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The economic contribution of unauthorized workers: An industry analysis

Ryan Edwards[1], Francesc Ortega*[,2]

Queens College, CUNY, United States

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 3.1% of GDP annually, which amounts to roughly $6 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 4.8% 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.

1. Introduction

There is wide consensus that the problem of the large unauthorized population in the United States needs to be addressed soon.[3] 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. We then conduct simulations to quantify the economic contribution of unauthorized workers to the level of production in each 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. Last, we also analyze the implications of these policies for the average wages of native and documented immigrant workers.

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

* Corresponding author.

E-mail addresses: edwards.ryan.d@gmail.com (R. Edwards), fortega@qc.cuny.edu (F. Ortega).

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[3] 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).

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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 CES framework. Importantly, we allow for heterogeneous productivity for each labor type and calibrate those parameters to match observed waged data for each group.

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, although we also report the effects of the policies on the average wages of native and documented foreign-born workers.

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.

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 removal of unauthorized workers reveals that these workers are responsible for 3.6% of private-sector GDP (or 3.1% of overall GDP), which amounts to approximately $6 trillion over a 10-year period. At first the removal of unauthorized workers would reduce aggregate production by about 1.9%, 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 GDP is lower at around 3.1%. 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. We also show that if we take into account that undocumented workers may be underpaid by their employers, the estimated economic contribution of undocumented workers increases in proportion to the degree of exploitation.

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.[4] Because documented foreign-born workers are about 35% 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%, with the largest increases experienced in Construction and Leisure and hospitality (at 3% and 2.3%, respectively).

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 and Section 5 the calibration. Section 6 outlines our counterfactual scenarios, while Section 7 reports our main results. Section 8 conducts sensitivity analysis and Section 9 concludes.

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).[5] 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 firemen, and some medical professions, are assumed to be authorized, as well as individuals in government or in the military.[6]

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).[7] The broader validity of these types of estimates is

[4] 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.

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

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

[7] 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.

less clear. Assessments remain constrained by lack of large representative surveys that ask legal status.[8]

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" (NAICS) industries 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*.[9]

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. However, in our main analysis we will focus on the more parsimonious option of pooling into two broad education categories, college graduates and non-college-graduates. 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 (2012), 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 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.[10]

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 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),[11] Construction (13 percent), and Leisure and Hospitality (10 percent), as can be seen in column 5. 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, 2015), roughly half of unauthorized immigrants are Mexican. Table A.1 reports a breakdown of unauthorized workers by national origin (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 differences in weekly earnings across industries, nativity and documentation status. As displayed in Table A.2, 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 right-most column of Table A.2. 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 employment are partly due to differences in educational attainment and in (potential) work experience. As documented in Table A.3, 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-

[8] 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.

[9] 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 industry 13 from the analysis.

[10] In absolute numbers, the five states with the most undocumented workers are California, Texas, New York, Florida, and Illinois (Table A.6).

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

Table 1
Data summary.

Industry	2013 GDP Billions	Emp. Millions	Emp. UFB Millions	FB/All Emp.	UFB/All Emp.	FB/All Hours	UFB/All Hours
1. Agric., forestry, fish/hunt	225.4	1.99	0.35	0.3	0.18	0.29	0.17
2. Mining	441.1	0.85	0.02	0.09	0.03	0.09	0.03
3. Construction	619.9	8.84	1.12	0.24	0.13	0.23	0.12
4. Manufacturing	2024.7	15.06	0.89	0.19	0.06	0.19	0.06
5. Wholesale and retail	1969.8	20.54	0.85	0.15	0.04	0.15	0.04
6. Transport. and utilities	754.1	7.04	0.22	0.16	0.03	0.16	0.03
7. Information	793.8	3.01	0.07	0.12	0.02	0.12	0.02
8. Financial activities	3295.5	9.42	0.20	0.13	0.02	0.13	0.02
9. Prof. and business svcs	1952.5	15.66	0.99	0.2	0.06	0.14	0.03
10. Educ. and health svcs	1373.2	33.15	0.51	0.14	0.02	0.14	0.02
11. Leisure and hospitality	625.7	13.7	1.30	0.22	0.1	0.24	0.11
12. Other Services	363.1	7.16	0.55	0.22	0.08	0.23	0.08
Total	14438.6	136.4	7.07	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 $16,549.2 billion.

born workers have 3.4 and 5.8 years of potential experience more than undocumented immigrants (Table A.4). 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 $j = 1, \ldots, J$ 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, omitting the industry j subindex to lighten notation. We allow workers to differ in education ($e = 1, \ldots, E$), potential years of work experience ($x = 1, \ldots, X$), 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 $3 \times E \times X$. In our preferred specification we will focus on two broad education groups ($E = 2$) and eight potential experience groups ($X = 8$).

