The Economic Contribution of Unauthorized Workers: An Industry Analysis

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Abstract

This paper provides a quantitative assessment of the economic contribution of unauthorized workers to the U.S. economy, and the potential gains from legalization. We employ a theoretical framework that allows for multiple industries and a heterogeneous workforce. Capital and labor are the inputs in production and the different types of labor are combined in a multi-nest CES framework that builds on Borjas (2003) and Ottaviano and Peri (2012). The model is calibrated using data on the characteristics of the workforce, including an indicator for imputed unauthorized status (Center for Migration Studies, 2014), and industry output from the BEA. Our results show that the economic contribution of unauthorized workers to the U.S. economy is substantial, at approximately 3% of private-sector GDP annually, which amounts to close to $5 trillion over a 10-year period. These effects on production are smaller than the share of unauthorized workers in employment, which is close to 5%. The reason is that unauthorized workers are less skilled and appear to be less productive, on average, than natives and legal immigrants with the same observable skills. We also find that legalization of unauthorized workers would increase their contribution to 3.6% of private-sector GDP. The source of these gains stems from the productivity increase arising from the expanded labor market opportunities for these workers which, in turn, would lead to an increase in capital investment by employers.

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1 Introduction

There is wide consensus that the problem of the large unauthorized population in the United States needs to be addressed soon.[1] A crucial input into the debate is an assessment of the economic contribution of unauthorized workers, and the potential gains from legalizing these workers. The main goal of our project is to offer such a quantitative assessment using a state-of-the-art theoretical framework that accounts for the large heterogeneity in the characteristics of the unauthorized workers that we observe in the data, and for the complementarities in production between these workers and the rest of the workforce.

More specifically, we adopt the multi-nest CES theoretical framework proposed by Borjas (2003) and Ottaviano and Peri (2012), and adapt it to analyze the contributions to output of unauthorized workers at the industry level. We calibrate the model using data from a special extract of the American Community Survey (years 2011-2013) provided by the Center for Migration Studies (2014), which contains a variable that assigns documentation status to all foreign-born workers in the sample along with detailed information on employment, skills and wages, and the Bureau of Economic Analysis' National Accounts.[2] We then conduct simulations to quantify the economic contribution of unauthorized workers to the level of production in the industry. We do so by comparing industry output as currently observed in the data to output in a counterfactual without unauthorized workers. Similarly, we also conduct simulations of the economic effects of providing legal status to these workers. We distinguish between short and long-run effects, where the latter scenario takes into account the adjustment to the capital stock following changes in the workforce.

A large body of literature has analyzed the labor market effects of immigration. Most studies in this literature estimate reduced-form models or econometric specifications derived from highly simplified models. In a very influential study, Borjas (2003) presented a multi-nest CES production model that emphasized the role of complementarities in production and allowed for a clear discussion of within and between skill group effects. Manacorda et al. (2012) and Ottaviano and Peri (2012) further extended the theoretical setup to allow for imperfect substitution in production between natives and immigrants with the same education and potential experience. We adopt their theoretical framework, extend it to consider documentation status, adding a new level to the multi-nest

[1] Several European countries also have, or have had in the recent past, a large unauthorized population within their borders. For a recent review, see Orrenius and Zavodny (2016).

[2] We describe these data and the documentation status imputation in Section 2.

CES framework. As we argue later, for our purpose of estimating the contribution of unauthorized workers to production, the calibration of the productivity terms for each type of labor is much more important quantitatively than the parametrization of the elasticities of substitution.

Our work is also related to the studies that estimate the effects of legalization and naturalization. The vast majority of these studies focus on the effects on the earnings of immigrants (Chiswick (1978), Bratsberg et al. (2002), Kossoudji and Cobb-Clark (2002), Lofstrom et al. (2013), Lynch and Oakford (2013), and Pastor and Scoggins (2012), among others). Instead our focus is on overall income and output at the industry level.

Relative to the existing literature, our analysis of the economic contribution of unauthorized workers is novel in several dimensions. First, we focus on the effects on the level of production at the industry level. Second, our analysis is based on a fully specified economic model that we calibrate using a combination aggregate and individual level data. This model accounts for the degree of complementarities in production between different types of workers, and allows us to assess the role played by these somewhat controversial parameters on the results. In addition we show that the model can be calibrated to incorporate the large heterogeneity among the unauthorized workforce in terms of skills and productivity. Finally, an important benefit of our structural approach is that we can simulate policy-relevant counterfactual scenarios, such as the removal of unauthorized workers or their legalization. To the best of our knowledge, our study is the first one providing estimates of the contribution of unauthorized workers along with the potential gains from providing legal access to these workers.

Our descriptive analysis of the data reveals some interesting patterns that play an important role in our simulation results. First, we document the large variation across industries in the share of unauthorized workers. Specifically, in the period 2011-2013 the share of unauthorized workers in employment is highest in Agriculture (18%), Construction (13%) and Leisure and hospitality (10%), well above the national average of 4.9%. Our data also reveal important differences in average wages by industry, nativity and documentation status. In most industries legal immigrants and natives have similar earnings, while the earnings of unauthorized workers are substantially lower. Naturally, these wage differences reflect, to a large extent differences in skills. In our data unauthorized immigrants have an average of 3 years of schooling less than the average U.S.-born and legal immigrant worker. Nonetheless unauthorized workers are not a homogeneous group, displaying large differences in educational attainment by industry of employment.

Turning to our main results, the simulation of the counterfactual where unauthorized workers are removed from each industry at a time reveals that these workers are responsible for about 3% of private-sector GDP, which amounts to approximately $5 trillion over a 10-year period. At first the removal of unauthorized workers would reduce aggregate production by about 1.7%, but the loss would be magnified as employers downsize the stock of capital in order to match the reduced workforce. These aggregate estimates hide large differences across industries, largely reflecting the shares of unauthorized workers in industry employment. Once capital has adjusted, value-added in Agriculture, Construction and Leisure and hospitality would fall by 8-9%. However, the largest losses in dollars would take place in Manufacturing, Wholesale and retail trade, Finance and Leisure and hospitality. Likewise we also find large differences across states that largely reflect the employment shares of unauthorized workers in each state, along with the state's industry specialization.

We also note that even though unauthorized workers are about 5% of employment, their contribution to private-sector GDP is around 3%. This is due to differences in productivity between these workers and the rest of the workforce. While part of the productivity differential is due to the lower measured skills, our calibration procedure also reveals large residual differences in productivity, after controlling for measured educational attainment and potential experience.

In order to gauge the role played by the challenges imposed by the lack of legal status on the productivity of unauthorized workers, we simulate a scenario where unauthorized workers are assumed to have the same productivity as legal immigrant workers with the same levels of education and potential experience.[3]

Because documented foreign-born workers are about 25% more productive than undocumented ones with the same levels of education and experience, legalization would have a large effect on the earnings of undocumented workers. The consequences in terms of industry production would be much more muted. After adjustments in the stock of capital, industry GDP would increase by 1-2% in Agriculture, Construction and Leisure and hospitality. For the economy as a whole, our results suggest an increase in private-sector GDP of about 0.6%.

The structure of the paper is as follows. In Section 2 we describe our data. Section 3 presents descriptive statistics. Section 4 describes our model. Section 5 describes our calibration of the parameters. Section 6 defines our counterfactual scenarios, while

[3] To the extent that acquiring legal status might induce undocumented immigrant workers to acquire more human capital or switch industry of employment, our estimates should be interpreted as a lower-bound on the economic effects of legalization. Indeed Rivera-Batiz (1999) provides some evidence of skill upgrading following legalization.

Section 7 reports our main results. Section 8 discusses some caveats and Section 9 gathers our conclusions.

2 Data

2.1 Sources

Most of our analysis draws from special extracts of the American Community Survey (ACS) of the U.S. Census Bureau for the years 2011, 2012, and 2013 provided by the Center for Migration Studies (2014). Our pooled sample across these three years contains 9,357,842 individuals in total, 4,154,227 of whom report employment.

The key variable in our analysis is an individual-level measure of *imputed undocumented status*. Although the ACS does not ask about legal status per se, it does ask about citizenship, country of birth, and year of immigration, in addition to a wide array of demographic and socioeconomic characteristics including employment status. The procedure is essentially a two-step process (Warren (2014)).[4] In the first step, the overall size of the undocumented population is obtained starting from Census estimates of total foreign-born residents and subtracting accumulated counts of legalized foreign born residents drawn from official statistics kept by the U.S. Department of Homeland Security. The second step imputes documentation status at the individual level, chiefly using information on year of arrival (because of the 1986 IRCA amnesty), country of origin, occupation, industry, and receipt of government benefits. Workers with certain occupations that require licensing, such as legal professions, police and fire, and some medical professions, are assumed to be authorized, as well as individuals in government or in the military.[5]

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, indicating "face validity" (Warren, 2014).[6] The broader validity of these types of estimates is less clear. Assessments remain constrained by lack of large representative

[4] 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 (2014, 2015).

[5] Anecdotal evidence shows that there are some unauthorized workers in these industries, particularly in the military. Nevertheless the size of this group is negligible.

[6] In a recent study, Pastor and Scoggins (2016) provide a comparison between several of the existing approaches to estimate the unauthorized population or subsets of it. Reassuringly, the results are fairly consistent across these studies. Likewise, the imputation carried out by Borjas (2016) also provides additional confirmation.

surveys that ask legal status.[7]

In addition to these data, our calibration also makes use of the GDP estimates produced by the Bureau of Economic Analysis (BEA). Our industry definitions consist of conventional "one-digit" industries identified via the North American Industry Classification System (NAICS) as used by Passel and Cohn (2015) and others. Specifically, we focus on the industries 1-12 below, which are often referred to as private-sector GDP: (1) Agriculture, forestry, fishing, hunting, (2) Mining, (3) Construction, (4) Manufacturing, (5) Wholesale and retail trade, (6) Transportation and utilities, (7) Information, (8) Financial activities, (9) Professional and business services, (10) Educational and health services, (11) Leisure and hospitality, (12) Other services, and (13) *Government*.[8]

2.2 Sample definitions

Because the calibration of our model will draw from Ottaviano and Peri (2012), we build skill cells closely following their definitions. We classify workers within each industry (and state) as belonging to one out of 96 possible categories on the basis of their education, potential experience, nativity and documentation status. We consider 4 educational groups: individuals with either 0–11 years, 12 years, 13–15 years, or 16 years and more of schooling. Potential experience measures years since the last year of schooling, and we build 8 categories: 1–5, 6–10, 11–15, 16–20, 21–25, 26–30, 31–35, or 36–40 years.

To build our samples we pool observations across the 2011, 2012, and 2013 waves of the ACS data in the CMS extracts, taking simple averages of quantities within each cell and weighted averages of dollar amounts converted to 2013 dollars using the consumer price index. We build two slightly different samples.

