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ABSTRACT

Occupational Barriers and the Labor Market Penalty from Lack of Legal Status*

Wage gaps between documented (including natives) and undocumented workers may reflect employer exploitation, endogenous occupational sorting and productivity losses associated with lack of legal status. Identification of the undocumented productivity penalty is crucial to estimate the aggregate economic gains from legalization. This paper presents a new identification strategy based on the interplay between educational attainment and occupational barriers. Our main finding is that lack of legal status reduces the productivity of undocumented workers by about 12%. We also find that Dreamers are positively selected compared to similarly skilled natives, as one would expect if they face occupational barriers (Hsieh et al., 2013). Our estimates also imply that the degree of employer exploitation is likely to be small, suggesting that employer competition bids up the wages of undocumented workers and aligns them with their productivity. Last, we also find evidence suggesting that the occupational choices of undocumented workers are heavily influenced by licensing requirements and by the degree of exposure to apprehension by immigration enforcement agencies. In sum, our results strongly suggest that occupational barriers associated with lack of legal status lead to misallocation of talent and negatively affect economic growth.

JEL Classification: J15,J24,J31

Keywords: migration, undocumented, legalization, amnesty, dreamers

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* Thanks to Marianne Bertrand, Janet Calvo, Kevin Shih, Suleyman Taspinar, Marcos Vera-Hernandez and seminar participants at Queens College for helpful comments.

1 Introduction

There is renewed interest among labor economists on the role of occupational barriers in determining income inequality across gender and race groups. In a recent study, Hsieh et al. (2013) argue that occupational barriers have severely disrupted the education and occupation decisions of women and blacks for many decades, leading to talent misallocation. Their analysis also shows that the gradual reduction in the occupational frictions affecting these groups of workers has led to a substantial increase in productivity and economic growth in the last decades.

The labor market opportunities of undocumented workers in the United States are almost certainly diminished by occupational barriers (Abrego (2011), Pope (2016), Amuedo-Dorantes and Antman (2017), Gonzales (2011)). These barriers reflect regulatory constraints, such as legal residence requirements associated with occupational licenses. However, they may also reflect specific task requirements. The need to hold face-to-face interactions with customers or government agencies, or to travel extensively, introduces high exposure to apprehension and deportation, effectively barring otherwise qualified undocumented workers from seeking employment in those occupations. The theory developed by Hsieh et al. (2013) suggests that these occupational barriers reduce the productivity of these workers in important ways.[1] If this is the case, providing work permits to undocumented workers will lead to aggregate gains in terms of GDP (Kossoudji (2013), Edwards and Ortega (2017)).

Quantification of the productivity loss associated with lack of legal status is typically done on the basis of the wage gaps between documented (including natives) and undocumented workers with the same observable skills (Ortega et al. (2018)). However, other factors will also affect documented-undocumented wage gaps. Some employers may take advantage of the vulnerability of undocumented workers and pay them below market rates (Gleeson and Gonzales (2012), Brown et al. (2013) and Naidu et al. (2016)). In these instances, gaining legal status will lead to income redistribution from employers to workers, with no net increase in income. In addition, measured wage gaps are also affected by endogenous occupational sorting. As seen in the generalized Roy model in Hsieh et al. (2013), the average ability of minority workers in an occupation is increasing in the size of the barriers they faced to enter that particular occupation.

[1] For example, in many states an undocumented individual with a degree in education is not allowed to work as a teacher. Instead her best alternative may have been to work as a nanny. However, since 2014 several states have allowed DACA recipients to obtain a teacher's license. For evidence consistent with this example, see Wong (2016).

The main goal of our paper is to develop a strategy to identify the productivity penalty associated with lack of legal status, taking into account that measured wage gaps between documented and undocumented workers also reflect employer exploitation and endogenous occupational sorting. Our study will also quantify the entry barriers faced by undocumented workers across different occupations.

The key to our identification strategy is to focus on the productivity loss arising from the inability of undocumented workers to access certain occupations. Because of these barriers, some undocumented workers will be employed in occupations for which they are *over-qualified*, while others will work in occupations that match their educational attainment. Our main identifying assumption is that undocumented workers that are *exactly qualified* may be subject to employer exploitation, but do not suffer a productivity penalty. The documented-undocumented wage gaps (conditional on skills) for this subset of workers will essentially identify the degree of employer exploitation. Netting out this factor, we can then identify the undocumented productivity penalty on the basis of (conditional) documented-undocumented wage gaps for *over-qualified* workers.

Our main findings are as follows. First, we estimate large unconditional wage gaps (over 50 log points) between documented and undocumented full-time workers. More than half of these gaps are explained by differences in demographics, educational attainment and English fluency. Second, we estimate that lack of legal status reduces the productivity of undocumented workers by about 12%. Third, we find that employed Dreamers are positively selected (in terms of productivity) compared to similarly skilled natives, as one would expect on the basis of the theory by Hsieh et al. (2013). Our estimates also imply that the degree of employer exploitation is likely to be very small, suggesting that employer competition bids up the wages of undocumented workers and aligns them with their productivity. Last, our results indicate that licensing requirements impose large barriers to undocumented workers in teaching and healthcare occupations. We also find evidence suggesting that the occupational choices of undocumented workers are heavily influenced by the degree of exposure to apprehension by immigration enforcement agencies.

Our analysis will pay particular attention to this group of workers for several reasons. First, Congress has been discussing plans to provide legal status to *Dreamers* for over a decade and President Obama used executive action to introduce *Deferred Action for Childhood Arrivals*, which provides temporary relief from deportation and work permits to eligible individuals. In addition, a unique feature of *Dreamers* is that a large proportion were schooled in the United States and are culturally indistinguishable from their native peers. As a result, the labor market frictions experienced by them may be lower than for other undocumented individuals.

The structure of the paper is the following. Section 2 summarizes the relevant literature. Section 3 presents the data. Section 4 describes our identification strategy and econometric specification. Section 5 contains summary statistics. Section 6 estimates conditional wage gaps and the productivity and exploitation wedges. Section 7 estimates the size of the occupational barriers faced by undocumented workers. Section 8 concludes.

2 Related Literature

Broadly speaking, our paper is related to the vast literature on gender wage gaps (e.g. Bertrand et al. (2014)) and labor market discrimination. In several ways, the most relevant study for our paper is Hsieh et al. (2013). These authors analyze the sources of misallocation of talent in the United States and their evolution over time emphasizing the role of occupational barriers. Their generalized Roy model considers four groups of individuals, defined by race and gender. In their dynamic model, individuals first choose education and later enter the labor market by choosing occupations. These groups face different degrees of barriers to human capital accumulation and discrimination in the labor market, along with differences in occupational preferences. Barriers to human capital and to occupational choice are modeled as *wedges*. Namely, some groups face a higher cost of acquiring education and occupation-specific discrimination 'taxes'. Using Census and ACS data they back out the evolution of these frictions over time and conduct simulations to evaluate their effects. Their results suggest that about one quarter of the economic growth in the last fifty years can be explained by the reduction in frictions and the resulting improved allocation of talent.

Our paper is also closely connected to the literature on the labor market outcomes of undocumented workers. There is a large literature in economics and sociology documenting the existence of large wage differentials between documented and undocumented workers with similar skills. Using the Survey of Income and Program Participation, Hall et al. (2010) estimated a 17 percentage wage disparity between documented and undocumented male Mexicans. A number of studies have examined the wage effects of the 1986 IRCA amnesty estimating the undocumented wage penalty to be around 20 percent (Kossoudji and Cobb-Clark (2002) and Lozano and Sorensen (2011)). Orrenius and Zavodny (2015) provide additional evidence of the wage penalty associated to undocumented status by showing 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.

While the existence of sizable documented-undocumented wage gaps is well established, their nature is less well understood. A number of studies have documented that illegality has a number of detrimental effects that are likely to negatively affect worker productivity. For example, the threat of deportation and depressed labor market opportunities increases the risk of depression and anxiety among undocumented youth (Abrego (2011), Gonzales (2011), Hainmueller et al. (2017), Patler and Pirtle (2018)). Other studies show 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)). Last, 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, which amounts implicitly to reduced wages relative to documented workers with similar educational attainment.

