, the requirements to obtain permanent residence in the DREAM Act will likely generate dynamic participation effects. As noted earlier, one of the routes to satisfy the permanent-residence requirement in the second stage is to obtain at least two years of college education. This will raise college attendance among individuals in conditional status, relative to what we would have observed otherwise. Thus, unlike for DACA, we may see a *negative* labor market participation effect in the short run when some employed DREAMers quit their jobs to enroll in college. In the long run, these workers will come back to the workforce with some college education and enhanced productivity, which will imply a *positive* participation effect. We believe that this *educational boost* will take place primarily among DREAMers with a high school degree, who are the most likely population to choose the college education route in order to fulfill the permanent residence requirement.[25]

7.2 Short-run participation effects

More specifically, we define γ_e^L and γ_e^N to be, respectively, the *increase* in the probability of college enrollment for working and non-employed DREAMers, respectively. Lacking empirical estimates of the size of these effects, we shall assume that these probabilities are zero for individuals with less than a high school education or already having some college education: $\gamma_e^L = \gamma_e^N = 0$ for $e \neq 2$. The reason is that it is much more likely that these individuals will choose to fulfill the permanent residence requirement by joining the Army or being continuously employed for the required number of years. However, many DREAMers with a high-school diploma are likely to choose to attend college in order to fulfill the additional requirement. Thus we will set $\gamma_2^L \geq 0$ and $\gamma_2^N \geq 0$ in our calibration.

As a result, the short-run counterfactual undocumented population under the DREAM Act is as follows. For each (e, a), a fraction ψ of all DREAMers (undocumented that

[25]Evidence of educational responses by DREAMers to increased returns to education is provided by Kuka et al. (2018). Because these dynamics are driven by the educational incentive built into the DREAM Act, the likely length of the transition phase is 2 to 4 years. At that point the long-run effects would materialize.

arrived in the country as children) receives conditional status:

$$\begin{aligned}
\widetilde{L}^{Undoc}_{e,a} &= L^{Undoc}_{e,a} - \psi L^{Dream}_{e,a} \\
\widetilde{C}^{Undoc}_{e,a} &= C^{Undoc}_{e,a} - \psi C^{Dream}_{e,a} \\
\widetilde{N}^{Undoc}_{e,a} &= N^{Undoc}_{e,a} - \psi N^{Dream}_{e,a}.
\end{aligned}$$

Turning now to the documented population, a fraction γ^L_e of the Dreamers in the workforce with education level e that received conditional status ($\psi L^{Dream}_{e,a}$) will quit their jobs in order to enroll in college. Likewise, a fraction γ^N_e of the non-employment Dreamers with education level e that received conditional status ($\psi N^{Dream}_{e,a}$) will enroll in college. More specifically, for each (e, a),

$$\begin{aligned}
\widetilde{L}^{Doc}_{e,a} &= L^{Doc}_{e,a} + \psi(1-\gamma^L_e) L^{Dream}_{e,a} \\
\widetilde{C}^{Doc}_{e,a} &= C^{Doc}_{e,a} + \psi\left(C^{Dream}_{e,a} + \gamma^L_e L^{Dream}_{e,a} + \gamma^N_e N^{Dream}_{e,a}\right) \\
\widetilde{N}^{Doc}_{e,a} &= N^{Doc}_{e,a} + \psi(1-\gamma^N_e) N^{Dream}_{e,a}.
\end{aligned}$$

In our calibration we shall set $\gamma^L_2 = \gamma^N_2 = \gamma$ for simplicity. We believe that a plausible value for this parameter is $\gamma = 1/2$, that is, one in two DREAMers with a high school degree will choose to obtain some college education in order to qualify for permanent residence. However, we will also produce estimates for higher and lower values of this parameter. Table 4 gathers the key parameter values in the simulation of the effects of the DREAM Act.

