The Labor Market Impact of Immigration:

Job Creation vs. Job Competition

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Online Appendix

A Educational Attainment and Identification Accuracy

Table A.1: Educational attainment of undocumented immigrants across datasets, 2012-2013

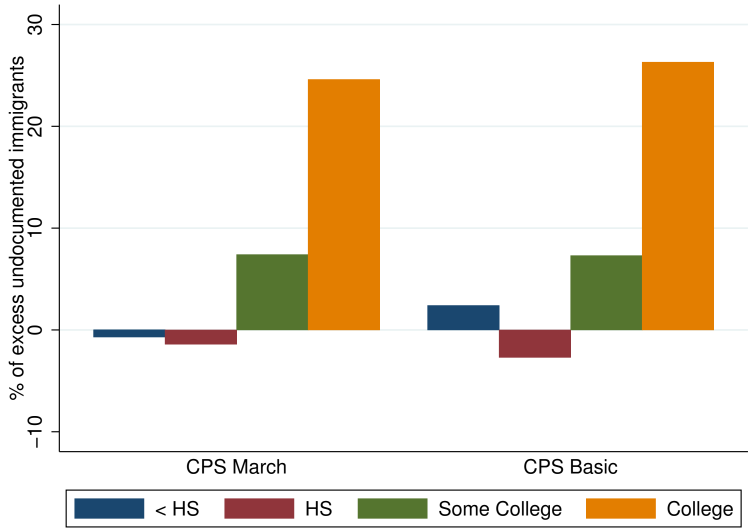
	Pew file	Borjas method	
	CPS March	CPS March	CPS Basic
< High school (%)	42	39.5	40.2
High school (%)	28.8	26.9	26.2
Some college (%)	13.2	13.5	13.3
College (%)	16	20.1	20.3
% of population	5.4	5.7	5.8

Notes: Following Borjas (2017) the statistics are calculated using a sample of individuals aged 20-64 from the years 2012-2013. The statistics from the Pew file are taken from Borjas (2017, Table 1).

In this Appendix section, I investigate how accurate Borjas' identification method is depending on the educational attainment of immigrants. The benchmark against which I make a comparison is the Pew CPS March file of the years 2012-2013, which includes the undocumented immigrant identifier developed by Passel and Cohn (2014). The description of its construction in Appendix C in their paper is not detailed enough to allow a replication of their method. However, Borjas was granted access to their datafile and presents some summary statistics based on it in Borjas (2017, Table 1).

Table A.1 presents the distribution of undocumented immigrants across education levels and their total population share in the Pew CPS March, the Borjas CPS March and the CPS basic monthly files. In the CPS basic, I use all variables that are also used by the Borjas identification method except those related to social security benefits or health insurance, because these are exclusively available in the CPS March. Compared to the Pew CPS March, the education level

Figure A.1: Excess of undocumented immigrants (%) in CPS 2012-2013



Notes: The excess percentages are calculated by comparing the population shares of undocumented immigrants for each education level in the CPS March and CPS Basic data using the simplified Borjas (2017) identification method with the corresponding shares in the Pew CPS March file, which are calculated based on in Table A.1 as described in the text.

of undocumented immigrants is higher in both the Borjas CPS March and the CPS basic. In particular, the share of college graduates is around 4 percentage points (or 25%) higher, whereas the shares of both high school dropouts and high school graduates are lower. Moreover, in both datasets the total population share of undocumented immigrants, shown in the last row, is somewhat higher than in the Pew CPS March. This indicates that too many high-skilled immigrants are classified as undocumented by the simplified Borjas method.[40] In the CPS basic, the total population share is somewhat lower than in the CPS March, which is unexpected as the absence of some variables for the identification of documented immigrants should lead to an additional excess of immigrants classified as undocumented. The fact that there is no excess compared to the CPS March suggests that there is little difference in the accuracy of the identification method in the CPS basic data due to the missing variables.

The sample statistics in Table A.1 allow to quantify the difference between the sample

[40]If I reclassify undocumented immigrants with college degree to being documented in the Borjas CPS March so that the percentage of the college-educated among undocumented immigrants equals 16% instead of 20.1%, I obtain an undocumented immigrant population share of 5.4% as in the Pew CPS March. The share of high school dropouts then increases to 41.6%, which is very close to the percentage in the Pew file.

size of undocumented immigrants classified by the Borjas method in the CPS March/basic and the sample size of those classified by the Pew CPS March for each education level. The population share of undocumented immigrants with education level e can simply be calculated by multiplying their total population share with the share of undocumented immigrants having education level e. Thus, the population share of undocumented immigrants that hold a college degree is $0.054 \cdot 0.16 = 0.00864 = 0.864\%$. The corresponding value for the Borjas CPS March is around 1.15%. Hence, if we believe that the Pew CPS March file identifies all undocumented immigrants correctly, around 25% ($= (1.15 - 0.864)/1.15$) of college educated immigrants are falsely identified as undocumented in the Borjas CPS March.

Figure A.1 shows the analogously calculated percentages of excess undocumented immigrants for all education levels in the Borjas CPS March and the CPS basic data. For the lowest two education levels, there is no excess of undocumented immigrants in neither of the datasets. The undocumented immigrant population shares in the Borjas CPS March and the Pew CPS March almost exactly coincide, suggesting that the identifier constructed by Borjas' simplified method is very accurate for immigrants with at most a high school diploma. In the CPS basic, the population share of undocumented high school graduates is even somewhat too low, whereas for high school dropouts the shares are very similar as well. In both datasets, there is an excess of undocumented immigrants with at least some college education, with the excess being especially large for college graduates. Given that it is much easier for highly skilled workers to enter the US legally, e.g. with H-1B visa, this result is actually not surprising. Altogether, Figure A.1 suggests that Borjas' simplified but easily replicable identification method is very accurate for the low-skilled, but classifies up to around 25% of college-educated immigrants and up to around 7% of immigrants with some college education mistakenly as undocumented.

B Decomposition of Impact of Immigration on Job Finding

In this section, I analyze the total impact of an increase in immigrant job searchers on the job finding rates of each worker type by decomposing it into job creation and competition effect. The sign of the latter can be established by taking the partial derivatives with respect to the queue lengths of each type. For natives we have

$$\begin{aligned}
\frac{\partial f_N}{\partial q_N} &= \frac{e^{-\mu q_N}(1+\mu q_N)-1}{q_N^2} e^{-\mu q_D} e^{-\mu q_U} < 0 \quad \forall\, q_N > 0, \\
\frac{\partial f_N}{\partial q_D} &= -\mu \frac{(1-e^{-\mu q_N})e^{-\mu q_U}}{q_N} e^{-\mu q_D} < 0 \quad \forall\, q_D > 0, \\
\frac{\partial f_N}{\partial q_U} &= -\mu \frac{(1-e^{-\mu q_N})e^{-\mu q_D}}{q_N} e^{-\mu q_U} < 0 \quad \forall\, q_U > 0.
\end{aligned}$$

For documented immigrants we have

$$\begin{aligned}
\frac{\partial f_D}{\partial q_N} &= 0, \\
\frac{\partial f_D}{\partial q_D} &= \frac{e^{-\mu q_D}(1+\mu q_D)-1}{q_D^2} e^{-\mu q_U} < 0 \quad \forall\, q_D > 0, \\
\frac{\partial f_D}{\partial q_U} &= -\mu \frac{(1-e^{-\mu q_D})}{q_D} e^{-\mu q_U} < 0 \quad \forall\, q_U > 0.
\end{aligned}$$

And for undocumented immigrants we have

$$\begin{aligned}
\frac{\partial f_U}{\partial q_N} &= 0, \\
\frac{\partial f_U}{\partial q_D} &= 0, \\
\frac{\partial f_U}{\partial q_U} &= \frac{e^{-\mu q_U}(1+\mu q_U)-1}{q_U^2} < 0 \quad \forall\, q_U > 0.
\end{aligned}$$

We can now analyze the total effect of a rise of unemployed immigrant workers. The arrival of more job searchers always leads to an increase in vacancies as the matching probability and hence the value of posting a vacancy rises. This drives down the queue length of workers of a different than the immigrating type. Taking derivatives with respect to u_D we get the impact of documented immigration on job finding rates as

$$\frac{df_N}{du_D} = \underbrace{\underbrace{\frac{\partial f_N}{\partial q_N}}_{<0}\underbrace{\frac{dq_N}{dv}}_{<0}\underbrace{\frac{dv}{du_D}}_{>0} + \underbrace{\frac{\partial f_N}{\partial q_U}}_{<0}\underbrace{\frac{dq_U}{dv}}_{<0}\underbrace{\frac{dv}{du_D}}_{>0}}_{\text{job creation effect}} \quad + \underbrace{\underbrace{\frac{\partial f_N}{\partial q_D}}_{<0}\underbrace{\frac{dq_D}{du_D}}_{>0}}_{\text{competition effect}} \lesseqgtr 0, \tag{20}$$

$$\frac{df_D}{du_D} = \underbrace{\underbrace{\frac{\partial f_D}{\partial q_U}}_{<0}\underbrace{\frac{dq_U}{dv}}_{<0}\underbrace{\frac{dv}{du_D}}_{>0}}_{\text{job creation effect}} \quad + \underbrace{\underbrace{\frac{\partial f_D}{\partial q_D}}_{<0}\underbrace{\frac{dq_D}{du_D}}_{>0}}_{\text{competition effect}} \lesseqgtr 0, \tag{21}$$

$$\frac{df_U}{du_D} = \underbrace{\underbrace{\frac{\partial f_U}{\partial q_U}}_{<0}\underbrace{\frac{dq_U}{dv}}_{<0}\underbrace{\frac{dv}{du_D}}_{>0}}_{\text{job creation effect}} > 0. \tag{22}$$

The impact of undocumented immigration on job finding rates is

$$\frac{df_N}{du_U} = \underbrace{\underbrace{\frac{\partial f_N}{\partial q_N}}_{<0}\underbrace{\frac{dq_N}{dv}}_{<0}\underbrace{\frac{dv}{du_U}}_{>0} + \underbrace{\frac{\partial f_N}{\partial q_D}}_{<0}\underbrace{\frac{dq_D}{dv}}_{<0}\underbrace{\frac{dv}{du_U}}_{>0}}_{\text{job creation effect}} \quad + \underbrace{\underbrace{\frac{\partial f_N}{\partial q_U}}_{<0}\underbrace{\frac{dq_U}{du_U}}_{>0}}_{\text{competition effect}} \lesseqgtr 0, \tag{23}$$

$$\frac{df_D}{du_U} = \underbrace{\underbrace{\frac{\partial f_D}{\partial q_D}}_{<0}\underbrace{\frac{dq_D}{dv}}_{<0}\underbrace{\frac{dv}{du_U}}_{>0}}_{\text{job creation effect}} \quad + \underbrace{\underbrace{\frac{\partial f_D}{\partial q_U}}_{<0}\underbrace{\frac{dq_U}{du_U}}_{>0}}_{\text{competition effect}} \lesseqgtr 0, \tag{24}$$

$$\frac{df_U}{du_U} = \underbrace{\underbrace{\frac{\partial f_U}{\partial q_U}}_{<0}\underbrace{\frac{dq_U}{du_U}}_{>0}}_{\text{competition effect}} < 0. \tag{25}$$

Equations (20) and (23) establish that the effect of both documented and undocumented immigration on natives' job finding (and thus their unemployment rate) is ambiguous. The larger is the difference in wages between natives and the type of immigrant entering the pool of the unemployed, the higher is the number of additional vacancies posted. Therefore, we know that $\frac{df_N}{du_U} > \frac{df_N}{du_D}$ must hold. However, only solving and simulating the model for different u_D and u_U will allow us to determine the signs of $\frac{df_N}{du_U}$ and $\frac{df_N}{du_D}$.