We aggregate all these types of workers by means of a multi-nested constant-elasticity of substitution (CES) aggregator, as in Borjas (2003) and Ottaviano and Peri (2012).[12] 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 comparability with previous studies, we choose the following nesting structure:

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

$$L_e = C(L_{e,x=1}, \ldots, L_{e,x=X} | \theta_{e,x}, \sigma_x), \text{ for } e = 1, 2, 3, E$$

$$L_{e,x} = C(Nat_{e,x}, L_{e,x}^{FB} | \theta_{e,x}^{Nat}, \theta_{e,x}^{FB}, \sigma_n), \text{ for } e = 1, \ldots, E \text{ and } x = 1, \ldots, X$$

$$L_{e,x}^{FB} = C(DFB_{e,x}, UFB_{e,x} | \theta_{e,x}^{DFB}, \theta_{e,x}^{UFB}, \sigma_d), \text{ for } e = 1, \ldots, E \text{ and } x = 1, \ldots, X,$$

where the CES aggregator is defined by

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

In words, we have four levels of CES aggregation. 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.[13]

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). On the basis of their results, we will consider two broad education groups ($E = 2$), distinguishing between individuals with a college degree ($e = 2$), and those with one ($e = 1$). The specific values for the elasticities of substitution are presented below.

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

[12] In these studies the production function was assumed to apply to the economy as a whole.

[13] Our nesting structure is based on models A and B in Ottaviano and Peri (2012), as we discuss further below. The main difference is that we have introduced an additional layer that disaggregates the foreign-born population by documentation status. However, given the lack of empirical estimates for the elasticity of substitution between these two types of workers, in our calibration we will assume they are perfect substitutes, though we still allow for productivity differences.

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, $K_j = \overline{\kappa}_j L_j$.[14] 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

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

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 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.[15]

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, $E = 2$ 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, we lack empirical estimates of the elasticity of substitution between documented and undocumented foreign-born workers (within education-experience cells), σ_d. Accordingly, we assume these two types of workers to be perfect substitutes. Specifically, we set $\sigma_d = 1,000$ and we have verified that our estimates are not sensitive to choosing much higher values for this elasticity.

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 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 Eq. (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. 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. Given that our calibration entails an effectively infinite value for this elasticity of substitution, and our normalization, $\theta_{e,x}^{DFB}$ is essentially given by the DFB-UFB relative wage for workers with the same education and potential experience.

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

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

where the last term follows from the assumption of perfect substitutes. We are now 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:[16]

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

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

[14] 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 $Y = A(K(L))^{\alpha} L^{1-\alpha} = (A\overline{\kappa}_j^{\alpha})L = B^{LR}L$. Note that we also assume that total factor productivity is constant throughout.

[15] 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.

[16] 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.

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

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

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

and then compute aggregate L_e for each e using[17]

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

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

$$\frac{w_2}{w_1} = \left(\frac{\theta_2}{1}\right)\left(\frac{L_2}{L_1}\right)^{-1/\sigma_e}, \tag{10}$$

and compute L using

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

At this point it is helpful to examine the values that we obtain for these parameters. Table 2 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 corresponding productivity terms obtained in a calibration using pooled data across all 12. Several observations are worth noting.

First, column 1 shows that across practically all education and experience cells, the productivity of DFB workers appears to be higher than that of UFB. The simple average across all groups is 1.35, reflecting that wages are 35% higher for documented workers compared to observationally equivalent undocumented ones. This is also the case in the three industries showcased in the table (columns 2–4), with relative DFB-UFB productivities ranging between 1.42 and 1.48. Second, columns 5-8 report the productivity of native labor, relative to foreign-born labor at the same levels of education and potential experience. Across all cells, the coefficients in these three columns are always higher than one, indicating that native labor is more productive than foreign-born labor, which includes both documented and undocumented workers. The simple average across cells in the column based on data pooled from the 12 industries (column 5) is 1.23. Columns 6-8 suggest that the native-immigrant relative productivity is even higher in Agriculture, Construction and Leisure and Hospitality. It is worth noting that our calibration assumes that all workers are paid according to their marginal productivity. While this is a reasonable assumption for native and documented foreign-born workers, it may not be the case for undocumented workers. Because of their vulnerability, employers may be able to underpay them, relative to their productivity. If this type of exploitation is pervasive, our estimated DFB-UFB productivity terms may be biased. We will return to this point in Section 7.4.

It is also interesting to move up one more level and examine the relative productivities across education groups. The results are reported in Table 3. All industries (except for Construction) exhibit large returns to a college degree, with a value of 1.66 based on a sample pooling all 12 industries. In some industries, the returns to a college degree are substantially higher, with values over 2 in Financial activities, Professional and business services, and Educational and health services.

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 A.5 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.

[17] 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.

Table 2
Relative productivities: agriculture, construction and leisure & hospitality.