7.3 Long-run participation effects

The DREAMers that were initially in the workforce or non-employed in the baseline data but decide to attend college because of the eligibility requirements, $\psi\gamma(L^{Dream}_{2,a} + N^{Dream}_{2,a})$, are now graduating from college with their enhanced skills. We make two conservative assumptions. First, we assume that the DREAMers that went back to school obtain only the *minimum* college education required to satisfy the permanent residence requirement. Namely, those individuals transition from education group 2 (high school graduate) to education group 3 (some college or an associate's degree). Second, we assume that individuals that were initially non-employed stay in that state despite their increased educational attainment.[26] Thus, the size of the workforce is unchanged relative to the

[26]This assumption is probably overly conservative but we are unsure what fraction of these newly minted graduates would ultimately enter the workforce. If all the DREAMers that transition from

baseline, although some individuals have upgraded their skills.

The long-run undocumented population under the DREAM Act is the same as it was in the short-run scenario. For each (e, a),

$$
\begin{aligned}
\widetilde{\widetilde{L}}^{Undoc}_{e,a} &= L^{Undoc}_{e,a} - \psi L^{Dream}_{e,a} \\
\widetilde{\widetilde{C}}^{Undoc}_{e,a} &= C^{Undoc}_{e,a} - \psi C^{Dream}_{e,a} \\
\widetilde{\widetilde{N}}^{Undoc}_{e,a} &= N^{Undoc}_{e,a} - \psi N^{Dream}_{e,a}.
\end{aligned}
$$

Turning now to the documented population, for each (e, a), the workforce will be given by

$$
\begin{aligned}
\widetilde{\widetilde{L}}^{Doc}_{e,a} &= L^{Doc}_{1,a} + \psi L^{Dream}_{1,a} \text{ , for } e = 1 \\
&= L^{Doc}_{2,a} + \psi(1 - \gamma^L_2) L^{Dream}_{2,a} \text{ , for } e = 2 \\
&= L^{Doc}_{3,a} + \psi \left(L^{Dream}_{3,a} + \gamma^L_2 L^{Dream}_{2,a} \right) \text{ , for } e = 3 \\
&= L^{Doc}_{4,a} + \psi L^{Dream}_{4,a} \text{ , for } e = 4,
\end{aligned}
$$

where the group with some college $(e = 3)$ includes the high school graduates that attended college to fulfill the permanent residence requirement. Importantly, these equations assume that initially non-employed DREAMers that decided to obtain some college education to qualify for permanent residence remain non-employed in the long-run counterfactual.

As for the non-employed and the college-enrolled population,

$$
\begin{aligned}
\widetilde{\widetilde{N}}^{Doc}_{e,a} &= N^{Doc}_{e,a} + \psi N^{Dream}_{e,a} \\
\widetilde{\widetilde{C}}^{Doc}_{e,a} &= C^{Doc}_{e,a} + \psi C^{Dream}_{e,a}, \text{ for all e and a.}
\end{aligned}
$$

education level 2 to education level 3 were to become employed, the number of documented individuals with education level 3 in the long-run DREAM Act scenario ($\widetilde{\widetilde{L}}^{Doc}_{3,a}$) would have to be increased by $\psi\gamma N^{Dream}_{2,a}$. Accordingly, $\widetilde{\widetilde{N}}^{Doc}_{3,a}$ would have to be decreased by the same amount. Clearly, this would have an additional positive effect on GDP growth.

7.4 Results

7.4.1 Effects of the DREAM Act on GDP

Our estimates for the long-run effects on GDP from passing the DREAM Act are reported in Table 7. We consider a variety of scenarios that differ in the value of the parameter governing the share of DREAMers with a high school degree that choose to attend college in order to obtain permanent residence ($\gamma_2^L = \gamma_2^N = \gamma$).

The top panel in the table (scenarios 1-3) presents the results corresponding exactly to the long-run effects on GDP according to the set of equations (15). It is helpful to begin by considering scenario 1, where college enrollment is unaffected by the DREAM Act ($\gamma = 0$). In this case we find that GDP will increase by 0.05%, which amounts to an overall increase of \$9 billion per year. To provide a more intuitive measure of the size of the effects, it helps to consider that 1.65 million individuals benefit from legalization in our calculations and, out of those, 0.99 million are working in the long-run counterfactual. On the basis of the latter figure, the average long-run increase in GDP per legalized worker results in \$9,104. Because there are no participation effects in this scenario, the short-run change in GDP coincides exactly with the short-run value.