Following Ottaviano and Peri, our **wage sample** drops individuals with potential experience less than 1 or greater than 40, eliminating workers at the extremes of the age distribution. We further eliminate individuals living in group quarters, those younger than 18, those who reported not working last year, those who did not report valid

[7] 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. Using the SIPP as their baseline of truth, Van Hook et al. (2015) show that imputed legal status within Census products such as ACS can produce significant bias in estimates of outcomes that are directly linked to legal status, such as health insurance coverage. For our purposes this concern is probably less relevant.

[8] Combined these thirteen industries produce all of national GDP. As we discussed earlier, our imputations of authorized status assume that there are no undocumented workers in public administration or the military, so we omit this industry from consideration.

salary income, and the self-employed. We use the wage sample to calibrate the worker productivity parameters in the model.

Our **employment sample** is more inclusive and includes all valid observations of employed workers within the ACS. In this sample definition, we treat experience groupings as bottom and top-coded, including those with less than 1 year of potential experience into the first experience group and those with more than 40 years into the top experience group. The worker counts (and hours worked) obtained from this sample will be the basis for the construction of our labor aggregates in each industry (and state).

3 Descriptive statistics

There is great heterogeneity in the distribution of unauthorized workers across industries and states in the United States. While the share of undocumented workers in employment is 4.9 percent for the U.S. as a whole, this figure is much higher in some states. In California, the employment share of undocumented workers is 10.2 percent, and it ranges between 6.2 and 8.7 percent in Texas, Nevada, New Jersey and New York.[9]

Likewise, the distribution of unauthorized workers across industries varies widely, as illustrated by Table 1. Of the roughly 7.1 million undocumented foreign-born workers in the U.S. in 2011–2013, the largest concentrations are found in the Leisure and Hospitality sector (1.3 million), Construction (1.1 million), Professional and Business services (1.0 million), and Manufacturing (0.9 million). However, the industries with the highest undocumented shares are Agriculture (18 percent),[10] Construction (13 percent), and Leisure and Hospitality (10 percent), as can be seen in column 4.[11] In other industries, the undocumented are smaller shares of total employment, but they are never absent altogether except from Government (due to the design of the imputation procedure). Even in industries with relatively high education requirements, such as Finance and Information, undocumented immigrants account for about 2 percent of the workforce.

Although their numbers and shares of unauthorized immigrants have been declining in recent years (Passel and Cohn, 2014), roughly half of unauthorized immigrants are Mexican. Table 2 reports a breakdown of unauthorized workers by national origin

[9]In absolute numbers, the five states with the most undocumented workers are California, Texas, New York, Florida, and Illinois (Table 12).

[10]The foreign-born share in Agriculture may be substantially higher than the ACS implies because of the high prevalence of seasonal workers.

[11]Note also that these shares are practically unchanged if we compute them on the basis of hours worked (as in column 6), rather than employment.

(Mexico, Central and South America, Asia and Others) and industry. According to our data 3.8 million unauthorized workers (55% of the total) are Mexican, 1.8 million (26%) originate from Central and South America, and 0.9 million from Asia (13%). The industries employing the highest numbers of unauthorized Mexican workers are Leisure and Hospitality (0.78 million) and Construction (0.74 million). These two industries also employ the highest numbers of Central and South American unauthorized workers. In contrast, the industries that employ the highest numbers of Asian unauthorized workers are Professional and business services (0.17 million), Leisure and hospitality (0.14 million) and Wholesale and retail trade (0.14 million).

Our data also reveal large difference in weekly earnings across industries, nativity and documentation status. As displayed in Table 3, on average across all industries, the weekly wages for U.S.-born workers are $1,039. Legal immigrants earn, on average, slightly more ($1,050). In comparison the earnings of unauthorized workers are about 40 percent lower ($581 per week). This ordinal ranking of wages is observed in several industries, although natives earn on average more than legal immigrants in some industries. In Agriculture, the weekly earnings of natives, documented foreign-born and undocumented foreign-born are $734, $491 and $378. Likewise in Construction natives earn $962, compared to $803 and $510 for documented and undocumented immigrants, respectively. In contrast, in Educational and health services, the highest earnings correspond to legal immigrants ($1,115), followed by natives ($962) and by undocumented immigrants ($641).

It is also interesting to scrutinize further the large variation in the average weekly wages earned by unauthorized workers across industries, shown in the rightmost column of Table 3. Across industries we observe large differences, ranging from the roughly $400 paid in Agriculture and Leisure and hospitality to these workers, to the approximately $1,300 paid in the Information sector.

To some extent these differences in average wages are due to the higher concentration of undocumented workers in low-wage industries, such as Leisure and hospitality or Agriculture. As one would expect, the differences in average wages that remain when we condition on industry of employed are partly due to differences in educational attainment and in (potential) work experience. As documented in Table 4, native and foreign-born workers with legal status have, respectively, 13.9 and 13.3 years of education, which is almost 3 years more than the average undocumented worker (10.6 years). Similarly, native and legal foreign-born workers have 3.4 and 5.8 years of potential experience more than undocumented immigrants (Table 5). Nonetheless, as we discuss later (in the calibration), residual productivity differences also play an important role in accounting for wage differences by nativity and documentation status, after accounting for industry of employment, and measured education and potential experience.

4 Theoretical framework

The economy consists of $j = 1, ..., J$ industries. Output in industry j is produced by means of a constant-returns Cobb-Douglas production function:

$$Y_j = A_j K_j^{\alpha_j} L_j^{1-\alpha_j}, \tag{1}$$

where $\alpha_j \in (0, 1)$ is the capital share in industry j.

4.1 Labor Aggregate

Let us now describe in detail the labor aggregate, L, in the previous equation.[12] We allow workers to differ in education ($e = 1, ..., E$), potential years of work experience ($x = 1, ..., X$), nativity (U.S.-born or foreign-born) and, if foreign-born, also by documentation status. In total the number of labor types is given by $3 \times E \times X$.

We aggregate all these types of workers by means of a multi-nested constant-elasticity of substitution (CES) aggregator.[13] To construct the labor aggregate we need data on the number of workers in each industry by education, experience, nativity, and documentation status. We denote the vector of data by $\mathbf{V} = \{Nat, DFB, UFB\}$, where Nat, DFB, and UFB stand for the counts (or hours worked) of native workers, documented foreign-born (DFB), and undocumented foreign-born (UFB). In addition we need values for an array of worker productivity terms $\Theta = \{\theta\}$, one for each worker type and industry, 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, for each industry, the labor aggregate is given by four levels of CES aggregation, with potentially different elasticities of substitution. To maximize compa-

[12]To simplify our notation we now omit the industry j subindex.

[13]The use of this multi-nest CES production function for the analysis of the economic effects of immigration was pioneered Borjas (2003) and later extended by Ottaviano and Peri (2012). In these studies the production function was assumed to apply to the economy as a whole.

rability with previous studies, we choose the following nesting structure:[14]

$$\begin{aligned}
L &= C(L_{e=1}, ..., L_{e=E}|\theta_e, \sigma_e) \\
L_e &= C(L_{e,x=1}, ..., L_{e,x=X}|\theta_{e,x}, \sigma_x), \text{ for } e = 1, 2, 3, E \\
L_{e,x} &= C(Nat_{e,x}, L^{FB}_{e,x}|\theta^{Nat}_{e,x}, \theta^{FB}_{e,x}, , \sigma_n), \text{ for } e = 1, ..., E \text{ and } x = 1, ..., X \\
L^{FB}_{e,x} &= C(DFB_{e,x}, UFB_{e,x}|\theta^{DFB}_{e,x}, \theta^{UFB}_{e,x}, \sigma_d), \text{ for } e = 1, ..., E \text{ and } x = 1, ..., X,
\end{aligned}$$

where the CES aggregator is defined by

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

In words, we have four levels of CES aggregation, depicted graphically in Figure 1. The fourth level aggregates the labor services of documented and undocumented foreign-born workers with the same education and experience. The third level aggregates the labor services of foreign-born and native workers with the same education and experience. The second level aggregates labor across experience groups, for a given education level, and the first level combines education groups. Each CES aggregator is parameterized by an elasticity of substitution and productivity coefficients for each labor input. One productivity term in each nest is normalized to unity.

We note that there are four relevant elasticities of substitution, collected in vector $\Sigma = (\sigma_e, \sigma_x, \sigma_n, \sigma_d)$. 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 through 4. The elasticities of substitution appearing in levels 1 through 3 have already been estimated by Ottaviano and Peri (2012). The elasticity of substitution between documented and undocumented foreign-born workers with the same education and potential experience has not been estimated in the literature, as far as we know.[15] Thus we will consider a range of different values and check our results for robustness.

Let us now discuss which parameters vary by industry and which do not. For industry j, the labor aggregate will be computed as follows: $L_j = L(V_j; \Theta_j, \Sigma)$. Namely, we shall assume that the elasticities of substitution estimated by Ottaviano and Peri (2012) apply

[14]This nesting structure is based on model A in Ottaviano and Peri (2012). The only difference is that we have introduced an additional layer that disaggregates the foreign-born population by documentation status. If documented and undocumented foreign-born workers are assumed to be perfect substitutes then this framework corresponds exactly to the one in Ottaviano and Peri (2012).

[15]Implicitly, previous studies have assumed it was infinity.

across all industries. Worker-type productivities and the counts of workers and hours worked, however, will vary by industry, as observed in the data.

4.2 Capital

Let us now turn to the stock of capital. We assume that employers have access to a perfectly elastic capital market, with a fixed rental rate $\overline{R}$. For our application it is conceptually helpful to distinguish between *short-run* and *long-run effects*. The key distinction between the two time horizons is whether the capital stock is assumed to remain fixed or adjusts over time.

In the long run, we assume that the capital stock adjusts over time so that when the workforce changes, the marginal product of capital in each industry adjusts so as to return to its original value ($\overline{R}$).

It is straightforward to verify that because of constant-returns to scale in the industry production functions, the long-run capital stock in each industry is proportional to the size of the labor aggregate, that is, $K_j = \overline{\kappa_j} L_j$.[16] As a result the long-run relationship between the labor aggregate and the level of output in an industry is given by

$$Y_j = B_j^{LR} L_j. \tag{2}$$

In contrast, we assume that the capital stock, K_j, is invariant to changes in labor in the short run. Thus the short-run relationship between output and labor will be given by

$$Y_j = A_j K_j^{\alpha_j} L_j^{1-\alpha_j} = \left(A_j K_j^{\alpha_j}\right) L_j^{1-\alpha_j} = B_j^{SR} L_j^{1-\alpha_j}. \tag{3}$$

These expressions show that changes in the workforce will affect industry output differently in the short and long runs, with the difference in the relative effects being entirely determined by the labor share in the industry, $1 - \alpha_j$. For instance, an increase (decrease) in the size of the workforce will typically lead to a smaller increase (decrease) in industry output in the short run than in the long run. The reason is that temporarily, production will have to be carried out with a sub-optimally low (high) stock of capital. Once the industry is able to resize its stock of capital, the full economic impact of the

[16] Let $\overline{R}$ denote the (constant) rate of returns of capital and MPK the marginal product of capital. Because of linear homogeneity in the production function, $\overline{R} = MPK(K_j, L_j) = MPK(\overline{\kappa_j}, 1)$. Thus capital per unit of labor will remain invariant to changes in the labor aggregate, once the capital stock has adjusted. As a result, we can write $Y = A\left(K(L)\right)^{\alpha} L^{1-\alpha} = \left(A\overline{\kappa_j}^{\alpha}\right) L = B^{LR} L$. Note that we also assume that total factor productivity is constant throughout.

change in the workforce will materialize. Because not all worker types are the same, the quantitative impact of a shock to the size of the workforce will not only depend on its overall size, but also on the skill composition of the new workers and on how substitutable they are with the rest of the workforce.[17]

5 Calibration

We need to assign values to the parameters of the model: $\{1-\alpha_j, B_j^{LR}, B_j^{SR}, \Theta_j, \Sigma\}$, where only the elasticities of substitution Σ are assumed to be equal across industries. In our calibration we will consider $J = 12$ industries, $E = 4$ levels of education and $X = 8$ potential experience brackets.