edu	exp	(1) $\theta^{DFB}_{e,x}$ **All Ind.**	(2) $\theta^{DFB}_{e,x}$ Agric.	(3) $\theta^{DFB}_{e,x}$ Cons.	(4) $\theta^{DFB}_{e,x}$ L & H	(5) $\theta^{Nat}_{e,x}$ **All Ind.**	(6) $\theta^{Nat}_{e,x}$ Agric.	(7) $\theta^{Nat}_{e,x}$ Cons.	(8) $\theta^{Nat}_{e,x}$ L & H
1	1	1.11	1.00	1.19	1.02	1.13	1.42	1.37	1.00
1	2	1.25	1.04	1.29	1.18	1.31	1.56	1.49	1.16
1	3	1.38	1.14	1.38	1.25	1.37	1.62	1.55	1.15
1	4	1.40	1.10	1.32	1.28	1.42	1.76	1.56	1.25
1	5	1.43	1.08	1.45	1.28	1.41	1.62	1.53	1.23
1	6	1.42	1.20	1.42	1.37	1.41	1.67	1.50	1.27
1	7	1.46	1.46	1.44	1.38	1.42	1.61	1.43	1.22
1	8	1.43	1.28	1.39	1.34	1.40	1.68	1.44	1.22
2	1	1.01	1.21	1.48	1.05	1.05	1.69	1.24	1.14
2	2	0.99	1.15	1.32	1.32	1.04	1.67	1.45	1.27
2	3	1.12	2.46	1.20	1.49	1.02	1.46	1.39	1.28
2	4	1.28	1.51	1.79	1.52	1.04	1.12	1.44	1.43
2	5	1.37	1.61	1.65	1.48	1.10	1.82	1.36	1.58
2	6	1.61	2.34	1.73	1.81	1.15	1.61	1.45	1.70
2	7	1.58	2.40	1.94	2.06	1.19	1.72	1.37	1.52
2	8	1.87	1.14	1.74	1.85	1.15	1.57	1.30	1.56
Avg.		**1.35**	1.44	1.48	1.42	**1.23**	1.60	1.43	1.31

Note: Education group 1 refers to individuals that do not possess a college degree, and education group 2 are college graduates. 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. $\theta^{Nat}_{e,x}$ is the productivity of native labor relative to foreign-born labor within the same education-experience cell. $\theta^{DFB}_{e,x}$ is the productivity of documented foreign-born labor relative to undocumented labor within the same education-experience cell. Columns 1 and 5 report the parameters obtained when we pool all 12 industries. The last row reports simple averages of each column. Calibration based on baseline elasticities (3, 6, 1000) and nesting with two broad education categories.

Table 3
Relative productivities by education.

	Non-college θ_1	College grad. θ_2
1. Agriculture, forestry, fish/hunt	1	1.24
2. Mining	1	1.22
3. Construction	1	0.98
4. Manufacturing	1	1.59
5. Wholesale and retail trade	1	1.46
6. Transportation and utilities	1	1.02
7. Information	1	1.55
8. Financial activities	1	2.14
9. Professional and business svcs	1	2.29
10. Educational and health svcs	1	2.12
11. Leisure and hospitality	1	1.43
12. Other Services	1	1.14
All industries pooled	1	1.66

Note: The second column is the productivity of college graduates relative to the productivity of workers with lower educational attainment in the same industry. Calibration based on baseline elasticities $\Sigma = (3, 6, 20, 1000)$.

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.[18]

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 Eqs. (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. 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.[19]

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 taking 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 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:

$$L_{e,x}^{FB} = C(DFB_{e,x}, UFB_{e,x} | \theta_{e,x}^{DFB}, \sigma_d) \tag{14}$$

$$\widetilde{L}_{0_{e,x}}^{FB} = C(DFB_{e,x}, 0 | \theta_{e,x}^{DFB}, \sigma_d) = (\theta^{DFB})^{\frac{\sigma_d}{\sigma_d - 1}} DFB_{e,x}, \tag{15}$$

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), where we omit the j subindex to lighten the notation. That is,

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

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.[20]

One remarkable feature of Eqs. (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:

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

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

Because the terms G^{SR} and G^{LR} will typically be lower than one, the

[18] Variation in labor shares across industries dwarfs both the small year-to-year fluctuations in industry labor shares visible in Table A.5 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. (2013) at the top of their Table 1.

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

[20] 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.

Table 4
The effects of removal on industry output.

	Billions $ GDP 2013	SR Hours. $\frac{\tilde{Y}}{Y}$	SR Emp. $\frac{\tilde{Y}}{Y}$	SR Emp. $\tilde{Y} - Y$ $B	LR Hours. $\frac{\tilde{Y}}{Y}$	LR Emp. $\frac{\tilde{Y}}{Y}$	LR Emp. $\tilde{Y} - Y$ $B
1. Agriculture, forestry, fish/hunt	225.4	0.978	0.977	−5.3	0.907	0.902	−22.0
2. Mining	441.1	0.995	0.994	−2.5	0.977	0.976	−10.8
3. Construction	619.9	0.948	0.946	−33.5	0.920	0.917	−51.5
4. Manufacturing	2024.7	0.981	0.980	−39.8	0.961	0.960	−82.0
5. Wholesale and retail trade	1969.8	0.979	0.979	−41.1	0.967	0.968	−63.8
6. Transportation and utilities	754.1	0.988	0.988	−9.2	0.977	0.977	−17.3
7. Information	793.8	0.992	0.991	−6.8	0.978	0.978	−17.6
8. Financial activities	3295.5	0.996	0.996	−14.3	0.983	0.983	−57.0
9. Professional and business svcs	1952.5	0.986	0.971	−57.3	0.981	0.961	−77.1
10. Educational and health svcs	1373.2	0.989	0.989	−14.7	0.988	0.988	−17.1
11. Leisure and hospitality	625.7	0.941	0.944	−35.0	0.917	0.922	−48.7
12. Other Services	363.1	0.959	0.959	−15.1	0.945	0.945	−19.9
All ind. pooled	14438.6	0.981	0.981	−280.6	0.964	0.964	−525.1
Sum indusries 1 through 12	14438.6	0.981	0.981	−274.6	0.966	0.966	−484.9

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 ($\tilde{Y}$) 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. Second to last row presents the results based on an aggregate calibration and simulation based on pooled data for all 12 industries. The last row presents the sum of the dollar amounts across industries 1 through 12. The short and long-run percent changes in the last row are calculated by dividing the dollar amounts ($274.6 and $484.9 Billion) by private-sector GDP in 2013 ($14,439 Billion) and adding one.

