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The Labor Market Impact of Immigration: Job Creation versus Job Competition[†]

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This paper studies the labor market effects of both documented and undocumented immigration in a search model featuring nonrandom hiring. As immigrants accept lower wages, they are preferably chosen by firms and therefore have higher job finding rates than natives, consistent with evidence found in US data. Immigration leads to the creation of additional jobs but also raises competition for natives. The dominant effect depends on the fall in wage costs, which is larger for undocumented immigration than it is for legal immigration. The model predicts a dominating job creation effect for the former, reducing natives' unemployment rate, but not for the latter. (*JEL* E24, J15, J23, J31, J61, M51)

Is immigration beneficial for native workers because it leads to the creation of additional jobs, or does it harm their labor market prospects through higher job competition? This question has been the subject of much debate, as many developed countries saw rising immigrant inflows over the last few decades. In the United States, the share of foreign-born residents among the population has increased from around 5 percent in the 1970s to over 13 percent today, triggered by a change in immigration policy that facilitated entry from Latin America and Asia. Another major change in the nature of US immigration since the beginning of the 1990s is a surge of illegal entries, especially by low-skilled workers. While the number of all immigrants residing in the United States doubled from around 20 million to 40 million between 1990 and 2013, the number of individuals without legal status increased almost fourfold from 3 million to over 11 million, of which more than one-third do not have a high school degree.

The aim of this paper is to shed new light on the distinct effects of documented and undocumented immigration in the low-skilled labor market. Using US survey

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data with legal status imputed following Borjas (2017b), I first document significant differences in labor market outcomes between natives and immigrants that vary with legal status. In particular, immigrants have lower wages and higher job finding rates than natives do, and both these gaps are much larger for undocumented immigrants. While wage differences that depend on legal status have already been documented in previous studies (Rivera-Batiz 1999, Kossoudji and Cobb-Clark 2002, Pan 2012), the finding of differences in job finding rates is novel in the literature.

To account for these empirical facts, I extend a standard job search model by a nonrandom hiring mechanism following Barnichon and Zylberberg (2019). Natives and immigrants are perfect substitutes in production but have different reservation wages due to heterogeneity in terms of unemployment benefits, bargaining power, and risk of deportation. Firms can receive multiple applications and choose the candidate that they can extract the highest surplus from. This implies higher job finding rates for workers that accept lower wages and therefore leads to gaps in job finding rates as in the data. In this model, a rise in the share of immigrant workers leads to more job creation because it decreases average wage costs. However, it also leads to higher job competition because firms prefer immigrants over natives. Job creation and job competition affect the employment rate of natives in opposite ways. Which of the two effects dominates depends on how large the difference in the wage rates of natives and immigrants is. The higher the wage costs that firms save by hiring an immigrant worker, the stronger the job creation effect and the more beneficial immigration is.

In my empirical analysis, I find that, conditional on observable characteristics, undocumented immigrants earn 8 percent less and have a 7 percentage points higher job finding rate than documented immigrants, who in turn earn 4 percent less and have a 7 percentage points higher job finding rate than natives. I estimate the model to match these estimates and use it to simulate the labor market effects of both types of immigration. The simulations show that the job creation effect is large enough to dominate the job competition effect in the case of undocumented immigration but not documented immigration. Therefore, only undocumented immigration is predicted to be unambiguously beneficial for natives as both their employment rate and wages increase, whereas documented immigration decreases natives' employment rate and has an ambiguous effect on wages depending on the assumed wage-bargaining mechanism. I test these predictions from the model empirically by estimating the effects of immigrant shares in the low-skilled labor force on vacancies and wages at the metropolitan statistical area (MSA) level. I find positive effects for the undocumented immigrant share on both vacancies and wages, but I do not find positive effects for the documented immigrant share. This supports the prediction that undocumented immigration increases employment opportunities and wages more than documented immigration does.

Finally, I use the framework to study the impact of a counterfactual policy of stricter immigration enforcement, which I simulate through an increase in the exogenous deportation rate of undocumented immigrants. I distinguish two cases: (i) a rise in the deportation rate that is the same independent of employment status, and (ii) a rise in the deportation rate for only employed workers, for example, because of an intensified use of worksite raids by authorities. In the first case, the policy leads to a marginal increase in legal workers' unemployment rates, as expected firm surplus and thus job creation are dampened weakly. In the second case, firms additionally have to pay a compensating differential to induce an undocumented worker to accept a job. As a result, wage costs increase and job creation is dampened more strongly, which implies a much stronger rise in unemployment and a fall in wages for legal workers. I test these predictions using the statewide implementation of omnibus immigration laws as a measure of stricter immigration enforcement and find that introducing these laws is associated with a lower job finding rate for all workers, which is evidence for muted vacancy creation. Moreover, I find that wages fall for natives and rise for undocumented immigrants, which is consistent with a compensating differential in their wages.

This paper contributes to the literature by documenting large job finding rate differences between natives and immigrants, which are inversely related to their gaps in wages, and by analyzing both documented and undocumented immigration in a search model that allows firms to choose their preferred applicant among several. This simple and intuitive extension enables the model to match the empirical fact of a variation in job finding rates across heterogeneous workers, which is a puzzle for the standard model with strictly random hiring.

There exists a large body of related literature investigating the labor market impact of immigration. Previous studies employed spatial correlations (Card 2001; Glitz 2012; Dustmann, Fasani, and Speciale 2017), skill cell correlations (Borjas 2003, Mishra 2007), or structural production function approaches (Ottaviano and Peri 2012; Manacorda, Manning, and Wadsworth 2012) to identify wage effects. More recently, some authors also employ search frameworks (Chassamboulli and Palivos 2014, Battisti et al. 2018), which allows them to study the effects of immigration on both wages and employment.

In a study that is closely related to this paper, Chassamboulli and Peri (2015) distinguish between documented and undocumented immigration in a search framework also featuring a job creation effect resulting from the arrival of workers that accept lower wages. Hiring is random in this model, implying that firms cannot discriminate between natives and immigrants in their hiring decisions. Therefore, all workers have the same job finding rates, and immigration, whether documented or undocumented, unambiguously drives up the wages and employment of natives. The extension with a nonrandom hiring mechanism that I propose in this paper generates job finding rate differences consistent with the data and gives rise to the competition effect, which implies that the beneficiality of immigration depends on the difference between the wages of natives and the entering immigrant type.

While there are several other studies that distinguish immigrants by legal status in theoretical models (Liu 2010, Edwards and Ortega 2017, Machado 2017), there exists little empirical work on the labor market impact of undocumented immigrants. Using administrative data from the US state of Georgia, in which undocumented immigrants can be identified through invalid social security numbers, Brown, Hotchkiss, and Quispe-Agnoli (2013) provide evidence that the employment of undocumented workers leads to lower exit rates of firms through a competitive advantage. Using the same dataset, Hotchkiss, Quispe-Agnoli, and Rios-Avila (2015) show that wages of documented workers increase with a higher share of undocumented workers at both the county-industry and the firm level. These findings of higher firm profits and improved labor market outcomes of natives due to a higher fraction of undocumented workers are in line with the predictions of the model proposed in this paper.

The remainder is organized as follows. The next section describes the data and the method to identify undocumented immigrants. Section II empirically investigates the wages and job finding rates of natives and documented and undocumented immigrants. Section III presents the model and outlines the parameterization strategy. Section IV explores the effects of simulated immigration in the model. Section V explores the effects of a counterfactual rise in the deportation risk. Section VI tests the main predictions derived from the model empirically. Section VII discusses some of the simplifying assumptions made in the model. Section VIII concludes the paper.

I. Data and Identification of Undocumented Immigrants

The main data sources are the March supplement of the Current Population Survey (CPS) obtained from the Integrated Public Use Microdata Series (IPUMS) (Flood et al. 2015) and the CPS basic monthly files (NBER 2017). The former provides detailed data on income at a yearly frequency, while the latter allows matching workers over two consecutive months to compute monthly transition rates between employment and unemployment, whereby I follow Shimer (2012). My analysis is restricted to the period beginning in 1994, as this is the first year with information on birthplace and citizenship status available. I only consider prime-age workers (age 25 to 65) in all samples. Individuals born outside the United States who are not American citizens by birth are defined as immigrants.

Neither the CPS basic monthly files nor the March supplement allow the direct identification of undocumented immigrants. However, as these surveys conducted by the US Census Bureau are address based and designed to be representative of the whole population, they also include undocumented respondents. The Department of Homeland Security (DHS) uses the CPS and the American Community Survey (ACS) as the main sources to estimate the size of the undocumented immigrant population using a residual method. The DHS obtains figures of legal immigrants in the United States from administrative data of officially admitted individuals and subtracts them from the foreign-born noncitizen population estimated from the surveys. The resulting residual is the estimated number of unauthorized residents.

Recently, a methodology for identifying undocumented immigrants at the individual level was developed by Passel and Cohn (2014) from the Pew Research Center. They add an undocumented status identifier based on respondents' demographic, social, economic, and geographic characteristics to the CPS March supplement. They use variables like citizenship status or coverage by public health insurance to identify a foreign-born respondent as legal and then classify the remaining immigrants as potentially undocumented. As a final step, they apply a filter on the potentially undocumented immigrants to ensure that the count of the immigrants that are finally classified as undocumented is consistent with the estimates from the residual method. Unfortunately, their code is not available for replication. However, Borjas (2017b) describes a simplified and replicable version of the methodology of Passel and Cohn (2014), which he uses to identify undocumented individuals in all CPS March supplements since 1994. This method consists of classifying as documented every immigrant who fulfills at least one of the following conditions:

- being a US citizen,
- residing in the United States since 1982 or before,
- receiving social security benefits or public health insurance,
- residing in public housing or receiving rental subsidies,
- being a veteran or currently in the Armed Forces,
- working in the government sector or in occupations requiring licensing,
- being Cuban, or
- being married to a legal immigrant or US citizen.

All remaining immigrants are then classified as undocumented. Thus, Borjas (2017b) does not apply a filter on the sample of potentially undocumented immigrants to make their final count consistent with estimates from the residual method as in Passel and Cohn (2014). To assess the accuracy of this simplified method without filtering, Borjas (2017b) compares summary statistics for the undocumented immigrant population in his CPS March sample with the corresponding summary statistics in the sample including the undocumented identifier constructed by Passel and Cohn (2014), to which he was granted access. As the total share of undocumented immigrants in the population is similar across the samples, Borjas (2017b) concludes that the simplified method is sufficiently accurate to identify undocumented immigrants. I apply his identification algorithm in the CPS March supplement as well as the CPS basic monthly data, and I investigate the accuracy of my replication in online Appendix A.[1] I find that there are too many immigrants classified as undocumented among those with at least some college education compared to the sample of Passel and Cohn (2014). However, the algorithm leads to a very similar number of undocumented immigrants among low-skilled individuals.