At the same time, some studies argue that the wages of undocumented workers are depressed as a result of employer exploitation. Through qualitative analysis, Gleeson and Gonzales (2012) find evidence of work conditions violations. They also provide evidence that undocumented workers are deterred from filing complaints due to their lack of legal status. Brown et al. (2013) analyze administrative data from Georgia state and identify which firms employ undocumented workers on the basis of erroneous social security numbers. The results suggest that firms with undocumented workers experience a competitive advantage, which translates into a higher rate of survival. It is not clear from these studies how widespread employer exploitation is, and whether it affects Dreamers or undocumented workers with higher levels of education.

In the last few years, several studies have focused on the effects of DACA on the labor market and educational outcomes of Dreamers. Pope (2016) and Amuedo-Dorantes and Antman (2017) use data from the ACS and CPS, respectively. Lacking information on immigrants' legal status, these authors were forced to assume that non-citizens in a given age range are undocumented. Both studies find positive effects of DACA on employment, but disagree on the effects on schooling. Hsin and Ortega (2016) use administrative data that allows for a precise identification of students' 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). In a recent study, Kuka et al. (2018) provide evidence that DACA incentivized human capital investments among teenagers. In comparison, our study uses data for the period immediately prior to DACA and focuses on the quantification of documented-undocumented wage gaps and identification of the factors generating those gaps.

Our work is also related to the literature on occupational licensing. Kleiner and Krueger (2013) documented that 25% of the workforce has attained a license. Licensing has been shown to increase wages and Kleiner and Vorotnikov (2017) argue that relaxing licensing constraints can lead to lower prices and higher consumer welfare. More recently, Blair and Chung (2017) have argued that occupational licensing can be a powerful tool to reduce the wage gaps of women and blacks relative to white men by reducing information asymmetries regarding worker productivity.[2] From this viewpoint, our paper analyzes the occupational barriers faced by undocumented workers. While in some occupations these barriers will be the result of licensing requirements, which often entail permanent residence, in other instances the barriers may have to do with the specific task content of those occupations.

3 Data

We use a special extract of the American Community Survey provided by the Center for Migration Studies (2014). Besides the usual information on employment, skills and wages, this confidential dataset contains a sophisticated imputation for documentation status developed by Warren (2014). These data have been used to estimate, by means of calibration and simulation methods, the economic contribution of undocumented workers (Edwards and Ortega, 2017) and the consequences of providing legal status to Dreamers (Ortega et al., 2018).

The unauthorized status imputation was first proposed in the 1990's and many authors have contributed to their development over the last few decades (Passel and Clark (1998), Baker and Rytina (2013), Warren and Warren (2013), Passel and Cohn (2015), and Warren (2014), among several others). The procedure is a 2-step process: (1) applying 'logical edits' to identify legal residents on the basis of the information in the ACS; and (2) re-weighting individual observations to match official unauthorized population estimates by country of origin. The main logical edits rely on information on year of arrival (because of the 1986 IRCA amnesty), country of origin, occupation, industry,

[2]Brucker et al. (2015) make a similar point in the context of native-immigrant wage gaps.

and receipt of government benefits.[3]

We use data for years 2010-2012. The reason is that President Obama's *Deferred Action on Childhood Arrivals* was rolled out starting at the very end of 2012. This program provided beneficiaries with reprieve from deportation and two-year renewable work permits, which has been shown to have improved substantially the labor market outcomes of its recipients (e.g. Pope (2016) and Amuedo-Dorantes and Antman (2017)). Since we cannot identify DACA recipients in the data, it is preferable to restrict the analysis to the pre-DACA period.

On the basis of these data, we observe that most undocumented have been present in the United States for 16 years or more, and some have resided in the country for three decades (Figure 1). As a result, undocumented immigrants are deeply rooted in their local communities and make up for 4.5% of the U.S. population. Furthermore, about a third of the undocumented (amounting to approximately 3 million individuals) were brought to the country as children (Dreamers).

4 Identification strategy

4.1 Setup

It is helpful to consider the following simple setup. We partition workers by documentation status: documented (D) or undocumented (U). Individuals are heterogeneous in *unconstrained* productivity ε. Specifically, we assume that log (unconstrained) productivity is drawn from CDF $F(\varepsilon)$ with $E(\varepsilon) = 1$.

For documented workers, actual and unconstrained productivity coincide and employers pay them according to their productivity: $\ln w_i^D = \varepsilon_i$. However, undocumented workers are subject to two 'wedges' and their wage is given by $\ln w_i^U = (1-\tau)(1-\phi)\varepsilon_i$. For undocumented workers, their *actual* productivity is constrained due to lack of legal status: $(1-\phi)\varepsilon_i$, with wedge $\phi \geq 0$. Lack of a work permit entails the inability to access some occupations (e.g. due to licensing requirements) and employers (e.g. due to E-verify mandates).[4]

[3] Warren (2014) argues that the imputation accounts for 89 percent of unauthorized residents, which increases to 93 percent if we add individuals that were unauthorized at some point in the past. Other studies assessing the validity of this methodology are Pastor and Scoggins (2016) and Van Hook et al. (2015).

[4] Orrenius and Zavodny (2015) show that the introduction of E-verify led to a reduction in the wages of likely undocumented workers.

In addition, undocumented workers may be exploited by their employers because lack of legal status reduces their bargaining power. Wedge $\tau \geq 0$ measures the extent to which employers underpay undocumented workers. As a result, conditional on productivity, the documentation (undocumented-documented) log wage gap is given by

$$\ln w_i^U - \ln w_i^D = (1-\tau)(1-\phi)\varepsilon_i - \varepsilon_i. \tag{1}$$

For simplicity we will assume that the average unconstrained (and actual) productivity among documented employed equals the unconditional mean: $E(\varepsilon_i|D) = 1$. However, the mean unconstrained productivity for undocumented workers is allowed to be higher, $E(\varepsilon_i|U) \geq 1$, as one would expect in the presence of barriers to work.

Averaging across individuals in each group we obtain the average log wage gaps:

$$\begin{aligned} E(\ln w_i|U) - E(\ln w_i|D) &= (1-\tau)(1-\phi)E(\varepsilon_i|U) - E(\varepsilon_i|D) \quad (2) \\ &= (1-\tau)(1-\phi)E(\varepsilon_i|U) - 1, \quad (3) \end{aligned}$$

where we used normalization $E(\varepsilon_i|D) = 1$. This expression makes clear that the above wage gaps are not enough to separately identify the exploitation wedge (τ), the productivity (ϕ) wedge, and the degree of sorting among undocumented workers ($E(\varepsilon_i|U)$).

Furthermore, if we assumed that unconstrained productivity (ε_i) were uncorrelated with documentation status then the documentation log wage gap would simplify to $(1-\tau)(1-\phi) - 1$. However, as we discuss later, this assumption is not required in our identification strategy. This is important because undocumented workers are likely to experience larger barriers of entry into some occupations, which should be expected to induce *positive selection* (in terms of potential ability) into those occupations (Hsieh et al., 2013).

4.2 Identification

To make progress we will now impose some additional structure, relying on the interplay between occupation and education. Similar to Hsieh et al. (2013), we will assume that the *productivity penalty* suffered by undocumented workers stems from the inability to access their optimal occupations on the basis of their unconstrained productivity. As noted earlier, these occupational barriers may have a legal nature (e.g. licensing requirements that include legal status), or stem from the specific tasks inherent to an occupation. For instance, some occupations require face to face interaction with customers or government officials, or extensive traveling, which may entail high risk of apprehension and could potentially lead to deportation proceedings.

Because of these barriers, some undocumented workers may end up employed in occupations for which they are *over-qualified*.[5] As we explain in detail later on, over-qualified individuals can be identified in the data as possessing higher educational attainment than is typical among documented workers in that same occupation. Similarly, we will define a worker to be *exactly qualified* if his or her educational attainment is the same as that of the typical documented individual employed in that occupation.

Our main identifying assumption is that undocumented workers that are *exactly qualified* may be subject to employer exploitation, but do not suffer a productivity penalty (i.e. $\phi = 0$).[6] Thus the documentation wage gap for this subset of workers becomes:

$$E(\ln w_{i,o}|U, Overq = 0) - E(\ln w_{i,o}|D, Overq = 0) = (1 - \tau)E(\varepsilon_i|U) - 1. \qquad (4)$$

Importantly, the log wage gap for *exactly qualified* workers is observable in the data. Let us denote it by γ. Hence,

$$\gamma = (1 - \tau)E(\varepsilon_i|U) - 1. \qquad (5)$$

Thus, we expect γ to be negative. However, it can take on positive value if there is a high degree of (positive) self-selection into employment among undocumented workers.