SRE and LRE dollar gains will be negative, that is, they will amount to losses, and the long-run losses will be larger than the short-run ones in each industry: $LRE < SRE \leq 0$.

7. Main 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 4. 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 hours work, while column 3 uses employment. 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. Because of the lower measurement error, we rely more heavily on the estimates based on employment. 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, with an income loss of 1.9% when pooling all 12 industries. 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, Professional and business services, and Leisure and hospitality, at about $40 billion each. Adding across the 12 industries, leads to an overall short-run loss of $274.6 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 (almost 10 percent), Leisure and Hospitality (8 percent), and Construction (8 percent). In terms of dollars, the largest losses again correspond to Manufacturing, followed by Wholesale and Retail trade, Financial activities, and Leisure and hospitality. The overall long-run annual loss when we add all industries amounts to $485 billion, almost doubling the short-run loss. This figure amounts to roughly 3.6% of the private-sector GDP, and 3.1% of overall GDP.

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 quantify the size of the bias in the robustness section.[21] 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 A.4, immigrants tend to be younger than natives (by about 3 years) and than legal immigrants (by about 6 years) in most industries. In addition they have an average of 3 years of schooling less than native and legal immigrants (Table A.3). 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 supplies, our calibration implied that documented foreign-born workers were on average 35 percent more productive than unauthorized ones (last row Table 2). In addition, relative to natives in the same skill group and industry, foreign-born labor also appears to be less productive than native labor by about 23 percent when averaging across all industries. We revisit the estimated productivity gaps in Section 8.

The last two rows of column 3 (SR Emp.) provide slightly different approaches to estimate the aggregate output loss. In the second to last row, we pool the data for all industries and calibrate the model using those data. Instead the last row is based on the calibration and simulation for each industry separately. We then add up the corresponding dollar amounts for each industry and express the resulting figure as a share of private-sector GDP. In the case of the estimation of the short-run effects of removal, both of these procedures deliver an output loss of 1.9% of private-sector GDP. The resulting figures for the long-run output losses from removal using the two methods are 3.6% and 3.4%, respectively. While both estimates are very similar, we note

[21] 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%, which is substantially higher than our estimated 3.1% drop in total GDP.

that the aggregate analysis tends to deliver slightly larger estimates of the overall output loss. Because this approach is more consistent with the estimated elasticities of substitution that we use, we rely more strongly on the results based on the pooled industry analysis when we are interested in the aggregate economic effects, rather than on the industry breakdown.

7.1.1. 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, although in reality the effects will persist beyond that period. 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 4 we found that the income losses amounted to $281 and $525 billion in the short and long runs, respectively, when conducting the analysis on the pooled industry dataset. Relative to the baseline year, these losses amounted to 1.9% and 3.6% of private-sector GDP. Relative to overall GDP, including also the private sector, the corresponding percentages are 1.7% and 3.1%, 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 1.7% loss. Likewise, the upper bound calculation is produced by applying an annual 3.1% loss to projected GDP for 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 3.1% in either 5 or 10 years.

Table 5 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 $3.8 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 $7.2 trillion. Columns 2 and 3 provide the estimates assuming that capital adjusts in 10 and 5 years, which amount to cumulative losses of $5.6 and $6.5 trillion, respectively. In conclusion, these calculations suggests that the 10-year cumulative loss associated to the removal of authorized workers in year 2017 would be approximately $6 trillion, in addition to the expenses associated to deportation and border enforcement.

Table 5
Cumulative effects of removal, 2017–2026.

Capital adjustment	1 None	2 10 years	3 5 years	4 Immediate
2017	322.4	322.4	322.4	603.3
2018	335.4	367.9	408.5	627.7
2019	347.7	415.0	499.2	650.7
2020	360.2	464.8	595.6	674.1
2021	374.3	519.2	700.4	700.4
2022	389.2	577.6	728.3	728.3
2023	404.8	640.0	757.6	757.6
2024	421.1	706.6	788.1	788.1
2025	438.2	777.6	820.0	820.0
2026	455.9	853.1	853.1	853.1
Cumulative 2017-2026	3,849.2 $ Billion	5,644.2 $ Billion	6,473.2 $ Billion	7,203.2 $ Billion

Notes: Column 1 assumes that capital remains constant at the 2016 level, and the annual GDP loss is 1.9% of private-sector GDP (or, equivalently, 1.7% of overall GDP). Column 4 assumes that capital fully adjusts by 2017, and the annual GDP loss is 3.6% of private-sector GDP (or, equivalently, 3.1% of overall GDP). Columns 2 and 3 assume that capital fully adjusts in 10 and 5 years, respectively. These calculations are based on the current-price (nominal) GDP projections produced by the CBO.