Figure 1 plots the share of undocumented immigrants among the total prime-age population and all prime-age immigrants since 1994 in the four groups commonly used for the classification of educational attainment: high school dropouts, high school graduates, workers with some college education, and college graduates. Among high school dropouts, the percentage of undocumented immigrants is by far the highest and increased the most, from 9 percent in 1994 to over 22 percent in 2007, remaining relatively constant since then. In the higher education groups, which should be viewed with caution due to the mentioned overcounting of undocumented immigrants, the percentage has risen only moderately, reaching just around

[1] Note that the CPS basic data does not include information on receiving social security benefits and public health insurance. Although the lack of this information might result in falsely classifying some immigrants as undocumented, I show in online Appendix A that the method is accurate in the CPS basic data. Moreover, as such a measurement error attenuates the differences between documented and undocumented immigrants, the estimated effects of being undocumented on transition rates shown in Section IIB are lower bounds of the true effects.

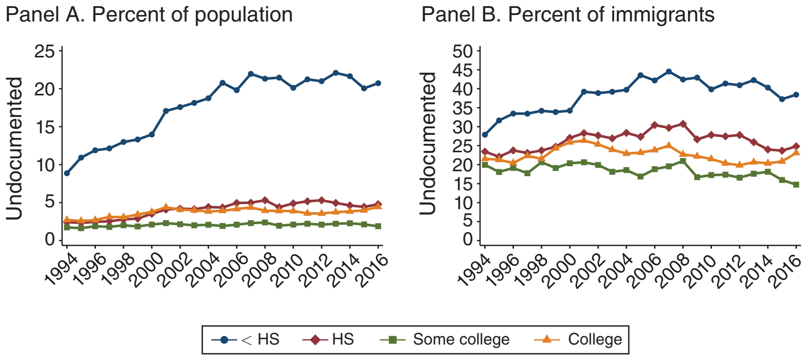

FIGURE 1. PERCENTAGE OF UNDOCUMENTED IMMIGRANTS

Source: CPS March supplement with Borjas (2017a) identification, prime-age workers only

5 percent for high school and college graduates.[2] Also among immigrants, the undocumented percentage is the largest and increased the most in the group of high school dropouts. This suggests that on average, undocumented immigrants have a lower education level than documented immigrants, and this difference has increased since 1994. (The percentage of high school dropouts is around 37 percent among the former and 19 percent among the latter in 2016.)

Figure E.1 in the online Appendix explores whether legal status is associated with a concentration in different industries. I identify 13 industries based on the one-digit level of the North American Industry Classification System (NAICS). The most salient feature of the figure is the high number of both documented and undocumented immigrant workers among high school dropouts, which in most industries is close to the number of native workers. Only *Wholesale and Retail Trade*, *Transportation and Utilities*, *Education and Health*, and *Government*[3] are largely dominated by a native workforce. In *Agriculture*, native workers are even a small minority. Most undocumented high school dropouts work in the *Construction* and *Leisure and Hospitality* industries. In the latter, which includes, for example, cooks and waiters, they even constitute the largest share of the three worker types. The upper-right and bottom panels of online Appendix Figure E.1 suggest that among workers with at least a high school degree, the number of immigrants is small compared to the number of natives across all industries.

Given the large size of the immigrant workforce among high school dropouts, I choose to restrict my empirical analysis to this education level (for simplicity, henceforth referred to as "low-skilled workers"). Besides the large share of both documented and undocumented immigrant workers, there are additional reasons for focusing on this group. First, the identification method is accurate among

[2] A part of the rise of the undocumented share among high school dropouts is due to the fact that the education levels of natives and documented immigrants have improved more strongly than the education levels of undocumented immigrants. (Between 1994 and 2016, the share of high school dropouts fell from 15 percent to 9 percent for the former and from 41 percent to 37 percent for the latter.)

[3] By construction of the identification method, no undocumented immigrants work for the government.

low-skilled workers only, as shown in online Appendix A. Second, concentrating on workers that are homogenous in terms of their education level is likely to lead to a more precise estimation of the effect of legal status. Third, unobserved skill differences between natives and documented and undocumented immigrants play a rather small role in the low-skilled labor market. Fourth, undocumented immigrants might face occupational barriers leading to employment in jobs for which they are overqualified (Ortega and Hsin 2018). Naturally, overqualification does not pose a problem among the workers with the lowest level of qualification.

II. Empirical Evidence

In this section, I present empirical evidence suggesting that there are large differences in both wages and job finding rates between natives and immigrants among low-skilled workers. In particular, I show that immigrants earn lower wages than natives do, whereas the difference is much larger for undocumented immigrants. The wage gap for natives falls over time in the United States, but it only disappears completely for documented immigrants. Moreover, both types of immigrants find jobs faster than natives do, and, analogously to wages, the gap is higher for undocumented immigrants and falling over time in the United States. I also find evidence for separation rate differences, but they are small and disappear for both types of immigrants after 25 years in the United States.

A. *Wages*

It has been well documented in the literature that immigrants are paid less than native workers even when controlling for observable characteristics. To find causal evidence for an additional wage difference due to legal status, previous studies exploited amnesty through the Immigration Reform and Control Act (IRCA) in 1986 as a quasi-experiment. Their estimates of the effect of legalization lie between 6 percent (Kossoudji and Cobb-Clark 2002) and 10 percent (Pan 2012). Borjas (2017b) introduces a novel, easily replicable strategy that does not rely on the IRCA and can be used to identify undocumented immigrants in more recent microdata. His estimate of the wage penalty of undocumented immigrants is around 12 percent (Borjas 2017a).[4] I also follow his strategy of using the CPS data with undocumented immigrants identified by the Borjas (2017b) algorithm to estimate differences in labor market outcomes beyond wages. However, I use a sample of only low-skilled workers, for which the accuracy of the identification method is much higher, and add further controls to the regression model to account for different industry and occupation choices. I exclude the self-employed, those working without pay, those not working full-time (52 weeks per year, at least 35 hours per week), and individuals living in group quarters. I construct real hourly wages by dividing the total wage income deflated to 1999 dollars by the number of hours worked per year and control for outliers by dropping the first and ninety-ninth percentile of the distribution.

[4] Edwards and Ortega (2017) also document wage differences between documented and undocumented immigrants within industries but do not perform a more in-depth regression analysis.

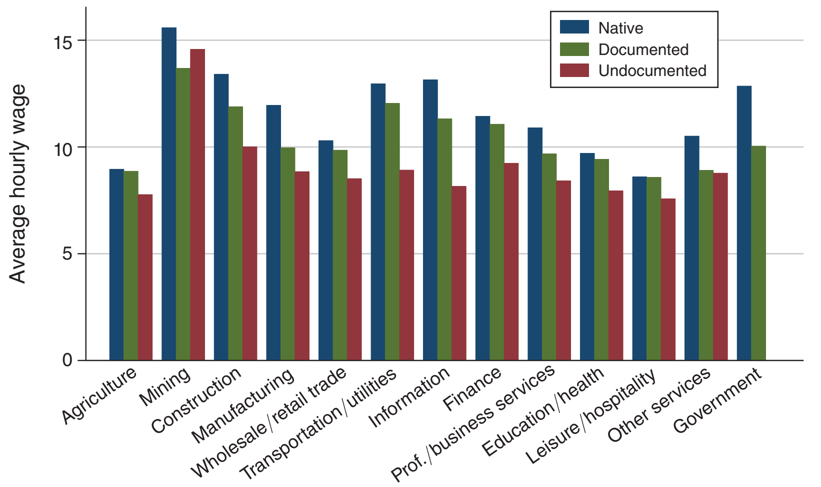

Figure 2. Hourly Wages of Low-Skilled Workers (1999 Dollars)

Note: The statistics are averages across the 2007–2016 CPS March supplement and drawn from the prime-age worker sample described in the text.

Figure 2 reports the average hourly wages of low-skilled workers by industry. As expected, natives earn the most in all industries. With the exception of *Mining*, documented immigrants have the second-highest wages, while undocumented immigrants have the lowest. The worst-paying industries, with earnings of under $10 for all types of workers, are *Leisure and Hospitality*, *Agriculture*, and *Education and Health*. Except for *Mining* and *Construction*, undocumented immigrants earn hourly wages well below $10 in all industries.

Several studies suggest that natives and immigrants are imperfect substitutes and tend to specialize in tasks that they have a comparative advantage in, which are more communication intensive for natives and more manual/physical for immigrants (Peri and Sparber 2009). Thus, they could perform very different jobs within the same industry. Information on specific job types is available through occupation codes in the data. Online Appendix Table E.1 therefore goes a step further by showing the wages in the 25 most common 3-digit occupations of low-skilled workers by status. The table indicates that with very few exceptions, the wage ranking evident within industries also exists within occupations. Moreover, it reveals that natives and both types of immigrants seem to be concentrated in similar occupations, confirming that occupational barriers are not very prevalent for low-skilled workers.[5] For all three types, *Truck/delivery/tractor drivers, Janitors, Cooks, Housekeepers/maids,* and *Construction laborers* are among the top ten occupations. Furthermore, 15 of the top 25 occupations are common to all types, while 20 are common to both types of immigrants. Figure E.2 in the online Appendix shows the

[5] By construction of the identifier of undocumented immigrants, they are never employed in occupations that require licensing. However, as these predominantly require high skills, only 1.4 percent of natives in the low-skilled sample work in any of these occupations.

composition of the workforce in the 20 most frequent occupations that natives are employed in. It suggests that immigrants are mainly barred from occupations like *Supervisors/proprietors in sales, Managers and administrators,* and *Supervisors of construction work*. Moreover, the share of undocumented immigrants is somewhat unbalanced, being particularly high among *Cooks, Construction laborers, Carpenters, Gardeners,* and *Food prep workers*. In all remaining occupations, the shares of the three worker types are relatively balanced. The Duncan index for occupational dissimilarity is 0.26 for natives and documented immigrants and 0.39 for natives and undocumented immigrants. This is much lower than the index by gender, which in my sample is 0.56.