Let us now take into account the increased incentives to attend college (scenario 2). Specifically, we assume $\gamma = 1/2$, that is, we assume that 1 in 2 high-school graduates with conditional status choose to obtain an associate's degree (or two years of schooling toward a bachelor's degree). In the short run, there will be two opposing effects on GDP. On the one hand, there is a productivity boost associated with obtaining conditional legal status, as was the case with DACA. However, this positive effect is practically neutralized by a sizable *negative* participation effect driven by the high school graduate DREAMers that leave the workforce to enroll in college. As a result, GDP is practically unaffected in the short run.[27] However, over time a sizable positive effect on income would emerge. The long-run effect on GDP reflects a sizable *positive participation effect*: the individuals that left for college (and were initially employed) return to the labor market with enhanced productivity. This leads to a 0.08% increase in GDP (or \$15.2 billion per year), which amounts to \$15,371 per employed legalized individual. Last,

[27] Even though not reported in Table 7, we can also calculate the short-run effects of legalization on GDP. These effects can be negative for high values of γ, reflecting the reduction in the workforce when DREAMers with a high-school degree choose to quit their jobs in order to enroll in college. However, this finding could easily be overturned if individuals can simultaneously work and attend college. In fact, this seems to be the case for a large share of immigrant students attending community colleges (Hsin and Ortega (2017)).

scenario 3 considers a more extreme participation effect, where all DREAMers with a high school degree choose to obtain some college education ($\gamma = 1$). In this case GDP would increase by 0.11%.

In sum, our analysis implies that passing the DREAM Act will increase the economic contribution of DREAMers that obtain legal status. We estimate that GDP will increase *annually* by an average of 9 to 21 thousand dollars for each worker obtaining legal status. This amount would add to the economic contribution of DREAMers prior to legalization, which can be quantified by comparing GDP in the baseline scenario (prior to legalization) to the level of GDP in a counterfactual where DREAMers are removed from the economy. As reported in the bottom row of Table 7, removal of DREAMers from the workforce would entail a 0.42% reduction in GDP, amounting to $46,061 per worker. As a result, passing the DREAM Act would increase the *overall* annual contribution of DREAMers to GDP to be around $60,000 per worker.

7.4.2 Effects of the DREAM Act on wages

Our estimates for the long-run effects on wages are collected in Table 8. Columns 1-3 refer to wage effects pertaining to individuals that did not experience a change in status, that is, documented individuals (who stayed documented) and undocumented individuals that did not benefit from legalization.[28] Column 1 reports the wage effects for this population by education-age groups. As expected, the wages of individuals with education level 3 (some college) fall whereas there is an increase in the wages of individuals in all other education-age groups. However, it is important to note that the magnitudes of the wage effects are very small. Column 3 reports the percent average wages by education level (using the weights reported in column 2). Workers with some college would see their wages fall by 0.22 percent on average, and workers with a high school degree would experience a 0.16 percent increase. At the same time the wages of individuals at the top and bottom of the education distribution would remain practically

[28] Recall that because of the assumption of perfect substitution in production among workers with the same education and age, the percent change in the wages of groups that did not change documentation status but share the same skills will be identical. Our setup also assumes that natives and legal immigrants with the same age and education are perfect substitutes. To the extent that undocumented workers are closer substitutes for legal immigrant workers than for natives, our predictions will tend to underestimate the wage effects for documented, immigrant workers. However, the small size of the Dreamer population as a fraction of the labor force, and the substantial differences in the education and age distributions between legal and undocumented immigrants imply that the degree of underestimation is probably negligible ? undocumented immigrants are younger and less educated than immigrants with legal status.

unaffected.