Consider now the documentation wage gaps for *over-qualified* workers:

$$E(\ln w_{i,o}|U, Overq = 1) - E(\ln w_{i,o}|D, Overq = 1) \;\; = \;\; (1 - \phi)(1 - \tau)E(\varepsilon_i|U) - 1,$$

where the last term follows from Equation (5). On the basis of this expression, we expect the wage gap for *over-qualified* workers to be lower than for *exactly* qualified workers given that $\phi \geq 0$.

Clearly, the log wage gap for *over-qualified* workers is also observable in the data,

[5] Over-qualification among undocumented workers has been shown to be pervasive (Gleeson and Gonzales (2012)).

[6] It is possible that, in reality, these individuals also see their productivity diminished on account of their lack of legal status (e.g. they cannot obtain a driver's license). If that is the case, our estimates for the undocumented productivity penalty will be too low.

which we will denote by $(\gamma+\lambda)$. Then

$$\begin{aligned} \gamma+\lambda &= (1-\phi)(1-\tau)E(\varepsilon_i|U)-1 && (6)\\ &= (1-\phi)(1+\gamma)-1, && (7) \end{aligned}$$

which can be simplified to

$$\phi = -\frac{\lambda}{1+\gamma}. \tag{8}$$

In sum, if we can rule out selection into undocumented status, so that $E(\varepsilon_i|U) = E(\varepsilon_i|D) = 1$, Equation (5) allows us to identify the exploitation wedge $\tau = -\gamma$ on the basis of the wage gap for *exactly qualified* individuals. However, this assumption is not required to identify the productivity wedge. As seen in Equation (8), the wage gaps for exactly qualified and over-qualified individuals are sufficient to identify productivity wage ϕ.[7]

4.3 Algorithm

Our analysis will be restricted to adult full-time employees. The estimation of the exploitation and productivity wedges will be carried out in 4 steps:

1. For each occupation $o = 1, ..., O$, determine educational requirement m_o, defined as the typical educational attainment $(e_{i,o})$ of documented workers employed in the occupation.

2. For each occupation, partition workers (denoted by i) between exactly qualified $(e_{i,o} = m_o)$ and overqualified $(e_{i,o} > m_o)$.

3. Estimate (conditional) log wage gaps for the sample of **exactly** qualified undocumented workers (γ). A convolution of the exploitation wedge and the degree of sorting in ability among undocumented workers is given by Equation (5).

4. Estimate (conditional) log wage gaps for **over-qualified** undocumented workers $(\gamma+\lambda)$.

5. Back out the productivity wedge using Equation (8).

[7] Recall that λ is the difference between the wage gaps for exactly and over-qualified individuals.

4.4 Econometric specification

To implement the previous method we need to generalize slightly our setup to allow for observable characteristics and occupation-specific wages. Specifically, we consider the log wage of individual i employed in occupation o as given by

$$\ln w_{i,o} \quad = \quad \alpha_o + \beta X_i + \gamma Undoc_i + Overq_i(\delta + \lambda Undoc_i) + u_{i,o}, \tag{9}$$

where X_i includes indicator variables for gender, age groups, education groups, state of residence and year, along with other proxies for individual productivity, such as English fluency or having arrived in the country before age 10. Clearly, these characteristics are important determinants of individual productivity. The reason we want to control for them is that providing legal status to an undocumented worker will not affect these measures of skill, at least in the short run. Our focus is on the productivity penalty that could disappear rapidly when an undocumented worker obtains a legal work permit.

On the basis of this specification, the mean *conditional* documented-undocumented log wage gap for *exactly* qualified workers is estimated by parameter γ. Similarly, the corresponding term for *over-qualified workers* will be given by $\gamma + \lambda$. Under the usual mean-independence assumptions, consistent estimates of the parameters in Equation (9) can be estimated by OLS.

5 Summary statistics

We restrict the analysis to adult full-time employed individuals. As shown in Appendix Table 8, there are slightly over 5 million undocumented workers, accounting for about 5 percent of full-time employment. In addition, about 1 in 4 undocumented arrived in the United States at age 17 or younger, and are often referred to as Dreamers.

We define educational requirements for each occupation. The ACS data provide 10 categories for the educational attainment of individual respondents. The lowest level is for individuals with completed education up to 4th grade, followed by individuals that completed up to 8th grade. The top two educational categories are a 4-year college degree, and having completed 5 or more years of college (including graduate studies). We code these educational categories numerically and compute the median attainment among documented workers in each 4-digit occupational category. The occupations with the highest educational requirements (5 or more years of college) include Dentists, Medical scientists, Teachers and Optometrists, among many others. The educational attainment of the occupations with the lowest educational requirements is high school graduation (e.g. Housekeepers, Farmers or individuals employed as Painters, or in Construction and Maintenance).

Table 1 compares over-qualification rates by documentation status. In order to have comparable groups we restrict to full-time employed aged 28-37. As shown in column 1, 30% of documented workers are classified as over-qualified, compared to 18% of undocumented workers. This finding likely reflects that there is a larger share of high-school dropouts among undocumented workers, and high-school dropouts cannot be over-educated by construction given that the lowest educational requirement in the data is having completed high school. Accordingly, when we restrict to high-school graduates (aged 28-37) we now see that 48% of documented workers were over-qualified, compared to 75% among undocumented workers. Likewise, 45% of documented college-graduates were over-qualified, compared to 70% among undocumented with a college degree. Thus, roughly, over-qualification is about 50% higher among undocumented workers with at least a high-school degree, relative to documented ones. The last row reports the figures for Dreamers. Controlling for age and education, Dreamers also display larger over-qualification rates than documented workers, although slightly lower than for other undocumented. Table 1 also shows that high-school dropouts are never classified as over-qualified given that there are no occupations with an educational requirement below their own educational attainment. As a result, these workers do not contribute to the identification of the productivity wedge.

Focusing now on undocumented workers, it is interesting to examine which occupations exhibit the highest over-qualification rates. Table 2 reports the top 20 (4-digit) occupations in terms of employed undocumented workers, sorted by over-qualification rates. Among undocumented workers, over-qualification is most prevalent in the following occupations: software developers, nurses and home health aides, cashiers, waiters and salespersons, ranging between 25 and 63 percent.

Let us now present descriptive statistics for the variables we will use in estimation (Table 3). Undocumented workers account for 3.5% of the sample. The mean log hourly wage is 6.8 and 26.9% of the workers are classified as over-qualified. In the sample, 6.6% individuals did not graduate from high-school and 35.2% obtained a 4-year college degree. The variables described at the bottom summarize the degree of English fluency, the origin continent, and an indicator for having arrived in the country before the age of 10.

6 Wage gaps and estimation of wedges

We now turn to the estimation of Equation (9). We will estimate documentation wage gaps both for the whole undocumented population, as well as for Dreamers. Prior to implementing our identification strategy, we will also report estimated documented-undocumented wage gaps that do not use information on occupations, which is useful in order to compare our estimates to the previous literature.

6.1 Undocumented workers

We begin by estimating documentation wage gaps for the whole undocumented population. The results are collected in Table 4 (top panel). Column 1 shows that the unconditional hourly wages of undocumented workers are 54 log points lower than the wages of documented workers. Controlling for age, gender and state of residence in column 2 has practically no effect on the size of the wage gap, though naturally the R^2 increases substantially. Controlling for education (column 3) reduces the wage gap to 25 log points.

In order to map these conditional wage gaps into productivity gaps, it is important to recognize that there may be important differences in skills, other than education, between natives and immigrants. Labor economists have long recognized (Chiswick (1991), Chiswick et al. (2005)) that immigrants with an imperfect command of English or lack of other local skills will suffer a wage loss until they acquire those skills. The richness of the ACS allows us to build accurate controls to mitigate this problem. Specifically, we next add controls for continent of origin dummies, an indicator for English fluency (taking a value of one for native speakers and for individuals with high fluency), and an indicator for having arrived in the country before the age of 10 (as in Bleakley and Chin (2010)). Adding these controls reduces the wage gap to 8 log points.