To test whether the wage differences are robust to controlling for both demographic variables and the distribution across occupations, I run a wage regression including age, age squared, and dummies for sex and Hispanic and Asian origin as well as industry and occupation fixed effects. As a final step, I include an interaction of industry and occupation, i.e., a dummy for each industry-occupation combination. By doing so, I assume that only within each industry-occupation cell are natives and documented and undocumented immigrants perfect substitutes. The regression specification has the following form:

$$\ln w_{it} = \beta_0 + \beta_1 D_{it} + \beta_2 U_{it} + \phi_t + X_{it}'\gamma + \epsilon_{it},$$

where the dummies D_{it} and U_{it} are indicators for being a foreign-born documented or undocumented worker, respectively; ϕ_t denotes year fixed effects; and X_{it}' is a vector containing the demographic, industry, and occupation controls as well as metropolitan statistical area dummies.

The regression results are reported in Table 1. The baseline specification without controls suggests that documented immigrants earn around 12 percent and undocumented immigrants around 27 percent less than the native reference group does. The inclusion of demographic controls shrinks the wage gaps to 7 percent and 21 percent, respectively. The results after additionally including year and MSA fixed effects in column 3 are in line with the results of a comparable specification in Table 2 of Borjas (2017a), which finds very similar coefficients despite using a sample with all education groups and only the years 2012–2013. Adding industry and occupation fixed effects shrinks both coefficients by around a half. Coefficients remain virtually identical when including industry-occupation interactions. Column 5 indicates that documented immigrants earn only 4.3 percent less than natives and that the undocumented status of an immigrant accounts for an additional wage gap of 8.3 percent. These estimates are well within the range of those obtained by the studies estimating the wage gain from legalization through the 1986 IRCA.[6]

The regression model considered above does not take the number of years spent in the United States into account, which on average is 21 for documented immigrants

[6] Recently, the Pew Research Center started to rely on the ACS, which offers a larger sample size, to investigate the characteristics of the undocumented population. In Table D.1 in the online Appendix, I replicate the regressions shown in Table 1 using a pooled census and ACS sample starting in 1990. All variables are defined exactly like they are in the CPS data. The results are almost identical except that the estimated wage gap of documented immigrants is somewhat lower.

Table 1—Legal Status and Hourly Wage of Low-Skilled Workers

	(1)	(2)	(3)	(4)	(5)
Documented	−0.118	−0.071	−0.094	−0.044	−0.043
	(0.0047)	(0.0104)	(0.0085)	(0.0065)	(0.0067)
Undocumented	−0.272	−0.207	−0.237	−0.128	−0.126
	(0.0051)	(0.0178)	(0.0151)	(0.0122)	(0.0123)
Demographics	No	Yes	Yes	Yes	Yes
Year/MSA fixed effects	No	No	Yes	Yes	Yes
Ind/occ fixed effects	No	No	No	Yes	No
Ind × occ fixed effects	No	No	No	No	Yes
Observations	68,563	68,563	68,563	68,563	68,563
R^2	0.050	0.138	0.165	0.271	0.295

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*. Standard errors are clustered at the metropolitan area level.

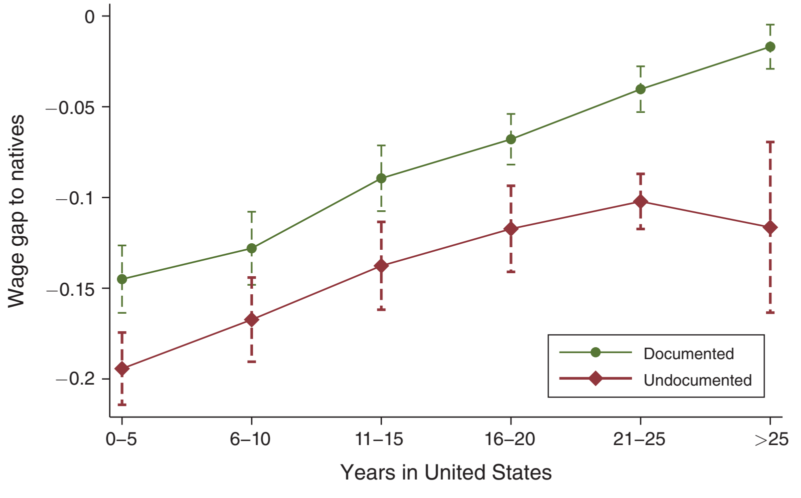

Figure 3. Wage Gap to Natives

Notes: The gaps are based on an extended sample including workers with at most a high school education. Vertical dashed lines show 10 percent confidence intervals.

and 12 for undocumented ones. It is well known that immigrants assimilate into their host country over time and that this is associated with earnings growth (e.g., Borjas 1985). To account for a potentially nonlinear and immigrant-type-specific growth in hourly wages over time, I augment the wage regression by an interaction between the documented and undocumented immigrant dummies and years in the United States, which I group in six five-year intervals (1–5, 6–10, 11–15, 16–20, 21–25, and >25) denoted by $y = 1, \ldots, 6$. The immigrant equation therefore becomes

$$\ln w_{iyt} = \beta_0 + \beta_{1y} D_{it} + \beta_{2y} U_{it} + \phi_t + X_{it}'\gamma + \epsilon_{it}.$$

Figure 3 plots the wage gap to natives for both immigrant types for each interval of years in the United States. To increase the number of immigrant observations per interval, I also include high school graduates in the regression underlying the figure and add a dummy indicating that they have completed high school as educational control.[7] The wage gaps of documented and undocumented immigrants residing in the United States for at most five years are around 15 percent and 20 percent, respectively. The speed of assimilation is almost identical for both types during the first 20 years; however, the assimilation of the undocumented slows down subsequently. Earning only 2 percent less than natives, documented immigrants have almost fully assimilated after 25 years, at which point the undocumented still earn around 12 percent less. Thus, Figure 3 suggests that first, even accounting for the length of stay in the United States, there is still a large wage gap between documented and undocumented immigrants. Second, the gap to natives disappears over time for the former but not the latter.

B. *Unemployment and Transition Rates*

This section analyzes the differences in unemployment and transition rates between employment and unemployment across worker types. The upper plot of Figure 4 shows the unemployment rates of low-skilled workers based on the CPS March supplement over time. Throughout most of the sample period, undocumented immigrants have the lowest unemployment rate, with the difference to natives reaching almost 10 percentage points in recent years. From 2004 onward, documented immigrants also consistently have a lower unemployment rate, which lies between the two other types in all years except 2007. Thus, the order of the three types in terms of unemployment seems to be inversely related to the order in terms of earnings.

To determine whether the unemployment rate gaps are driven by immigrants finding jobs at a higher rate or immigrants separating from jobs at a lower rate (or a combination of both), I decompose the unemployment rates into the underlying job finding (UE transition) and separation (EU transition) rates.[8] For this, I match individuals over two consecutive months in the CPS basic monthly files and correct the flows for time aggregation bias, which arises because data are only available at discrete interview dates, potentially missing transitions happening between two interviews (Shimer 2012). Some of the variables for the identification of legal respondents—for example, social security benefits or health insurance—are not available in the CPS basic data. Although this might lead to a lower precision of the undocumented immigrant identifier, I show in online Appendix A that there is no excess of undocumented immigrants among the low skilled in the CPS basic data.

The bottom-left plot of Figure 4 presents the series of job finding rates. In all years except 2006 and 2016, undocumented immigrants have the highest job finding rate of all workers. Natives, on the other hand, have the lowest rate, with the difference to undocumented immigrants reaching up to 23 percentage points. The

[7] Coefficients are almost identical but less precisely estimated when including high school dropouts only.

[8] Given the law of motion $u_{t+1} = u_t + s_t(l_t - u_t) - f_t u_t$, where l_t denotes the total labor force, s_t the separation, and f_t the job finding rate, the steady-state unemployment rate can be approximated by $u_t/l_t = s_t/(s_t + f_t)$, which Shimer (2012) shows to almost exactly match the actual unemployment rate.

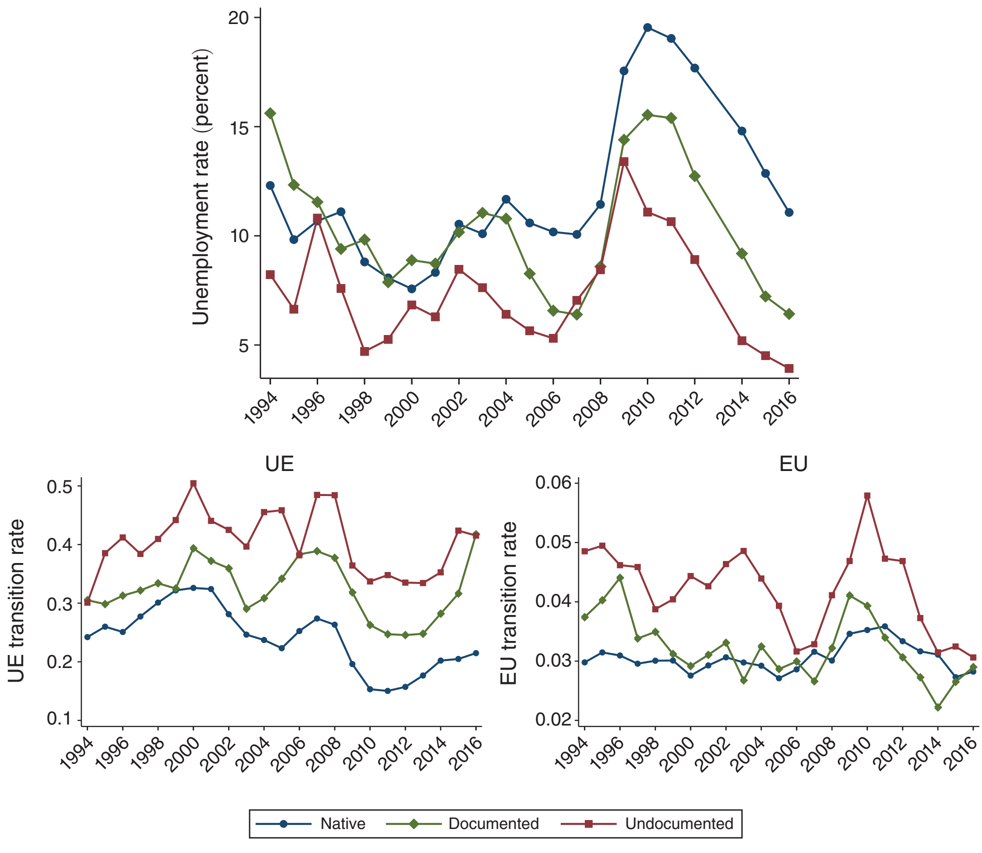

Figure 4. Unemployment and Transition Rates of Low-Skilled Workers

Notes: The upper plot shows the unemployment rates of prime-age workers based on the CPS March data. The lower plots show the yearly averages of transition rates constructed using the CPS basic monthly files and corrected for time aggregation bias following Shimer (2012).

bottom-right plot presents the series of separation rates. While there is almost no difference between natives and documented immigrants, the series is higher over most of the period for undocumented immigrants. As a higher separation rate is associated with a *higher* unemployment rate, but undocumented immigrants actually have a *lower* unemployment rate than the other types, their higher job finding rate more than compensates for the differential in the separation rate. Altogether, the decomposition therefore suggests that the unemployment rate gaps are primarily driven by job finding rates. This is a surprising finding in light of previous studies suggesting that the variation in unemployment rates across workers—e.g., skill types in Mincer (1991)—is almost solely driven by variation in separation rates. The speed of job finding, on the other hand, has been found to mainly account for cyclical fluctuations of unemployment over time (Shimer 2012).