5.1 Elasticities of substitution

The first step consists in choosing values for the elasticities of substitution. As noted earlier, $(\sigma_e, \sigma_x, \sigma_n)$ have already been estimated in the literature. We follow Ottaviano and Peri (2012) and set $(\sigma_e, \sigma_x, \sigma_n) = (3, 6, 20)$. The elasticities of substitution across education groups and across experience groups (with a given education) are fairly uncontroversial. The elasticity of substitution between native and immigrant labor within education-experience cells is more disputed. Borjas (2003) assumes that this elasticity is infinite, whereas Manacorda et al. (2012) estimate it to be around 10 using data for the U.K. Thus our choice of a value of 20 seems reasonable. At any rate we will examine the sensitivity of our results to the value assumed for this parameter.

In contrast, the elasticity of substitution between documented and undocumented foreign-born workers (within education-experience cells), σ_d, is unknown. As far as we know, all previous studies have implicitly assumed this elasticity to be infinite. Accordingly, we pick a high value for this parameter ($\sigma_d = 1,000$), and will carry out sensitivity analysis.

5.2 Productivities by type of labor and labor aggregates

We follow a sequential process to calibrate productivity terms Θ_j and to compute the CES aggregates at each level. The process relies crucially on data on relative wages and

[17] We also note that the labor share $1-\alpha_j$ varies widely across industries, as we will discuss in the next section. This will imply that some industries will be much more responsive in the short run to changes in the workforce than others.

employment (or hours worked). We carry out this process separately for each industry, but in the remainder of the section we omit the industry subindex j to ease notation.

We begin with level 4, which combines documented and undocumented foreign-born workers. Using equation (1), we first calculate the relative marginal product of labor for documented and undocumented foreign-born workers with a specific level of education and experience. Under the assumption that wages are given by marginal products, we have

$$\frac{w_{e,x}^{DFB}}{w_{e,x}^{UFB}} = \left(\frac{\theta_{e,x}^{DFB}}{\theta_{e,x}^{UFB}}\right)\left(\frac{DFB_{e,x}}{UFB_{e,x}}\right)^{-1/\sigma_d}. \tag{4}$$

This expression says that the relative DFB-UFB wage depends on the relative productivity between these two types of workers and their relative abundance.[18] We normalize $\theta_{e,x}^{UFB} = 1$. Thus given a value for σ_d, and data on relative wages and relative labor supplies, we can compute the value for $\theta_{e,x}^{DFB}$. More intuitively, relative productivities are determined by relative wages, after adjusting for relative supplies.

Once the relative productivity term has been backed out, we can then compute, for each cell (e, x), the labor aggregate $L_{e,x}^{FB}$ using

$$L_{ex}^{FB} = C(DFB_{e,x}, UFB_{e,x}|\theta_{e,x}^{DFB}, \sigma_d). \tag{5}$$

We are then ready to move up to level 3. Analogous to the previous argument, we derive the expression for relative wages between native and foreign-born labor with the same education and experience:

$$\frac{w_{e,x}^{Nat}}{w_{e,x}^{FB}} = \left(\frac{\theta_{e,x}^{Nat}}{\theta_{e,x}^{FB}}\right)\left(\frac{Nat_{e,x}}{L_{e,x}^{FB}}\right)^{-1/\sigma_n}. \tag{6}$$

As before, we normalize $\theta_{e,x}^{FB} = 1$. Given data on the relative wage on the left-hand side, and the relative employment supply of the two labor types, we can pin down the value for the relative native-immigrant productivity terms $\theta_{e,x}^{Nat}$. In turn we can then compute labor aggregate $L_{e,x}$ using

$$L_{ex} = C(Nat_{e,x}, L_{e,x}^{FB}|\theta_{e,x}^{Nat}, \sigma_n). \tag{7}$$

[18] This equation is also the basis for the estimation of σ_d in Ottaviano and Peri (2012). Conditional on fixed effects for education and experience, the elasticity of substitution is identified on the basis of the correlation between changes in the relative size of the two groups and the relative wage.

Turning now to level 2, for each cell e, we can obtain $\theta_{e,x}$ from

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

and then compute aggregate L_e for each e using[19]

$$L_e = C(L_{e,1}, ..., L_{e,X}|\boldsymbol{\theta_{e,x}}, \sigma_x), \text{ for } x = 2, ..., X. \tag{9}$$

Finally, level 1 relates the relative wages between education level $e = 2, ..., E$ and the lowest level of education. For each cell e, we obtain $\boldsymbol{\theta_e}$ from

$$\frac{w_e}{w_1} = \left(\frac{\theta_e}{\theta_1}\right)\left(\frac{L_e}{L_1}\right)^{-1/\sigma_e}, \text{ for } e = 2, ..., E, \tag{10}$$

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. Table 6 reports the relative productivities for three select industries characterized by high shares of undocumented foreign-born employment (Agriculture, Construction, and Leisure and Hospitality), along with the average for the corresponding productivity terms across all 12 industries (columns 6 and 10). Several observations are worth noting. First, columns 3 to 6 show that on average across education-experience groups, the productivity of native relative to foreign-born labor is larger than one (after adjusting for relative scarcity).[20] In Agriculture the mean (across skill groups) for this parameter is 1.41, in Construction 1.31, and in Leisure and Hospitality, 1.12. In comparison, averaging across all industries, we find that native workers tend to be about 21 percent more productive than foreign-born labor with the same education and potential experience. Let us now turn to columns 7-10, which focus on the productivity of documented foreign-born workers relative to observationally equivalent undocumented ones. Averaging across all industries (and skill groups), we find that documented workers are 27 percent more productive than undocumented ones with the same education and experience. In Agriculture, Construction, and Leisure and Hospitality the documentation

[19]We have normalized $\theta_{e,1} = 1$ and $\boldsymbol{\theta_{e,x}}$ denotes the vector of relative productivity terms across experience groups with education level e.

[20]Strictly speaking, native workers earn more than foreign-born workers with the same education and potential experience, after controlling for their relative employment (or aggregate hours worked).

premium is higher, ranging from 27 to 39 percent.

It is also interesting to move up one more level and examine the relative productivities across education groups. The results are reported in Table 7. For any given industry, as we move toward higher education levels (to the right on the table), the coefficients increase almost always monotonically. This is a reflection of the returns to education in each industry. On average across all industries, the productivity of high-school graduates relative to high-school dropouts in the same industry is twice as high. Having some college education leads to an additional (but moderate) increase in productivity. Finally, our calibration implies that college graduates are more than 4 times as productive as high-school dropouts, and about twice as productive as high-school graduates.

5.3 Labor shares

Having calibrated the relative productivities and computed the level-1 labor aggregate for each industry, L_j, we are now able to turn toward the parameters of the industry production functions: labor shares and aggregate productivity terms.

We computed the labor shares at the industry level using data from the Bureau of Economic Analysis and following the methodology in Figura and Ratner (2015). In essence, we construct labor shares in each industry as compensation of employees divided by value added less taxes on production and imports (net of subsidies). We calculated these shares for years 2011, 2012 and 2013 separately and then took the average. Table 8 reports the resulting values. There is a large amount of variation in labor shares across industries, which range here between 0.23 and 0.86. Agriculture, Mining and Financial activities have the lowest labor shares of all industries (below 0.25). In contrast, service industries display labor shares that range between 0.70 and 0.86. When considering all industries together (excluding defense) the labor share we obtain is 0.57. Our estimates of industry labor shares are consistent with the historical patterns discussed by Elsby et al. (2013) in a recent review.[21]

[21] Variation in labor shares across industries dwarfs both the small year-to-year fluctuations in industry labor shares visible in Table 8 and the recent secular decline in the aggregate labor share. The latter is the main focus of Elsby et al. (2013) and Karabarbounis and Neiman (2014), who suggest that either import competition or declining prices of investment goods, or both, may be at play. Elsby et al. (2013) helpfully explore the array of extant measures of the labor share. Our measures are essentially equal to those of Figura and Ratner (2015), which match the "compensation (payroll share)" measure presented by Elsby et al. at the top of their Table 1.

5.4 Aggregate productivity by industry

We calibrate aggregate productivities on the basis of the relationships between industry output and the overall labor aggregates derived in equations (2) and (3). Given the values for the labor aggregate in each industry, and the value of GDP for that industry in year 2013, we back out the aggregate productivity terms.[22] Specifically, for each industry j, we set

$$B_j^{SR} = \frac{Y_j^{2013}}{L_j^{1-\alpha_j}} \tag{12}$$

$$B_j^{LR} = \frac{Y_j^{2013}}{L_j}. \tag{13}$$

Respectively, these are the short and long-run aggregate productivity terms for each industry j. We are now equipped to use the calibrated model for our counterfactual analysis.

6 Counterfactuals

We are now ready to tackle the main goal of the paper: to assess the economic contribution of the undocumented foreign-born population to the industries that employ them. In a manner analogous to how trade economists assess the gains from trade, we estimate the contribution of undocumented foreign-born workers (UFB) by comparing industry production in a counterfactual scenario without UFB to the baseline with the observed workforce in year 2013.[23]

Our thought experiment is also helpful to estimate the economic costs associated to removing unauthorized workers from the United States. However, it is important to keep in mind that a full treatment of this question would require to take into account the direct costs of locating and deporting all these individuals, in addition to the costs of increasing border enforcement, and the consequences of disrupting families and communities throughout the whole country. Thus our analysis only provides a very narrow interpretation of the economic costs of mass deportation.

It is helpful to consider the following stylized timing. Period 0 is the baseline and corresponds to the data in 2013. The labor force contains over 7 million unauthorized

[22] In this calculation we build labor aggregates on the basis of hours worked.

[23] The gains from trade are assessed by comparing income under a no-trade counterfactual to the baseline with the observed trade levels.

workers. In period 1 the unauthorized population is removed but the stock of capital remains constant (short run). Because of its relative abundance, the marginal product of capital (MPK) falls below its rental rate. In period 2 the stock of capital has adjusted (downward) so that the MPK rises back to equate the rental rate (long run). The following table summarizes the key information.