C Model extensions

C.1 Production using Capital and Labor

The first extension of the baseline model introduces an aggregate production function that uses capital and labor to generate a final output good. Thus, the productivity of a match is not constant but depends on the price of labor. Instead of assuming that a large representative firm directly posts vacancies and hires workers, I assume that recruiting agencies hire workers and bargain over their wages and then sell their labor services at the equilibrium price to competitive final good firms, which take the price for labor as given. This keeps the model tractable and as close as possible to the baseline version.

The final output is produced with a Cobb-Douglas function:

$$Y = AL^{\alpha}K^{(1-\alpha)}.$$

Perfect competition implies that the price for labor services equals their marginal product:

$$p_L = \alpha A(K/L)^{(1-\alpha)}.$$

In equilibrium, labor supply is determined by the number of workers of each type matched to recruiting agencies, which depends on the price of labor services:[41]

$$\begin{aligned} e_i(p_L) &= \frac{\omega_i f_i(p_L)}{s_i + f_i(p_L) + \lambda_i^W}, \\ L(p_L) &= \sum_i e_i(p_L). \end{aligned}$$

Thus, this extended model is solved by replacing the previously fixed match output y with the expression for p_L, adding the labor supply equation and setting parameters α, A, initial capital K and the degree of the elasticity of capital supply. With perfect elasticity, L^* denoting the equilibrium labor supply in the baseline model and α, A and K normalized such that $\alpha A(K/L^*)^{(1-\alpha)} = 1$, we obtain a version of the model that is identical to the baseline. If on the other hand capital is inelastic, a change in labor supply, for example due to immigration, decreases the capital-labor ratio and leads to an equilibrium with a lower price for labor services

[41] The stock of matched workers is derived from the law of motion $\dot{e}_i = f_i(p_L)(\omega_i - e_i) - (s_i + \lambda_i^W)e_i$.

compared to the baseline.

To illustrate how the predictions change depending on the degree of capital supply elasticity, I set $\alpha = 0.66$, the labor share of output, and normalize A and K so that $p_L = 1$ in the equilibrium with the calibration shown in Table 4. I then simulate immigration for different capital supply elasticities, ranging from 0 (K stays fixed) to infinity (the baseline case). Figures C.1 and C.2 show the effects of a one percentage point increase in the share of documented and undocumented immigrants (i.e. the slopes of the lines in Figures 7 and 8) depending on the elasticity of capital supply. The limit on the left depicts the case with fixed capital, whereas the limit on the right depicts the baseline case of infinite elasticity. Immigration drives down the marginal product of labor more strongly when the capital supply elasticity is lower, resulting in fewer vacancies and lower wages. Accordingly, the effect on the unemployment rates of all worker types is more positive and the effect on their wages more negative.

In case of documented immigration, the signs of the effects on unemployment for each type remain the same for any degree of the capital supply elasticity (undocumented immigrants' unemployment rate decreases even with zero elasticity), whereas the effect on the overall unemployment rate becomes negative when the elasticity is low enough. In case of undocumented immigration, all signs are unaffected. That is, even when capital remains fixed, the unemployment rate of natives as well as the overall unemployment rate fall, although for natives the change is just around a third of the change with perfectly elastic capital supply. For both types of immigration, wages start to fall when the capital supply is only somewhat inelastic. This prediction would contradict the positive wage effects of undocumented immigrants found in section 7.1.

In sum, the qualitative predictions in terms of the employment effects of the two types of immigration hold even under the most extreme assumption of fixed capital. On the other hand, effects on wages are negative when the capital supply is somewhat inelastic, which stands in contrast to the empirical evidence shown in Section 7.1. This might suggest that capital supply is rather elastic in reality, at least in the low-skilled sector that is the subject of the paper.

Figure C.1: Effects of documented immigration depending on capital supply elasticity

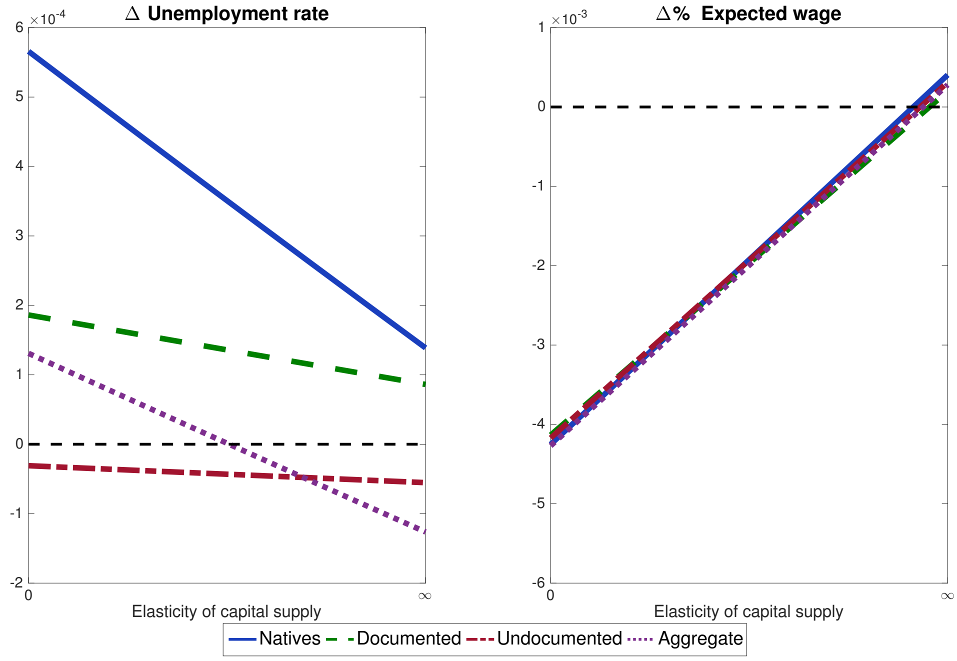
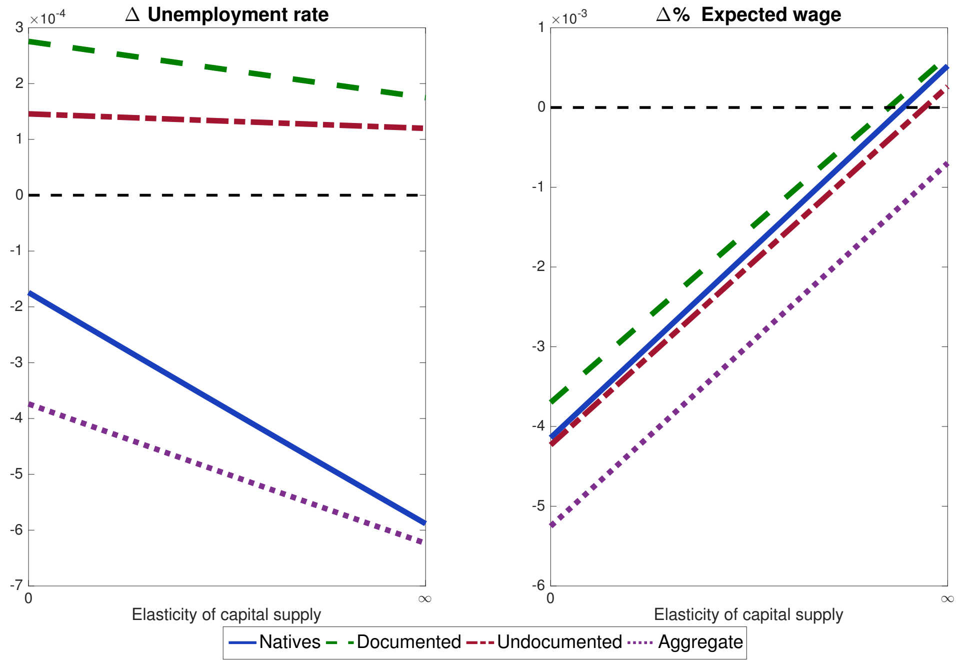


Figure C.2: Effects of undocumented immigration depending on capital supply elasticity



C.2 Imperfect Substitution between Natives and Immigrants

The second model extension allows for imperfect substitution between native and immigrant workers in production. I maintain the assumption that workers apply to the same jobs as otherwise the competition effect would be absent in the model. This implies that firms cannot affect the relative quantities of native and immigrant labor by posting type-specific vacancies. Rather, the quantities result from population shares and job finding and separation rates of natives and immigrants. Apart from the production function, the labor market has the same structure as described in Section C.1.

As a consequence of imperfect substitution, an inflow of immigrants will reduce the marginal product of immigrant labor and increase the marginal product of native labor, whereby the sizes of the effects depend on the degree of imperfect substitution. Due to the lack of an estimate for the elasticity of substitution between documented and undocumented immigrants, I assume that these two labor types are perfectly substitutable.[42] Thus, production is given by

$$Y = AK^{(1-\alpha)}[(\theta_N L_N^{\frac{\sigma-1}{\sigma}} + \theta_I L_I^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}}]^{\alpha},$$

where θ_N and θ_I are productivity parameters and σ is the elasticity of substitution between native and immigrant labor. The prices for labor services for each type $j \in \{N, I\}$ equal their marginal products and are given by

$$p_j = \alpha A(K/L)^{(1-\alpha)}\theta_j(\frac{L}{L_j})^{1/\sigma}.$$

The equilibrium labor supplies are

$$L_N(p_N) = e_N(p_N) = \frac{\omega_N f_N(p_N)}{s_N + f_N(p_N)},$$
$$L_I(p_I) = e_D(p_I) + e_U(p_I) = \frac{\omega_D f_D(p_I)}{s_D + f_D(p_I)} + \frac{\omega_U f_U(p_I)}{s_U + f_U(p_I) + \lambda_U^W}.$$

Analogously to Section C.1, the model is solved by replacing match output with the prices

[42]Edwards and Ortega (2017) allow documented and undocumented workers to be potentially imperfectly substitutable in their model but ultimately assume an elasticity of 1000, which practically is equivalent to perfect substitutability.

of labor services for each type, which are now different for natives and immigrants. Without loss of generality, I define the auxiliary parameter $\phi_j \equiv \alpha A(K/L)^{(1-\alpha)}\theta_j$ and set ϕ_N and ϕ_I so that $p_N = p_I = 1$ when all other parameters are set as shown in Table 4.[43] Hence, the productivity parameters are consistent with the parameterization that replicates the data.[44] I base the calibration of σ on Ottaviano and Peri (2012). They find an overall elasticity of substitution around 20 considering all education levels but a value of only 12.5 among high school dropouts, which is the estimate I use.