Potentially, these transition rate differences could be explained by demographic or occupational heterogeneity between the worker types and not by the type itself. I therefore estimate a linear probability model with a dummy indicating a UE

TABLE 2—LEGAL STATUS AND UE TRANSITION OF LOW-SKILLED WORKERS

	(1)	(2)	(3)	(4)	(5)
Documented	0.069	0.061	0.071	0.068	0.069
	(0.0047)	(0.0063)	(0.0078)	(0.0073)	(0.0072)
Undocumented	0.142	0.126	0.141	0.139	0.140
	(0.0053)	(0.0084)	(0.0106)	(0.0116)	(0.0117)
Demographics	No	Yes	Yes	Yes	Yes
Year/state fixed effects	No	No	Yes	Yes	Yes
Ind/occ fixed effects	No	No	No	Yes	No
Ind × occ fixed effects	No	No	No	No	Yes
Observations	75,634	75,634	75,634	75,634	75,634
R^2	0.016	0.029	0.044	0.057	0.079

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.

transition or a dummy indicating an EU transition as dependent variable including the same controls as in the wage regressions.

The regression results for job finding rates are reported in Table 2 and confirm the patterns seen in Figure 4: both types of immigrants find jobs faster than natives do, and undocumented workers even faster than documented ones. Controlling for observables does not influence the results, which are almost identical across all specifications.[9] With the average monthly job finding probability of all workers being around 23 percent, the coefficients suggest that documented workers find jobs with a probability that is around one-third higher than the average and that undocumented workers do so with a probability that is even 60 percent higher than the average.[10]

Another possible explanation for these differentials in job finding rates could be a higher search effort exerted by immigrants. To control for this, I combine information on job search activities available in the monthly CPS data with information on overall time spent searching from the American Time Use Survey (Hofferth, Flood, and Sobek 2018) to impute search time for each CPS respondent following Mukoyama, Patterson, and Şahin (2018). The data suggest that immigrants tend to spend *less* time searching for a job than natives do, and including imputed search time as control variable leaves the results shown in Table 2 virtually unchanged. A detailed description of the data, the imputation, and the results are found in Section D.2 in the online Appendix.

Analogous to Figure 3, Figure 5 plots the predicted differences in job finding rates between immigrants and natives depending on time spent in the United States. As for wages, the gaps become more narrow over time, although they do not disappear completely for either immigrant type after having spent more than 25 years in

[9] If the sample also includes individuals that report to be out of the labor force, then the results are qualitatively similar, but coefficients are somewhat larger.

[10] Transitions to self-employment, which make up around 10 percent of all transitions to employment, are excluded. The differences in transition rates to self-employment between natives and immigrants are of similar magnitude as the differences in transition rates to salary employment. Thus, including both types of transitions virtually yields the same estimates.

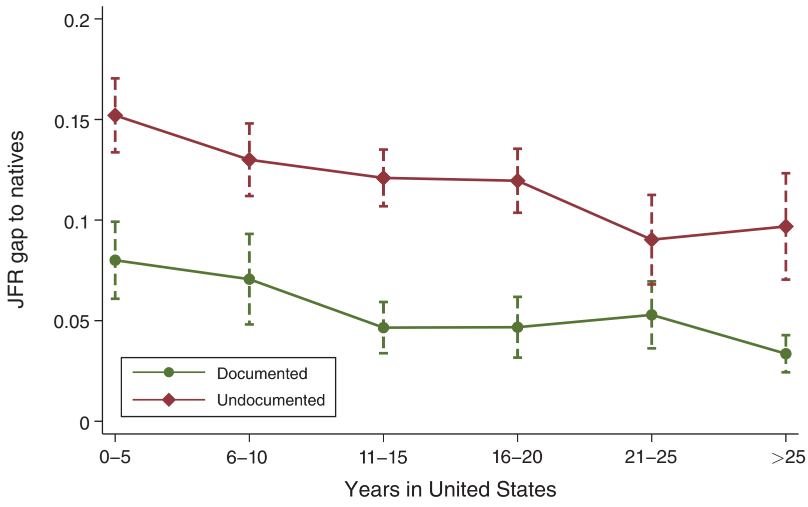

FIGURE 5. JOB FINDING RATE GAP TO NATIVES

Notes: The gaps are based on an extended sample including workers with at most a high school education. Vertical dashed lines show 10 percent confidence intervals.

TABLE 3—LEGAL STATUS AND EU TRANSITION OF LOW-SKILLED WORKERS

	(1)	(2)	(3)	(4)	(5)
Documented	−0.001	−0.001	−0.001	−0.003	−0.003
	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.0004)
Undocumented	0.001	−0.001	−0.002	−0.006	−0.006
	(0.0005)	(0.0009)	(0.0009)	(0.0007)	(0.0007)
Demographics	No	Yes	Yes	Yes	Yes
Year/state fixed effects	No	No	Yes	Yes	Yes
Ind/occ fixed effects	No	No	No	Yes	No
Ind × occ fixed effects	No	No	No	No	Yes
Observations	566,368	566,368	566,368	566,368	566,368
R^2	0.000	0.001	0.002	0.007	0.013

Notes: Dependent variable is the probability of an EU 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.

the United States. The difference between the immigrant types persistently lies at around 6 to 8 percentage points.

Table 3 presents the regression results with EU transitions as dependent variable. To be consistent with the sample of the wage regressions, I only consider separations from full-time jobs. Further, I only consider transitions to unemployment if the reason for unemployment is either losing a job or leaving a job.[11] The coefficients with the full set of controls suggest that documented immigrants have a 0.3 percentage point and undocumented immigrants a 0.6 percentage point lower separation

[11] The other unemployment reasons are: temporary job ended, re-entrant, and new entrant.

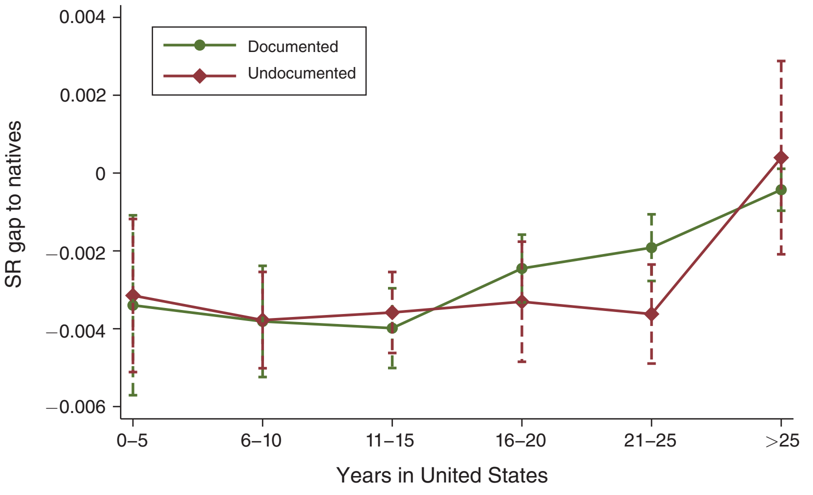

Figure 6. Separation Rate Gap to Natives

Notes: The gaps are based on an extended sample including workers with at most a high school education. Vertical dashed lines show 10 percent confidence intervals.

rate than natives do. These differences are much smaller compared to the differences in job finding rates and also when relating them to the average separation probability of around 1.6 percent.

Figure 6 plots the predicted differences in separation rates to natives depending on length of stay in the United States. There is no significant difference in separation rates between immigrants, and both types have lower separation rates than natives initially do but fully catch up after 25 years.

III. Model

This section presents a labor market model that extends the canonical search and matching framework (Mortensen and Pissarides 1994) with a nonrandom hiring mechanism based on the ranking assumption of Blanchard and Diamond (1994), which allows firms to gather and rank several applications. This is not only intuitive but also consistent with evidence concluding that firms usually interview many applicants at once (Barron, Bishop, and Dunkelberg 1985; Barron and Bishop 1985). The ranking as well as the wage-bargaining mechanism are adopted from Barnichon and Zylberberg (2019). It assumes that applicant types are ranked according to the surplus that firms can extract by hiring them and that when bargaining for the wage with the best type, a firm can threaten to hire the second-best applicant at his reservation wage.[12]

[12] In Barnichon and Zylberberg (2019), firm surplus depends on the applicant type due to differing productivities.

A. *Basics*, *Matching Mechanism, and Wage Bargaining*

There is a continuum of measure one of risk-neutral, infinitely lived workers in the economy who are either natives, documented immigrants, or undocumented immigrants. Their type is denoted by $i \in \{N, D, U\}$, and each represents an exogenous share ω_i of the total work force P. A worker of a given type is either employed, inelastically supplying one unit of labor earning wage w_i, or unemployed, receiving a flow payment z_i. I assume that the flow payment consists of unemployment benefits z^{UI} and home production z_i^H for natives and documented immigrants, whereas undocumented immigrants are not eligible for unemployment benefits. Therefore, we have $z^{UI} + z_N^H \geq z^{UI} + z_D^H > z_U^H = z_U$. I also allow the bargaining powers β_i to differ between worker types, accounting for the fact that hiring an unauthorized worker is unlawful and thus undocumented immigrants are likely to have a lower bargaining power in negotiating wages.[13] Moreover, I introduce the possibility for undocumented workers to be detected and deported.[14] I allow the probability of detection to be potentially different for an employed worker and an unemployed one.[15] I denote the rate of deportation for an employed worker by λ_i^W and for an unemployed worker by λ_i^U, both being strictly positive only for $i = U$. Deportation (officially termed removal) not only implies job loss (in case of being employed) but also the loss of an utility amount $R > 0$, which captures the cost (for example, psychological) associated with being deported.