Counterfactual scenarios: Removal of UFB

Scenario	Output	Labor	Capital	MPK
(0) Baseline	Y_0	L_0	$K_0 = \overline{\kappa} L_0$	$MPK(K_0, L_0) = \overline{R}$
(1) Short run	$\widetilde{Y}_{SR}$	$\widetilde{L}_1 = L_0 - UFB$	K_0	$MPK(K_0, \widetilde{L}_1) < \overline{R}$
(2) Long run	$\widetilde{Y}_{LR}$	$\widetilde{L}_1 = L_0 - UFB$	$\widetilde{K}_1 = \overline{\kappa}\widetilde{L}_1$	$MPK(\widetilde{K}_1, \widetilde{L}_1) = \overline{R}$

Notes: Variables with a tilde denote counterfactual values that are not observed in the data, such as the workforce or the stock of capital in the removal scenario. UFB stands for undocumented foreign-born. $\overline{R}$ denotes the (constant) rental rate of capital. $\widetilde{L}_1 = L_0 - UFB$ is symbolic notation for the labor aggregate after removing undocumented workers.

To be more specific, this is how we compute the foreign-born labor aggregates in the baseline and in the counterfactual scenario without UFB workers:

$$
\begin{aligned}
L^{FB}_{e,x} &= C(DFB_{e,x}, UFB_{e,x} | \theta^{DFB}_{e,x}, \sigma_d) && (14)\\
\widetilde{L_0}^{FB}_{e,x} &= C(DFB_{e,x}, 0 | \theta^{DFB}_{e,x}, \sigma_d) = \left(\theta^{DFB}\right)^{\frac{\sigma_d}{\sigma_d - 1}} DFB_{e,x}, && (15)
\end{aligned}
$$

for each education-experience cell.

We define the *short-run effect* of the removal of the undocumented foreign-born population to industry j as the ratio of the output in the long-run scenario and the baseline (as observed in the 2013 data).[24] That is,

[24]We omit the j subindex to lighten the notation.

$$G^{SR} = \left(\frac{\widetilde{Y}_{SR}}{Y_0}\right) = \frac{AK_0^{\alpha}\widetilde{L}_1^{1-\alpha}}{AK_0^{\alpha}L_0^{1-\alpha}} = \left(\frac{\widetilde{L}_1}{L_0}\right)^{1-\alpha}. \tag{16}$$

Similarly, we define the *long-run* cost of the removal of the undocumented foreign-born population to industry j as the ratio of the output in long-run scenario to baseline. That is,

$$G^{LR} = \left(\frac{\widetilde{Y}_{LR}}{Y_0}\right) = \frac{A\widetilde{K}_1^{\alpha}\widetilde{L}_1^{1-\alpha}}{AK_0^{\alpha}L_0^{1-\alpha}} = \frac{A(\overline{\kappa}\widetilde{L}_1)^{\alpha}\widetilde{L}_1^{1-\alpha}}{A(\overline{\kappa}L_0)^{\alpha}L_0^{1-\alpha}} = \frac{\widetilde{L}_1}{L_0}, \tag{17}$$

where $\overline{\kappa}$ is the capital-labor ratio that results when the stock of capital in the industry is such that its marginal product equals the rental rate for capital.[25]

One remarkable feature of equations (16) and (17) is that the short and long-run contributions, as we have defined them, are not functions of the stock of capital. They are solely functions of the ratio of labor aggregates with and without the undocumented population. We also note that both G^{SR} and G^{LR} will be smaller than (or equal to) one given that $\widetilde{L}_0 > L_1$ and $0 < \alpha < 1$. Furthermore, the short-run cost of removal will always be smaller than the long-run one, with the gap between the two being exclusively determined by the labor share in the industry. As a result, in industries with higher labor share the short and long-run effects will be closer to each other.

We calculate dollar amounts for the short and long-run effects as follows:

$$SRE = \widetilde{Y}_{SR} - Y_0 = \left(\frac{\widetilde{Y}_{SR}}{Y_0} - 1\right) Y_0 = \left(G^{SR} - 1\right) Y_0 \tag{18}$$

$$LRE = \widetilde{Y}_{LR} - Y_0 = \left(\frac{\widetilde{Y}_{LR}}{Y_0} - 1\right) Y_0 = \left(G^{LR} - 1\right) Y_0. \tag{19}$$

Because the terms G^{SR} and G^{LR} will typically be lower than one, the SRE and LRE dollar gains will be negative, that is, they will amount to losses, and the long-run losses

[25] By definition, the long-run is characterized by a capital-labor ratio at which the MPK equals the rental rate of capital. We are also assuming that at the baseline the economy is at a long-run equilibrium.

will be larger than the short-run ones in each industry: $LRE < SRE \leq 0$.

7 Results

7.1 Removal of Unauthorized Workers

We are now ready to turn to our estimates of the contribution of the undocumented population to the output of each industry. We do so by quantifying the reduction in output in the counterfactual removal scenario compared to the baseline.

The results are reported in Table 9. The first column reports GDP (in billions of dollars) for each industry in year 2013. Columns 2-4 report the short-run effects associated to the thought experiment of removing all unauthorized workers, measured by the ratio of industry output in the removal scenario relative to the baseline. Column 2 measures labor services using employment, while column 3 uses hours worked. As it turns out, the results (in this and the other tables) are practically identical regardless of which of the two measures of work we use. Naturally, all coefficients in columns 2 and 3 are below 1, indicating that output is lower in the removal scenario in all industries. The highest short-run costs in terms of relative output lost are suffered by Construction and Leisure and Hospitality, at over 5 percent. Column 4 quantifies the short-run contributions in 2013 dollar amounts, taking into account the size in terms of GDP of each of the industries. By this measure the largest losses associated to removal are found in Manufacturing, Wholesale and retail trade, and Leisure and hospitality, at about \$30-40 billion each. The overall short-run loss across the 12 industries amounts to \$241 billion.

We now turn to columns 5-7, which report the long-run effects. As expected, once employers downsize their capital to match the reduced workforce, output falls further. As seen in columns 5 and 6, the largest relative losses are found in Agriculture (9 percent), Leisure and Hospitality (8 percent), and Construction (8 percent). In terms of dollars, the largest losses again correspond to Manufacturing, followed by Financial activities, Wholesale and Retail trade, and Leisure and hospitality. The overall long-run annual loss amounts to $434 billion, doubling the short-run loss. This figure amounts to 3% of the private-sector GDP accounted for by our 12 industries.

It is worth noting that a naïve calculation that did not take into account the skill distribution of unauthorized workers, their relative productivity, and their substitutability in terms of native (and documented foreign-born) workers, would have led to substantial overestimates of losses from the removal of unauthorized workers, and thus, their economic contribution. We measure this bias in the robustness section.[26]

The chief reason for the lower contribution to output, relative to employment, is found in the lower productivity of unauthorized workers relative to native workers in most skill cells and industries. The lower relative productivity stems from two different sources. The first is due to the 'worse' distribution in terms of education and potential work experience. As shown in Table 5, immigrants tend to be younger than natives (by about 3 years) and than legal immigrants (by about 6 years) in most industries. In addition their average educational attainment is lower by about 3 years of schooling than that of native and legal immigrants (Table 4). The second source of the productivity disadvantage of unauthorized workers is reflected in the relative productivity parameters. Compared to documented foreign-born workers with the same education and potential experience in the same industry, and after adjusting for relative supply, our calibration implied that documented foreign-born workers were on average 27 percent more productive than unauthorized ones (last row Table 6).[27] In addition, relative to natives in the same skill

[26]In our setup with constant returns to scale in industry production functions, and the elastic long-run supply of capital, the naïve calculation would map, one-for-one, the employment shares of unauthorized workers into shares in output. Thus a reduction of almost 5% in employment would imply a long-run reduction in output of about 5%, but our estimate is a substantially lower 3% drop in output.

[27]The table also uncovers a great deal of heterogeneity across industries, averaging across all skill groups in Agriculture and Construction, we find that the relative productivity of DFB over UFB is 39

group and industry, foreign-born labor also appears to be less productive than native labor by about 21 percent when averaging across all industries.[28]

7.2 Robustness

We now consider several robustness checks in order to assess the sensitivity of our main results to the values assumed for the elasticities of substitution, and to gauge the importance of allowing for heterogeneous productivity across all types of labor. Throughout this section we focus on long-run results, which do not depend on the values adopted for the labor shares.

Given the higher uncertainty around the specific values for the elasticities of substitution between natives and immigrants (σ_n) and between documented and undocumented foreign-born workers (σ_d), we will focus our sensitivity analysis on these two elasticities. Under the restriction that the elasticities of substitution need to be weakly increasing as we move up the CES nests ($0 \leq \sigma_e \leq \sigma_x \leq \sigma_n \leq \sigma_d$), a reasonably large range of elasticities around our preferred values is contained in the first three scenarios in the table below:

Robustness Scenarios

Scenario	Educ. σ_e	Exp. σ_x	Nat-FB σ_n	DFB-UFB σ_d	Productivities Θ
Baseline	3	6	20	1,000	Calibrated
Low σ_d	3	6	20	20	Calibrated
High σ_n	3	6	1,000	1,000	Calibrated
Equal productivities	3	6	20	1,000	1

After examining the quantitative role of the elasticities of substitution, we turn to gauge the role played by the labor productivity terms (Θ). Accordingly, the fourth

and 36 percent, respectively.

[28] We stress that this comparison is based on labor aggregates, which already incorporate productivity terms. Specifically, the native-immigrant productivity gap partly reflects the fact that an important share of all foreign-born workers are unauthorized and, thus, faces the productivity penalty discussed earlier. As a result, it is not entirely correct to simply add up the productivity penalties of levels 4 (DFB-UFB) and 3 (Nat-FB).

scenario adopts the baseline elasticities but imposes equal productivities across all groups of workers.[29]

7.2.1 Low substitution between documented and undocumented

One of the innovations in our setup is to allow for imperfect substitution between documented and undocumented foreign-born workers, conditional on the same education and potential experience. Due to the lack of available estimates for this elasticity, in our baseline calibration we have assumed a fairly high elasticity ($\sigma_d = 1,000$) in order to take a conservative approach toward the contributions of the undocumented to production, and to be consistent with the existing literature, which has implicitly assumed and infinite value.

We now evaluate quantitatively the role played by this parameter. To do this we consider a scenario where the only departure from the baseline parameter values is that the documented-undocumented elasticity is set at $\sigma_d = 20$, which is the lowest value subject to the constraint requiring that elasticities of substitution increase (weakly) as we move up the CES levels and compare workers that are increasingly more similar in terms of skills. Because this assumption is relatively extreme, we view the resulting loss of removal to be unrealistically large.