Figure C.3 plots the effects of an inflow of documented immigrants on the equilibrium outcomes predicted by this extended model. Because $\phi_I < \phi_N$, the job creation effect of immigration is weaker than in the baseline model, which results in a somewhat steeper increase in natives' unemployment rate. However, the most notable deviation from the baseline model can be seen in the wage plots. Because of the change in relative labor supplies of natives and immigrants, the marginal productivity of the former rises whereas that of the latter falls. Accordingly, wages now strongly increase for natives and decrease for both types of immigrants, whereas they remained almost constant before.

Figure C.4, which depicts the effects of undocumented immigration, shows that due to the weaker job creation effect, the fall in natives' unemployment rate is somewhat less steep, although the difference to the baseline figure is marginal. The wage reactions largely resemble those in C.3 because they are now primarily driven by the effects on relative productivities, which are similar in the two figures.

Altogether, introducing imperfect substitutability has little impact on the predictions regarding unemployment rates. However, the shifts in relative labor supplies due to immigration imply positive effects on natives' and negative effects on immigrants' wages. An important caveat is the maintained assumption that all workers apply to the same jobs. If imperfect substitution induces firms to create different vacancies for natives and immigrants, the competition effect might be lower and the effects on natives' unemployment rates more positive than predicted by the model .

[43] Capital is therefore assumed to be perfectly elastic again in this extension.

[44] This implies that ϕ_I is somewhat smaller than ϕ_N because there are less immigrants than natives employed and thus the marginal product of immigrant labor would be larger, if the parameters were the same.

Figure C.3: Effects of documented immigration with imperfect substitution

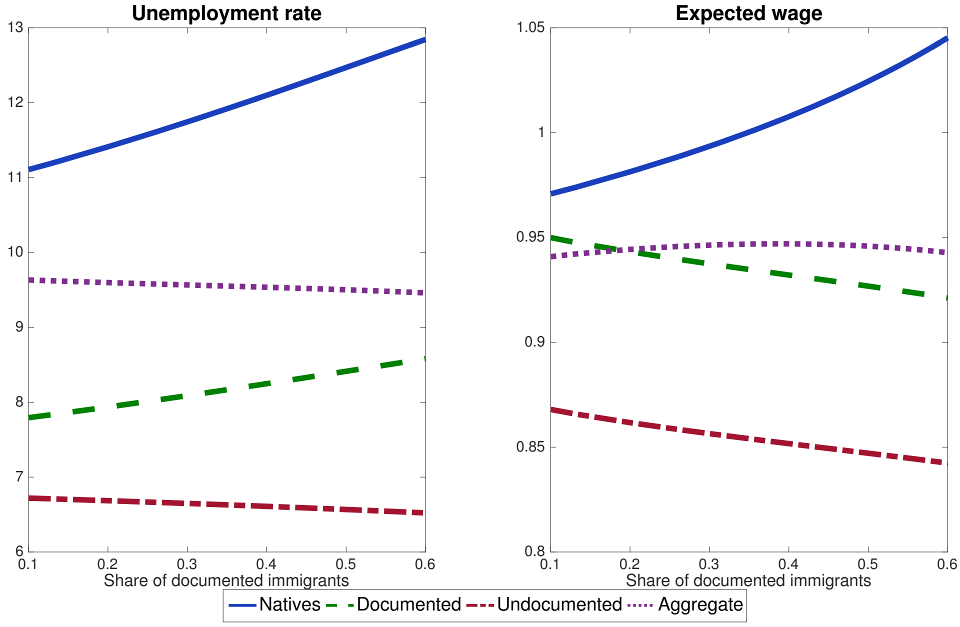
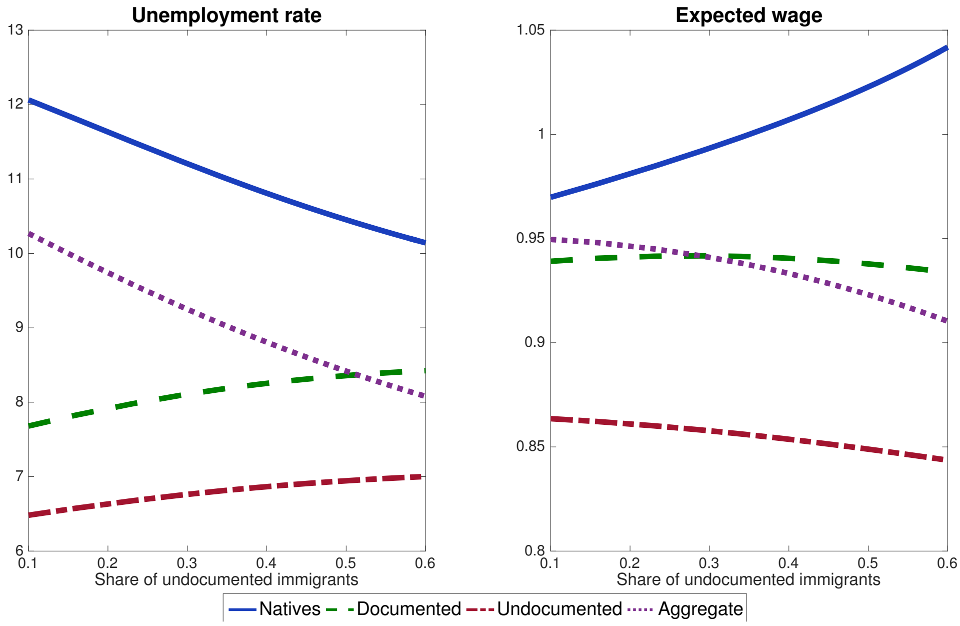


Figure C.4: Effects of undocumented immigration with imperfect substitution



D Robustness Checks

D.1 Wage gaps using Census/ACS data

Table D.1: Legal status and hourly wage of low-skilled workers

	(1)	(2)	(3)	(4)	(5)
Documented	-0.136	-0.033	-0.064	-0.026	-0.025
	(0.0021)	(0.0232)	(0.0146)	(0.0126)	(0.0125)
Undocumented	-0.344	-0.205	-0.238	-0.144	-0.139
	(0.0022)	(0.0207)	(0.0155)	(0.0132)	(0.0131)
Demographics	No	Yes	Yes	Yes	Yes
Year/MSA FE	No	No	Yes	Yes	Yes
Ind/occ FE	No	No	No	Yes	No
Ind x occ FE	No	No	No	No	Yes
Observations	508720	508720	508720	508720	508720
R-squared	0.071	0.174	0.220	0.314	0.325

Notes: Dependent variable is the logarithm of the hourly wage. Data come from the Census 1990/2000 and ACS 2009-2011 and include high school dropouts aged 25-65. Demographic controls include *sex*, *race*, *age* and *age squared*. Standard errors are clustered at the metropolitan area level.

D.2 Job finding rate gaps and search effort

If (undocumented) immigrants search for jobs more intensively and the job finding rate positively depends on search effort, this could be driving the job finding rate difference observed in the data. To control for this possibility, I use additional variables in the basic CPS and data from the American Time Use Survey (ATUS).

Job seekers in the CPS can indicate up to six different search methods in response to the question “What are all of the things you have done to find work during the last 4 weeks?”. Figure D.1 shows the possible methods and their frequencies by worker type among low-skilled job seekers. Being used by almost half of them, the most frequent method for all types is to contact employers directly. It also stands out that immigrants tend to contact more often friends and relatives and less often send resumes than natives. Figure D.2 shows the average number of different job search methods used over time. Except in the very beginning of the period, both types of immigrants use less methods than natives.

Figure D.1: Search methods used by unemployed low-skilled workers (%)

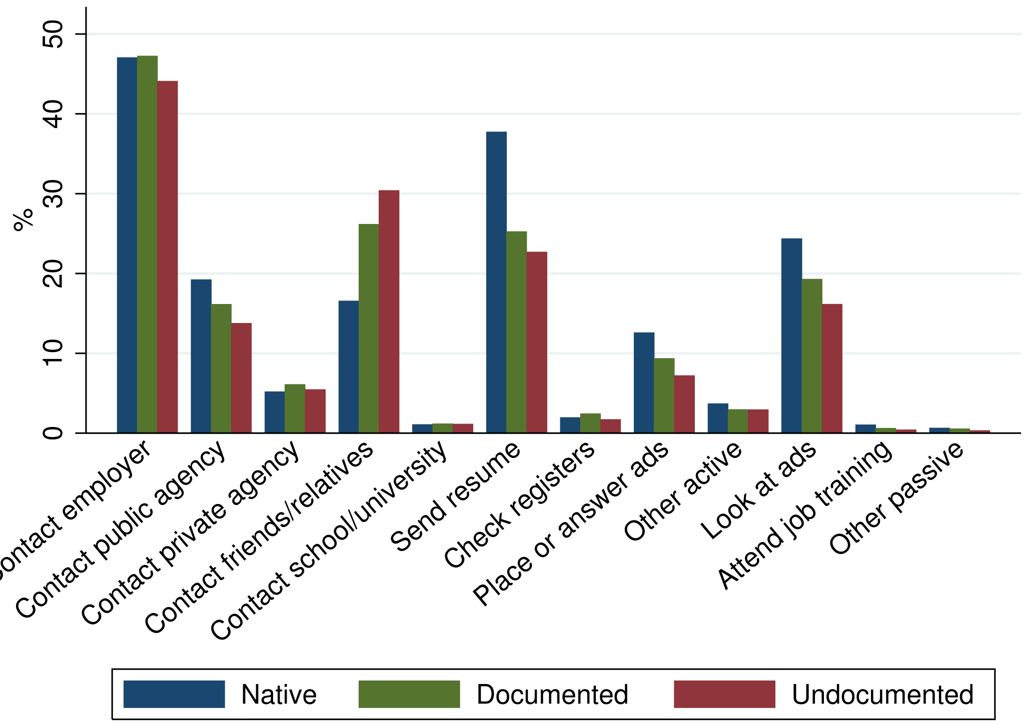
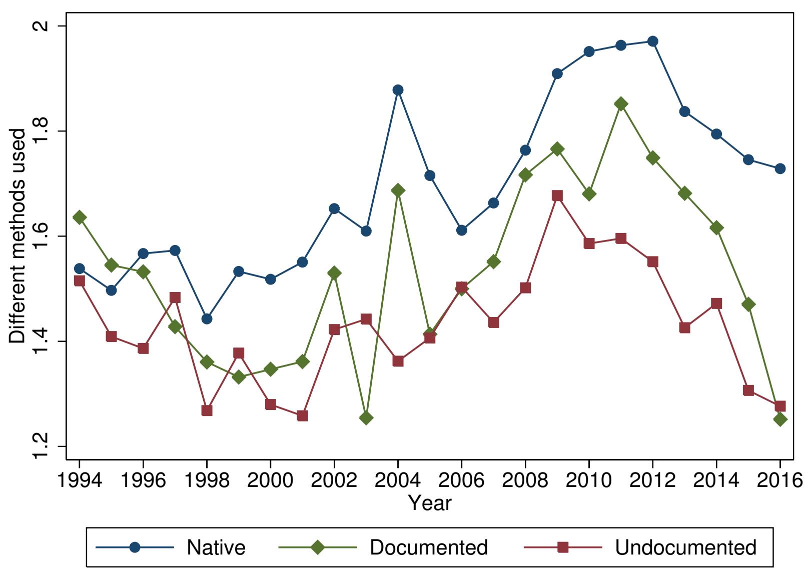


Figure D.2: Number of search methods used by unemployed low-skilled workers



However, immigrants might use these search methods more intensively, i.e. spend more time using a specific method. To investigate this possibility, I use additional data from the ATUS. In this survey, a sample of respondents interviewed for the CPS report their time spent on various activities during the day before the interview. Importantly, one of the categories is "Job search activities". I use this information to calculate for all unemployed in the ATUS the daily time spent searching for a job (in minutes). Although the observations in the ATUS and the CPS monthly data can be linked and I therefore have observed search time for a subset of CPS observations, the ATUS sample size is too small to analyze the determinants of job finding rates (there are around 1300 unemployed high school dropouts).