Next, we turn to the individuals who obtain legal status (columns 4-6).[29] Naturally, the wages of these workers will experience much larger changes. However, we find a great deal of heterogeneity in the size of the wage effects. On the basis of the results in column 6, college graduates that obtain legal status will experience a meager 0.67% average increase in their wages. The reason for this small increase can be traced back to the calibration for the documented-undocumented productivity gap, which was basically non-existing. In contrast, individuals with some college education that obtain legal status will see their wages increase by an average of 15.33% thanks to the elimination of a substantial undocumented productivity penalty. Yet, our estimates suggest that the largest average wage increase would correspond to high-school graduate DREAMers obtaining legalization, with a 52% increase. The reason is that the average individual in this group benefits both from the increase in productivity associated with legal status and from rewards to the increased educational attainment.

Lastly, it is important to keep in mind that, on the basis of our analysis, the wage increases experienced by individuals that obtain legal status largely reflect increases in productivity arising from enhanced education as well as improved access to jobs where workers can make a better use of their skills. To the extent that the wage increase is productivity-driven, rather than due to increased bargaining power on the part of the worker, employers' labor costs need not be affected.

8 Conclusions

This paper has developed a simple general equilibrium model that can be used to quantify the economic gains from legalizing undocumented workers that arrived in the United States as children. Our model extends the framework proposed by Edwards and Ortega (2017) by considering a variety of participation and education effects. We use the model to simulate the effects of temporary legalization as implemented through the DACA program, as well as the effects of offering a track to permanent residence through the 2017 Senate version of the DREAM Act.

At some level both modes of legalization share the feature that they are likely to increase the productivity of workers who obtain legal status because of the improved labor market opportunities. However, there are important differences between the two

[29]Under our assumptions, only DREAMers with a high school degree are eligible under the DREAM Act.

modes of legalization, stemming from participation effects of different sign and magnitude. DACA entails a positive participation effect, driven by the many undocumented college students that dropped out in order to take advantage of the improved labor market opportunities. While this effect increases the short-run effect of DACA on GDP, it may entail a cost in the long run given that it is unlikely that these individuals return to college in the future.

In comparison the DREAM Act entails a *negative* participation effect in the short run because it is likely to induce some undocumented high-school graduates that were initially employed to quit their jobs and enroll in college in order to obtain permanent residence.[30] In contrast, the long-run effect on GDP can be rather large when the new college graduates return to the workforce. We estimate that the long-run increase in GDP will range between 0.05% and 0.11%.

We have also analyzed the wage effects of legalization under DACA and the DREAM Act. Because DREAMers are only a small fraction of the population, legalization has very small effects on the wages of native workers. In contrast, the wages of most individuals gaining legal status will increase substantially, with the largest increases being experienced by DREAMers that increase their educational attainment in order to qualify for legalization.

Our analysis has not explicitly considered tax implications such as the role of payroll taxes. At some level, it is possible that payroll tax considerations might compel employers to shift some demand toward workers who originally were documented. This provides an alternative explanation, in addition to the basic complementarity story, for why the wages of documented workers go up when DREAMers become authorized. However, it is also worth noting that many undocumented workers have been hired using someone else's social security number (Brown et al. (2013)). In those cases, employers are already paying payroll taxes and legalization will not affect the employer cost of labor.

Providing legal status to DREAMers could entail a fiscal cost because of increased access to public services (Cascio and Lewis (2019)). According to the Congressional Budget Office (memo *S. 1615, Dream Act of 2017*), passing the DREAM Act will increase government spending by $2.68 billion per year. Our analysis predicts that passing the DREAM Act would boost GDP by about $15.2 billion, which will increase tax revenue. Again based on CBO forecasts, each dollar increase in GDP translates into 18 cents of federal tax revenue. Thus, our estimated GDP gains translate into an increase

[30]Under some parameter values this effect is large enough that it may overshadow the productivity gains associated with legal status.

in federal tax revenue of \$2.73 billion per year. Hence, passing the DREAM Act is likely to be essentially budget-neutral.