The results are presented in Table 10. Columns 1 and 2 reproduce the long-run effects of removal reported earlier (scenario 0). Columns 3 and 4 (scenario 1) collect the results that we obtain we we set $\sigma_d = 20$, leaving all parameters as in the baseline scenario. The overall long-run loss of removal is now $478 billion, about 6% higher than in scenario 0. This is intuitive given that, generally, lowering the elasticity of substitution makes inputs less replaceable. The important take-away is that despite the fairly substantial

[29] Note that we are still treating labor as an aggregate of many different types, as indicated by the less than infinite elasticities of substitution. We are only assuming that if two groups in the same nest are equal in size (in terms of employment or hours) their wages need to be equal as well.

reduction in the elasticity, the overall estimate of the long-run effects of removal is fairly close to the value in scenario 0.

7.2.2 High substitution between natives and immigrants

One of the main differences between the results in Borjas (2003) and Ottaviano and Peri (2012) lies in the value for the elasticity of substitution between natives and foreign-born workers with the same education and potential experience. While the former study imposed a value of infinity, the latter estimated this parameter and found it to be around 20, which is the value we adopted in our calibration.

In order to assess the implications of this choice for our results, we now examine a scenario where native and foreign-born workers are effectively perfect substitutes of each other. Specifically, the only difference relative to the parameters in scenario 0 is that the native-immigrant elasticity is now set at $\sigma_n = 1,000$. Since this is the highest value consistent with the values assumed for the other elasticities and the monotonicity constraint, we view the resulting estimate as a sort of lower bound.

The results are collected in columns 5 and 6 (scenario 2) in Table 10. The overall loss associated to the removal of unauthorized workers is \$440 billion, less than 3% lower than in scenario 0. Once again, the qualitative finding of a lower value is consistent with the intuition that as elasticities of substitution increase, workers are more easily replaceable and therefore the loss associated to removal of a subset of the workforce is reduced. More importantly, this result shows that our main estimates are robust to considering substantially higher values for the elasticity of substitution between native and immigrant workers.

7.2.3 No productivity differences

We now assess the role played by heterogeneity in the type-productivity terms, a key element in our approach. To gauge this point we compute counterfactuals where we force all productivity terms Θ_j to be equal to one. As a result, while still considered as different types of labor that are not perfectly substitutable, all worker types are now assumed to be equally productive.[30]

The results are reported in columns 7 and 8 in Table 10. What stands out in these columns is that the losses from removal are now substantially larger than before for most industries. In total the dollar amount associated to the removal of unauthorized workers is $747 billion, which is 65 percent larger than our main estimates (scenario 0). The reason why removing productivity differences between workers produces an overestimate of the production effect is that our calibration uncovered large productivity differences between documented and undocumented workers, as well as between foreign-born and U.S.-born labor. Imposing a value of one for all relative productivity terms overestimates the productivity and, therefore, the contribution to output of unauthorized workers.

7.2.4 Summing up

In sum, the sensitivity tests just presented show that our main results are robust to a wide range of values for the elasticities of substitution across labor types. We have also learned that accounting for relative productivity differences across labor types is crucial to obtain an accurate quantitative assessment of the economic contribution of unauthorized workers.

[30] Clearly, the resulting relative wage gaps in the model will typically not be consistent with the data on relative wages and relative employment.

7.3 Cumulative effects

From a policy perspective it is interesting to produce cumulative effects over a period of several years. Naturally, doing this requires taking a stance about the speed of adjustment of the capital stock at the industry level. As discussed earlier, following a reduction in the workforce, industry capital-labor ratios will adjust downward. This adjustment is likely to be gradual but can take place fairly rapidly if equipment can be reallocated easily to other industries or countries.

To fix ideas, we consider the following thought experiment. Suppose that in year T all unauthorized workers are removed from the U.S. economy and let us compute the cumulative effects over the following decade. A lower bound estimate for this effect can be obtained by assuming that capital remains constant over the 10-year period. In this case there's an abundance of capital that limits the size of the income loss associated to the removal. Likewise an upper bound estimate can be computed by assuming that already in year T the capital stock has fully adjusted. In this case the loss of labor is accompanied by the reduction in the stock of capital, maximizing the loss in terms of income and production. We also consider two intermediate scenarios where capital adjustment occurs gradually and takes 5 or 10 years, respectively, to complete.

The first step in the calculation is to express our estimated income losses as a share of overall GDP, including the public sector. In Table 9 we found that the income losses amounted to \$241 and \$434.4 billion in the short and long runs, respectively. As a share of baseline GDP, these losses were 1.4% and 2.6% in the short and long runs, respectively. Next, we simulate the effects of the removal of unauthorized workers in year $T = 2017$. For our lower bound calculation, we obtain GDP projections for years 2017-2026 (from the Congressional Budget Office) and apply an annual 1.4% loss.[31] Likewise, the upper bound calculation is produced by applying an annual 2.6% loss to projected GDP for

[31] We use the current-price GDP projections produced by the CBO.

each year between 2017 and 2026. For the intermediate scenarios we linearly interpolate the annual loss rates so that we reach the long-run loss rate of 2.6% in 5 and 10 years, respectively.

Table 11 reports our findings. Column 1 reports the lower-bound calculation. Over time the dollar amount of the income loss grows, reflecting the projected increase in GDP over the period 2016-2027. The resulting cumulative loss over the decade is $3.36 trillion. Column 4 reports the projected losses under the assumption that capital adjustment takes place immediately on the year of the removal. In this case the cumulative loss over the decade almost doubles to $6.06 trillion. Columns 2 and 3 provide the estimates assuming that capital adjusts in 10 and 5 years, which amount to cumulative losses of $4.8 and $5.5 trillion, respectively. In conclusion, these calculations suggests that the 10-year cumulative loss associated to the removal of authorized workers in year 2017 would probably be around $5 trillion.[32]

7.4 State-level estimates

The geographic distribution of the unauthorized population in the United States is highly uneven. In California the unauthorized share in employment is 10.2%, twice the national average of 4.9%.[33] Thus the economic contribution of unauthorized workers will also vary widely across states, with larger (relative) effects in states with a higher share of unauthorized workers.

Providing estimates at the state level poses a challenge in terms of data. When attempting to construct industry-education-experience cells at the state level, we found many cells that were empty or populated by an extremely low number of observations. As

[32]It is worth noting though that a full analysis of the costs associated to such a policy would need to take into account many other factors, such as the costs of implementing the deportation and enforcing borders.

[33]Nevada and Texas immediately follow California in the ranking by the unauthorized share in employment with 8.7%. For the values for all states, see Table 12.

a result we chose to adopt a less demanding approach that pools together all industries. In addition we calibrated type-productivities (Θ) at the national level (pooling also all industries) and imposed those calibrated values on all states. In terms of our earlier notation, we now calculate baseline levels for the labor aggregates at the state level as functions of state-level workforce data (pooling all industries), and national level type-productivities and elasticities of substitution, that is, $L(V_s; \Theta, \Sigma)$ in our previous notation.

Table 13 collects the results for the top-10 states with the highest unauthorized shares in hours worked (and employment).[34] In California, unauthorized workers make up 11 percent of all hours worked. Removal of these workers would lead to a 4 percent drop in private-sector output in the short-run. This loss would increase up to 7 percent once capital adjusts to the reduced workforce. In dollar terms, the annual losses for California would be \$83 and \$136 billion in the short and long runs, respectively. In dollar terms, the other two states experiencing the largest losses are Texas and New York, with long-run annual losses of \$83 and \$54 billion. Relative to baseline GDP, the annual long-run losses from removal would range from 4 to 7 percent in the 10 states considered here.

7.5 The Gains from Legalization

We next consider the gains from providing legal status to unauthorized workers. Kossoudji and Cobb-Clark (2002) analyzed the wage effects of the 1986 IRCA amnesty and found that the wage penalty for being unauthorized amounted to 14 to 24 percent. More recently, Lynch and Oakford (2013) have estimated that gaining legal status and citizenship would allow unauthorized immigrants to earn 25% more within five years of the reform, increasing U.S. GDP by \$1.4 trillion cumulatively over a 10-year period.

[34] These states are California, Nevada, Texas, New Jersey, New York, Arizona, Florida, Georgia, Illinois and Maryland.

Lofstrom et al. (2013) reported that legalization produced earnings gains of about 20 percent to unauthorized workers in that obtained legal status in 2003-2004, measuring from their first U.S. job to earnings one year after legalization. More recently, Orrenius and Zavodny (2014) have analyzed the effects of the E-Verify program and provided evidence of a negative effect on the productivity of unauthorized workers.[35] Our calibration is largely consistent with these findings.[36]

We can think about legalization as allowing undocumented foreign-born (UFB) workers to operate under the same conditions as documented immigrants (DFB). In our framework this can be simulated by assuming that UFB workers become undistinguishable from DFB workers possessing the same education and potential experience. Namely, in the legalization scenario we compute the foreign-born labor aggregate as:

$$\widetilde{L}^{FB}_{2_{e,x}} \quad = \quad C(DFB_{e,x} + UFB_{e,x}, 0|\theta^{DFB}_{e,x}, \sigma_d) = \left(\theta^{DFB}_{e,x}\right)^{\frac{\sigma_d}{\sigma_d - 1}} \left(DFB_{e,x} + UFB_{e,x}\right).$$

for each education-experience cell.

Because unauthorized workers are now endowed with the higher productivity of documented foreign-born workers (that may also have been naturalized), legalization entails an increase in the overall amount of labor. As a result, our theoretical model will imply that in the short-run there will be a shortage of capital, which will push up its marginal product. Over time industries will invest more in physical capital to regain the desired capital-labor ratio, which will provide an additional boost to production.

Let us now turn to the quantitative assessment of the effects of legalization, summa-

[35] Following the pioneer work of Chiswick (1978), several studies have attempted to estimate the income gains from naturalization (for legal immigrants). Bratsberg et al. (2002) found wage gains of about 5 percent associated to obtaining citizenship. More recently, the analysis in Pastor and Scoggins (2012) concludes that naturalization appears to lead to income gains of about 10 percent.

[36] Our calibration implies that the relative productivity of documented foreign-born workers is almost 30 percent higher than that of unauthorized workers. We have not distinguished between naturalized foreign-born individuals and legal immigrants who are not U.S. citizens. Thus our documented foreign-born group (DFB) contains both groups. Accordingly, the higher productivity relative to undocumented foreign-born workers reflects the returns of both legalization and citizenship.

rized in Table 14. Columns 1 and 2 report the short-run results. Clearly, the relative increases in industry output are fairly small (column 1), reaching 1% only for Construction and Leisure and hospitality. Column 2 translates the results into dollar amounts. The total short-run gains from legalization amount to $47 billion annually. Columns 3 and 4 report the corresponding figures for the long-run analysis. The largest relative gains are now for Construction, with roughly a 2 percent increase in production (column 3). In dollar terms the largest long-run annual gains accrue to Construction, Manufacturing and Wholesale and retail trade, with $12-13 billion each. The overall long-run annual gains total $81.5 billion.