Therefore, to be able to control for search time in the regressions using the full CPS sample, I exploit the fact that also ATUS respondents report the methods used for job search. This allows me to estimate a relationship between search time and methods in the ATUS data and then, based on this relationship, impute search time for all CPS observations. I thereby follow Mukoyama et al. (2018) and use a Heckman selection model, which estimates the effects of search methods and demographic variables on the probability of observing positive search time in the first step and the effects on minutes spent searching conditional on positive search time in the second step. I then predict search time based on the estimated model in the CPS sample.

Additionally to the demographic variables used by Mukoyama et al. (2018) in both steps of the estimation, I also include the two immigrant dummies to allow for systematic differences in search time between natives, documented and undocumented immigrants. Figure D.3 plots the resulting imputed daily minutes spent searching by worker type. Both types of immigrants spend less time searching than natives and the difference widens from around two to six minutes over the period. In 2016, natives have spent around 50% more time per day on searching for a job than immigrants according to this imputation. If higher search effort positively affects the speed of job finding, we would therefore expect immigrants to find jobs at a *lower* rate than natives.

Table D.2 shows the results of the job finding rate regressions controlling for imputed search time. The coefficients are virtually the same as in the baseline Table 2. Thus, the empirical evidence does not support that varying search effort drives the job finding rate differentials.

Figure D.3: Imputed minutes spent searching by unemployed low-skilled workers

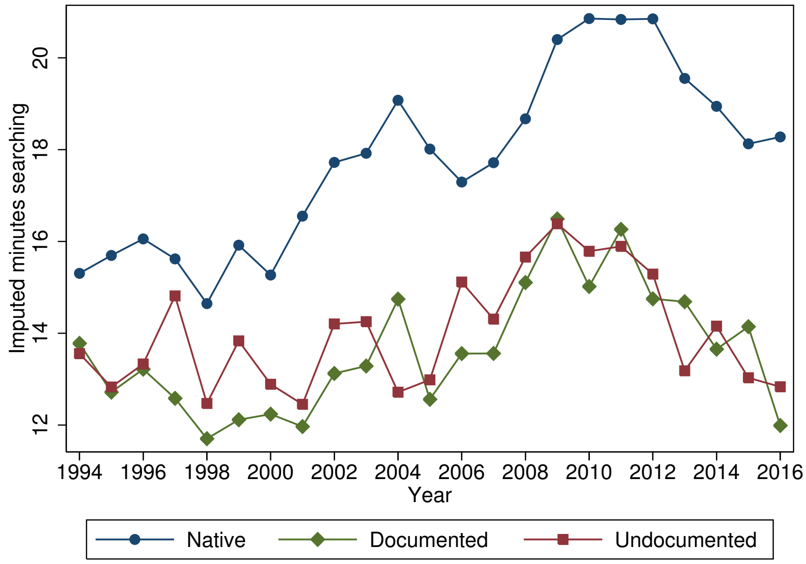


Table D.2: UE regressions controlling for imputed time spent on job search

	(1)	(2)	(3)	(4)	(5)
Documented	0.063	0.058	0.068	0.066	0.067
	(0.0047)	(0.0062)	(0.0084)	(0.0078)	(0.0078)
Undocumented	0.136	0.121	0.137	0.137	0.138
	(0.0054)	(0.0100)	(0.0118)	(0.0123)	(0.0123)
Demographics	No	Yes	Yes	Yes	Yes
Year/State FE	No	No	Yes	Yes	Yes
Ind/occ FE	No	No	No	Yes	No
Ind x occ FE	No	No	No	No	Yes
Observations	75032	75032	75032	75032	75032
R-squared	0.021	0.039	0.052	0.064	0.086

Notes: Dependent variable is the probability of a UE transition. Data come from the CPS basic files 1994-2016 and include high school dropouts aged 25-65. Demographic controls include *sex*, *race*, *age* and *age squared*. Standard errors are clustered at the state level.

D.3 Wage and job finding rates when excluding occupations with disproportionally high concentration of undocumented immigrants

Table D.3: Legal status and hourly wage of low-skilled workers

	(1)	(2)	(3)	(4)	(5)
Documented	-0.127	-0.073	-0.094	-0.047	-0.046
	(0.0051)	(0.0100)	(0.0080)	(0.0066)	(0.0067)
Undocumented	-0.268	-0.195	-0.223	-0.128	-0.126
	(0.0057)	(0.0197)	(0.0172)	(0.0130)	(0.0133)
Demographics	No	Yes	Yes	Yes	Yes
Year/MSA FE	No	No	Yes	Yes	Yes
Ind/occ FE	No	No	No	Yes	No
Ind x occ FE	No	No	No	No	Yes
Observations	57393	57393	57393	57393	57393
R-squared	0.046	0.148	0.176	0.277	0.305

Notes: Dependent variable is the logarithm of the hourly wage. Data come from the CPS March supplement 1994-2016 and include high school dropouts aged 25-65. Demographic controls include *sex*, *race*, *age* and *age squared*. The dropped occupations are *Cooks, Construction laborers, Carpenters, Gardeners* and *Food prep workers*. Standard errors are clustered at the metropolitan area level.

Table D.4: Legal status and UE transition of low-skilled workers

	(1)	(2)	(3)	(4)	(5)
Documented	0.059	0.053	0.062	0.059	0.060
	(0.0051)	(0.0060)	(0.0067)	(0.0063)	(0.0064)
Undocumented	0.132	0.119	0.134	0.130	0.130
	(0.0059)	(0.0076)	(0.0099)	(0.0116)	(0.0119)
Demographics	No	Yes	Yes	Yes	Yes
Year/State FE	No	No	Yes	Yes	Yes
Ind/occ FE	No	No	No	Yes	No
Ind x occ FE	No	No	No	No	Yes
Observations	62653	62653	62653	62653	62653
R-squared	0.014	0.025	0.040	0.055	0.080

Notes: Dependent variable is the probability of a UE transition. Data come from the CPS basic files 1994-2016 and include high school dropouts aged 25-65. Demographic controls include *sex*, *race*, *age* and *age squared*. The dropped occupations are *Cooks, Construction laborers, Carpenters, Gardeners* and *Food prep workers*. Standard errors are clustered at the state level.

D.4 Robustness to alternative bargaining mechanism

The bargaining mechanism described in the main text implies that with some probability, which depends on the bargaining power, workers send their firm wage offers before the hiring decision. However, a sensible alternative might be to assume that firms first commit to hire the candidate that yields the highest expected surplus and then engage in bargaining with the chosen worker. As a consequence, hired workers could capture the full match surplus with probability β_i independently of the number and nature of the competitors. While contractually committing to a wage after the hiring decision certainly resembles the real world more closely, the assumption that competitors do not influence the wage negotiation at all seems extreme as well. Reality most likely lies somewhere in-between the two alternatives. To check whether the predictions of the model are robust to this alternative assumption, I estimate and solve the model with wage bargaining after the hiring decision. Thus, a hired worker of type i always earns $\underline{w}_i + \beta_i(y - \underline{w}_i)$.

Figure D.4 shows the resulting effects documented immigration. While the reactions of the unemployment rates to documented immigration are unaffected, the expected wage of natives experiences a (barely visible) decline, whereas in the baseline model it increases. The rationale behind this is the following. Previously, natives could only capture a share of the match surplus when having no competitors, as indicated by case 1 in Table E.2. As there is a positive job creation effect due to documented immigration, probability f_1 increases and thus there are more natives earning a wage higher than the reservation wage, although there are overall less natives employed because of the decline in f_2. The higher probability of finding a job with some surplus over staying unemployed increases the reservation wage (see equation (4)) and therefore the actual wage. This wage effect of natives shifting to matches with positive surplus vanishes under the alternative bargaining mechanism as natives receive a wage above the reservation wage in all matches. Therefore, now the expected wage of natives is initially higher, but falls when the share of immigrants increases as f_2 declines due to the additional immigrant competitors.

Figure D.5 plots the reactions of unemployment rates and wages to undocumented immigration. The unemployment rates of natives and documented immigrants are now higher initially compared to Figure 8. This is because for a low share of undocumented immigrants, wages of all workers are higher and therefore there are less vacancies in equilibrium. When the share increases, the wages of legal workers increase less steeply and the wages of undocumented immigrants decrease. Thus, expected wage costs of firms fall more sharply, leading to a stronger job creation effect and a steeper decline in the unemployment rate of natives. The reason for the weaker wage increase (or decrease in case of undocumented immigrants) is again the lack of the wage effect caused by workers shifting to jobs with wages above the reservation wage that arises under the baseline bargaining assumption.

In sum, the competition effect has no impact on natives' wages under the baseline assumption because competition only decreases the number of natives with jobs that generate no surplus above staying unemployed anyways. This is not true anymore when the wage is bargained after being hired and therefore generally wages move in the opposite direction of unemployment rates because a lower job finding rate necessarily translates into a lower reservation wage, if every job that can be found yields a surplus. Hence, the effects of immigration on unemployment rates are qualitatively robust and quantitatively even stronger for natives in case of undocumented immigration with the alternative bargaining mechanism, whereas the effects on wages are both qualitatively and quantitatively different.