There is a large measure of risk-neutral firms, which enter the economy by posting vacancies at cost $c > 0$. A firm paired with a worker produces output y, which is independent of the worker type.[16] A match is dissolved at the exogenous, type-specific separation rate s_i. I assume that workers can apply at most to one job and that their application is randomly allocated to a vacancy by an urn-ball matching function (Butters 1977). Hence, due to coordination frictions, some firms will receive multiple applications, while others will receive none. With a large number of vacancies v and a large number of homogeneous applicants, the probability for a firm to be matched with exactly k applicants can be approximated by a Poisson distribution $P(k) = (q^k/k!)e^{-q}$, where $q = u/v$ is the candidate to vacancy ratio (queue length).[17] To fit the model to the data, I introduce a matching efficiency parameter μ, thereby proceeding as Blanchard and Diamond (1994) and Barnichon and Zylberberg (2019). This implies that every period, a worker sends out an application with probability μ. Denoting $q_i = u_i/v$ the queue length for type i, the

[13] I also allow the bargaining power of documented immigrants to be different from that of natives in order to replicate their wage difference found in the data. Chassamboulli and Peri (2015) take an alternative route and allow the unemployment flow payments to differ, arguing that documented immigrants have higher job search costs than natives. For the results of this paper, it is not essential whether the wage gaps between worker types arise because of differences in z_i, β_i, or a combination of both.

[14] I abstract from fines for firms in case of detection; see Section VIID for a discussion of this assumption.

[15] This is motivated by the fact that under the presidency of George W. Bush, conducting worksite raids and deporting caught undocumented workers was the prevalent method against illegal hiring. Under the presidency of Barack Obama, this policy changed toward targeting employers, which seldom led to the deportation of workers.

[16] As in many previous studies (e.g., Ottaviano and Peri 2012), I assume that capital adjusts quickly so that labor supply has no effect on productivity. In online Appendix C.1, I extend the model by a final good sector producing with capital and labor and show the model predictions for a range of values of the capital supply elasticity.

[17] See Blanchard and Diamond (1994) for the derivation of this result in continuous time.

probability to be matched with k_N natives, k_D documented, and k_U undocumented workers is given by

$$P(k_N, k_D, k_U) = \frac{(\mu q_N)^{k_N}}{k_N!} e^{-\mu q_N} \frac{(\mu q_D)^{k_D}}{k_D!} e^{-\mu q_D} \frac{(\mu q_U)^{k_U}}{k_U!} e^{-\mu q_U}.$$

I implement the wage-bargaining mechanism between firm and worker described in Barnichon and Zylberberg (2019). The job finding rate and bargaining position of an applicant will depend on the labor market tightness, i.e., the total number of candidates to vacancies (capturing the degree of job creation) as well as the composition of the candidate pool (capturing the degree of competition by better types). Whenever a firm receives one or more applications, the firm makes a take-it-or-leave-it offer to its highest ranked candidate with probability $(1 - \beta_i)$, capturing all the surplus by offering a wage that makes the candidate indifferent between taking the job and staying unemployed. With a probability β_i, the highest-ranked applicant sends an offer to the firm demanding a wage that makes the firm indifferent between her and the second-best candidate. Hence, if a firm is only matched with one applicant, then the expected payoffs are as in the standard Nash bargaining game, and in expectation the worker receives a share β_i of the surplus S_i, which is the difference between output y and the worker's reservation wage $\underline{w}_i$. With the ranking $S_U > S_D > S_N$, which will hold throughout, the following six cases are to be distinguished for the determination of S^W, the part of the surplus going to the worker, when a firm faces more than one applicant:

(i) *All applicants are of the same type*. Candidates will bid their wages down to their reservation wage, and the firm captures all the surplus: $S^W = 0$.

(ii) *More than one documented and no undocumented immigrant applicant*. As in case (i), the applicant will only receive her reservation wage: $S^W = 0$.

(iii) *More than one undocumented applicant*. As in case (i), the applicant will only receive her reservation wage: $S^W = 0$.

(iv) *One documented immigrant, at least one native, and no undocumented immigrant applicant*. The documented immigrant will send an offer to make the firm indifferent between hiring him and a native worker with probability β_D and therefore in expectation capture a share β_D of the surplus generated over and above the surplus generated by a native worker: $S^W = \beta_D(S_D - S_N)$.

(v) *One undocumented immigrant, at least one native, and no documented immigrant applicant*. The undocumented immigrant will send an offer to make the firm indifferent between hiring him and a native worker with probability β_U and therefore in expectation capture a share β_U of the surplus generated over and above the surplus generated by a native worker: $S^W = \beta_U(S_U - S_N)$.

(vi) *One undocumented and at least one documented immigrant applicant*. The undocumented immigrant will send an offer to make the firm indifferent between hiring him and a documented immigrant with probability β_U and therefore in expectation capture a share β_U of the surplus generated over and above the surplus generated by a documented worker: $S^W = \beta_U(S_U - S_D)$.

Thus, this form of wage bargaining implies that a worker can only extract any surplus from a match if he is either the only candidate or a strictly better candidate than any other candidate applying to the same firm. In Section D.4 in the online Appendix, I consider an alternative bargaining mechanism in which bargaining takes place *after* the firm has committed to hire a particular candidate. With this timing, the surplus that a hired candidate can capture does not depend on the competitors anymore, and thus, the outcome is always that of Nash bargaining.

B. *Workers*

Time is continuous, r denotes the worker's discount rate, and therefore the flow value of being employed is given by

$$(1) \qquad rW_i = w_i + s_i\big(U_i - W_i(w)\big) + \lambda_i^W\big(U_i - R - W_i(w)\big).$$

As implied by (1), I assume that undocumented workers still receive their unemployment value after deportation, which is not essential for the results but improves the tractability of the model.[18] The flow value of being unemployed is given by

$$(2) \qquad rU_i = z_i + \int \max\big(W_i(w) - U_i, 0\big)\, dF_i(w) - \lambda_i^U R,$$

where F denotes the distribution of the negotiated wages, which depends on the number and type of candidates applying for the same job. To find the reservation wage $\underline{w}_i$, note that when earning the reservation wage, a worker is indifferent between employment and unemployment, so we get $rU_i = rW(\underline{w}_i) = \underline{w}_i - \lambda_i^W R$. Combining this with (1) and (2) yields

$$(3) \qquad \underline{w}_i = z_i + \frac{1}{r + s_i + \lambda_i^W}\int_{\underline{w}_i}^{\infty} (w - \underline{w}_i)\, dF_i(w) + (\underbrace{\lambda_i^W - \lambda_i^U}_{\Delta\lambda_i})R.$$

The wage distribution F, which can be derived from the above-described matching probabilities and wage-bargaining mechanism, is summarized in online Appendix Table E.2.[19] Combining the distribution of wages with (3), one can solve for the reservation wages of each type. For simplicity, let $\tilde{r}_i \equiv r + s_i + \lambda_i^W$ and

[18] This can be rationalized by defining $R = \tilde{R} + U_U - U_H$, where U_H is the (exogenous) unemployment value that a removed worker receives in his home country after deportation and $\tilde{R}$ is the disutility directly received from being removed (e.g., temporary arrest, moving costs, family separation, etc.). Being an endogenous variable, U_i cancels out in the term in the last bracket in equation (1). However, as this would complicate calculations, I instead assume $R = \tilde{R} + \bar{U}_U - U_H$, where $\bar{U}_U$ and therefore R are exogenous.

[19] The wage of a documented immigrant in case (ii) is derived from $(y - w_D)/(r + s_D + \lambda_D^W) = (y - \underline{w}_N)/(r + s_N + \lambda_N^W)$, i.e., equating the surplus from hiring a documented immigrant with the surplus from hiring a native at the reservation wage (analogously for undocumented immigrants' wages). To save space, I define $\tilde{r}_i \equiv r + s_i + \lambda_i^W$.

impose $\lambda_N^W = \lambda_N^U = \lambda_D^W = \lambda_D^U = 0$. Then, defining $f_1 \equiv e^{-\mu q_N} e^{-\mu q_D} e^{-\mu q_U}$, the reservation wage of natives is

$$(4) \qquad \underline{w}_N = \frac{z_N + \frac{\beta_N}{\tilde{r}_N}\mu f_1 y}{1 + \frac{\beta_N}{\tilde{r}_N}\mu f_1}.$$

Defining $f_2 \equiv \left(1 - e^{-\mu q_N}\right) e^{-\mu q_D} e^{-\mu q_U}$, for documented immigrants we get

$$(5) \qquad \underline{w}_D = \frac{z_D + \frac{\beta_D}{\tilde{r}_D}\left(\mu f_1 y + \mu f_2\left(\frac{\tilde{r}_D}{\tilde{r}_N}\underline{w}_N + \left(1 - \frac{\tilde{r}_D}{\tilde{r}_N}\right)y\right)\right)}{1 + \frac{\beta_D}{\tilde{r}_D}\mu e^{-\mu q_D} e^{-\mu q_U}}.$$

Finally, defining $f_3 \equiv \left(1 - e^{-\mu q_D}\right) e^{-\mu q_U}$, for undocumented immigrants we get

$$(6) \qquad \underline{w}_U = \frac{z_U + \frac{\beta_U}{\tilde{r}_U}\left(\mu f_1 y + \mu f_2\left(\frac{\tilde{r}_U}{\tilde{r}_N}\underline{w}_N + \left(1 - \frac{\tilde{r}_U}{\tilde{r}_N}\right)y\right) + \mu f_3\left(\frac{\tilde{r}_U}{\tilde{r}_D}\underline{w}_D + \left(1 - \frac{\tilde{r}_U}{\tilde{r}_D}\right)y\right)\right) + \Delta\lambda R}{1 + \frac{\beta_U}{\tilde{r}_U}\mu e^{-\mu q_U}}.$$

If all workers were identical, i.e., $z_N = z_D = z_U$, $\beta_N = \beta_D = \beta_U$, and $\lambda_U^W = \lambda_U^U = 0$, then the reservation wages of all types would be equal. A decrease in either z_i or β_i leads to a decline in the reservation wage for worker type i, which can be easily verified using equations (4)–(6). As I assume $z_N \geq z_D > z_U$, a sufficient condition for $\underline{w}_N > \underline{w}_D > \underline{w}_U$ is $\beta_N > \beta_D > \beta_U$. This condition is also sufficient if $\Delta\lambda R$ is close to zero, as then λ^W just acts as a separation rate differential between documented and undocumented workers, and a rise in this differential decreases $\underline{w}_U$ relative to $\underline{w}_N$ and $\underline{w}_D$. If $\Delta\lambda R$ is large enough, then we could have $\underline{w}_D < \underline{w}_U$. However, as this implies higher wages for undocumented immigrants than for documented immigrants, which is not consistent with the data, all model parameter constellations used throughout the paper will ensure that $\underline{w}_N > \underline{w}_D > \underline{w}_U$ is satisfied. Given that this ranking holds, the wage distribution implies that firms prefer to hire undocumented immigrants over documented immigrants and documented immigrants over natives.