In conclusion, granting legal status to unauthorized workers would increase their annual economic contribution substantially in several industries. In Leisure and hospitality, Construction and Agriculture, the long-run contribution of these workers would increase private-sector GDP by 1.1 to 1.9 percent. For the economy as a whole, the long-run gains would amount to about 0.5 percent of private-sector GDP.

8 Caveats

8.1 Native labor supply response

Our analysis has assumed that the removal of unauthorized workers would not trigger compensating labor flows from the rest of the economy. This assumption has allowed us to keep the theoretical framework as simple as possible. While clearly restrictive, we believe it is not implausible.

Even though our calculations were produced for each industry in isolation of the others, the spirit of the analysis is to assess the effects of a simultaneous removal of unauthorized workers from all industries. Thus unauthorized workers from one industry would not be able to offset the departure of unauthorized workers in another. Even though native workers and legal immigrants could potentially relocate to those industries, this is also unlikely. The reason is that once the stock of capital adjusts to the reduced size of the workforce in a given industry, the marginal product of labor in the industry will go back to its baseline level (prior to the removal). As a result, the incentives of native and legal immigrant workers to move to that industry would not be different from the incentives they faced in the baseline scenario.[37]

Besides the theoretical arguments just presented, the empirical analysis in Clemens (2013) in the context of agriculture in North Carolina provide evidence of a highly unresponsive short-run supply of native labor following changes in foreign employment. It is not obvious that these results can be generalized to other industries. But, given that unauthorized workers are probably less substitutable with native workers than the foreign-born population at large, we believe it is unlikely that our results are biased due to omitting employment responses of natives.[38]

The most compelling empirical analysis of the labor-market consequences of the removal of a large share of immigrant labor from an industry can be found in the recent work by Clemens et al. (2017). This study analyzes the 1964 policy that removed 0.5 Million seasonal agricultural Mexican workers (the so-called *braceros*) with the stated intention of improving the wages and employment of native workers. As a result of the policy, some states lost around 1/3 of their seasonal workforce in agriculture. Nonetheless, the employment and wages of natives did not increase. Instead employers moved to adopt labor-saving technologies and shifted toward less labor-intensive crops. While

[37]Offsetting labor flows could potentially happen during the transition, while capital is undergoing adjustments, but in practice short-run wage rigidities and other frictions would probably pose a substantial impediment to this short-lived adjustment.

[38]Empirical work analyzing the broader effects of immigration on the labor force participation and employment rates of natives suggests that the labor supply response of native workers is very small (e.g. Card (2005)). Additionally, work by Cortes and Tessada (2011), Farre et al. (2011) and Furtado (2016) has shown that low-skilled immigration increases the labor supply of highly skilled native women, by providing more affordable child and elderly care. Thus the removal of unauthorized workers may even reduce the labor supply of some groups of native workers.

these findings reinforce our finding of a substantial output loss in the removal counterfactual, we also note that the mechanisms uncovered by Clemens et al. (2017) might not spark into action in other sectors of the economy with different technological conditions, such as leisure and hospitality or construction.

8.2 Exploitation of undocumented workers

Anecdotal evidence suggests that undocumented workers may not be paid their marginal products. 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 this is the case, our calibration method will underestimate the productivity of undocumented workers relative to legal immigrants and natives with the same education and experience. Accordingly, our estimates for the output loss associated to the removal of undocumented workers will underestimate the true loss, resulting in a larger contribution of these workers to GDP.

9 Conclusions

We have found the economic contribution to U.S. GDP of unauthorized workers to be substantial, at approximately 3% of private-sector GDP annually, and close to $5 trillion over a 10-year period. These aggregate estimates mask large differences across industries and states. Unauthorized workers may be responsible for 8-9% of the value-added in Agriculture, Construction, and Leisure and Hospitality. Naturally, the economic contribution of unauthorized workers is larger in states where this workers account for a large share of employment, amounting to 7% of California's GDP.

It is important to note that, compared to their shares in employment, the contribution of unauthorized workers to production is relatively smaller. The reason is that unauthorized workers are less skilled, on average, and appear to be less productive than natives and legal immigrants with the same observable skills. This may be a reflection of their more limited job opportunities. In fact, our findings suggest that this productivity penalty can be mitigated in part through legalization, which could increase the economic contribution of unauthorized workers by about 20%, to 3.6% of private-sector GDP.

We hope our analysis will spur additional research on these important questions. We have focused on the implications for industry output and overall GDP, but the model can be readily used to analyze the effects on wages. Our setup can also be used to simulate real-life policies currently under discussion, such as the economic effects of the DREAM Act or revoking the work permits to recipients of the Deferred Action on Childhood Arrivals.

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Table 1: Data summary

Industry	2013 GDP Billions	Emp Millions	FB/All Emp.	UFB/All Emp.	FB/All Hours	UFB/All Hours
1. Agriculture, forestry, fish/hunt	225.44	1.99	0.30	0.18	0.29	0.17
2. Mining	441.05	0.85	0.09	0.03	0.09	0.03
3. Construction	619.87	8.84	0.24	0.13	0.23	0.12
4. Manufacturing	2024.65	15.06	0.19	0.06	0.19	0.06
5. Wholesale and retail trade	1969.8	20.54	0.15	0.04	0.15	0.04
6. Transportation and utilities	754.07	7.04	0.16	0.03	0.16	0.03
7. Information	793.82	3.01	0.12	0.02	0.12	0.02
8. Financial activities	3295.46	9.42	0.13	0.02	0.13	0.02
9. Professional and business svcs	1952.48	15.66	0.20	0.06	0.14	0.03
10. Educational and health svcs	1373.22	33.15	0.14	0.02	0.14	0.02
11. Leisure and hospitality	625.66	13.7	0.22	0.10	0.24	0.11
12. Other Services	363.09	7.16	0.22	0.08	0.23	0.08
Total	14,438.61	136.4	0.17	0.05	0.17	0.05

Notes: Statistics are averages across the 2011, 2012, and 2013 waves of the augmented American Community Survey (ACS) files supplied by Center for Migration Studies (2014). Statistics are drawn from the employment sample described in the text. The total in the last row refers to the 12 industries reported in the table. Overall GDP in 2013, including Government, amounted to $16,549.23 billion.

Table 2: Unauthorized immigrants by industry and origin, pooled CMS sample 2011–2013

Employed unauthorized immigrants	Total	Mexico	Central & South America	Asia	Other
All industries	7,070,329	3,854,716	1,832,998	918,205	464,409
1. Agriculture, forestry, fish/hunt	351,783	314,133	32,073	3,276	2,300
2. Mining	24,737	19,360	2,500	1,662	1,215
3. Construction	1,122,134	743,586	326,855	17,324	34,370
4. Manufacturing	889,081	517,764	194,227	124,878	52,212
5. Wholesale and retail trade	853,261	414,951	229,925	141,155	67,230
6. Transportation and utilities	218,234	86,304	72,225	27,301	32,404
7. Information	69,517	19,097	16,234	24,659	9,527
8. Financial activities	196,158	58,161	55,491	59,990	22,516
9. Professional and business svcs	985,278	495,845	255,094	171,247	63,092
10. Educational and health svcs	505,259	126,156	154,197	133,814	91,092
11. Leisure and hospitality	1,302,300	784,098	318,018	141,205	58,980
12. Other services	552,587	275,262	176,158	71,695	29,472

Notes: Statistics are averages across the 2011, 2012, and 2013 waves of the augmented American Community Survey (ACS) files supplied by Center for Migration Studies (2014) and described by Warren (2014). Statistics are drawn from the employment sample described in the text.

Table 3: Weekly wages by industry and nativity, pooled CMS sample 2011-2013

Average weekly wage	Total	U.S born	Legal immigrants	Unauthorized immigrants
All industries	1,016	1,039	1,050	581
1. Agriculture, forestry, fish/hunt	594	734	491	378
2. Mining	1,460	1,460	1,638	1,093
3. Construction	880	962	803	510
4. Manufacturing	1,135	1,165	1,167	674
5. Wholesale and retail trade	835	853	820	555
6. Transportation and utilities	1,038	1,066	934	648
7. Information	1,346	1,323	1,546	1,303
8. Financial activities	1,413	1,406	1,524	1,132
9. Professional and business svcs	1,288	1,328	1,330	734
10. Educational and health svcs	975	962	1,115	641
11. Leisure and hospitality	547	568	574	402
12. Other services	722	769	608	464
13. Public administration	1,170	1,163	1,255	

Notes: Statistics are averages across the 2011, 2012, and 2013 waves of the augmented American Community Survey (ACS) files supplied by Center for Migration Studies (2014) and described by Warren (2014). Dollars are inflated to 2013 levels using the consumer price index. Statistics are drawn from the wage sample described in the text.

Table 4: Average education by industry and nativity, pooled CMS sample 2011–2013

Average years of education	Total	U.S born	Legal immigrants	Unauthorized immigrants
All industries	13.7	13.9	13.3	10.6
1. Agriculture, forestry, fish/hunt	11.2	12.7	8.0	7.7
2. Mining	13.0	13.1	13.0	11.0
3. Construction	12.1	12.7	11.0	9.3
4. Manufacturing	13.1	13.4	12.6	10.5
5. Wholesale and retail trade	13.1	13.2	12.8	11.3
6. Transportation and utilities	13.0	13.1	12.7	11.3
7. Information	14.5	14.4	15.0	14.5
8. Financial activities	14.4	14.4	14.7	13.6
9. Professional and business svcs	14.4	14.6	14.2	11.1
10. Educational and health svcs	14.9	14.9	14.8	13.3
11. Leisure and hospitality	12.5	12.9	11.7	10.2
12. Other services	13.0	13.4	11.9	10.4
13. Public administration	14.5	14.5	14.9	

Notes: Statistics are averages across the 2011, 2012, and 2013 waves of the augmented American Community Survey (ACS) files supplied by Center for Migration Studies (2014) and described by Warren (2014). Statistics are drawn from the employment sample described in the text.

Table 5: Average potential work experience by industry and nativity, pooled CMS sample 2011–2013

Average years of experience	Total	U.S born	Legal immigrants	Unauthorized immigrants
All industries	20.6	20.5	23.0	17.2
1. Agriculture, forestry, fish/hunt	22.8	23.7	25.3	17.6
2. Mining	20.9	20.9	22.0	17.5
3. Construction	21.9	22.4	24.1	17.1
4. Manufacturing	23.0	23.0	24.8	18.5
5. Wholesale and retail trade	19.0	18.7	22.6	16.5
6. Transportation and utilities	24.2	24.2	25.0	18.5
7. Information	19.5	19.6	20.0	14.8
8. Financial activities	21.6	21.7	21.7	15.6
9. Professional and business svcs	20.6	20.8	21.4	16.9
10. Educational and health svcs	21.1	21.0	22.7	17.8
11. Leisure and hospitality	14.2	12.8	22.1	15.7
12. Other services	22.1	21.8	25.3	19.4
13. Public administration	22.6	22.5	23.2	

Notes: Statistics are averages across the 2011, 2012, and 2013 waves of the augmented American Community Survey (ACS) files supplied by Center for Migration Studies (2014) and described by Warren (2014). Statistics are drawn from the employment sample described in the text. Years of potential work experience are calculated from age and years of education as described in the text.