7.1.2. 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%.[22] 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 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 6 collects the results for the top-10 states with the highest unauthorized shares in hours worked (and employment). 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 $73.1 and $135.5 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 $84 and $53 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.

7.2. Legalization of unauthorized workers

We next consider the gains from providing legal status to unauthorized workers. Kossoudji and Cobb-Clark (2002) and Lozano and Todd (2011) analyzed the wage effects of the 1986 IRCA amnesty and estimated the wage penalty for being unauthorized to be around 20 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. In contrast to those studies, Lofstrom et al. (2013) find no evidence of improved employment outcomes attributable to legal status, except among the high-skilled. More recently, Orrenius and Zavodny (2014) have analyzed the effects of the E-Verify program and provided evidence of a

[22] 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 A.6.

Table 6
The Effects of Removal at the state level (annual loss). All industries pooled.

State	1 GDP	2 Hours FB/All	3 Hours UFB/All	4 Short run $\tilde{Y}/Y$	5 Short run $\tilde{Y}-Y$	6 Long run $\tilde{Y}/Y$	7 Long run $\tilde{Y}-Y$
California	1938.4	0.36	0.11	0.96	−73.1	0.93	−135.5
Nevada	112.8	0.27	0.09	0.97	−3.5	0.94	−6.5
Texas	1398.4	0.23	0.09	0.97	−45.3	0.94	−84.2
New Jersey	474.8	0.29	0.08	0.97	−13.7	0.95	−25.6
New York	1168.3	0.29	0.06	0.98	−28.2	0.95	−52.7
Florida	696.4	0.26	0.06	0.98	−14.7	0.96	−27.5
Illinois	640.7	0.19	0.06	0.98	−14.5	0.96	−27.1
Georgia	392.1	0.14	0.06	0.98	−7.9	0.96	−14.8
Maryland	264.1	0.2	0.06	0.98	−6.0	0.96	−11.1
Arizona	235.4	0.18	0.06	0.98	−5.0	0.96	−9.3
	$ Billion				$ Billion		$ 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.

negative effect on the productivity of unauthorized workers.[23] Our calibration is largely consistent with these findings.[24]

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:

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

for each education-experience cell.

Because unauthorized workers are now endowed with the higher productivity of documented foreign-born workers, 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 that 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, summarized in Table 7. 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, Professional and business services, and Leisure and hospitality. Translating these estimates into dollar amounts (column 2), we find that the total short-run gains from legalization amount to $92 billion annually on the basis of the calibration using data pooling all industries. Columns 3 and 4 report the corresponding figures for the long-run analysis. The largest relative gains are for Construction and Leisure and hospitality, with a 2 to 3 percent increase in production (column 3). In dollar terms the largest long-run annual gains accrue to Construction, Manufacturing and Professional and business services, ranging between $19 billion and $29 billion each. On the basis of the analysis pooling all industries, the overall long-run annual gains total $174 billion, or 1.2% of private-sector GDP. In conclusion, granting legal status to undocumented foreign-born workers would increase their economic contribution from the current 3.6% to 4.8% of private-sector GDP. In a nutshell, this result is driven by the increased productivity that undocumented foreign-born workers would experience thanks to the increased labor market opportunities offered by legal status.

Table 7
The effect of legalization.

	Short run $\tilde{Y}/Y$	Short run Billions $ $\tilde{Y}-Y$	Long run $\tilde{Y}/Y$	Long run Billions $ $\tilde{Y}-Y$
1. Agriculture, forestry, fish/hunt	1.004	0.8	1.016	3.7
2. Mining	1.001	0.6	1.006	2.5
3. Construction	1.020	12.1	1.031	19.0
4. Manufacturing	1.006	11.4	1.012	23.7
5. Wholesale and retail trade	1.005	10.8	1.009	16.9
6. Transportation and utilities	1.004	2.7	1.007	5.2
7. Information	1.001	1.0	1.003	2.6
8. Financial activities	1.001	2.6	1.003	10.5
9. Professional and business svcs	1.011	21.4	1.015	29.0
10. Educational and health svcs	1.005	6.4	1.005	7.5
11. Leisure and hospitality	1.015	9.5	1.022	13.5
12. Other Services	1.007	2.6	1.010	3.5
All ind. pooled	1.006	91.8	1.012	173.8
Sum industries 1 through 12	1.006	82.0	1.010	137.5

Notes: Columns 1 and 2 report the ratio of the short-run counterfactual GDP after legalization to actual GDP in the industry in 2013. Columns 3 and 4 are analogous but the numerator refers to the long-run counterfactual. The second to last row presents the results based on an aggregate calibration and simulation using pooled data for all 12 industries. The last row presents the sum of the dollar amounts across industries 1 through 12.

7.3. Wage Effects

Up until now we have focused exclusively on the effects of removal or legalization on output, by industry or for the aggregate of the economy. This section analyzes the implications of these policies regarding the undocumented population on wages. More specifically, we have computed the wages for each of the 48 types of workers (defined by education, experience, nativity and documentation status) for a variety of parameter configurations, using the dataset that pools all industries as well as for each industry separately.[25] For brevity, and comparability with the literature, we focus on average wages by skill

[23] 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.