Figure D.4: Documented immigration with alternative bargain mechanism

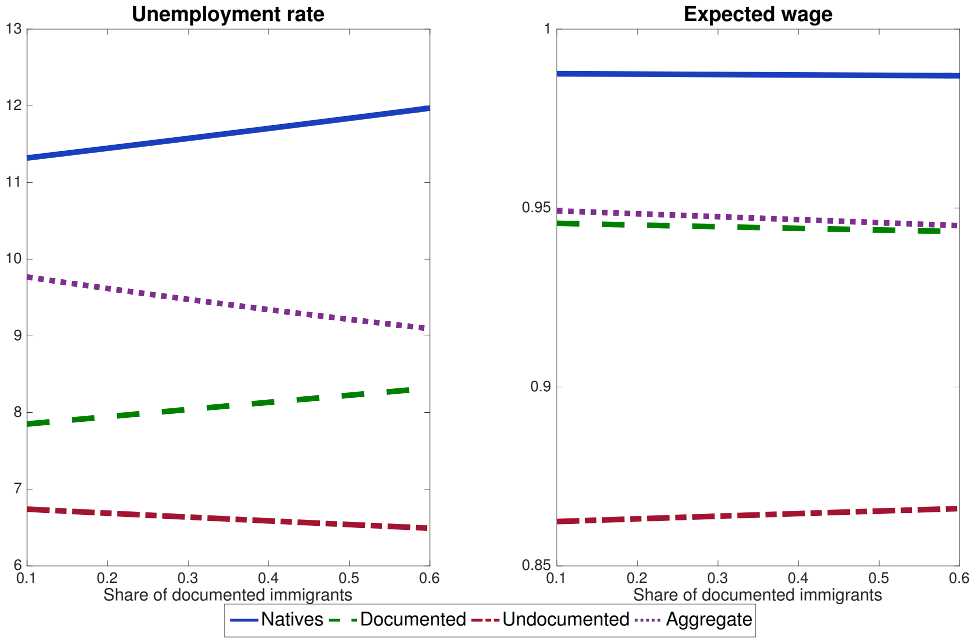
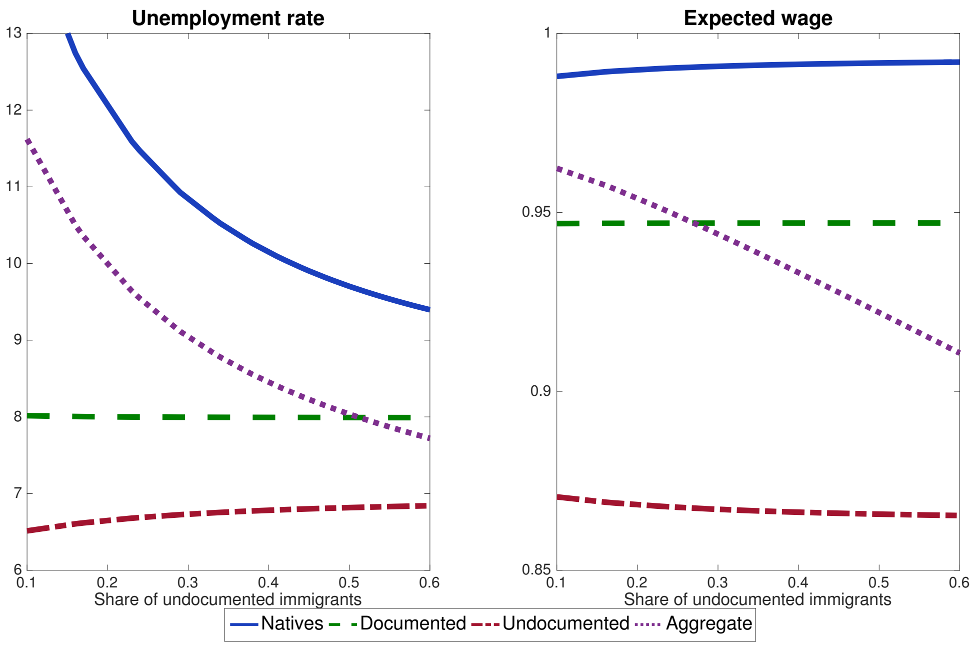


Figure D.5: Undocumented immigration with alternative bargain mechanism



D.5 Robustness to calibration of the deportation disutility

The existence of two opposing forces whose magnitudes depend on the parameterization suggests that the findings might be sensitive to particular parameters, in particular the size of the surplus firms make by hiring undocumented workers. Therefore I next check whether the predictions of Figures 7 and 8 are robust to allowing $\Delta\lambda$ to be different from zero and to changes in the value of R. In particular, I consider the extreme case in which only employed undocumented workers can be detected and deported, i.e. $\lambda^U = 0$ and $\lambda^W = \Delta\lambda$. I recalibrate λ^W following the same method of calibration as described in section 5 except that I divide monthly interior removals by the number of employed undocumented immigrants instead of the total number. The resulting probability is 0.22%. As now $\Delta\lambda$ is strictly greater than zero, R always has a positive effect on $\underline{w}_U$. Thus, it affects undocumented immigrants' wages and as a consequence the wage gap between worker types. The value of R also affects job finding rates because a rise in $\underline{w}_U$ makes hiring undocumented workers more expensive, which mutes the vacancy creation effect. Therefore, it is necessary to re-estimate c, μ, β_D and β_U to match the moments from the data after a change in R. Figures D.6 and D.7 present the effects of immigration when setting R equal to 75% of an undocumented job seeker's lifetime utility U_U, which is the most extreme value I consider throughout the paper, and compare them to the benchmark calibration with $\Delta\lambda = 0$ (in light colors). Both unemployment rates and expected wages are virtually unaffected when choosing a high value for R. The unemployment rate of undocumented workers is somewhat elevated as their overall separation probability $(s_U + \lambda_W)$ is now higher. Moreover, undocumented immigration has a weaker effect on vacancy creation, because the higher separation probability decreases their hiring surplus. This can be seen by a slightly less steep decline in the unemployment rate of natives in Figure D.7. In sum, for any reasonable calibration of the deportation disutility and deportation risk, undocumented immigration is unambiguously beneficial for native workers.

Figure D.6: Documented immig. with $\lambda^W = 0.0022$, $\lambda^U = 0$ and $R = 0.75 U_U$

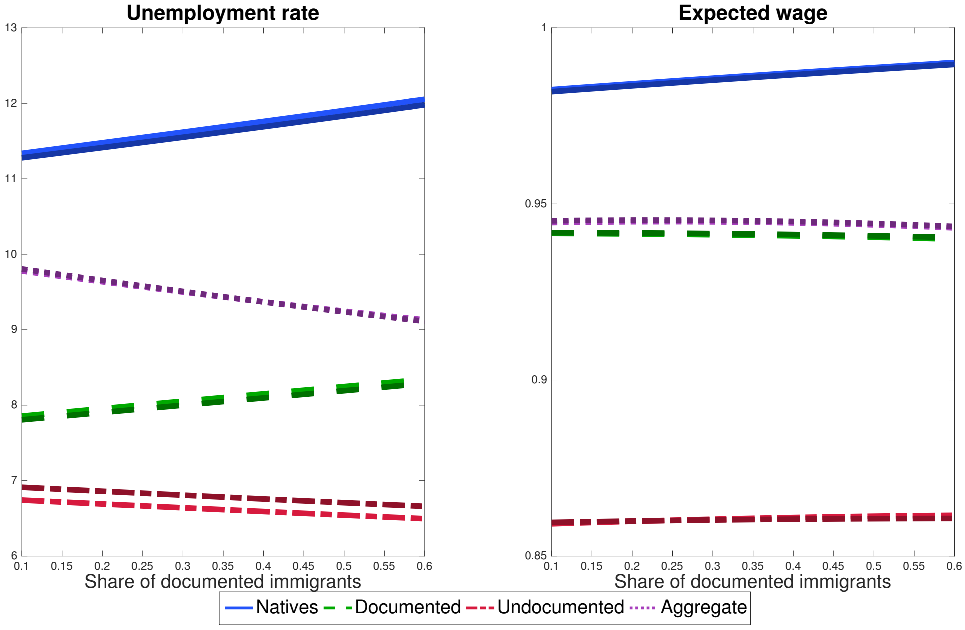
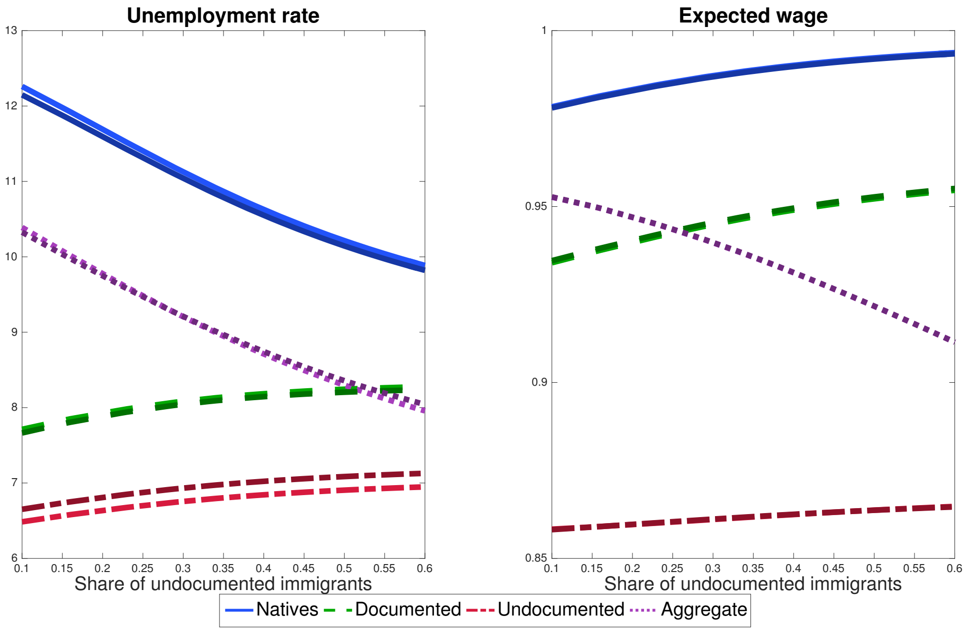


Figure D.7: Undocumented immig. with $\lambda^W = 0.0022$, $\lambda^U = 0$ and $R = 0.75 U_U$



D.6 Robustness to using inflow rates to capture immigration shocks

The analysis in section 7.1 differs from the extensive literature employing the previous settlement instrument with respect to the measurement of immigration. While most studies examine immigration in a perfect competition model, in which the increase in the mere supply of workers affects the equilibrium wage, I examine immigration in a model, in which only the change in the composition of the worker supply but not its size matters for the equilibrium. This is why my empirical measurement of immigration is the change in the population share and not the inflow rate, i.e. the change in the number of immigrants in a region divided by the population level. These two measure can be very different as the former takes into account changes in the total population, which becomes especially important when there are adjustments through internal migration. If a higher labor market tightness due to an increase in undocumented immigrants attracts natives, total population changes additionally to the immigration shock between two points in time. This is reflected in the population shares, but not the inflow rate, which is commonly calculated as the number of inflowing immigrants relative to the initial population level.