Table 6: Relative Productivities: Agriculture, Construction and Leisure & Hospitality

		Agric.	Cons.	L&H	**Avg12**	Agric.	Cons.	L&H	**Avg12**
edu	exp	$\theta_{e,x}^{Nat}$	$\theta_{e,x}^{Nat}$	$\theta_{e,x}^{Nat}$	$\theta_{e,x}^{Nat}$	$\theta_{e,x}^{DFB}$	$\theta_{e,x}^{DFB}$	$\theta_{e,x}^{DFB}$	$\theta_{e,x}^{DFB}$
1	1	0.99	1.13	0.74	0.96	1.03	0.90	0.82	0.94
1	2	1.24	1.16	0.89	1.08	1.13	1.05	0.90	1.03
1	3	1.14	1.16	0.87	1.13	0.98	1.10	1.02	1.13
1	4	1.21	1.19	0.90	1.14	1.05	1.16	1.10	1.20
1	5	1.18	1.29	0.92	1.17	1.00	1.20	1.09	1.22
1	6	1.13	1.28	0.86	1.11	1.07	1.23	1.18	1.22
1	7	1.34	1.16	0.95	1.21	1.26	1.31	1.21	1.28
1	8	1.35	1.21	0.94	1.17	1.21	1.33	1.18	1.24
2	1	1.44	1.28	1.00	1.20	0.98	1.10	0.95	1.05
2	2	1.40	1.36	1.05	1.23	0.94	1.23	1.14	1.11
2	3	1.43	1.42	1.03	1.26	1.23	1.34	1.14	1.19
2	4	1.65	1.37	1.09	1.31	1.09	1.23	1.12	1.18
2	5	1.46	1.33	1.06	1.26	1.19	1.48	1.19	1.27
2	6	1.50	1.34	1.14	1.28	1.24	1.32	1.25	1.29
2	7	1.56	1.32	1.10	1.29	1.36	1.39	1.19	1.31
2	8	1.36	1.29	1.19	1.22	1.18	1.18	1.28	1.26
3	1	1.55	1.25	1.05	1.28	0.92	1.10	1.01	1.04
3	2	1.63	1.35	1.12	1.26	0.74	1.27	1.14	1.11
3	3	1.35	1.34	1.07	1.22	1.46	1.45	1.25	1.27
3	4	1.66	1.38	1.20	1.25	1.29	1.29	1.44	1.26
3	5	1.71	1.37	1.18	1.26	1.07	1.46	1.38	1.27
3	6	1.37	1.27	1.15	1.27	1.95	1.57	1.43	1.49
3	7	0.69	1.34	1.06	1.18	3.20	1.60	1.47	1.71
3	8	1.21	1.30	0.98	1.22	2.08	1.40	1.43	1.48
4	1	1.69	1.24	1.14	1.15	1.21	1.48	1.05	1.16
4	2	1.67	1.45	1.27	1.18	1.15	1.32	1.32	1.11
4	3	1.46	1.39	1.28	1.16	2.46	1.20	1.49	1.28
4	4	1.12	1.44	1.43	1.16	1.51	1.79	1.52	1.34
4	5	1.82	1.36	1.58	1.27	1.61	1.65	1.48	1.36
4	6	1.61	1.45	1.70	1.31	2.34	1.73	1.81	1.57
4	7	1.72	1.37	1.52	1.34	2.40	1.94	2.06	1.53
4	8	1.57	1.30	1.56	1.28	1.14	1.74	1.85	1.67
Avg.		1.41	1.31	1.12	**1.21**	1.39	1.36	1.28	**1.27**

Note: $\theta_{e,x}^{Nat}$ is the productivity of native labor relative to foreign-born labor within the same education-experience cell. $\theta_{e,x}^{DFB}$ is the productivity of documented foreign-born labor relative to undocumented labor within the same education-experience cell. The last row reports simple averages of each column. Columns 4 and 8 report simple averages of all 12 industries columns.

Table 7: Relative Productivities by Education

	No degree θ_1	HS grad. θ_2	Some College θ_3	College grad. θ_4
1. Agriculture, forestry, fish/hunt	1	1.67	1.63	2.63
2. Mining	1	1.50	1.48	2.39
3. Construction	1	1.91	1.96	2.42
4. Manufacturing	1	2.13	2.52	4.76
5. Wholesale and retail trade	1	2.24	2.47	4.41
6. Transportation and utilities	1	2.15	2.22	2.84
7. Information	1	3.18	4.45	7.78
8. Financial activities	1	2.85	3.96	9.48
9. Professional and business svcs	1	2.15	3.11	8.03
10. Educational and health svcs	1	2.06	3.04	7.07
11. Leisure and hospitality	1	1.76	2.00	3.46
12. Other Services	1	1.91	1.99	2.84
Simple average	1	2.12	2.57	4.84
GDP-weighted average	1	2.31	2.96	6.21

Note: All productivity terms are relative to the productivity of high-school dropouts in the same industry.

Table 8: Labor shares across industries, 2011-2013

	2011	2012	2013	Average
Private industries (1-12)	0.532	0.535	0.533	0.533
All non-defense industries (1-13)	0.572	0.571	0.569	0.571
1. Agriculture, forestry, fish/hunt	0.208	0.258	0.217	0.228
2. Mining	0.224	0.244	0.234	0.234
3. Construction	0.647	0.636	0.634	0.639
4. Manufacturing	0.484	0.483	0.479	0.482
5. Wholesale and retail trade	0.653	0.641	0.636	0.643
6. Transportation and utilities	0.521	0.533	0.533	0.529
7. Information	0.381	0.392	0.382	0.385
8. Financial activities	0.257	0.252	0.252	0.254
9. Professional and business svcs	0.728	0.738	0.752	0.739
10. Educational and health svcs	0.855	0.863	0.867	0.862
11. Leisure and hospitality	0.705	0.709	0.702	0.706
12. Other services	0.751	0.748	0.755	0.751
13. Public administration	0.792	0.785	0.783	0.787

Notes: We construct labor shares as compensation of employees divided by value added less taxes on production and imports less subsidies, per Figura and Ratner (2015). Underlying statistics are from the Bureau of Economic Analysis.

Table 9: Baseline Results

	1	2	3	4	5	6	7
		Emp. SR	Hours SR	Hours SR	Emp. LR	Hours LR	Hours LR
	GDP 2013	$\widetilde{Y}/Y$	$\widetilde{Y}/Y$	$\widetilde{Y}-Y$	$\widetilde{Y}/Y$	$\widetilde{Y}/Y$	$\widetilde{Y}-Y$
1. Agriculture, forestry, fish/hunt	225.44	0.979	0.980	-4.6	0.910	0.914	-19.4
2. Mining	441.05	0.993	0.993	-2.9	0.971	0.972	-12.3
3. Construction	619.87	0.948	0.950	-30.9	0.920	0.923	-47.6
4. Manufacturing	2024.65	0.981	0.982	-35.8	0.962	0.964	-73.8
5. Wholesale and retail trade	1969.8	0.979	0.979	-41.8	0.968	0.967	-64.9
6. Transportation and utilities	754.07	0.988	0.988	-9.3	0.977	0.977	-17.5
7. Information	793.82	0.992	0.992	-6.7	0.978	0.978	-17.5
8. Financial activities	3295.46	0.996	0.996	-13.7	0.983	0.984	-54.3
9. Professional and business svcs	1952.48	0.973	0.986	-26.7	0.963	0.982	-36.1
10. Educational and health svcs	1373.22	0.989	0.989	-14.7	0.988	0.988	-17.0
11. Leisure and hospitality	625.66	0.944	0.938	-38.5	0.922	0.914	-53.6
12. Other Services	363.09	0.959	0.958	-15.4	0.945	0.944	-20.4
Total	14438.61		0.983	-241.0		0.970	-434.4
	$ Billion			$ Billion			$ Billion

Notes: Column 1 reports the actual industry GDP in year 2013. Columns 2-4 report the short-run results. Columns 2 and 3 report the ratio of the counterfactual industry GDP ($\widetilde{Y}$) to the baseline value (Y). The former measures labor using employment and the latter uses hours worked. Column 4 reports the dollar value of the short-run effects on industry GDP based on the hours worked measurement. Columns 5-7 are analogous to columns 2-4 but refer to the long-run effects. The short and long-run percent changes in the Sum row are calculated by dividing the dollar amounts ($241.0 and $434.4) by private-sector GDP in 2013 ($14,438.6 billion.)

Table 10: Robustness. Long-run effects

Scenario	0	0	1	1	2	2	3	3
σ_e	3	3	3	3	3	3	3	3
σ_x	6	6	6	6	6	6	6	6
σ_n	20	20	20	20	1000	1000	20	20
σ_d	1000	1000	20	20	1000	1000	1000	1000
Θ	calibration	calibration	calibration	calibration	calibration	calibration	1	1
	$\widetilde{Y}/Y$	$\widetilde{Y}-Y$ Billions \$	$\widetilde{Y}/Y$	$\widetilde{Y}-Y$ Billions \$	$\widetilde{Y}/Y$	$\widetilde{Y}-Y$ Billions \$	$\widetilde{Y}/Y$	$\widetilde{Y}-Y$ Billions \$
1. Agriculture, forestry, fish/hunt	0.91	-19.4	0.91	-20.5	0.91	-20.5	0.82	-40.6
2. Mining	0.97	-12.3	0.97	-13.5	0.97	-12.7	0.97	-13.2
3. Construction	0.92	-47.6	0.92	-50.7	0.92	-48.6	0.86	-86.8
4. Manufacturing	0.96	-73.8	0.96	-81.2	0.96	-74.7	0.93	-141.7
5. Wholesale and retail trade	0.97	-64.9	0.96	-71.7	0.97	-65.4	0.95	-98.5
6. Transportation and utilities	0.98	-17.5	0.97	-19.6	0.98	-17.7	0.96	-30.2
7. Information	0.98	-17.5	0.98	-19.7	0.98	-17.6	0.97	-23.8
8. Financial activities	0.98	-54.3	0.98	-61.6	0.98	-54.4	0.97	-98.9
9. Professional and business svcs	0.98	-36.1	0.98	-40.7	0.98	-36.2	0.96	-78.1
10. Educational and health svcs	0.99	-17.0	0.99	-19.6	0.99	-17.0	0.98	-27.5
11. Leisure and hospitality	0.91	-53.6	0.91	-57.1	0.91	-54.4	0.88	-75.1
12. Other Services	0.94	-20.4	0.94	-22.1	0.94	-20.7	0.91	-32.7
Total	0.97	-434.4	0.97	-478.2	0.97	-440.0	0.95	-747.0

Notes: In the baseline scenario (0) the elasticities of substitution are $(\sigma_e, \sigma_x, \sigma_n, \sigma_d) = (3, 6, 20, 20)$ and the type productivities are those obtained in the calibration. Columns 1 and 2 report the long-run effects for scenario 0. Relative to the baseline, scenario 1 assumes a low elasticity of substitution between documented and undocumented foreign-born workers, and the results are reported in columns 3 and 4. Relative to baseline, scenario 2 assumes a high elasticity of substitution between native and foreign-born workers, and the results are reported in columns 5 and 6. Relative to baseline, scenario 3 assumes that all type productivities equal one, and the results are reported in columns 7 and 8. The relative values in the totals row are computed on the basis of the corresponding total dollar amount and private-industry GPD in year 2013.