The job finding rates for each worker type can be derived from $f_i = m_i/u_i$, where m_i denotes the number of vacancies filled by worker type i. The probabilities of a vacancy being filled by a native, a documented immigrant, and an undocumented immigrant are given by f_2, f_3, and $f_4 \equiv 1 - e^{-\mu q_U}$, respectively. Thus, the job finding rates are

$$(7) \qquad f_N = f_2 V/u_N = \frac{\left(1 - e^{-\mu q_N}\right)e^{-\mu q_D} e^{-\mu q_U}}{q_N},$$

$$(8) \qquad f_D = f_3 V/u_D = \frac{\left(1 - e^{-\mu q_D}\right)e^{-\mu q_U}}{q_D},$$

$$(9) \qquad f_U = f_4 V/u_U = \frac{1 - e^{-\mu q_U}}{q_U}.$$

C. *Firms*

The flow value of hiring a worker for a firm with profits denoted by $\pi = y - w$ is

$$rJ_i(\pi) = \pi + \left(s_i + \lambda_i^W\right)\left(V - J_i(\pi)\right), \tag{10}$$

and the flow value of posting a vacancy rV is given by

$$rV = -c + \int \max\left(J_i(\pi) - V, 0\right) dG(\pi, i). \tag{11}$$

The number of posted vacancies is determined by the free entry condition $V = 0$, setting vacancy costs equal to expected match surplus for the firm:

$$c = \int_0^{\infty} J_i(\pi)\, dG(\pi, i). \tag{12}$$

The distribution of profits presented in online Appendix Table E.3 is again derived for every case considering the wages paid and the respective probabilities.

D. *Equilibrium*

As in the standard search framework, the ratio of job seekers to vacancies for each worker type is independent of the size of the total unemployment pool $u = u_N + u_D + u_U$. What determines the equilibrium is the composition of the pool, i.e., the shares of documented and undocumented immigrants among the unemployed u_D/u and u_U/u. The higher that u_U/u is, the higher the probability of a match with an undocumented applicant and the higher the expected firm profits. Hence, an increase in u_U ceteris paribus leads to an increase in vacancies that is overproportional to the increase of the total unemployment pool and thus a higher labor market tightness. The effect of a relative increase of u_D on the equilibrium is less obvious. If documented immigrants' wages are closer to natives' wages, then expected firm profits decrease and labor market tightness falls. If, on the contrary, they are closer to undocumented immigrants' wages, then labor market tightness goes up.

To close the model, we need to consider the laws of motion of the number of unemployed workers and the work force given by

$$\dot{u}_N = s_N\left(\omega_N P - u_N\right) - f_N u_N, \tag{13}$$

$$\dot{u}_D = s_D\left(\omega_D P - u_D\right) - f_D u_D, \tag{14}$$

$$\dot{u}_U = s_U\left(\omega_U P - u_U\right) + u_{NU} - f_U u_U - \lambda^U u_U, \tag{15}$$

$$\dot{P} = u_{NU} - \lambda^W\left(\omega_U P - u_U\right) - \lambda^U u_U, \tag{16}$$

where u_{NU} is the inflow of new undocumented immigrants, who I assume to be initially unemployed.[20] To obtain a static equilibrium, I set $u_{NU} = \lambda^{W}\left(\omega_U/P - u_U\right) + \lambda^{U} u_U$, which implies that outflows of deported immigrants are compensated by an equal amount of inflows. With the normalization $P = 1$, the steady-state numbers of unemployed workers are given by

$$u_N^* = \frac{\omega_N s_N}{s_N + f_N}, \tag{17}$$

$$u_D^* = \frac{\omega_D s_D}{s_D + f_D}, \tag{18}$$

$$u_U^* = \frac{\omega_U\left(s_U + \lambda^W\right)}{s_U + \lambda^W + f_U}. \tag{19}$$

The static solution of the model is determined by equations (4), (5), (6), (10), (12), (17), (18), and (19) and consists of the equilibrium queue lengths q_N^*, q_D^*, and q_U^*.

E. *Parameterization*

In the following, I describe the parameterization of the model, for which I use several methods. Some parameters are calibrated by setting them equal to their data equivalents or taking them from the literature; others are jointly estimated using the generalized method of moments.

Calibration.—The levels of productivity and population are both normalized to 1. The annual interest rate is 4 percent, implying a monthly discount factor $\delta = 0.96^{1/12}$ and $r = \left(1 - \delta\right)/\delta = 0.0034$. Instead of fixing the population shares ω_D and ω_U and determining u_D/u and u_U/u from the steady-state unemployment equations, I set these ratios equal to their data equivalents of 0.19 and 0.16, respectively. I do so because my targets for the job finding rate gaps are the coefficients of the immigrant dummies in Table 2, and these gaps will determine u_D/u and u_U/u in equilibrium. The empirical shares, on the other hand, are generated by the unconditional transition rates in the data and therefore inevitably different from the model result if the population shares ω_i are set to their data equivalents. After fixing u_D/u and u_U/u, the population shares implied by the steady-state unemployment are computed by solving (18) for ω_D and (19) for ω_U.

Estimates of the flow payment of unemployment range between 0.4, the upper end of the range of income replacement rates in Shimer (2005), and 0.955, that in Hagedorn and Manovskii (2008). I follow Hall and Milgrom (2008) and Pissarides (2009) and choose a value of 71 percent of the average wage $\bar{w}_i$ for documented workers, yielding $z_N = 0.70$ and $z_D = 0.67$.[21] I assume that unemployment

[20] For the sake of simplicity, I drop the redundant subscripts of λ_U^W and λ_U^U from here on.

[21] These values are not the same, because the average wages of natives and documented immigrants differ due to different bargaining powers (see also footnote 13).

benefits are 40 percent of the average wage and thus the flow value of home production for natives is $z_N^H = z_N - z^{UI} = 0.31$, which I take as value for $z_U^H = z_U$. After correction for time aggregation bias, I get an average separation rate for low-skilled native workers of 0.031. As Table 3 suggests that, conditional on observables, the separation rate is 0.003 lower for documented immigrants and 0.006 lower for undocumented immigrants, I set $s_D = 0.028$ and $s_U = 0.025$.

To obtain a value of the deportation rate, I use yearly figures of unauthorized immigrants that are deported through so-called interior removals by the Department of Homeland Security, which are available from 2008 through 2015. I convert these figures to a monthly frequency, divide them by the total number of undocumented immigrants residing in the United States in the respective year, and take the average across years. The resulting rate is 0.0013. Unfortunately, to the best of my knowledge, there is no information on the employment status of deported immigrants available. I therefore assume $\lambda^W = \lambda^U = 0.0013$ in the baseline calibration and show how the predictions change when deviating from this assumption, i.e., $\Delta\lambda \neq 0$. The value of the disutility of deportation R only matters if $\Delta\lambda \neq 0$. I check the robustness of the results to using different values of R in this case in Section D.5 in the online Appendix.

Estimation by GMM.—Five parameters remain to be determined: β_N, β_D, β_U, c, and the matching efficiency μ. As only the differences between these bargaining power parameters can be identified and actually matter for the model predictions, I get rid of one redundant parameter by assuming an average bargaining power in the economy of 0.5 (as in many papers in the search literature). Hence, I impose the restriction $\omega_N\beta_N + \omega_D\beta_D + \omega_U\beta_U = 0.5$. This leaves four parameters to be estimated by matching five moments from the data: the relative wages of immigrants $\bar{w}_D/\bar{w}_N$ and $\bar{w}_U/\bar{w}_N$ and the job finding rates f_N, f_D, and f_U. I obtain the targets for the relative wages from the last column of Table 1. I set the target for f_N equal to the mean of the job finding probability of natives, which equals 0.24, and obtain $f_D - f_N$ and $f_U - f_N$ from Table 2. The resulting data moments are $\bar{w}_D/\bar{w}_N = 0.957$, $\bar{w}_U/\bar{w}_N = 0.874$, $f_N = 0.24$, $f_D = 0.31$, and $f_U = 0.38$.

Let $\hat{g}$ denote the 5×1 vector of data moments. Let θ denote the 4×1 vector of model parameters to be estimated: β_D, β_U, c, and μ. The corresponding moments generated by the model are a function of these parameters, denoted by $g(\theta)$. The GMM estimator is defined as the vector $\hat{\theta}$ that minimizes the distance between the model-generated and data moments $\Psi(\theta) = g(\theta) - \hat{g}$. Hence, it is given by $\hat{\theta} = \operatorname{argmin}_{\theta \in R^5} \Psi(\theta)'\Psi(\theta)$. To obtain the standard errors of the GMM estimator, note that the true data moments are a function of the true parameter vector, i.e., $g_0 = g(\theta_0)$. We then have $\sqrt{n}\left(\hat{\theta} - \theta_0\right) \xrightarrow{d} N\left(0, \left[D'V^{-1}D\right]^{-1}\right)$, where $D = \left[\partial g(\theta_0)/\partial\theta_0'\right]$ and V is the covariance matrix of the data moments, i.e., $\sqrt{n}\left(\hat{g} - g_0\right) \xrightarrow{d} N(0, V)$ (Hansen 1982). I obtain V by the Eicker-Huber-White sandwich covariance estimator and the matrix of derivatives by numerically differentiating the model at $\hat{\theta}$.[22] The resulting estimates with standard errors in

[22] I use the tool Adaptive Robust Numerical Differentiation, written by John D'Errico for MATLAB.