We close by noting that the GDP effects of the DREAM Act could be substantially larger than the estimates presented here. The reason is that we have limited our analysis to DREAMers that have completed high school. However, one would expect that passing the DREAM Act is likely to encourage many DREAMers that had not completed high school to go back to school in order to become eligible for legalization. Our framework could be extended in order to incorporate this additional educational response to the eligibility requirements of the DREAM Act.

9 Declarations

9.1 Ethics approval and consent to participate

No human subjects are involved in the research. The data are anonymous and the research design was approved by the custodian of the data, the Center for Migration Studies (New York).

9.2 Consent for publication

Not applicable.

9.3 Availability of data and material

The data that support the findings of this study are available from the Center for Migration Studies (New York) but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of the Center for Migration Studies (New York). The data used is a version of the American Community Survey that includes an imputation for undocumented status. Except for that variable, all other variables can be obtained from the public version of the dataset on IPUMS.

9.4 Competing Interests

The authors declares that they have no competing interests.

9.5 Funding

The research was funded by the MacArthur Foundation (grant 15-1643). The funding body did not influence the design, analysis or interpretation of the findings.

9.6 Authors' contributions

The three authors are jointly responsible for the research analysis. RE was the leading author in acquiring and processing the data. FO was responsible for the coding of the equations using in the simulation. The three authors were jointly responsible for the interpretation of the findings. AH and FO are responsible for the drafting of the text. All authors have approved the submitted version and agree both to be personally accountable for the author's own contributions and to ensure that questions related to the accuracy or integrity of any part of the work, even ones in which the author was not personally involved, are appropriately investigated, resolved, and the resolution documented in the literature.

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Table 1: Data summary

	All	Docum.	Undoc.	Undoc17	Undoc17 HSG+	Undoc17 HSG+, 32-
Employed (%)	61	61	68	60	60	57
College (%)	11	11	6	12	22	25
Non-employed (%)	28	28	27	27	18	18
Total count (Mn)	232.43	222.03	10.40	2.93	1.65	1.42
Wage ($)	20.61	20.82	16.39	14.73	15.94	14.40
as % Pop	100	95.53	4.47	1.26	0.71	0.61
as % Emp	100	95.53	4.99	1.24	0.70	0.57

Notes: The data are based on the 2012 American Community Survey (CMS version). We restrict to individuals age 17-70. Non-employed means not working and not in college. Total count refers to the estimated number of individuals in each column (in millions). Hourly wages computed on the basis of full-time workers (35 hours minimum worked usually) at year 2012 prices. Column 1 reports on the total population, including documented (US-born or foreign-born) and likely undocumented. Column 2 refers to (likely) documented individuals only. Column 3 refers to the (likely) undocumented individuals. Column 4 reports on unauthorized individuals who arrived in the country at age 17 or younger. Column 5 adds the additional restriction of having a high school diploma or equivalent. Column 6 adds the additional restriction of being less than 32 years old in year 2012.

Table 2: Baseline Data (2012 ACS) on documented population and DREAMers. Shares of column totals