Before turning to the identification of the wedges, it is interesting to quantify the within-occupation conditional wage gaps. Column 5 adds 4-digit occupation dummies to the specification estimated in the previous column. The wage gap now falls to just 3 log points, which suggest that occupational barriers are important determinants of documentation wage gaps.

Finally, let us turn to our main goal: the identification of the roles played by employer exploitation and diminished productivity as factors accounting for the wage gap between documented and undocumented workers with similar levels of unconstrained productivity. Column 6 in Table 4 estimates the full specification in Equation (9), including occupation dummies. The estimates show that there is no evidence of a wage gap for *exactly qualified* workers. Instead, *over-qualified* undocumented workers experience a 12 log-point wage gap vis-a-vis over-qualified documented workers with the same observable skills and employed in the same occupation. Hence, the small within-occupation wage gap in column 5 masks very different labor market experiences for workers that managed to obtain employment commensurate with their skills and those that did not.

Let us now try to back out the wedges implied by these estimates. On the basis of the estimated coefficients in column 6 and by virtue of Equation (8), the productivity wedge is estimated to be

$$\hat{\phi} \;=\; -\frac{\lambda}{1+\gamma} = \frac{0.12}{0.99} = 0.12.$$

Hence, the productivity wedge is substantial, introducing a roughly 12% wage gap between observationally similar documented and undocumented workers. This suggests an important role for occupational barriers in accounting for conditional wage gaps between documented and undocumented workers. These barriers entail an aggregate welfare loss due to the unproductive use of the human capital of undocumented workers.

In turn, Equation (5) and the estimated wage gap for *exactly qualified* workers, implies that the exploitation wedge is given by

$$\hat{\tau} \;=\; 1 - \frac{1+\gamma}{E(\varepsilon_i|U)} = 1 - \frac{0.99}{E(\varepsilon_i|U)}.$$

If we assume that the average unconstrained productivity of undocumented workers is the same as for documented ones, this expression implies a small exploitation wedge ($\hat{\tau} = 0.01$). However, exact identification of this wedge requires (unavailable) information on the average unconstrained productivity of undocumented workers (relative to documented ones in the same occupation).

6.2 Dreamers

Let us now turn to the wage gaps experienced by Dreamers. As shown in the bottom panel of Table 4, Dreamers experience an even larger 64 log-point unconditional wage gap, vis-a-vis the rest of full-time employed workers (column 1). However, a substantial part of the gap is due to demographics. The wage gap falls to 41 log points when we account for age, gender and state of residence (column 2). Accounting for educational differences further reduces the wage gap to 7 log points (column 3).

As before, it is important to control for English fluency and other proxies for local skills. Dreamers are undocumented individuals who arrived in the country as children. However, their command of English and cultural assimilation to their local communities are likely to vary as a function of age at arrival. Dreamers that arrived at an early age and went to school in the United States are likely to be indistinguishable from US-born individuals growing up in the same communities, while this is probably not the case for Dreamers who arrived as teenagers. Column 4 includes the controls for English fluency, continent of origin and age at arrival. Conditional on these controls, Dreamers now earn 7 log points *more* than comparable documented workers. As shown in column 5, this reversed wage gap is also found within occupations.

Let us now distinguish between *exactly qualified* and *over-qualified* workers. As can be seen in column 6, among *exactly qualified* workers, Dreamers earn approximately 8 percent more than non-Dreamers. However, when restricting to *over-qualified* workers, we find that Dreamers earn 5 log points less than non-Dreamers (0.08-0.13).

Next, we turn to the identification of the exploitation and productivity wedges for Dreamers. As before, we can estimate the productivity wedge by

$$\hat{\phi} \quad = \quad -\frac{\lambda}{1+\gamma} = \frac{0.13}{1.08} = 0.12,$$

which essentially coincides with the estimate based on the whole undocumented population. In turn, the exploitation wedge is given by

$$\hat{\tau} \quad = \quad 1 - \frac{1+\gamma}{E(\varepsilon_i|U)} = 1 - \frac{1.08}{E(\varepsilon_i|U)}.$$

Given the reversed wage gap for exactly qualified workers and the non-negativity constraint on the exploitation tax ($\tau \geq 0$), the expression above implies that the unobservable unconstrained productivity of Dreamers (U) is higher on average than that of non-Dreamers employed in the same occupation: $E(\varepsilon_i|U) > E(\varepsilon_i|D) = 1$. This finding is in line with the predictions of the generalized Roy model in Hsieh et al. (2013): occupational barriers induce positive sorting in ability (unconstrained productivity) among minority workers subject to those barriers.[8]

Clearly, in the absence of information on the average unconstrained productivity

[8]This finding of positive selection is also reminiscent of the finding that undocumented students have higher academic achievement than comparable documented students in some large public universities (Conger and Chellman (2013) and Hsin and Reed (2018)).

of undocumented workers, relative to documented ones, it is not possible to identify the exploitation wedge. However, our estimates suggest that it is unlikely to be large. For instance, if we assume that the mean unconstrained productivity for undocumented workers is at most 10% higher than for documented workers ($E(\varepsilon_i|U) \leq 1.1$), the upper bound for the exploitation wedge would be 0.02 (2%).[9]

In conclusion, while there's some uncertainty regarding the size of the exploitation wedge for undocumented workers, it is likely to be small. Furthermore, the productivity wedge affecting undocumented workers is estimated to be large, approximately 12%. These results strongly suggest that there exist large occupational barriers that prevent undocumented workers from accessing higher-paying occupations on account of their lack of legal status, leading to underutilization of their human capital.

6.3 Robustness

The analysis so far has ignored the fact that some individuals are *under-qualified*, which is the case when a worker has lower educational attainment than is typical in his/her occupation ($e_{io} < m_o$). This is rather prevalent. Among workers with a high school degree, the under-qualification rate is 24% among documented workers, 9% among undocumented ones, and 14% among Dreamers. In addition, all high-school dropouts are classified as *under-qualified* because the lowest educational requirement for any occupation turns out to be high school graduation.

Since the identification of the undocumented productivity penalty is essentially based on the documented-undocumented wage gap for over-qualified workers, *under-qualified* workers (including all high-school dropouts) do not play a direct role in the identification of this parameter. However, in the analysis above *under-qualified* workers were considered part of the *exactly qualified* group and, hence, contributed to the identification of the exploitation wedge. It is thus important to evaluate the sensitivity of our results to excluding this set of workers from the sample.

Accordingly, Table 5 presents estimates based on a sample that excludes *under-qualified* workers. The sample size falls by 0.81 million observations, to 2.76 million. As seen in the top panel of the table, the raw wage gap for undocumented workers is 42 log points, substantially smaller than the 54 log points estimated earlier. However, controlling for demographics and educational attainment brings the conditional wage

[9]The analogous calculation for the case of all undocumented workers delivers an upper bound for the exploitation wedge of 0.10, which is not very informative.

gap to 27 log points (column 3), which is very similar to the 25 log points reported in Table 4. If, in addition, we control for English fluency and arrival at an early age the wage gap falls to 10 log points, only 2 points higher than in the previous table. Using the estimates in column 6, we estimate the productivity wedge due to lack of legal status to be

$$\hat{\phi} \ = \ -\frac{\lambda}{1+\gamma} = \frac{0.09}{0.98} = 0.09,$$

which is only slightly lower than the 0.12 obtained using the full sample of workers.

In the case of Dreamers (bottom panel of the table), the raw wage gap is almost the same as before (68 versus 64 log points). However, the wage gap conditional on demographics and education is now much larger: 15 versus 7 log points (column 3). Once again, accounting for English fluency and arrival at an early age produces a *reversed* wage gap, with undocumented workers earning wages approximately 3% higher than documented ones. However, this gap is now about half of the size as before (approximately 7%). The estimated productivity wedge is almost the same as for all undocumented: $\hat{\phi} = \frac{0.10}{1.05} = 0.10$. Once again, only slightly lower than the 0.12 obtained using the full sample of workers. In conclusion, excluding seemingly *under-qualified* workers from the sample has little impact on the estimated productivity wedges, which only fall slightly.

7 Occupational barriers and lack of legal status

The previous results emphasize the existence of barriers of entry into certain occupations affecting undocumented individuals. The goal of this section is to investigate the nature of these barriers. Occupational barriers can be the result of licensing requirements, which often include legal residence. However, these barriers may also stem from the tasks involved in a given occupation. Some occupations require wide exposure to the public or extensive travel, which increases the risk of apprehension faced by undocumented workers.[10]

Building on the insight by Hsieh et al. (2013), we quantify the occupational frictions faced by undocumented workers by comparing their occupation shares to the shares of documented workers, which we assume are unconstrained in their choices.[11] The charac-

[10]In addition, in some occupations requiring face-to-face interactions with customers, language and cultural factors may be crucial for the performance of the company.