Table 4—Baseline Parameterization

Parameter	Definition	Value (SE)	Target
Panel A. Calibrated			
y	Match productivity	1	Normalization
P	Size of population	1	Normalization
u_D/u	Unemployed share	0.19	Data equivalent
u_U/u		0.16	Data equivalent
z_N	Unemployed flow payment	0.70	70% of wage
z_D		0.67	70% of wage
z_U		0.31	$z_N - z^{UI}$
β_N	Bargaining power	0.90	Average bargaining power of 0.5
s_N	Separation rate	0.031	Data equivalent
s_D		0.028	SR gap from regression
s_U		0.025	SR gap from regression
r	Monthly interest rate	0.0034	Annual interest rate of 4%
λ^W	Removal rate	0.0013	Data equivalent
λ^U		0.0013	Data equivalent
R	Removal disutility	56 to 170	25% to 75% of lifetime utility
Panel B. Estimated			
β_D		0.40 (0.038)	$\overline{w}_D/\overline{w}_N = 0.957$
β_U		0.28 (0.017)	$\overline{w}_U/\overline{w}_N = 0.874$
c	Vacancy cost	0.915 (0.065)	$f_U - f_D = f_D - f_N = 0.07$
μ	Matching efficiency	0.39 (0.016)	$f_N = 0.24$

parentheses and calibrated parameters are presented in Table 4. While the wages can be matched exactly by estimating the bargaining power of each worker type, this is not possible for the job finding rates, as only two parameters are available to target three moments. The moments yielded by the model are $f_N = 0.239$, $f_D = 0.325$, and $f_U = 0.370$, which are reasonably close to the targets. The estimates imply that the wage-bargaining power of documented immigrants is 0.4 and therefore almost as low as the value of 0.28 for undocumented immigrants. This is because for the former, the wage gap to natives is almost entirely generated by the difference in bargaining powers, while for the latter, a significant part is generated by the assumed difference in the unemployment flow value. Whether the targeted wage gaps are matched by differences in the z_i, the β_i, or a combination of both does not affect the results.

IV. The Effects of Immigration

A. *Job Creation and Competition Effect*

The model outlined in the previous section features two effects of a rise in the population share of undocumented immigrants that affect the job finding rate of natives in opposite ways. With a higher probability of receiving an application from an immigrant, the expected wage costs of firms and the number of vacancies change. As explained in Section IIID, wage costs fall when there are more undocumented immigrants in the pool of unemployed because this implies a higher probability of matching with the cheapest worker type, resulting in a strong job creation effect. The effect of documented immigration on wage costs is ambiguous, as expected wages can go up or down depending on the parameterization. The more similar that documented immigrants are to natives, the more that wage costs go up and the number of additional jobs goes down.

While the strength and sign of job creation depend on the immigrant type and parameters, the impact of the competition effect is unambiguous. Given a fixed number of vacancies, an increase in the share of either immigrant type decreases the job finding rate of natives as the probability of competing with a cheaper worker for the same job rises. Equations (7)–(9) show that the job finding rate of a worker is affected by the queue length of all workers of the same type and of all workers that are ranked higher. Thus, undocumented immigrants are only affected by other undocumented immigrants, documented immigrants are affected by all immigrants, and natives are affected by all types of workers. Online Appendix B shows this formally and decomposes the overall impact of immigration into the job creation and competition effect.

B. *Simulating Documented Immigration*

To assess whether the job creation effect or the competition effect dominates in a case of documented immigration with the parameterization that replicates the data, I solve the model varying the population share ω_D.[23]

Figure 7 plots the resulting steady-state unemployment rates, which are monotonic functions of the job finding rates according to equations (17)–(19), and the expected wages by worker type and in the aggregate. The unemployment rates of both natives and documented immigrants increase, which suggests that the competition effect dominates the job creation effect. The latter is weak because the expected wage of documented immigrants is very close to the aggregate expected wage, implying only a small decline in the average wage costs of firms. Therefore, only a small number of additional vacancies are posted, and this does not compensate for the higher degree of job competition for natives and documented immigrants. Undocumented immigrants' unemployment, on the other hand, falls because documented immigrants pose no competition for them, which is why they fully benefit from the new vacancies.

Despite the fall in their job finding rate, the expected wage of natives increases. This result is due to the assumed wage-bargaining mechanism, according to which a native worker receives a wage above the reservation wage if and only if she is the only applicant for a firm. This happens with probability f_1, which is the only variable affecting the reservation wage of natives (see equation (4)) and positively depends on the total queue length q. As documented immigration leads to some job creation, q and f_1 increase. This implies a higher expected wage for natives for two reasons. First, the higher reservation wage implies higher wages paid to all natives in a job. Second, the higher probability of being matched to a firm without competitors implies that more natives find jobs in which they are paid above the reservation wage relative to jobs in which they are just paid the reservation wage.

[23] I assume that the new immigrants crowd out natives and undocumented immigrants proportionally, i.e., ω_N/ω_U remains constant.

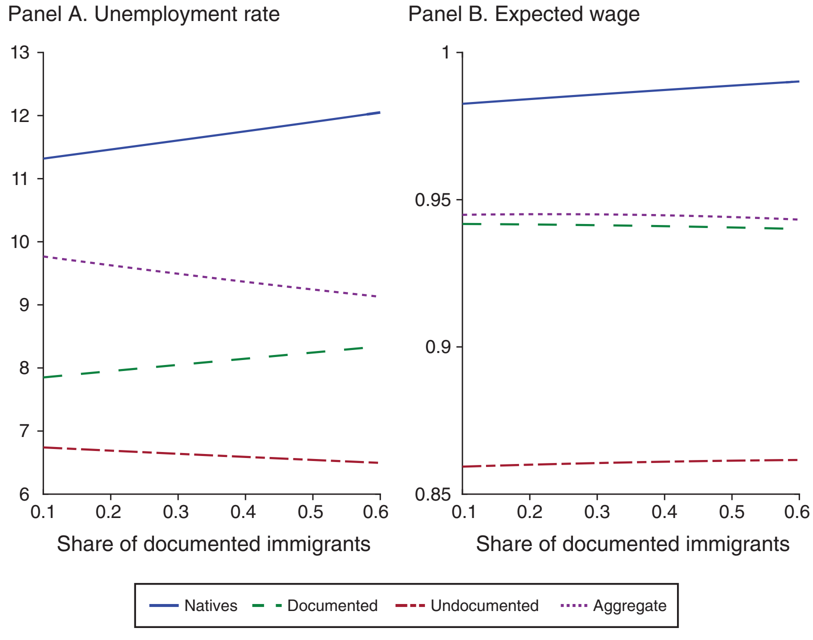

Figure 7. Unemployment (Percent) and Wages Depending on Documented Immigrant Share

This is because if a native is matched to a firm with other competitors, it is more likely that at least one of them is a documented immigrant. Hence, some natives that would have been hired at their reservation wage when there were less documented immigrants in the economy now remain unemployed without earning any wage.

The result that natives' expected wage increases due to documented immigration does not hold if natives receive a wage above the reservation wage when there are other natives (but no immigrants) applying for the same job. This would be the case under the alternative assumption that firms first commit to hire the candidate that yields the highest expected surplus and then engage in bargaining with the chosen worker, who would then capture the full match surplus with probability β_i independent of the number and nature of the competitors. I explore this alternative in Section D.4 in the online Appendix. With this simpler bargaining mechanism, the expected wage of natives experiences a slight decline because of documented immigration.

C. *Simulating Undocumented Immigration*

Figure 8 illustrates the effects of undocumented immigration by plotting the steady-state equilibria depending on ω_U. Panel A shows that the unemployment rate of natives strongly declines with the share of undocumented immigrants. This result confirms that wages of undocumented workers are low enough that their job creation dominates their competition effect. Firms post so many additional vacancies that the fall in the queue length of natives compensates the rise in the queue length of undocumented immigrants. On the other hand, the unemployment rate of documented

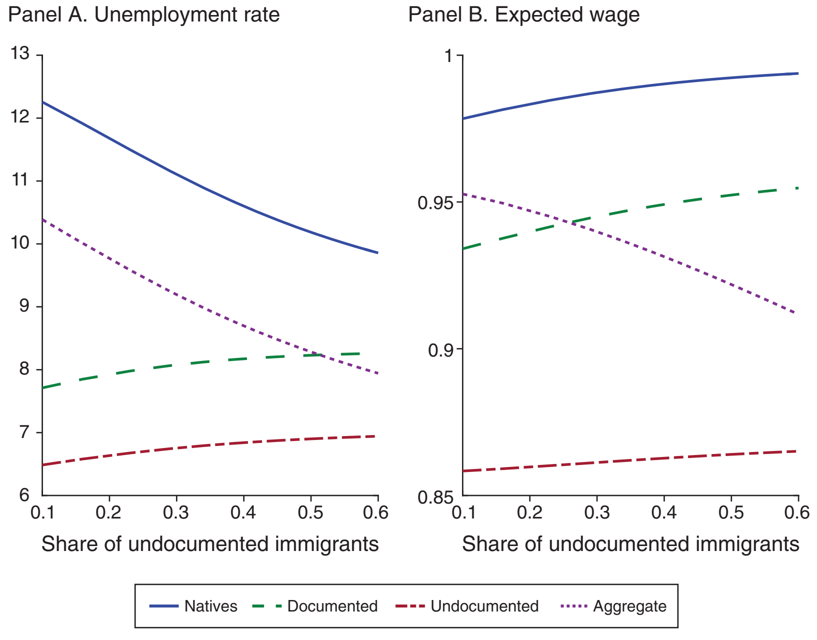

Figure 8. Unemployment (Percent) and Wages Depending on Undocumented Immigrant Share

immigrants increases, which indicates that the job creation effect is not dominant for them, although it is for natives. This suggests that in this framework with three worker types, the competition through the type most preferred by firms affects the type in the middle more strongly than it does the least preferred type. Because only the competition effect is present for undocumented workers, their unemployment rises. Expected wages of all worker types increase because the additional vacancies posted lead to a rise in reservation wages, and this in turn leads to higher wages in all jobs. Moreover, the higher total queue length results in more workers matching with firms as single applicants and thus more workers entering high-paying jobs. Because the share of workers earning the lowest wage goes up, the aggregate expected wage falls strongly, which is the reason behind the strong job creation effect. The combination of higher employment and higher earnings implies that the welfare of natives unambiguously increases through undocumented immigration.