Edu	Age	(1) Doc L	(2) Doc C	(3) Doc N	(4) U17 L	(5) U17 C	(6) U17 N	(7) U17HSG L	(8) U17HSG C	(9) U17HSG N
HSD	1	0.02	0	0.1	0.18	0	0.42	0	0	0
HSD	2	0.01	0	0.03	0.18	0	0.16	0	0	0
HSD	3	0.02	0	0.03	0.08	0	0.05	0	0	0
HSD	4	0.02	0	0.04	0	0	0	0	0	0
HSD	5	0.01	0	0.06	0	0	0	0	0	0
HSG	1	0.06	0.21	0.06	0.2	0.32	0.19	0.35	0.32	0.52
HSG	2	0.06	0.02	0.05	0.13	0.02	0.08	0.22	0.02	0.22
HSG	3	0.07	0.01	0.05	0.03	0	0.02	0.06	0	0.05
HSG	4	0.08	0.01	0.07	0	0	0	0	0	0
HSG	5	0.05	0	0.15	0	0	0	0	0	0
SoCo	1	0.06	0.37	0.02	0.09	0.51	0.03	0.17	0.51	0.09
SoCo	2	0.06	0.09	0.03	0.05	0.05	0.02	0.09	0.05	0.06
SoCo	3	0.06	0.04	0.03	0.01	0.01	0.01	0.02	0.01	0.01
SoCo	4	0.06	0.02	0.04	0	0	0	0	0	0
SoCo	5	0.04	0.01	0.08	0	0	0	0	0	0
CoGrad	1	0.03	0.08	0.01	0.02	0.06	0.01	0.04	0.06	0.03
CoGrad	2	0.08	0.07	0.02	0.02	0.03	0.01	0.04	0.03	0.02
CoGrad	3	0.08	0.03	0.03	0	0	0	0.01	0	0
CoGrad	4	0.08	0.02	0.03	0	0	0	0	0	0
CoGrad	5	0.06	0.01	0.09	0	0	0	0	0	0
Total (M)		134.78	24.03	63.23	1.77	0.37	0.8	0.99	0.37	0.29
Total (M)			222.03			2.93			1.65	

Notes: The population is restricted to ages 17-70 and is based on the 2012 ACS. Columns 1-3 refer to the documented population (born in the United States or abroad). Columns 4-6 refer to the likely unauthorized individuals that arrived in the country by age 17 (DREAMers), and columns 7-9 restrict to the subset of DREAMers with a high school diploma (or similar) in 2012. Education levels are defined as (HSD) high school dropouts, (HSG) high school graduates, (SoCo) some college education, and (CoGrad) college graduates. The age groups are defined as (1) 17-26, (2) 27-36, (3) 37-46, (4) 47-56 and (5) 57-70.

Table 3: Calibration productivity terms

Edu	Age	(1) $\theta_{e,a}^{Doc}$	(2) $\theta_{e,a}$	(3) θ_e
HSD	1	1.04	1	
HSD	2	1.18	2.02	
HSD	3	1.26	2.39	1
HSD	4	1.35	2.56	
HSD	5	1.39	2.28	
HSG	1	1.06	1	
HSG	2	1.26	1.87	
HSG	3	1.38	2.31	2.27
HSG	4	1.44	2.59	
HSG	5	1.59	2.19	
SoCo	1	1.04	1	
SoCo	2	1.32	2.27	
SoCo	3	1.46	2.89	2.65
SoCo	4	1.42	3.1	
SoCo	5	1.38	2.64	
CoGrad	1	1	1	
CoGrad	2	1	2.18	
CoGrad	3	1.07	3.09	5.58
CoGrad	4	1.44	3.4	
CoGrad	5	1.6	2.87	
Avg.		1.22		

Notes: Productivity terms based on the hourly wages of the corresponding full-time workers, assuming no exploitation. Column 1 reports the productivity (wage) of documented workers relative to undocumented workers who arrived as children in the same education and age groups. The average value reported in the last row uses the distribution of undocumented workers arrived as children over education-age groups as weights – the mode is 15% for HSD in age groups 2 and 3. Column 2 reports the productivity of each education-age type of labor, relative to the first age category in each of the education groups. For groups $(CoGrad, 1)$ and $(CoGrad, 2)$, the average wages for likely undocumented workers is slightly higher than for likely documented workers. We cap these ratios at 1 because they likely reflect the sampling variability due to small cell sizes. Column 3 reports the productivity of each education group relative to the HSD category. The age groups are (1) 17-26, (2) 27-36, (3) 37-46, (4) 47-56 and (5) 57-70.