[24] Our calibration implies that the relative productivity of documented foreign-born workers is about 35 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.

[25] The computation is based on the numerical calculation of the gradient of the production function evaluated at the corresponding labor allocation. The CES framework allows for an analytical derivation, but it requires a lot of notation in a four-nested setup like ours.

Table 8
Effects on Average Wages. Changes in percentage points.

Nativity Education Paremeters	σ_e	σ_x	σ_n	(1) Nat All	(2) Nat Edu1	(3) Nat Edu2	(4) DFB All	(5) DFB Edu1	(6) DFB Edu2
Counterfactual: Removal of UFB									
1. Baseline	3	6	20	−0.2	0.2	−0.6	0.7	1.7	−0.2
2. Perfect subs. Natives – Immigrants	3	6	1000	0.0	0.5	−0.5	−0.1	0.5	−0.5
3. Perfect subst. by exp. and nativity	3	1000	1000	0.0	0.5	−0.5	−0.1	0.5	−0.5
4. Perfect subst. at all levels	1000	1000	1000	0.0	0.0	0.0	0.0	0.0	0.0
Counterfactual: Legalization of UFB									
1. Baseline	3	6	20	0.1	−0.1	0.3	−8.8	−4.5	−2.3
2. Perfect subs. Natives - Immigrants	3	6	1000	0.0	−0.2	0.2	−8.6	−4.1	−2.2
3. Perfect subst. by exp. and nativity	3	1000	1000	0.0	−0.2	0.2	−8.4	−4.1	−2.2
4. Perfect subst. at all levels	1000	1000	1000	0.0	0.0	0.0	−8.4	−3.9	−2.4

Notes: In all parameter configurations, the elasticity of substitution between documented and undocumented foreign-born workers (with the same education and experience) is kept fixed at 1000. The results are robust to increasing the value of this elasticity at much higher levels. Columns 1–3 refer to the change in the average wage of natives across potential experience groups. In columns 2 and 3 we condition by education level, with *Edu1* referring to individuals that did not graduate from college and *Edu2* to college graduates. Similarly, columns 4–6 refer to documented foreign-born workers. Note that in the legalization scenario the group of DFB workers increases in size as it absorbs the UFB workers.

and nativity, pooling workers of different potential experience levels.

We begin by imposing our preferred set of elasticities, $(\sigma_e, \sigma_x, \sigma_n) = (3, 6, 20)$, and gradually progress toward the case of perfect substitution $(\sigma_e, \sigma_x, \sigma_n) = (1000, 1000, 1000)$. Throughout we keep the same values for the relative productivity parameters, calibrated to match the wages for each education-experience-nativity-documentation-industry cell in the pooled industry data, which typically implies large productivity differences across labor types.

Table 8 reports our findings. The top panel focuses on the effects of removing UFB workers, and the bottom panel reports on the effects of legalizing them. Unlike previous tables, here we reported wage changes in percentage points. With our baseline elasticities (row 1), average native wages (*Nat All*) would decline by 0.2% (though the drop could be as large as 0.7% in Agriculture). This figure masks an important composition effect: small increases in average unskilled native wages (*Nat Edu1*) of 0.2% but larger drops for skilled natives (*Nat Edu2*) around 0.6%. In essence, the removal of UFB would lead to a reduction in the relative supply of unskilled workers in the economy, resulting in the usual distributional effects: unskilled natives would benefit but skilled natives would be hurt. However, the quantitative magnitudes are fairly small for the economy as a whole. In Agriculture, the industry with the largest share of UFB in employment, unskilled native wages would increase by just 0.6% and skilled native wages would fall by 3%. Because of the perfect substitutability between DFB and UFB workers with the same education and potential experience, the removal of UFB would lead to an average increase in the wages of DFB of 1.7%, and a reduction of average skilled wages among DFB workers of 0.2%.

The second parameter configuration, presented in row 2, differs from the previous one by imposing perfect substitution between natives and immigrants within education-experience cells, as in Borjas (2003). Intuitively, the figures show the same changes in average wages by skill group for natives and for DFB in response to the removal of UFB workers, with an increase in unskilled wages (of 0.5%) that sits between the previous lower value for natives (at 0.2%) and the previous higher value for DFB (at 1.7%). Row 3 assumes also perfect substitution across experience groups, which has practically no effect on the estimates. Last, row 4 imposes perfect substitution across all levels (education, experience, nativity and documentation status), effectively rendering the labor aggregate linear. Obviously, in this case, the removal of UFB has no impact on the wages of native or DFB workers.

Next, we turn to the effects of legalization, reported in the bottom panel of the table. With our baseline elasticities of substitution (row 1), we find that the legalization of UFB would lead to a 0.1% increase in average native wages. As before, this figure is the result of a reduction in average unskilled native wages (by 0.1%) and a larger increase in average native wages (of 0.3%). These changes are what one would expect given that legalization entails a net increase in the efficiency units of (immigrant) unskilled labor in the economy because of the removal of the undocumented productivity penalty discussed earlier.