[11]The model by Hsieh et al. (2013) implies that a correction is needed if the two groups differ in their occupational preferences. This correction requires controlling for occupational wage gaps. In the

teristics of the occupations exhibiting the largest barriers to the entry of undocumented workers will be informative regarding the nature of those barriers.

7.1 Unconditional gaps in occupational shares

In our data, *unconditional* occupational shares can be computed easily as the proportion of individuals employed in each occupation relative to the total number of full-time employed individuals in the group. Accordingly, for each occupation o and group $g = D, U$, we compute $p_o^g = \frac{Emp_o^g}{Emp^g}$. Then the *unconditional* documented-undocumented gap in occupational shares is simply $p_o^U - p_o^D$, computed using the appropriate sampling weights.

The *unconditional* gaps referring to undocumented workers as a whole are presented in column 1 of Table 6. The top panel lists the 10 occupations exhibiting the largest unconditional gaps, which are led by *Teachers*. The share of employment in this occupation among undocumented workers is 4 percentage points lower than for documented workers. Given that the share of documented workers employed as teachers (preschool, elementary and secondary grades) is only 4.4% (column 3), this means that practically no undocumented workers are employed in this occupation.[12] Similarly, while 2.7% of documented workers are employed in *Healthcare* occupations, the corresponding share is 2.6 percentage points lower for undocumented workers. In both cases (as well as for policemen, firefighters and security guards), the almost complete absence of undocumented workers in these occupations is due to licensing requirements, which include legal residence. Interestingly, among the occupations exhibiting the largest barriers to the entry of undocumented workers we also find occupations that do not require licensing, such as secretaries, sales personnel and managers. Most likely, the reason is that these occupations entail face-to-face interactions with customers or government officials, exposing undocumented workers to a high risk of apprehension.

It is also interesting to examine the occupations where undocumented workers are over-represented. As seen at the bottom panel of Table 6, the largest gaps (favoring undocumented workers) are found in *Building and Grounds cleaning and maintenance* (8.8 percentage points), *Cooks* (7.6 pp.), *Construction* (7.1 pp.) and among *Agricultural*

remainder we assume that occupational preferences are the same for documented and undocumented workers with observationally similar skills.

[12]The true occupational share for undocumented workers in teaching occupations is likely to be even closer to zero given that until 2014 licensing requirements for teachers in all U.S. states required legal residence. The small discrepancy may be due to imputation error in documentation status or to teachers on temporary visas.

workers (4.9 pp.). All of these occupations are characterized by taking place in rural areas or in enclosed areas with low risk of apprehension.

We have also conducted the analysis for the Dreamers sub-sample. As can be seen in Table 7, the unconditional occupational shares for this group are very similar to those experienced by undocumented workers in general. For instance, the 3 occupations displaying the largest barriers to the employment of undocumented workers are the same as for all undocumented workers as a whole: *Teachers*, *Healthcare practitioners* and *Managers*. The occupational gaps (relative to documented workers) in these occupations are 4.2%, 2.7% and 2.5%, respectively, which are very similar to the figures presented in Table 6.

7.2 Conditional gaps in occupational shares

Clearly, the differences in age and educational attainment between documented and undocumented workers will also shape their occupations of employment. To account for observable skill differences and characterize *conditional* gaps in occupational shares, we estimate a series of occupation-specific binomial Probit models. Specifically, let d_{io} denote an indicator function taking a value of one if individual i is employed in occupation o, and zero otherwise. Then we postulate that

$$Prob(d_{io} = 1|X_i) = \Phi(\alpha_o + \beta_o Undoc_i + \gamma_o X_i), \tag{10}$$

where Φ is the CDF of the standard normal distribution. A coefficient $\beta_o < 0$ indicates that there exists a barrier to occupation o affecting the entry of undocumented workers. On the basis of the (maximum likelihood) estimates of the coefficients above, we compute *conditional* average effects of undocumented status on occupational shares:

$$E^U(d_{io}|X_i) - E^D(d_{io}|X_i) \;\;=\;\; \frac{1}{N^U}\sum_{i\in U}\Phi(\hat{\alpha_o} + \hat{\beta_o} + \hat{\gamma_o}X_i) - \frac{1}{N^D}\sum_{i\in D}\Phi(\hat{\alpha_o} + \hat{\gamma_o}X_i),$$

where E^g indicates that the expectation integrates over the subset of individuals belonging to group $g = D, U$, and N^g denotes the corresponding sample size. These documented-undocumented gaps in occupational shares provide information on the size of the barriers faced by undocumented workers in seeking employment in each (2-digit) occupation.

Estimated *conditional* occupational gaps are reported in column 2 of Table 6. The occupations where undocumented status entails a larger reduction in the probability of employment (in that occupation) are: (38) Police, firefighters and security guards, (23) Teachers and (32) Healthcare practitioners. In the case of the first of these occupations, there are no undocumented workers in our sample. As a result, lack of legal status presents an insurmountable barrier to employment in this occupation. In the other two occupational groups, lack of legal status is estimated to reduce the probability of employment by about 20 percentage points. It is also interesting to examine the bottom of the panel, containing the occupations with the largest over-representation of undocumented workers, after conditioning on demographics and education. In this case, the ranking and size of the gaps is very similar to what we obtained in the unconditional analysis. Once again, the findings for the subset of Dreamers are very similar to those obtained for the whole undocumented population.

8 Conclusions

Our paper provides new estimates for the wage gaps between documented and undocumented workers. The *unconditional* wage gaps between the two groups of workers are very large, in excess of 50 log points. As one would expect, we find that these gaps shrink down considerably after accounting for differences in education and demographic characteristics, particularly in the case of Dreamers.

But our main contribution is the identification of the main factors generating the *conditional* wage gaps between documented and undocumented workers. Our results show that these gaps are mainly due to occupational barriers that depress the productivity of undocumented workers. We estimate that lack of legal status prevents undocumented workers from finding employment that matches their educational attainment, entailing a productivity loss of at least 10-13 percent. The overall productivity loss may be substantially higher if undocumented youth under-invest in human capital because of the anticipation of labor market barriers in occupations with high skill requirements, as suggested by Kuka et al. (2018), or lack of legal status reduces productivity through other channels, such as increases in stress and anxiety (Hainmueller et al. (2017), Patler and Pirtle (2018)).

In addition, our estimates suggest a small role for employer exploitation and uncover positive selection into employment among Dreamers, vis-a-vis similarly skilled documented workers. The model by Hsieh et al. (2013) provides a plausible interpretation for this finding. In the presence of group-specific occupational barriers, the average talent among minority workers in those occupations is bound to be higher than for the average worker from groups not subject to those barriers.

Last, we quantify the occupational barriers faced by undocumented workers by comparing the distribution of occupations between documented and undocumented workers. We find that occupational barriers are often due to legal constraints tied to licensing requirements, as in the cases of police, teachers and healthcare practitioners. However, we also find large occupational barriers in occupations that entail face-to-face interaction with customers or government officials (such as sales personnel, secretaries and managers). Importantly, our period of analysis pre-dates the implementation of the DACA program in 2012, which offered eligible Dreamers temporary work permits and relief from deportation. Several authors have shown positive economic effects associated with DACA permits (Pope (2016), Amuedo-Dorantes and Antman (2017), Hsin and Ortega (2016)), suggesting that the beneficiaries experienced an important reduction in occupational barriers.

In line with the findings in Hsieh et al. (2013), our results strongly suggest that occupational barriers associated with lack of legal status lead to misallocation of talent and negatively affect economic growth. In addition, occupational barriers entail a wasteful use of resources, particularly in the case of Dreamers, many of whom have attended public schools and may have also enjoyed in-state college tuition.[13] Thus, providing legal status to undocumented workers is likely to increase the productivity of these workers and lead to net economic gains.

[13]Since 2014, several states (such as California and New York) have taken action against this waste of resources and have adopted changes in licensure requirements to allow DACA recipients access to these occupations (Calvo (2017)).