Table 11: Projected losses 2017-2026

	1	2	3	4
Capital adjustment	None	10 years	5 years	Immediate
2017	279.1	279.1	279.1	503.1
2018	291.1	317.1	349.5	524.7
2019	302.4	356.3	423.7	545.0
2020	314.0	398.0	503.0	566.0
2021	326.8	443.3	589.0	589.0
2022	340.3	492.0	613.4	613.4
2023	354.3	543.9	638.6	638.6
2024	368.9	599.1	664.9	664.9
2025	384.1	658.1	692.4	692.4
2026	400.1	721.1	721.1	721.1
Cumulative 2017-2026	3,361.0	4,807.9	5,474.6	6,058.1
	$ Billion	$ Billion	$ Billion	$ Billion

Notes: Column 1 assumes that capital remains constant at the 2016 level, and the annual GDP loss is 1.4%. Column 4 assumes that capital fully adjusts by 2017, and the annual GDP loss is 2.6%. Columns 2 and 3 assume that capital fully adjusts in 10 and 5 years, respectively. The short and long-run GDP losses are calculated by dividing the annual dollar loss by the overall GDP in the baseline year, taking into account the 12 private-sector industries and the public sector.

Table 12: Employment by state of residence, nativity and documentation status, 2011–2013

State	Emp in 000's	Pct foreign born	Pct undoc	Pct Mex & undoc	State	Emp in 000's	Pct foreign born	Pct undoc	Pct Mex & undoc
AL	2,000	4.8	2.1	1.5	MT	476	1.9	0.2	0.0
AK	354	9.1	1.4	0.1	NE	963	7.4	2.8	1.8
AZ	2,752	17.1	5.5	4.7	NV	1,240	25.9	8.7	6.1
AR	1,246	6.5	2.7	1.9	NH	691	6.4	0.9	0.1
CA	16,888	35.4	10.2	6.9	NJ	4,225	28.0	7.4	1.5
CO	2,562	12.1	4.2	3.3	NM	873	12.6	4.5	4.0
CT	1,768	17.4	4.6	0.8	NY	9,142	28.1	6.2	1.4
DE	423	11.5	3.2	1.5	NC	4,293	10.7	4.9	3.1
DC	324	18.2	3.5	0.2	ND	379	2.8	0.3	0.0
FL	8,321	25.2	5.6	1.4	OH	5,297	4.8	1.0	0.4
GA	4,291	13.7	5.3	3.1	OK	1,709	7.8	3.5	2.8
HI	645	22.8	3.8	0.2	OR	1,751	13.2	4.4	3.5
ID	707	8.0	3.1	2.7	PA	5,938	7.4	1.5	0.4
IL	6,034	18.1	5.8	4.1	RI	517	15.8	3.6	0.3
IN	2,997	5.8	2.1	1.4	SC	2,027	6.7	2.8	1.8
IA	1,556	5.6	1.8	1.0	SD	424	3.1	0.8	0.3
KS	1,395	8.5	3.3	2.3	TN	2,830	6.5	2.5	1.5
KY	1,865	4.4	1.3	0.8	TX	11,817	21.8	8.7	6.5
LA	2,000	5.4	1.9	0.8	UT	1,302	11.4	4.5	3.3
ME	643	3.5	0.2	0.0	VT	327	4.6	0.6	0.1
MD	2,960	18.7	5.4	0.6	VA	3,946	15.6	4.5	0.8
MA	3,342	18.4	3.0	0.1	WA	3,202	17.2	4.9	3.1
MI	4,279	7.3	1.3	0.5	WV	755	1.7	0.2	0.1
MN	2,792	8.8	2.1	1.0	WI	2,839	5.6	1.8	1.4
MS	1,195	3.0	1.1	0.6	WY	292	3.3	1.2	1.0
MO	2,774	5.0	1.3	0.6	USA	143,369	16.9	4.9	2.7

Notes: Statistics are averages across the 2011, 2012, and 2013 waves of the augmented American Community Survey (ACS) files supplied by Center for Migration Studies (2014) and described by Warren (2014). They are drawn from the employment sample described in the text.

Table 13: The Effects of Removal at the state level (annual loss). All industries pooled.

State	1 GDP 2013	2 Hours FB/All	3 Hours UFB/All	4 Short run $\widetilde{Y}/Y$	5 Short run $\widetilde{Y}-Y$	6 Long run $\widetilde{Y}/Y$	7 Long run $\widetilde{Y}-Y$
California	1938.4	0.36	0.11	0.96	-82.7	0.93	-135.8
Nevada	112.8	0.27	0.09	0.96	-4.1	0.94	-6.7
Texas	1398.4	0.23	0.09	0.96	-50.5	0.94	-83.1
New Jersey	474.8	0.29	0.08	0.97	-16.3	0.94	-26.8
New York	1168.2	0.29	0.06	0.97	-33.0	0.95	-54.6
Arizona	235.4	0.18	0.06	0.98	-5.8	0.96	-9.7
Florida	696.4	0.26	0.06	0.97	-17.6	0.96	-29.1
Georgia	392.1	0.14	0.06	0.98	-9.2	0.96	-15.2
Illinois	640.7	0.19	0.06	0.97	-17.2	0.96	-28.5
Maryland	264.1	0.20	0.06	0.97	-7.1	0.96	-11.7
USA	14438.6 $ Billion	0.18	0.05	0.98	-241.0 $ Billion	0.97	-434.4 $ Billion

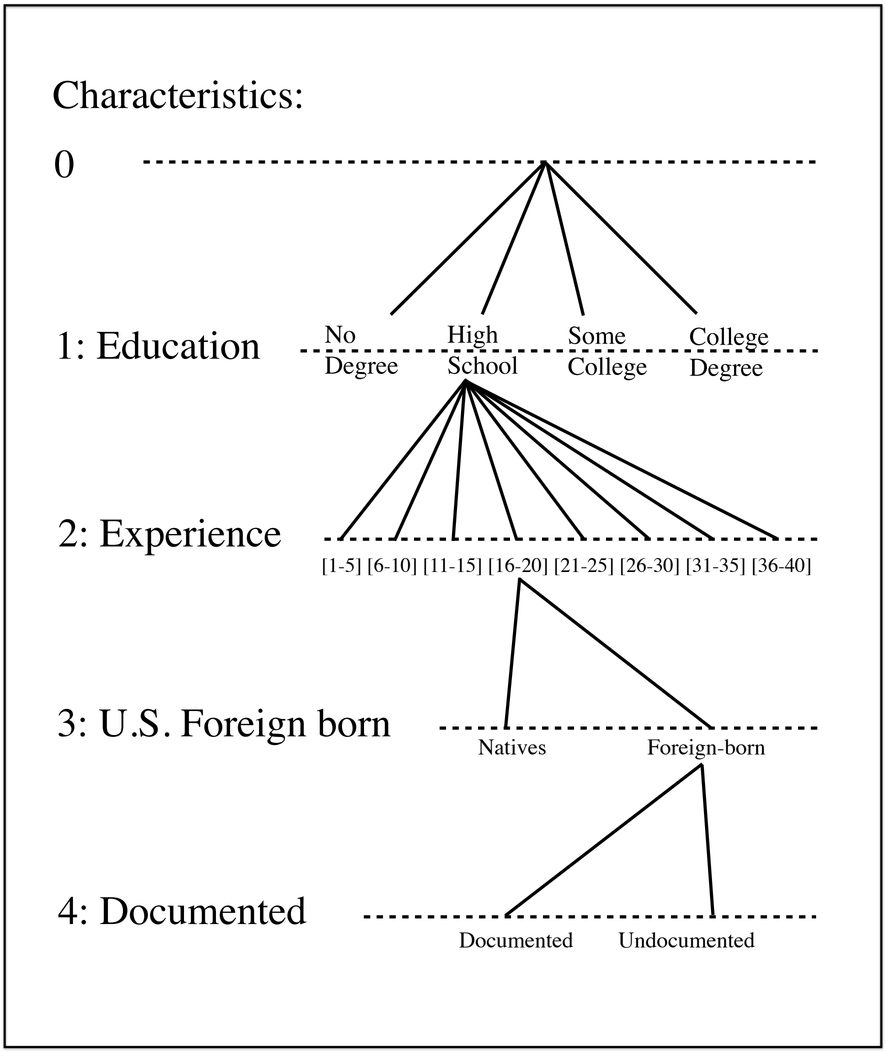
Notes: Columns 1-3 report data for baseline year 2013. Columns 4-5 report short-run estimates of removal. Columns 6-7 report long-run estimates of removal. The elasticities of substitution used in the calibration are the same as in the baseline for the national results. The type-productivity terms are calculated on the basis of national data with all industries pooled and imposed on all states. The bottom row (USA) reproduces the country-wide main results from Table 9.

Table 14: Legalization

	Short run $\widetilde{Y}/Y$	Short run Billions \$ $\widetilde{Y}-Y$	Long run $\widetilde{Y}/Y$	Long run Billions \$ $\widetilde{Y}-Y$
1. Agriculture, forestry, fish/hunt	1.003	0.6	1.011	2.5
2. Mining	1.001	0.6	1.006	2.5
3. Construction	1.012	7.7	1.019	12.1
4. Manufacturing	1.003	6.4	1.007	13.3
5. Wholesale and retail trade	1.004	7.9	1.006	12.3
6. Transportation and utilities	1.003	2.0	1.005	3.8
7. Information	1.001	0.6	1.002	1.7
8. Financial activities	1.001	1.9	1.002	7.5
9. Professional and business svcs	1.003	5.5	1.004	7.5
10. Educational and health svcs	1.004	5.8	1.005	6.7
11. Leisure and hospitality	1.011	6.6	1.015	9.3
12. Other Services	1.005	1.7	1.006	2.2
Total	1.003	47.2	1.006	81.5

Notes: Columns 1 and 2 report the ratio of the short-run counterfactual GDP after legalization to actual GDP in the industry in 2013, measuring the workforce in terms of hours worked. Columns 3 and 4 are analogous but the numerator refers to the long-run counterfactual. The relative values in the totals row are computed on the basis of the dollar gains and GDP in the baseline year.

Figure 1: CES Nesting Labor Aggregate



Notes: Adapted from Ottaviano and Peri (2012).