Table 4: Additional Parameters

Parameter values		
ϕ	0.56	DACA take-up rate
δ^C	0.07	Increased prob. of employment for college students
δ^N	0	Increased prob. of employment for 'idle' individuals
ψ	1	DREAM Act take-up rate
γ_2^L	0.50	Increased prob. of college enrollment for employed individuals
γ_2^N	0.50	Increased prob. of college enrollment for 'idle' individuals

Notes: Key parameter values. The scenario more consistent with the estimates by Pope (2016) is $\delta^C = 0$ and $\delta^N = 0.07$. And in any case we need to have $\delta^C + \delta^N = 0.07$.

Table 5: Effects of DACA on GDP

Scenarios	(1) Δ GDP pct. change	(2) Δ GDP \$ Billions	(3) Legalized All	(4) Legalized Employed	(5) Δ GDP \$ per worker
(1) No participation effect	0.0144	2.8	0.79	0.45	6,217
(2) College participants	0.0178	3.5	0.79	0.47	7,454
(3) Non-emp. participants	0.0170	3.3	0.79	0.46	7,181
(4) Universal take-up	0.0289	5.6	1.42	0.83	6,777
(5) Full exploitation	0.0032	0.6	0.79	0.47	1,340

Notes: The eligible group consists of likely unauthorized individuals that entered the country younger than 17 with a high school diploma (or equivalent), and were younger than 32 in year 2012, as required by DACA. Columns 3 and 4 report the number of legalized individuals in our simulation, considering only employed (column 4) or also individuals in college or non-employed (column 3). In scenario 1, $(\phi, \delta_C, \delta_N) = (0.56, 0, 0)$. In scenarios 2 and 5, $(\phi, \delta_C, \delta_N) = (0.56, 0.07, 0)$. In scenario 3, $(\phi, \delta_C, \delta_N) = (0.56, 0, 0.07)$. In scenario 4: $(\phi, \delta_C, \delta_N) = (1, 0.07, 0)$. The dollar amounts in column 2 are computed multiplying the pct. change in GDP in column 1 by the latest GDP estimate available – third quarter of 2017. The last column is the ratio of column 2 to column 5.

Table 6: Wage Effects of DACA. Percent changes relative to baseline

Edu group	Age group	(1) wage growth Doc-Doc Undoc-Undoc	(2) labor shares Doc	(3) wage growth by edu Doc-Doc	(4) wage growth Legalized Undoc-Doc	(5) labor shares DREAMers	(6) wage growth by edu Legalized
HSD	1	0.01	0.24	0.00	.	0	.
HSD	2	0.01	0.17		.	0	
HSD	3	0.01	0.20		.	0	
HSD	4	0.01	0.23		.	0	
HSD	5	0.01	0.16		.	0	
HSG	1	-0.03	0.19	-0.01	5.96	0.68	12.43
HSG	2	-0.04	0.18		26.17	0.32	
HSG	3	0	0.21		.	0	
HSG	4	0	0.26		.	0	
HSG	5	0	0.16		.	0	
SoCo	1	-0.02	0.22	-0.01	3.98	0.72	11.73
SoCo	2	-0.02	0.22		31.64	0.28	
SoCo	3	0	0.21		.	0	
SoCo	4	0	0.22		.	0	
SoCo	5	0	0.14		.	0	
CoGrad	1	0	0.10	0.00	0.00	0.53	0.00
CoGrad	2	0.01	0.25		0.00	0.47	
CoGrad	3	0.01	0.25		.	0	
CoGrad	4	0.01	0.23		.	0	
CoGrad	5	0.01	0.17		.	0	

Notes: We report percent changes in DACA counterfactual relative to baseline. Doc-Doc (Undoc-Undoc) refers to individuals that were Documented (Undocumented) both in the baseline and in the counterfactual. Legalized individuals are those that had Undocumented status in the baseline but were Documented in the DACA counterfactual. Because documented and undocumented that do not change legal status with the same education and age are perfect substitutes in production, they experience identical wage growth rates. We use the baseline elasticities (scenario 2 in Table 5). Columns 1 and 4 report wage growth (in percent) by education-age. Columns 2 and 5 report the labor shares in the baseline among documented workers (column 2) and among DREAMers eligible for DACA (column 5). Columns 3 and 6 report age-weighted average wages by education on the basis of the respective previous two columns. A '.' denotes a missing value due to the fact that there are no individuals in that education-age-documentation status category. The age groups are (1) 17-26, (2) 27-36, (3) 37-46, (4) 47-56 and (5) 57-70.