To investigate the results with the traditional measurement of immigration, I repeat the regressions with inflow rates $m_{i,r,t} = I_{i,r,t}/P_{r,t}$ as endogenous regressors and predicted inflow rates $m^Z_{i,r,t} = I^Z_{i,r,t}/P_{r,t}$ as instruments. The second stage results in Panel C of Table D.6 confirm the baseline results. However, the effects of undocumented immigration in columns (1), (3) and (4) are not significant in Panel B. This is likely to be caused by the failure of inflow rates to account for internal migration. If internal migration reacts sluggishly (due to migration costs) and immigrant inflows are correlated over time, population changes triggered by previous immigration shocks are correlated to current immigration shocks and therefore the estimates of the conventional IV model are biased. Long-term adjustment mechanisms like internal migration are precisely what the JRS IV strategy controls for, which explains why only the coefficients of Panel C remain significant when using inflow rates.

Table D.5: First stage with immigrant inflow rates as regressors

	IV		JRS IV			
	(1)	(2)	(3)	(4)	(5)	(6)
	Doc. inflow	Undoc. inflow	Doc. inflow	Undoc. inflow	(Doc. inflow)$_{t-1}$	(Undoc. inflow)$_{t-1}$
(Doc. inflow)^Z	0.723	-0.271	1.221	1.261	-0.598	-0.250
	(0.460)	(0.924)	(0.127)	(0.259)	(0.379)	(0.390)
(Undoc. inflow)^Z	0.025	0.509	0.093	0.844	1.035	2.010
	(0.191)	(0.332)	(0.206)	(0.410)	(0.291)	(0.825)
(Doc. inflow)$^Z_{t-1}$			0.091	0.331	0.838	-0.220
			(0.191)	(0.216)	(0.487)	(0.936)
(Undoc. inflow)$^Z_{t-1}$			-0.458	-1.403	-0.374	-0.533
			(0.132)	(0.320)	(0.124)	(0.216)
Observations	99	99	66	66	66	66
R-squared	0.523	0.255	0.629	0.631	0.674	0.455
F-stat.	169.7	62.07	27.28	42.21	376.2	195.1
SW F-stat.	25.87	85.02	40.47	82.11	51.21	24.38

Notes: Population data are from the US Census 1980-2000 and ACS 2009-2011 and include high school dropouts participating in the labor force. The sample consists of 33 MSAs, for which data on job openings are available. Standard errors are clustered at the MSA level. The observations are weighted by MSA population.

Table D.6: Second stage with immigrant inflow rates as regressors

	(1)	(2)	(3)	(4)
	Vacancies	Native wage	Doc. wage	Undoc. wage
Panel A: OLS				
Doc. inflow	-2.113	-0.356	-0.439	-0.487
	(1.313)	(0.119)	(0.152)	(0.162)
Undoc. inflow	1.449	0.463	0.269	0.280
	(0.468)	(0.044)	(0.111)	(0.093)
Observations	99	99	99	97
R-squared	0.770	0.327	0.056	0.127
Panel B: IV				
Doc. inflow	-1.998	-0.314	-0.312	-0.460
	(3.625)	(0.185)	(0.212)	(0.242)
Undoc. inflow	-1.084	0.504	0.105	0.070
	(2.887)	(0.148)	(0.155)	(0.155)
Observations	99	99	99	97
R-squared	0.653	0.319	0.045	0.095
Panel C: JRS IV				
Doc. inflow	-1.679	-0.284	-0.526	-0.765
	(1.153)	(0.192)	(0.419)	(0.422)
Undoc. inflow	1.877	0.449	0.496	0.620
	(0.514)	(0.078)	(0.168)	(0.191)
(Doc. inflow)$_{t-1}$	-4.285	0.359	0.370	0.764
	(1.567)	(0.352)	(0.331)	(0.3300)
(Undoc. inflow)$_{t-1}$	1.379	-0.241	-0.027	-0.310
	(1.242)	(0.201)	(0.201)	(0.216)
Observations	66	66	66	66
R-squared	0.879	0.558	0.078	0.119

Notes: Population data are from the US Census 1980-2000 and ACS 2009-2011 and include high school dropouts participating in the labor force. The sample consists of 33 MSAs, for which data on job openings are available. Standard errors are clustered at the MSA level. The observations are weighted by average MSA population.

D.7 Robustness to using 1980 as base period for the IV

As an additional robustness check, I change the base period for the distribution of immigrants according to which the national inflows are allocated to MSAs. Instead of taking the distribution in the initial year, I take the distribution in the year 1980 for the allocation of all national inflows in the periods 1980-1990, 1990-2000 and 2000-2010. As shown in Table D.8, with the recalculated instruments the effects of undocumented immigration are qualitatively unchanged in the preferred model in Panel C. Quantitatively, the response of vacancies is somewhat smaller and the response of wages somewhat larger compared to the responses in Table 6.

Table D.7: First stage with base period 1980

	IV		JRS IV			
	(1)	(2)	(3)	(4)	(5)	(6)
	Doc. share	Undoc. share	Doc. share	Undoc. share	(Doc. share)$_{t-1}$	(Undoc. share)$_{t-1}$
(Doc. share)^Z	0.589	0.093	0.517	0.647	0.387	-0.165
	(0.072)	(0.306)	(0.071)	(0.168)	(0.155)	(0.137)
(Undoc. share)^Z	0.126	0.580	-0.016	0.408	-0.043	0.908
	(0.024)	(0.120)	(0.039)	(0.186)	(0.082)	(0.059)
(Doc. share)$^Z_{t-1}$			0.025	0.465	0.459	-0.193
			(0.083)	(0.146)	(0.060)	(0.130)
(Undoc. share)$^Z_{t-1}$			0.109	-0.701	0.119	0.581
			(0.051)	(0.100)	(0.050)	(0.081)
Observations	99	99	66	66	66	66
R-squared	0.646	0.463	0.692	0.524	0.783	0.918
F-stat.	49.75	85.7	47.92	17.91	84.48	120.6
SW F-stat.	8.16	34.06	32.82	57.97	32.33	98.02

Notes: Population data are from the US Census 1980-2000 and ACS 2009-2011 and include high school dropouts participating in the labor force. The sample consists of 33 MSAs, for which data on job openings are available. Standard errors are clustered at the MSA level. The observations are weighted by MSA population.

Table D.8: Second stage with base period 1980

	(1) Vacancies	(2) Native wage	(3) Doc. wage	(4) Undoc. wage
Panel A: OLS				
Doc. share	-4.834	-0.291	-0.542	-0.729
	(1.068)	(0.2500)	(0.328)	(0.359)
Undoc. share	2.108	0.578	0.267	0.267
	(0.259)	(0.056)	(0.153)	(0.137)
Observations	99	99	99	97
R-squared	0.792	0.314	0.053	0.130
Panel B: IV				
Doc. share	-4.688	-0.286	-0.123	-0.751
	(1.673)	(0.367)	(0.366)	(0.475)
Undoc. share	1.195	0.459	-0.031	0.103
	(1.156)	(0.169)	(0.188)	(0.222)
Observations	99	99	99	97
R-squared	0.787	0.305	0.031	0.122
Panel C: JRS IV				
Doc. share	0.737	-0.832	-0.121	-1.036
	(3.793)	(0.445)	(0.5600)	(0.713)
Undoc. share	1.858	0.421	0.270	0.425
	(0.5100)	(0.106)	(0.148)	(0.179)
(Doc. share)$_{t-1}$	-6.127	0.759	-0.099	0.337
	(2.756)	(0.397)	(0.543)	(0.687)
(Undoc. share)$_{t-1}$	0.325	-0.311	-0.098	-0.098
	(0.788)	(0.084)	(0.157)	(0.197)
Observations	66	66	66	66
R-squared	0.886	0.569	0.095	0.090

Notes: Population data are from the US Census 1980-2000 and ACS 2009-2011 and include high school dropouts participating in the labor force. The sample consists of 33 MSAs, for which data on job openings are available. Standard errors are clustered at the MSA level. The observations are weighted by average MSA population.

E Additional Figures and Tables

Figure E.1: Worker distribution across industries by education

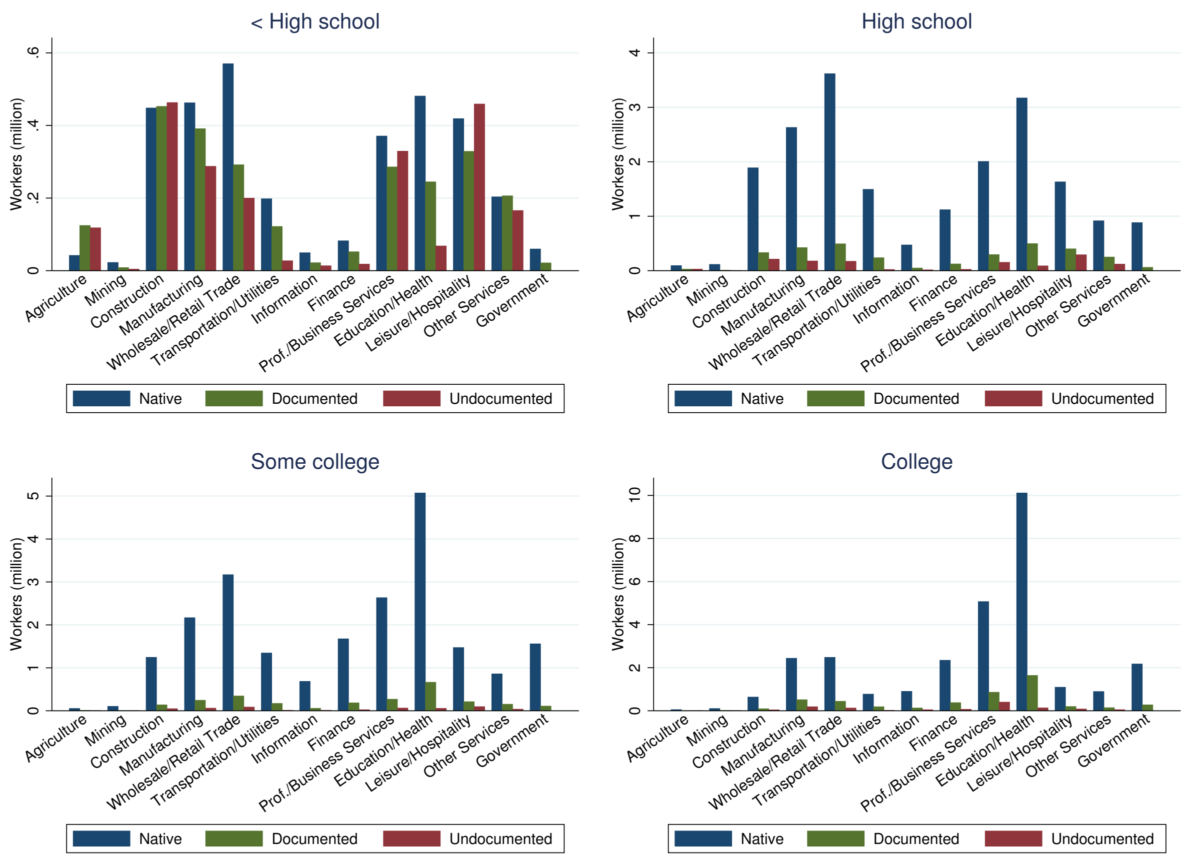


Figure E.2: Composition of low-skilled workers in most frequent occupations of natives