References

Abrego, Leisy J, "Legal consciousness of undocumented Latinos: Fear and stigma as barriers to claims-making for first-and 1.5-generation immigrants," *Law & Society Review*, 2011, *45* (2), 337–370.

Amuedo-Dorantes, Catalina and Francisca Antman, "Schooling and labor market effects of temporary authorization: evidence from DACA," *Journal of Population Economics*, January 2017, *30* (1), 339–373.

Baker, Bryan C. and Nancy Rytina, "Estimates of the Unauthorized Immigrant Population Residing in the United States: January 2012," 2013. Washington, DC: Of ce of Immigration Statistics, Policy Directorate, US Department of Homeland Security. http://www.dhs.gov/sites/default/ les/publications/ois_ill_pe_2012_2.pdf.

Bertrand, Marianne, Sandra E. Black, Sissel Jensen, and Adriana Lleras-Muney, "Breaking the Glass Ceiling? The Effect of Board Quotas on Female Labor Market Outcomes in Norway," NBER Working Papers 20256, National Bureau of Economic Research, Inc June 2014.

Blair, Peter and Bobby Chung, "OccupationalLicensingReducesRacialandGenderWageGaps:EvidencefromtheSurveyofIncomeandProgramParticipation," Technical Report 2017.

Bleakley, Hoyt and Aimee Chin, "Age at Arrival, English Proficiency, and Social Assimilation among US Immigrants," *American Economic Journal: Applied Economics*, January 2010, *2* (1), 165–192.

Brown, J. David, Julie L. Hotchkiss, and Myriam Quispe-Agnoli, "Does employing undocumented workers give firms a competitive advantage?," *Journal of Regional Science*, 2013, *53* (1), 158–170.

Calvo, Janet, "Professional Licensing and Teacher Certification for Non-Citizens: Federalism, Equal Protection And A States Socio-Economic Interests," *Columbia Journal of Race and Law*, 2017, *8* (1).

Center for Migration Studies, "Estimates of the Unauthorized Population," 2014. Dataset based on the augmented American Community Survey datafiles hosted by IPUMS (Integrated Public Use Microdata Series), 2010 to 2014.

Chiswick, Barry R, "Speaking, Reading, and Earnings among Low-Skilled Immigrants," *Journal of Labor Economics*, April 1991, *9* (2), 149–170.

Chiswick, Barry, Yew Lee, and Paul Miller, "Family matters: the role of the family in immigrants' destination language acquisition," *Journal of Population Economics*, November 2005, *18* (4), 631–647.

Cho, Esther Yoona, "Revisiting Ethnic Niches: A Comparative Analysis of the Labor Market Experiences of Asian and Latino Undocumented Young Adults," *RSF*, 2017.

Conger, Dylan and Colin C. Chellman, "Undocumented College Students in the United States: In-State Tuition Not Enough to Ensure Four-Year Degree Completion," *Education Finance and Policy*, July 2013, *8* (3), 364–377.

Edwards, Ryan and Francesc Ortega, "The Economic Contribution of Unauthorized Workers: An Industry Analysis," *Regional Science and Urban Economics*, 2017, *67*, 119–134.

Gleeson, Shannon and Roberto G. Gonzales, "When Do Papers Matter? An Institutional Analysis of Undocumented Life in the United States," *International Migration*, 2012, *50* (4), 1–19.

Gonzales, Roberto G., "Learning to Be Illegal: Undocumented Youth and Shifting Legal Contexts in the Transition to Adulthood," *American Sociological Review*, 2011, *76* (4), 602–619.

Hainmueller, Jens, Duncan Lawrence, Linna Martén, Bernard Black, Lucila Figueroa, Michael Hotard, Tomás R Jiménez, Fernando Mendoza, Maria I Rodriguez, Jonas J Swartz et al., "Protecting unauthorized immigrant mothers improves their childrens mental health," *Science*, 2017, *357* (6355), 1041–1044.

Hall, Matthew and Emily Greenman, "The Occupational Cost of Being Illegal in the United States: Legal Status, Job Hazards, and Compensating Differentials," *International Migration Review*, 2015, *49* (2), 406–442.

— , — , and George Farkas, "Legal Status and Wage Disparities for Mexican Immigrants," *Social Forces*, 2010, *89* (2), 491–513.

Hsieh, Chang-Tai, Erik Hurst, Charles I. Jones, and Peter J. Klenow, "The Allocation of Talent and U.S. Economic Growth," NBER Working Papers 18693, National Bureau of Economic Research, Inc January 2013.

Hsin, Amy and Francesc Ortega, "The Effects of Deferred Action for Childhood Arrivals on the Educational Outcomes of Undocumented Students: Evidence from a Large Public University," Technical Report 2016.

— and Holly Reed, "The Effect of Immigration Status on the Educational Outcomes of Undocumented College Students," Technical Report 2018.

Kleiner, Morris M. and Alan B. Krueger, "Analyzing the Extent and Influence of Occupational Licensing on the Labor Market," *Journal of Labor Economics*, 2013, *31* (S1), 173–202.

— and Evgeny Vorotnikov, "Analyzing occupational licensing among the states," *Journal of Regulatory Economics*, October 2017, *52* (2), 132–158.

Kossoudji, Sherrie A., "Back to the Future: the Impact of Legalization Then and Now," Technical Report 2013.

— and Deborah A. Cobb-Clark, "Coming out of the Shadows: Learning about Legal Status and Wages from the Legalized Population," *Journal of Labor Economics*, July 2002, *20* (3), 598–628.

Kuka, Elira, Na'ama Shenhav, and Kevin Shih, "Do Human Capital Decisions Respond to the Returns to Education? Evidence from DACA," NBER Working Papers 24315, National Bureau of Economic Research, Inc February 2018.

Lozano, Fernando A. and Todd A. Sorensen, "The Labor Market Value to Legal Status," IZA Discussion Papers 5492, Institute for the Study of Labor (IZA) February 2011.

Naidu, Suresh, Yaw Nyarko, and Shing-Yi Wang, "Monopsony Power in Migrant Labor Markets: Evidence from the United Arab Emirates," *Journal of Political Economy*, 2016, *124* (6), 1735–1792.

Orrenius, Pia M. and Madeline Zavodny, "The impact of E-Verify mandates on labor market outcomes," *Southern Economic Journal*, 2015, *81* (4), 947–959.

Ortega, Francesc, Ryan Edwards, and Amy Hsin, "The Economic Effects of Providing Legal Status to DREAMers," IZA Discussion Papers 11281, Institute for the Study of Labor (IZA) January 2018.

Passel, Jeffrey S. and D'Vera Cohn, "Share of Unauthorized Immigrant Workers in Production, Construction Jobs Falls Since 2007: In States, Hospitality, Manufacturing and Construction are Top Industries," March 26 2015. Washington, D.C.: Pew Research Center.

— and Rebecca L. Clark, "Immigrants in New York: Their Legal Status, Incomes and Taxes," 1998. Washington, DC: Urban Institute.

Pastor, Manuel and Justin Scoggins, "Estimating the Eligible-to-Naturalize Population," March 8 2016. Center for the Study of Immigrant Integration.

Patler, Caitlin and Whitney Laster Pirtle, "From undocumented to lawfully present: Do changes to legal status impact psychological wellbeing among latino immigrant young adults?," *Social Science Medicine*, 2018, *199*, 39 – 48. The role of Racism in Health Inequalities: Integrating Approaches from Across Disciplines.

Peri, Giovanni and Chad Sparber, "Task Specialization, Immigration, and Wages," *American Economic Journal: Applied Economics*, July 2009, *1* (3), 135–169.

Pope, Nolan G., "The Effects of DACAmentation: The Impact of Deferred Action for Childhood Arrivals on Unauthorized Immigrants," *Journal of Public Economics*, 2016, *143* (C), 98–114.

Van Hook, Jennifer, James D. Bachmeier, Donna L. Coffman, and Ofer Harel, "Can We Spin Straw Into Gold? An Evaluation of Immigrant Legal Status Imputation Approaches," *Demography*, February 2015, *52* (1), 329–354.

Warren, Robert, "Democratizing Data about Unauthorized Residents in the United States: Estimates and Public-Use Data, 2010 to 2013," *Journal on Migration and Human Security*, December 2014, *2* (4), 305–328.