Turning now to the effects on the average wages of DFB, legalization would trigger a large drop of 4.5% in average unskilled wages and a smaller drop in average skilled wages of 2.3%, leading to an overall 8.8% reduction in the average wage for DFB workers. These large drops reflect both the increase in the relative supply of unskilled labor, and the 'worsening' composition of each skill group in terms of potential experience due to the lower average age of UFB relative to DFB. To disentangle the two effects it is helpful to consider the scenario of perfect substitution at all nesting levels, which eliminates adjustments in relative wages. As can be seen in row 4, the changes in average DFB wages by skill group (under perfect substitution across all labor types) are very similar to those in row 1, which implies that the main driving force behind the reduction in the average wages of DFB is the composition effect due to the lower potential experience of UFB.

7.4. Exploitation of undocumented workers

A wealth of evidence (Hotchkiss and Quispe-Agnoli, 2013; Brown et al., 2013; Hirsch and Jahn, 2015) suggests that undocumented workers are often not paid their full marginal product. Clearly, their bargaining power is diminished by their lack of legal status, and employers can appropriate a larger part of the surplus generated by the employer-employee match. If this is the case, our calibration method is *underestimating* 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 underestimate the true loss.

To formalize this point it is convenient to assume that UFB are 'taxed' at a rate τ by employers. In our context with inelastic labor supply, the only effect of this exploitation tax operates through the changes in the relative productivities recovered from relative wages. In this context, the calibration of the relative productivity between DFB and UFB with the same education and experience is given by

$$\frac{\theta_{e,x}^{DFB}}{\theta_{e,x}^{UFB}} = (1 - \tau)\frac{W_{e,x}^{DFB}}{W_{e,x}^{UFB}}, \tag{20}$$

where we normalize $\theta_{e,x}^{UFB} = 1$. Clearly, ignoring the exploitation tax

Table 9
Exploitation tax. Change in income ($ Billions). All industries pooled.

Exploitation tax	$\tau = 0$	$\tau = 0.1$	$\tau = 0.2$
Elast. $(\sigma_e, \sigma_x, \sigma_n) = (3, 6, 20)$			
Removal	−525.1	−533.6	−542.4
Legalization	173.8	106.2	36.4
Elast. $(\sigma_e, \sigma_x, \sigma_n) = (3, 1000, 1000)$			
Removal	−524.8	−533.2	−541.9
Legalization	176.2	107.9	37.3

Notes: In all parameter configurations, the elasticity of substitution between documented and undocumented foreign-born workers (with the same education and experience) is kept fixed at 1000. The results are robust to increasing the value of this elasticity at much higher levels.

Table 10
Robustness. Long-run Effects of Removal.

Scenario	0	1	2	3
Educ. Groups	2	4	2	2
σ_e	3	3	3	3
σ_x	6	6	6	6
σ_n	20	20	1000	20
σ_d	1000	1000	1000	1000
Θ	calibration	calibration	calibration	1
	$\tilde{Y}/Y$	$\tilde{Y}/Y$	$\tilde{Y}/Y$	$\tilde{Y}/Y$
1. Agriculture, forestry, fish/hunt	0.907	0.910	0.906	0.840
2. Mining	0.977	0.971	0.977	0.970
3. Construction	0.920	0.920	0.921	0.890
4. Manufacturing	0.961	0.962	0.962	0.940
5. Wholesale and retail trade	0.967	0.968	0.967	0.960
6. Transportation and utilities	0.977	0.977	0.977	0.970
7. Information	0.978	0.978	0.978	0.980
8. Financial activities	0.983	0.983	0.983	0.980
9. Professional and business svcs	0.981	0.963	0.981	0.970
10. Educational and health svcs	0.988	0.988	0.988	0.980
11. Leisure and hospitality	0.917	0.922	0.918	0.900
12. Other Services	0.945	0.945	0.945	0.920
All ind. pooled	0.964	0.962	0.964	0.950

Notes: In the baseline scenario (0), the first-level nest contains two broad education categories (college graduates and non-college graduates), the elasticities of substitution are $(\sigma_e, \sigma_x, \sigma_n, \sigma_d) = (3, 6, 20, 1000)$ and the productivities are those obtained in the calibration. Relative to baseline, scenario 1 considers 4 education groups, with the same elasticities of substitution as in the baseline case. Relative to the baseline, scenario 2 assumes perfect substitution between natives and immigrants with the same education and potential experience ($\sigma_d = 1000$). Relative to baseline, scenario 3 assumes that all type productivities equal one.

leads to upwardly biased estimates of $\theta_{e,x}^{DFB}$ because we are mistaking the low after-tax relative wage of UFB by low relative productivity.[26]

The lower values for the relative DFB-UFB productivity term $\theta_{e,x}^{DFB}$ that result when we explicitly take into account the exploitation tax has two important consequences. First, in the removal scenario the output loss will be larger because of the higher relative productivity of UFB. Second, in the legalization scenario the output gain will be smaller because the increase in productivity associated to the change in legal status will now be smaller.