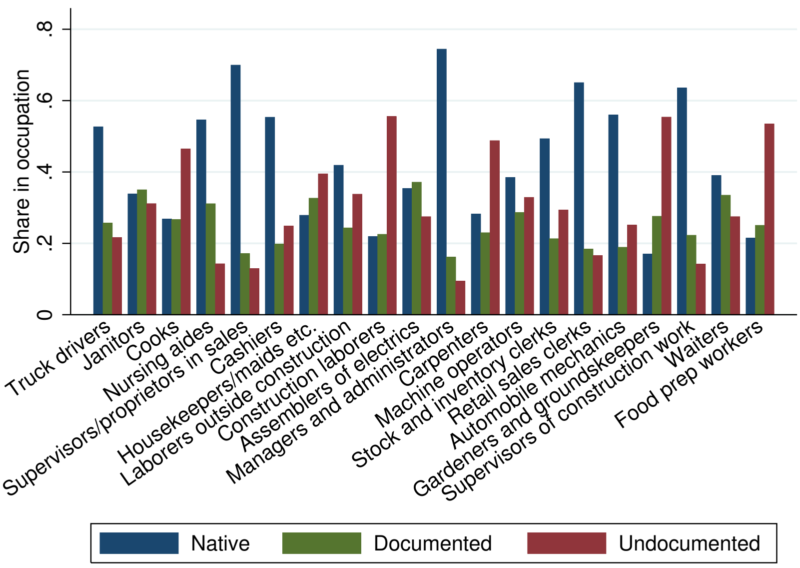
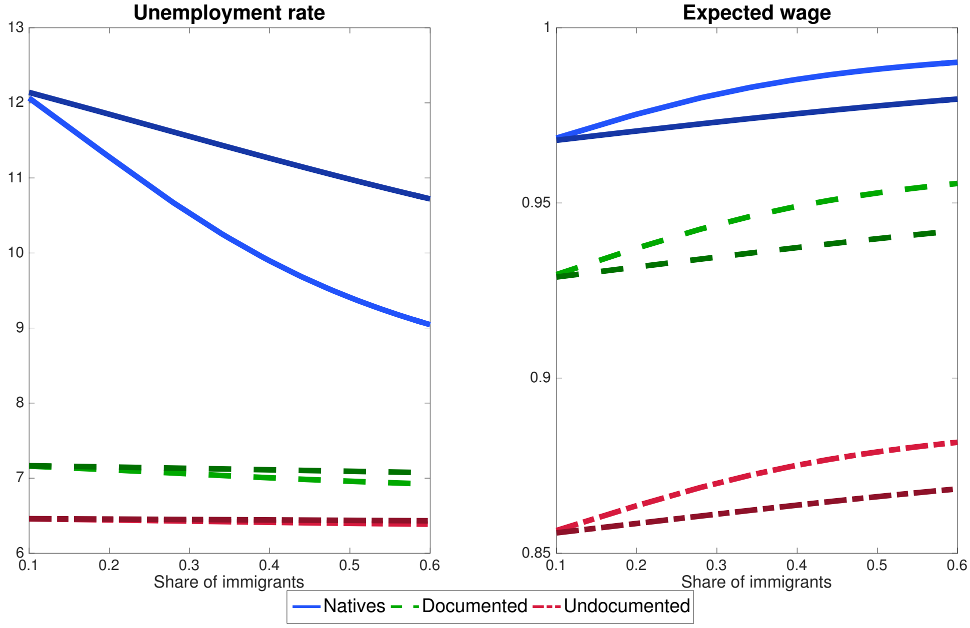
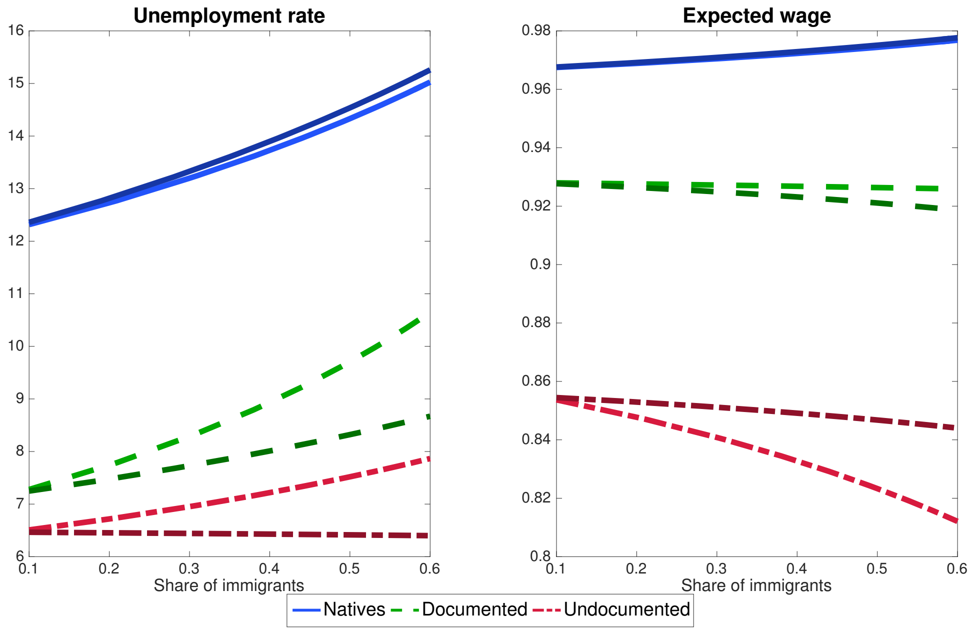


Figure E.3: Job creation effect of documented and undocumented immigration



Notes: The plots show the effects of the same decrease in total queue length q as implied by immigration but without changing the actual composition of population. Darker colors correspond to documented immigration, lighter colors to undocumented immigration.

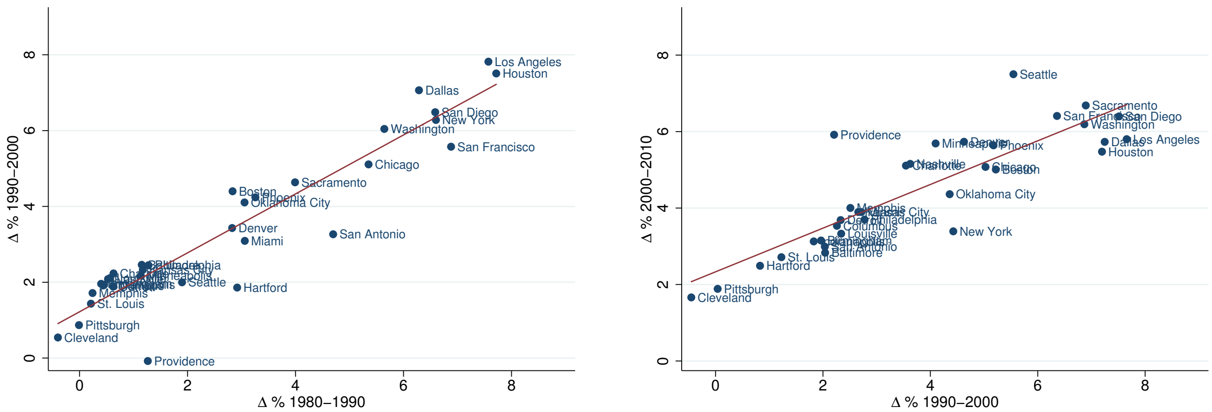
Figure E.4: Competition effect of documented and undocumented immigration



Notes: The plots show the effects of a change in the population composition implied by immigration but without changing total queue length q. Darker colors correspond to documented immigration, lighter colors to undocumented immigration.

Figure E.5: Serial correlations of predicted changes in immigrant shares

Documented immigrants:



Undocumented immigrants:

Figure E.6: Effects of undocumented immigration depending on fine for firms

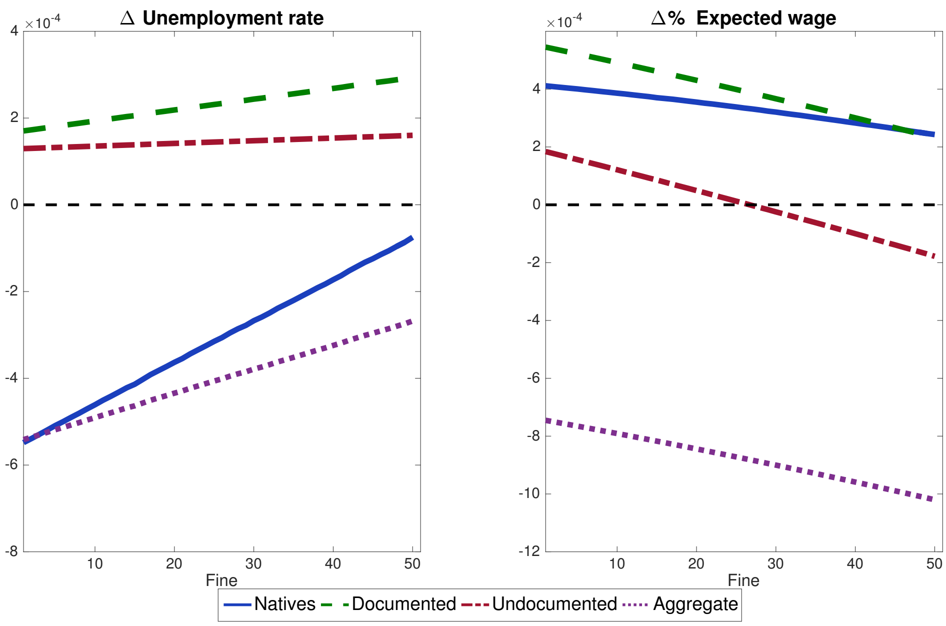


Table E.1: Top 25 most common occupations of low-skilled workers by status

Native			Documented Immigrant			Undocumented Immigrant		
Occupation	*Wage*	%	*Occupation*	*Wage*	%	*Occupation*	*Wage*	%
Truck/delivery/tractor drivers	12.8	7.7	Janitors	8.7	6.7	Cooks	7.3	8.2
Janitors	8.8	4.1	Cooks	8.5	6.1	Construction laborers	8.9	8.0
Cooks	8.2	3.9	Truck/delivery/tractor drivers	12.1	5.9	Gardeners and groundskeepers	7.5	5.9
Nursing aides	8.0	3.8	Housekeepers/maids etc.	7.4	5.0	Housekeepers/maids etc.	7.0	4.7
Supervisors/proprietors in sales	12.2	3.1	Construction laborers	11.4	4.2	Janitors	7.7	4.6
Cashiers	7.3	2.7	Gardeners and groundskeepers	8.8	3.8	Carpenters	9.6	4.3
Housekeepers/maids etc.	7.1	2.7	Assemblers of electrics	9.4	3.5	Truck/delivery/tractor drivers	10.9	3.8
Laborers outside construction	9.8	2.7	Nursing aides	9.4	3.4	Food prep workers	7.4	3.5
Construction laborers	10.1	2.6	Carpenters	14.0	2.6	Farm workers	7.2	3.5
Assemblers of electrics	11.3	2.1	Laborers outside construction	11.2	2.4	Painters/construction/maintenance	8.8	3.1
Managers and administrators	19.1	2.1	Machine operators	10.9	2.3	Laborers outside construction	8.3	2.6
Carpenters	13.6	2.1	Food prep workers	7.6	2.1	Machine operators	8.9	2.0
Machine operators	11.2	2.0	Farm workers	8.4	2.1	Assemblers of electrics	8.2	2.0
Stock and inventory clerks	8.6	1.9	Waiters	7.6	1.7	Packers and packagers by hand	7.1	1.8
Retail sales clerks	10.1	1.9	Textile sewing machine operators	7.5	1.6	Masons, tilers, and carpet installers	9.9	1.8
Automobile mechanics	11.5	1.7	Packers and packagers by hand	7.4	1.6	Cashiers	7.2	1.5
Gardeners and groundskeepers	8.7	1.5	Cashiers	7.7	1.5	Drywall installers	9.4	1.5
Supervisors of construction work	15.9	1.4	Painters/construction/maintenance	9.9	1.4	Roofers and slaters	9.0	1.5
Waiters	6.6	1.3	Welders and metal cutters	12.3	1.3	Stock and inventory clerks	8.0	1.4
Food prep workers	6.7	1.2	Stock and inventory clerks	8.9	1.3	Textile sewing machine operators	6.8	1.4
Production supervisors or foremen	14.4	1.2	Wood lathe machine operators	11.3	1.2	Waiter's assistant	7.3	1.3
Salespersons	13.4	1.2	Supervisors/proprietors in sales	12.4	1.2	Nursing aides	7.7	1.2
Secretaries	11.9	1.1	Hairdressers and cosmetologists	7.2	1.2	Butchers and meat cutters	9.0	1.2
Customer service reps/investigators/adjusters	9.9	1.0	Mechanics and repairers	11.1	1.2	Packers, fillers, and wrappers	7.7	1.1
Welders and metal cutters	12.0	1.0	Packers, fillers, and wrappers	8.3	1.0	Waiters	7.6	1.1

Notes: The table ranks occupations by frequency among high school dropout workers. Wages are hourly and calculated as described in the text. Occupations refer to the 3-digit *occ1990* categories provided by IPUMS.

Table E.2: Wage distribution

Case	Probability	Wage		
		Native	Documented	Undocumented
1) No competitors	$f_1 = e^{-\mu q_N} e^{-\mu q_D} e^{-\mu q_U}$	$\underline{w}_N + \beta_N(y - \underline{w}_N)$	$\underline{w}_D + \beta_D(y - \underline{w}_D)$	$\underline{w}_U + \beta_U(y - \underline{w}_U)$
2) Only N competitors	$f_2 = (1 - e^{-\mu q_N}) e^{-\mu q_D} e^{-\mu q_U}$	$\underline{w}_N$	$\underline{w}_D + \beta_D(\frac{\tilde{r}_D}{\tilde{r}_N}\underline{w}_N + (1 - \frac{\tilde{r}_D}{\tilde{r}_N})y - \underline{w}_D)$	$\underline{w}_U + \beta_U(\frac{\tilde{r}_U}{\tilde{r}_N}\underline{w}_N - (1 - \frac{\tilde{r}_U}{\tilde{r}_N})y - \underline{w}_U)$
3) ≥ 1 D, no U competitor	$f_3 = (1 - e^{-\mu q_D}) e^{-\mu q_U}$	$rU_N = \underline{w}_N$	$\underline{w}_D$	$\underline{w}_U + \beta_U(\frac{\tilde{r}_U}{\tilde{r}_D}\underline{w}_D - (1 - \frac{\tilde{r}_U}{\tilde{r}_D})y - \underline{w}_U)$
4) ≥ 1 U competitor	$f_4 = (1 - e^{-\mu q_U})$	$rU_N = \underline{w}_N$	$rU_D = \underline{w}_D$	$\underline{w}_U$

Table E.3: Profit distribution

Case	Probability	Profit	Hire
1) One N, no D, no U	$\mu q_N e^{-\mu q_N} e^{-\mu q_D} e^{-\mu q_U}$	$(1 - \beta_N)(y - \underline{w}_N)$	N
2) One D, no N, no U	$\mu q_D e^{-\mu q_D} e^{-\mu q_N} e^{-\mu q_U}$	$(1 - \beta_D)(y - \underline{w}_D)$	D
3) One U, no N, no D	$\mu q_U e^{-\mu q_U} e^{-\mu q_N} e^{-\mu q_D}$	$(1 - \beta_U)(y - \underline{w}_U)$	U
4) $>$ one N, no D, no U	$(1 - e^{-\mu q_N} - \mu q_N e^{-\mu q_N}) e^{-\mu q_D} e^{-\mu q_U}$	$y - \underline{w}_N$	N
5) $>$ one D, no U	$(1 - e^{-\mu q_D} - \mu q_D e^{-\mu q_D}) e^{-\mu q_U}$	$y - \underline{w}_D$	D
6) $>$ one U	$(1 - e^{-\mu q_U} - \mu q_U e^{-\mu q_U})$	$y - \underline{w}_U$	U
7) $\geq$ one N, one D, no U	$(1 - e^{-\mu q_N}) \mu q_D e^{-\mu q_D} e^{-\mu q_U}$	$y - \underline{w}_D - \beta_D(\frac{\tilde{r}_D}{\tilde{r}_N}\underline{w}_N + (1 - \frac{\tilde{r}_D}{\tilde{r}_N})y - \underline{w}_D)$	D
8) $\geq$ one N, no D, one U	$(1 - e^{-\mu q_N}) e^{-\mu q_D} \mu q_U e^{-\mu q_U}$	$y - \underline{w}_U - \beta_U(\frac{\tilde{r}_U}{\tilde{r}_N}\underline{w}_N + (1 - \frac{\tilde{r}_U}{\tilde{r}_N})y - \underline{w}_U)$	U
9) $\geq$ one D, one U	$(1 - e^{-\mu q_D}) \mu q_U e^{-\mu q_U}$	$y - \underline{w}_U - \beta_U(\frac{\tilde{r}_U}{r+s_D}\underline{w}_D + (1 - \frac{\tilde{r}_U}{\tilde{r}_D})y - \underline{w}_U)$	U

Table E.4: MSAs used in Section 7.1 and immigrant population shares among low-skilled

MSA	Documented imm. (%)				Undocumented imm. (%)			
	1980	1990	2000	2010	1980	1990	2000	2010
Baltimore, MD	1.8	2.7	3.8	9.0	0.6	1.3	3.2	11.6
Birmingham, AL	0.3	0.6	2.0	3.7	0.1	0.5	3.6	14.7
Boston, MA/NH	12.9	15.1	19.6	23.4	5.9	12.2	15.9	24.4
Charlotte-Gastonia-Rock Hill, NC/SC	0.7	1.5	5.6	11.2	0.4	1.1	12.9	21.5
Chicago, IL	10.4	14.9	19.7	24.6	7.9	15.1	23.3	29.2
Cleveland, OH	5.9	5.6	3.8	5.0	1.5	1.8	2.0	3.4
Columbus, OH	1.6	1.6	4.0	7.2	0.4	0.9	4.6	9.4
Dallas-Fort Worth, TX	3.9	12.0	17.4	23.4	3.7	13.9	27.8	37.0
Denver-Boulder, CO	4.5	7.4	13.4	16.4	2.3	5.3	21.6	30.9
Detroit, MI	5.1	5.2	6.8	9.9	2.0	2.0	5.2	6.6
Hartford-Bristol-Middleton- New Britain, CT	14.5	19.1	18.7	19.3	6.3	10.4	8.2	20.5
Houston-Brazoria, TX	7.0	15.8	22.2	27.7	6.9	18.2	27.0	37.6
Indianapolis, IN	0.8	1.2	2.7	7.1	0.3	0.4	5.4	14.3
Kansas City, MO/KS	1.9	2.8	5.2	9.3	0.7	1.3	8.3	16.5
Los Angeles-Long Beach, CA	16.2	24.2	32.4	38.3	26.1	42.6	39.7	40.0
Louisville, KY/IN	0.5	1.2	2.5	6.1	0.1	0.3	1.7	8.8
Memphis, TN/AR/MS	0.6	0.7	3.3	6.5	0.1	0.8	5.0	14.3
Miami-Hialeah, FL	46.1	52.5	56.2	57.2	6.6	18.8	19.8	23.0
Minneapolis-St. Paul, MN	2.3	3.5	7.9	14.3	0.6	2.0	10.3	18.3
Nashville, TN	0.5	0.9	4.6	12.6	0.2	0.8	8.3	18.4
New York, NY-Northeastern NJ	21.3	26.6	32.1	34.8	10.2	18.3	25.8	33.0
Oklahoma City, OK	1.8	4.7	8.1	15.3	1.0	3.9	10.6	22.2
Philadelphia, PA/NJ	4.4	5.0	7.2	11.7	1.2	2.1	4.7	13.3
Phoenix, AZ	6.7	10.8	15.5	21.0	3.6	11.4	27.0	31.2
Pittsburgh, PA	2.8	2.8	2.3	3.3	0.3	0.6	0.8	0.8
Providence-Fall River-Pawtucket, MA/RI	12.1	18.5	19.4	24.2	10.5	15.8	12.6	19.4
Sacramento, CA	9.0	11.7	18.5	27.5	5.3	9.1	12.7	23.1
St. Louis, MO/IL	1.6	1.5	2.3	3.2	0.2	0.6	1.8	3.8
San Antonio, TX	10.4	14.3	16.1	20.4	4.8	9.0	12.8	19.8
San Diego, CA	14.3	20.3	27.0	32.8	11.3	25.9	29.1	34.8
San Francisco-Oakland-Vallejo, CA	15.8	21.7	29.2	36.7	10.3	22.9	27.9	35.7
Seattle-Everett, WA	6.2	7.6	14.6	25.9	2.0	5.3	11.4	21.1
Washington, DC/MD/VA	5.3	10.8	18.1	25.0	3.6	14.8	23.0	35.1

Notes: Population data are from the US Census 1980-2000 and ACS 2009-2011 and include high school dropouts participating in the labor force.

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