— and John Robert Warren, "Unauthorized Immigration to the United States: Annual Estimates and Components of Change, by State, 1990 to 2010," *International Migration Review*, Summer 2013, *47* (2), 296–329.

Wong, Tom K., "New Study of DACA Beneficiaries Shows Positive Economic and Educational Outcomes," Technical Report 2016.

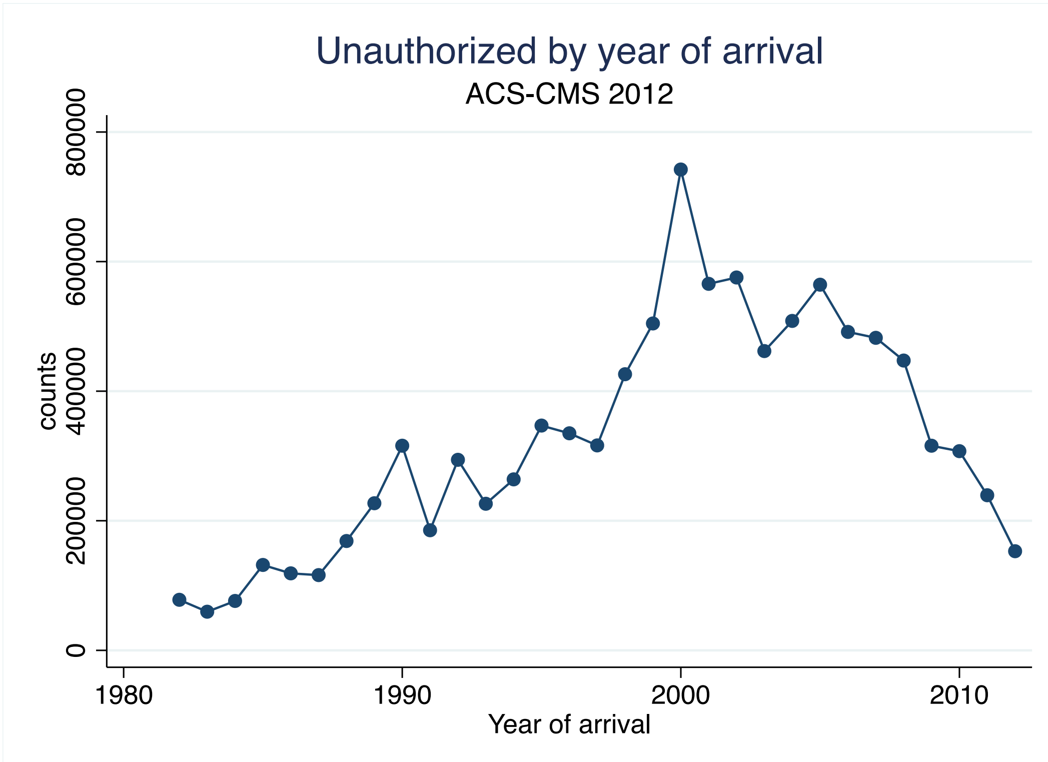

Table 1: Over-qualification rates for full-time employed by documentation status.

	All	HSD	HSG	CoG
Documented	0.30	0	0.48	0.45
Undocumented	0.18	0	0.75	0.70
Dreamers	0.10	0	0.62	0.67

Notes: CMS-ACS 2010-2012. Full-time, employed individuals age 28-37. Dreamers defined as likely undocumented individuals arrived in the United States at age 17 or younger. High-school dropouts did not complete 12th grade (or obtained a GED). College graduates have at least 4 years of college. Survey weights used.

Table 2: Overqualification rates by occupation. Undocumented workers

OCC	Occ. description	Count Undoc.	overqualif. rate
1020	Software developers	1886	0.63
3600	Nursing, Psychiatric, and Home Health Aides	1358	0.39
4720	Cashiers	2168	0.27
4110	Waiters and waitresses	1607	0.25
4760	Retail salesperson	1167	0.25
5620	Stock clerks	1193	0.19
9130	Driver/Sales workers and truck drivers	2268	0.16
4230	Maids and Housekeeping Cleaners	2947	0.14
4220	Janitors and Building Cleaners	3381	0.12
7750	Miscellaneous Assemblers and Fabricators	1240	0.12
4030	Food Preparation Workers	1370	0.11
8965	Other production workers	2051	0.11
4020	Cooks	5607	0.11
9620	Laborers and Freight, Stock, and Material Movers, Hand	2346	0.10
6230	Carpenters	2282	0.09
6420	Painters, Construction and Maintenance	1645	0.08
6260	Construction Laborers	4253	0.07
9640	Packers and Packagers, Hand	1605	0.07
4250	Grounds	3963	0.05
6050	Misc. agricultural workers	5450	0.04

Notes: CMS-ACS 2010-2012. Full-time, employed individuals older than 18. Undocumented workers only. We restricted to the top 20 occupations by number of undocumented workers employed. Then sorted by overqualification rate. No weights used.

Table 3: Summary statistics 2010-2012

Variable	Obs	Mean	Std. Dev.	Min	Max
Year	2,763,238	2011.001	.819	2010	2012
Undocumented	2,763,238	.035	.185	0	1
Dreamer	2,763,238	.008	.089	0	1
Over-qualified	2,763,238	.269	.443	0	1
Log hourly wage	2,763,252	6.822	.772	-3.209	9.806
Age 18-27	2,763,238	.114	.318	0	1
Age 28-37	2,763,238	.21	.407	0	1
Age 38-47	2,763,238	.247	.431	0	1
Age 48-57	2,763,238	.275	.447	0	1
Age 58-67	2,763,238	.138	.345	0	1
Age 68-77	2,763,238	.016	.127	0	1
Female	2,763,238	.454	.498	0	1
HSD	2,763,238	.066	.249	0	1
HSG	2,763,238	.234	.423	0	1
COG4	2,763,238	.352	.478	0	1
English fluent	2,763,238	.922	.268	0	1
Origin south or central America	2,763,238	.066	.249	0	1
Origin Europe	2,763,238	.022	.146	0	1
Origin Asia or Oceania	2,763,238	.048	.213	0	1
Origin Africa	2,763,238	.005	.074	0	1
Arrival by age 10	2,763,538	.029	.168	0	1

Notes: Pooled data for the CMS-ACS for period 2010-2012. Unweighted statistics. The sample restricts to full-time employed individuals (with over 30 weekly work hours), older than 18 years old. HSD is an indicator for high-school dropouts, HSG is an indicator for high-school graduation (but no more education) and COG4 is an indicator for having completed at least 4 years of college. All US-born individuals are assumed to be fluent in English and to have arrived in the U.S. before the age of 10.

Table 4: Estimates

Ln hourly wage	1	2	3	4	5	6
All Undocumented						
Undoc	-0.54***	-0.53***	-0.25***	-0.08***	-0.03***	-0.01
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]
$Undoc \times Overq$						-0.12***
						[0.01]
R-squared	0.025	0.142	0.3	0.303	0.414	0.414
Dreamers						
Dreamer	-0.64***	-0.41***	-0.07***	0.07***	0.07***	0.08***
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
$Dreamer \times Overq$						-0.13***
						[0.01]
R-squared	0.009	0.123	0.294	0.307	0.414	0.414
Observations	2,763,252	2,763,252	2,763,252	2,763,252	2,763,252	2,763,252
Number of occ					491	491
Fixed-Effects						
Age, gender, state	No	Yes	Yes	Yes	Yes	Yes
Education	No	No	Yes	Yes	Yes	Yes
Additional controls	No	No	No	Yes	Yes	Yes
Occupation	No	No	No	No	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Pooled data for the CMS-ACS for period 2010-2012. The sample restricts to full-time employed individuals (with over 30 weekly work hours), older than 18 years old. The dependent variable is the hourly wage in logs. In panel 1 the *Undoc* indicator takes a value of one for likely undocumented individuals. In panel 2, indicator *Dreamer* identifies Dreamers, defined as likely undocumented who arrived in the country at age 17 or younger. The first set of controls is: age dummies 28-37, 38-47, 48-57 and 68-77 (with omitted category age 18-27), a female dummy, and state of residence dummy variables. The second set of controls includes continent of origin dummies, an indictor for english fluency (taking a value of one for native English speakers of very good command of English), and an indicator for having arrived in the country before the age of 10 (taking the value of one for all US-born individuals). Educational fixed-effects based on 10 educational categories starting with no schooling and ending with 5 or more years of college education. Occupational fixed-effects based on 3-digit occupations. Columns 5 and 6 include dummy for overqualified as a regressor. Regressions are weighted using the (population) survey weights adjusted to match the aggregate counts of undocumented nationwide and the foreign-born population by origin country and state of residence. Heteroskedasticity-robust standard errors reported in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Robustness: excluding under-qualified