Table 9 summarizes the results of our simulations for varying values of the exploitation tax (0, 0.10 and 0.20) on the basis of computations performed on the pooled industry data. The top panel presents our estimates for the baseline elasticities $(\sigma_e, \sigma_x, \sigma_n) = (3, 6, 20)$. Column 1 reproduces our earlier results, with $\tau = 0$. In this case removal of UFB leads to a GDP loss of $525 billion and their legalization increases GDP by $174 billion. Column 2 assumes an exploitation tax of $\tau = 0.10$. As expected, the cost of removal is now increased. However, the effect is quantitatively small, with an estimated output loss from removal of $534 billion, only 2% higher than in column 1. As anticipated earlier, the gains from legalization now fall to $106 billion. Column 2 considers an exploitation tax of $\tau = 0.20$. The loss from removal rises again, but also by a small amount (1.5%), and the gains from legalization shrink further to merely $36 billion. As illustrated in Eq (20), the size of the exploitation tax directly affects the estimated documented-undocumented relative productivity. Quantitatively, this is the crucial parameter in the legalization simulation, with a large effect on the income effects. The GDP effect of removal is somewhat less sensitive to the size of the exploitation tax because it depends only partially on the documented-undocumented productivity gain, and much more on the level of productivity of foreign-born workers in general, regardless of their documentation status.

The bottom panel of the table conducts the analysis under the assumption of perfect substitution across all labor types, though allowing for varying productivity terms in order to match the wages observed in the data. The resulting estimates are practically identical to those obtained under the baseline values for the elasticities.

In sum, to the extent that undocumented workers may be exploited by employers and paid below their marginal productivity, our earlier estimates of the output loss from their removal would have to be revised upwardly. At the same time, the estimates of the effects of legalization would have to be lowered correspondingly.

8. Robustness

We now consider several robustness checks in order to assess the sensitivity of our main results to the nesting structure, the values of 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 the long-run output effects of removal.

The results are collected in Table 10. The first column in the table refers to our preferred specification, with two broad education groups (college graduates versus those without a college degree), and baseline elasticities of substitution $(\sigma_e, \sigma_x, \sigma_n, \sigma_d) = (3, 6, 20, 1000)$. As discussed earlier, the removal of UFB workers would lead to a long-run output loss of 3.6% of private-sector GDP on the basis of the calibration and simulation using the pooled industry data.

Scenario 1, displayed in the second column, considers a nesting structure that defines the first-level nest on the basis of four education groups: high-school dropouts, high-school graduates, individuals with some college, and college-graduates.[27] Clearly, columns 1 and 2 are almost identical, implying that the implications of a removal policy for output are robust to conducting the analysis on the basis of broad or narrower education groups.

Scenario 2 (column three) departs from the scenario 0 by assuming that natives and immigrants are perfect substitutes within education-experience cells, as in Borjas (2003). To analyze this scenario we set $\sigma_n = 1,000$, which effectively amounts to perfect substitution between these two types of labor. Once again, the industry estimates obtained under this scenario are identical (up to two decimals) to those obtained in the baseline scenario (column 1). The results so far show that the effects of removal on output are very robust to the specific assumptions on the nesting structure and the elasticities of substitution within each nest.

We now assess the role played by heterogeneity in the type-productivity terms, a key element in our approach. To gauge this point, scenario 3 presents estimated effects under the assumption that all productivity terms Θ_j equal to one, rather than calibrating them to match the wages for each labor type observed in the data. The key insight is that the long-run effects of removal would now be substantially larger, entailing an output loss of 5%, compared to 3.6% in our preferred scenario, that climbs up to 16% for Agriculture. The reason

[26] For a related critique in the context of the econometric estimation of these parameters, see Dupuy and Sorensen (2014).

[27] This was the nesting structure employed in an earlier version of this paper.

why ignoring productivity differences between workers produces an overestimate of the production effect is that our calibration uncovered a large productivity disadvantage for undocumented workers, relative to documented immigrants and natives. Accordingly, imposing a value of one for all relative productivity terms overestimates the productivity and, therefore, the contribution to output of unauthorized workers.

9. Conclusions

We have found the economic contribution to U.S. GDP of unauthorized workers to be substantial, at approximately 3.1% of GDP, 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 if this productivity penalty were removed through legalization, it could increase the economic contribution of unauthorized workers by one full percentage point, to 4.1% of GDP.

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, there are several reasons to believe it is not implausible. First, the spirit of our 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. Second, 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 aggregate marginal product of labor in the industry will go back to its baseline level (prior to the removal), substantially mitigating the incentives of native and legal immigrant workers to move to that industry.

Besides the theoretical arguments just presented, recent empirical analyses in the context of agriculture provide evidence of highly inelastic native labor supply in response to reductions in foreign employment (Clemens, 2013).[28] Along these lines, 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 half a 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.

We hope our analysis will spur additional research on these important questions. There are important extensions of the model that should be explored, such as explicitly accounting for the labor supply response of natives and legal immigrants, and input-output linkages across industries. We believe our analysis has shown that our approach can be useful to policy-makers interested in simulating real-life policies currently under discussion, such as the economic effects of the DREAM Act.

Appendix A

See Tables Table A.1–A.6.

Table A.1
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.

[28] Empirical work analyzing the broader effects of immigration on the labor force participation and employment rates of natives also 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.

Table A.2
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 A.3
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 A.4
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 A.5
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 A.6
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.

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