Table 7: Long-run effects of the DREAM Act on GDP

Scenarios	(1) ΔGDP pct. Change	(2) ΔGDP \$ billions	(3) Legalized - All Millions	(4) Legalized - Workers Millions	(5) ΔGDP \$ per worker
Legalization					
(1) $\gamma = 0$	0.05	9.0	1.65	0.99	9,104
(2) $\gamma = 0.50$	0.08	15.2	1.65	0.99	15,371
(3) $\gamma = 1$	0.11	21.3	1.65	0.99	21,519
Removal	-0.42	-81.5	2.93	1.77	-46,061

Notes: Scenarios 1-3 report the long-run gains in GDP associated with passing the DREAM Act when a fraction γ of DREAMers with a high-school degree chooses to enroll in college to obtain an associate degree (education level 3). In all scenarios the new graduates are assumed to work only if they were working in the baseline scenario. GDP amounts in columns 2 and 5 are in 2017 prices. Columns 3 and 4 report the number of individuals that obtain legalization according to our simulation (in millions), with the latter restricting to legalized individuals that are working in the long-run DREAM Act scenari. Column 5 is computed by dividing column 2 by column 4. The last row (Removal scenario) reports the change in GDP associated with removing all DREAMers (undocumented individuals that arrived as children).

Table 8: Wage Effects of DREAM Act. Percent changes relative to baseline

Edu	Age	(1) Doc %Δ wage	(2) Doc labor shares	(3) Doc %Δ wage	(4) Legalized %Δ wage	(5) Legalized labor shares	(6) Legalized %Δ wage
HSD	1	0.03	0.24	0.03	.	0	.
HSD	2	0.03	0.17		.	0	
HSD	3	0.03	0.20		.	0	
HSD	4	0.03	0.23		.	0	
HSD	5	0.03	0.16		.	0	
HSG	1	0.37	0.19	0.16	22.20	0.55	52.37
HSG	2	0.21	0.18		85.09	0.35	
HSG	3	0.1	0.21		115.36	0.09	
HSG	4	0.08	0.26		.	0	
HSG	5	0.08	0.16		.	0	
SoCo	1	-0.42	0.22	-0.22	3.56	0.61	15.33
SoCo	2	-0.34	0.22		31.21	0.32	
SoCo	3	-0.15	0.21		45.33	0.07	
SoCo	4	-0.08	0.22		.	0	
SoCo	5	-0.07	0.14		.	0	
CoGrad	1	0.03	0.10	0.03	0.03	0.42	0.67
CoGrad	2	0.03	0.25		0.03	0.49	
CoGrad	3	0.02	0.25		7.23	0.09	
CoGrad	4	0.03	0.23		.	0	
CoGrad	5	0.03	0.17		.	0	

Notes: The table reports long-run percent changes in wages in the DREAM Act scenario. Eligible individuals are required to have a high school diploma in the baseline data. Columns 1-3 refer to documented individuals (Doc), either foreign-born or US-born. Columns 4-6 refer to individuals that obtained legal status through the DREAM Act. Columns 1 and 4 report wage growth (in percent) by education-age. Columns 2 and 5 report the labor shares in the baseline among documented workers (column 2) and among DREAMers (column 5). Columns 3 and 6 report age-weighted average wages by education. A '.' denotes a missing value due to the fact that there are no individuals in that education-age-documentation status category. The simulation assumes that a fraction $\gamma = 0.50$ of high-school graduate DREAMers will obtain some college education (education level 3) in order to obtain legal permanent residence. Because documented and undocumented workers with the same education and age are perfect substitutes in production, they experience identical education-age specific wage growth rates. Thus column 2 can also be applied to undocumented workers that did not obtain legal status.