Ln hourly wage	1	2	3	4	5	6
Undoc	-0.42***	-0.42***	-0.27***	-0.10***	-0.05***	-0.02***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
$Undoc \times Overq$						-0.09***
						[0.01]
R-squared	0.007	0.135	0.323	0.329	0.434	0.434
Dreamers						
Undoc	-0.68***	-0.42***	-0.15***	0.02**	0.03***	0.05***
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
$Undoc \times Overq$						-0.10***
						[0.00]
R-squared	0.004	0.13	0.32	0.329	0.434	0.434
Observations	1,952,901	1,952,901	1,952,901	1,952,901	1,952,901	1,952,901
Number of occ					491	491
Fixed-Effects						
Age, gender, state	No	Yes	Yes	Yes	Yes	Yes
Education	No	No	Yes	Yes	Yes	Yes
Additional controls	No	No	No	Yes	Yes	Yes
Occupation	No	No	No	No	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Pooled data for the CMS-ACS for period 2010-2012. The sample restricts to full-time employed individuals (with over 30 weekly work hours), older than 18 years old. Compared to Table 4, we have dropped *under-qualified* individuals, defined as those with lower educational attainment than typical among documented workers in that same occupation. The dependent variable is the hourly wage in logs. In panel 1 the *Undoc* indicator takes a value of one for likely undocumented individuals. In panel 2, indicator *Dreamer* identifies Dreamers, defined as likely undocumented who arrived in the country at age 17 or younger. The first set of controls is: age dummies 28-37, 38-47, 48-57 and 68-77 (with omitted category age 18-27), a female dummy, and state of residence dummy variables. The second set of controls includes continent of origin dummies, an indictor for english fluency (taking a value of one for native English speakers of very good command of English), and an indicator for having arrived in the country before the age of 10 (taking the value of one for all US-born individuals). Educational fixed-effects based on 10 educational categories starting with no schooling and ending with 5 or more years of college education. Occupational fixed-effects based on 3-digit occupations. Columns 5 and 6 include dummy for overqualified as a regressor. Regressions are weighted using the (population) survey weights adjusted to match the aggregate counts of undocumented nationwide and the foreign-born population by origin country and state of residence. Heteroskedasticity-robust standard errors reported in brackets. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table 6: Gaps in occupational shares (×100): Documented vs. Undocumented workers.

Occ1990	Description	Unconditional Undoc-Doc	Conditional Undoc-Doc	Share Doc
Top 10				
23	Teachers (up to sec.)	-4.0	-22.6	4.4
32	Healthcare practitioners	-2.6	-19.1	2.7
4	Misc. Managers	-2.3	-9.9	3.2
57	Secretaries and Administrative Assistants	-2.2	-10.1	2.7
8	Financial specialists	-2.1	-14.0	2.3
48	Sales	-1.8	-8.6	2.5
1	Managers	-1.8	-8.0	2.6
20	Commuity and social services	-1.5	-7.9	1.9
47	Sales	-1.5	-8.6	6.3
38	Police, firefighters, security guards	-1.3	$-\infty$	1.3
Bottom 10				
89	Production workers	1.3	1.1	1.0
83	Textile workers	1.4	0.6	0.3
78	Food production	1.6	1.4	0.5
64	Insulation workers	2.2	1.9	0.6
41	Waiters, food servers and dishwashers	2.9	2.1	1.0
96	Transportation, movers and packers	3.6	2.7	2.3
60	Agricultural workers	4.9	3.8	0.5
62	Construction	7.1	6.4	2.1
40	Cooks	7.6	6.3	2.3
42	B&G cleaning and maintenance	8.8	9.8	3.0

Notes: Pooled data for the CMS-ACS for period 2010-2012. The sample restricts to full-time employed individuals (with over 30 weekly work hours), older than 18 years old. We divide the sample into Dreamers and non-Dreamers (including documented workers). For each (of the 99) 2-digit occupations, column 1 (unconditional gaps) reports the difference in the proportion of undocumented workers in an occupation and the proportion of documented workers in that same occupation, computed using sampling weights. Column 2 (conditional gaps) is based on the estimation of occupation-specific (2-digit) binomial Probits for the probability that an individual is employed in each specific occupation. In addition to undocumented (or Dreamer) status, the regressors are: controls for age (using dummies for 28-37, 38-47, 48-57 and 68-77 year-olds (with omitted category age 18-27), a female dummy, state of residence dummy variables, and educational fixed-effects based on 10 educational categories. Estimation employs survey weights adjusted to match the aggregate counts of undocumented nationwide and the foreign-born population by origin country and state of residence. We report the average marginal effect of undocumented (or Dreamer) status, using sampling weights. The figures reported in this column should be interpreted as the change in the probability of employment in that occupation associated to undocumented status. No undocumented are employed in occupation 38 (Police, firefighters and security guards).

Table 7: Gaps in occupational shares ($\times 100$): Dreamers vs. non-Dreamers.

Occ1990	Description	Unconditional Undoc-Doc	Conditional Undoc-Doc	Share Doc
Top 10				
23	Teachers (up to sec.)	-4.2	-25.5	4.4
32	Healthcare practitioners	-2.7	-22.5	2.7
4	Misc. Managers	-2.5	-9.8	3.2
8	Financial specialists	-2.2	-16.7	2.3
1	Managers	-2.0	-8.6	2.6
57	Secretaries and Administrative Assistants	-2.0	-7.3	2.7
10	Computer occupations	-1.7	-9.1	2.3
48	Sales	-1.7	-8.2	2.5
20	Community and social services	-1.6	-9.0	1.9
38	Police, firefighters, security guards	-1.3	$-\infty$	1.3
Bottom 10				
65	Metal workers and roofers	1.0	0.7	0.2
89	Production workers	1.4	1.0	1.0
78	Food production	1.6	1.2	0.5
64	Insulation workers	2.5	1.9	0.6
41	Waiters, food servers and dishwashers	3.5	1.4	1.0
96	Transportation, movers and packers	4.3	2.2	2.3
60	Agricultural workers	5.8	3.2	0.5
42	B&G cleaning and maintenance	7.0	7.7	3.0
40	Cooks	7.8	4.3	2.3
62	Construction	8.3	6.6	2.1

Notes: Pooled data for the CMS-ACS for period 2010-2012. The sample restricts to full-time employed individuals (with over 30 weekly work hours), older than 18 years old. We divide the sample into Dreamers and non-Dreamers (including documented workers). For each (of the 99) 2-digit occupations, column 1 (unconditional gaps) reports the difference in the proportion of undocumented workers in an occupation and the proportion of documented workers in that same occupation, computed using sampling weights. Column 2 (conditional gaps) is based on the estimation of occupation-specific (2-digit) binomial Probits for the probability that an individual is employed in each specific occupation. In addition to undocumented (or Dreamer) status, the regressors are: controls for age (using dummies for 28-37, 38-47, 48-57 and 68-77 year-olds (with omitted category age 18-27), a female dummy, state of residence dummy variables, and educational fixed-effects based on 10 educational categories. Estimation employs survey weights adjusted to match the aggregate counts of undocumented nationwide and the foreign-born population by origin country and state of residence. We report the average marginal effect of undocumented (or Dreamer) status, using sampling weights. The figures reported in this column should be interpreted as the change in the probability of employment in that occupation associated to undocumented status. No undocumented are employed in occupation 38 (Police, firefighters and security guards).

Appendix

Table 8: Full-time employed by documentation status

year	Undoc	Dreamers	Undoc/All	Dreamers/All
2010	5,126,668	1,178,365	5.4%	1.2%
2011	5,065,635	1,180,535	5.3%	1.2%
2012	5,093,545	1,193,015	5.2%	1.2%
2013	5,135,646	1,249,600	5.1%	1.3%
2014	5,156,098	1,305,851	5.1%	1.3%

Notes: CMS-ACS 2010-2014. Full-time, employed individuals older than 18. Dreamers defined as likely undocumented individuals arrived in the United States at age 17 or younger. Survey weights used.