Under the alternative simpler bargaining mechanism, the effects of undocumented immigration are qualitatively unchanged, but the job creation effect is even stronger and the fall in natives' unemployment even steeper, as shown in Figure D.5 in the online Appendix.

Figures E.3 and E.4 in the online Appendix compare the job creation and competition effect of the two types of immigration. To isolate the job creation effect, I set the total queue length equal to the one implied by the simulations but keep the population composition fixed. To isolate the competition effect, I change the population composition as in Figures 7 and 8 but fix the queue length; i.e., the ratio of job seekers to vacancies remains at the initial level. Darker lines represent documented immigration, while lighter lines represent undocumented immigration.

Online Appendix Figure E.3 confirms that natives benefit more from the stronger job creation triggered by undocumented immigration, which decreases their unemployment and increases their wages much more. Online Appendix Figure E.4 suggests that the strength of the competition effect for natives is independent of the immigrating type, as it drives up their unemployment almost equally. Undocumented immigrants, on the other hand, are unaffected by documented immigration, except that their wages slightly decrease, as competing with them instead of natives means capturing a lower share of the match surplus.

V. The Effects of Higher Deportation Risk

In what follows, I investigate how the equilibrium depends on the deportation risk parameters λ^W and λ^U and how their effect on the equilibrium changes with R. Recalling equation (6), we know that the effect of λ^W on undocumented workers' reservation wage is ambiguous. Given R is zero or sufficiently small, λ^W tends to decrease $\underline{w}_U$, acting like a rise in the job separation probability. However, if the disutility associated with deportation is high enough, then a rise in λ^W increases $\underline{w}_U$ because $\Delta\lambda$; i.e., the risk of detection when employed relative to the risk when unemployed rises, and therefore the compensation needed to accept the risk of having a job goes up more strongly. Independently of the size of R, a higher λ^W will mute the job creation effect because the surplus that firms expect to make by hiring an undocumented worker shrinks. If $R>0$, then the job creation effect is additionally muted due to a higher risk compensation. This negative effect of λ^W on vacancy creation is increasing in R. A rise in λ^U, the risk of being deported when unemployed, unambiguously decreases the reservation wage because the opportunity cost to having a job falls and hence undocumented workers accept lower wages. As the aim is simulating an exogenous policy change by varying λ^W and λ^U, I use comparative statics and therefore keep the remaining parameters fixed.

Figure 9 shows the effect of an equal increase in both λ^W and λ^U (keeping the population share of undocumented immigrants constant).[24] As $\Delta\lambda$ remains zero, the rise in the deportation rate only affects the match separation probability. An increase in this probability by 1 percentage point results in a rise of undocumented immigrants' unemployment rate by around 2.3 percentage points. At the same time, their wages fall by around 4 percent, as the expected length of a match is now shorter and thus the surplus lower. This induces firms to create fewer vacancies, which also affects native and documented immigrant workers. However, the effect on them is moderate. A 1 percentage point increase in the deportation rate leads to an increase in the unemployment rate by 0.14 percentage points for natives and 0.4 percentage points for documented immigrants while their wages remain almost at the same level.

Figure 10 plots the case in which only the deportation risk for employed undocumented immigrants λ^W rises. As mentioned above, the sizes of the effects depend on the calibration of the disutility from deportation. The larger that R is, the larger

[24] This is equivalent to a calibration in which $R = 0$ and only λ^W increases, as in both cases, a risk compensation for accepting a job does not play any role.

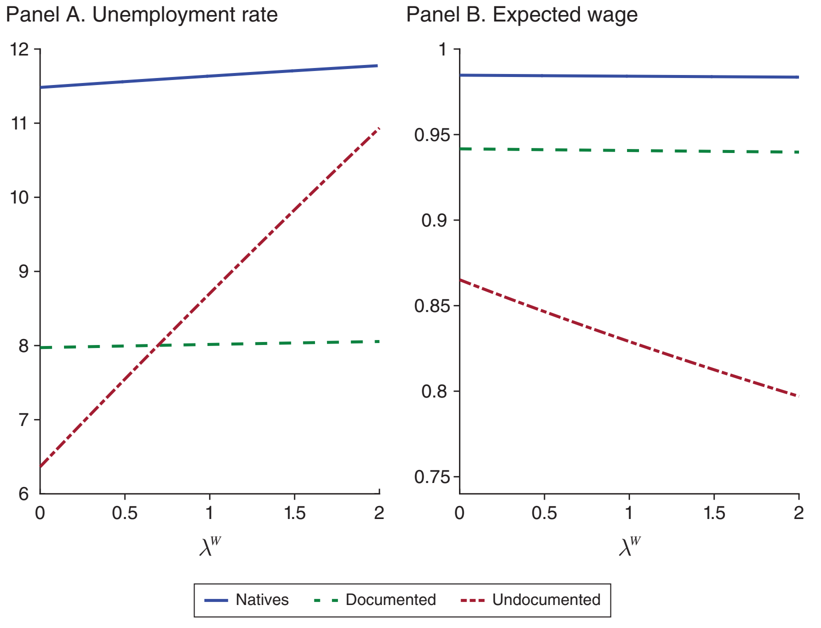

Figure 9. Unemployment (Percent) and Wages Depending on λ^W with $\lambda^W = \lambda^U$

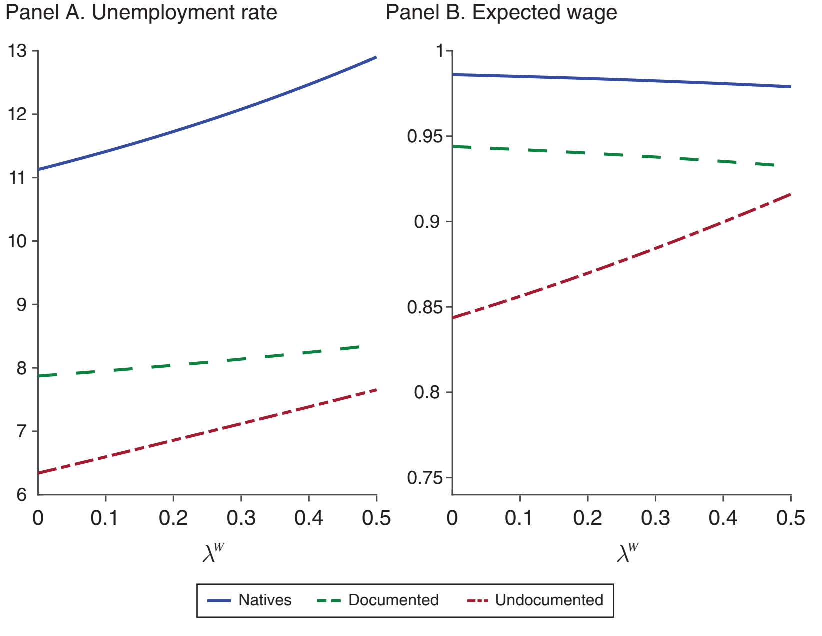

Figure 10. Unemployment (Percent) and Wages Depending on λ^W with λ^U Constant

the impact of an increase in the deportation risk only affecting employed workers. For the plots, I assume an intermediate deportation disutility of 50 percent of an undocumented immigrants' lifetime utility, but in the following, I give the ranges of the effects of a 1 percentage point increase in λ^W for a deportation disutility between 25 percent and 75 percent of the lifetime utility. The effect on unemployment rates is now strongly enhanced. It ranges from 1.7 to 5.7 percentage points for natives, 0.5 to 1.5 percentage points for documented immigrants, and 2.5 to 2.8 percentage points for undocumented immigrants. Wages of the two former types decrease by 0.67 percent to 2.3 percent and 1.1 percent to 3.7 percent, respectively. Hence, natives are the group most negatively affected by the policy in terms of employment. The underlying mechanism is the strong additional fall in the hiring surplus of undocumented workers due to the risk compensation in their wages, which mutes vacancy posting much more strongly than just an increase in their separation probability does. This is reflected in the rise of undocumented immigrants' wages, ranging from 5.3 percent to 23.7 percent.

Altogether, the analysis in this section suggests that increased deportation efforts lower welfare for not only undocumented workers but also documented ones. The negative impact on employment is especially large for natives if efforts concentrate on worksite raids that make it more risky (but still worthwhile) for an undocumented immigrant to accept a job. The detrimental effect of worksite raids would be even larger if the model also considered penalties for firms that hire workers illegally, as this would mute vacancy creation further.

VI. Testing the Model Predictions

A. *The Effects of Immigration*

The model predicts that undocumented immigration has a strong positive effect on vacancy creation, whereas the effect of documented immigration is close to zero. The predictions for wages are somewhat ambiguous, as they depend both qualitatively and quantitatively on the assumed bargaining mechanism (see online Appendix Section D.4). In the baseline version of the model with workers making offers before hiring, wages always increase with immigration. In contrast, wages of legal workers decline with documented immigration and rise with undocumented immigration in the alternative version featuring bargaining after hiring. However, as comparing Figure 7 with Figure 8 and Figure D.4 with Figure D.5 suggests, under both assumptions, the change in wages is predicted to be unambiguously larger in absolute terms for undocumented immigration than it is for documented immigration; i.e., $dw_i/d\omega_U > dw_i/d\omega_D$ (except for undocumented immigrants' wages under the second assumption). In the following, I test these predictions using an early settlement instrument inspired by the approach of Card (2001) as well as a refinement of this instrument suggested by Jaeger, Ruist, and Stuhler (2018).

Data and Instrument Construction.—For the following empirical analysis, I use decennial data between 1980 and 2010. I obtain the samples of the years 1980, 1990, and 2000 from the US Census Bureau. From 2001 onward, the census is replaced by the annual ACS, which has a smaller sample size. Therefore, I pool the ACS 2009–2011 to obtain the 2010 sample to get a similar number of observations as the previous years.[25] All samples are downloaded from IPUMS (Ruggles et al. 2016). I predict regional immigrant inflows by assigning the national inflows of documented and undocumented immigrants to an MSA using the initial geographic distribution of immigrants with the same legal status in the respective base year. National inflows $I_{c,e,i,t}$ are defined as the difference in the number of immigrants from origin country c with status $i \in \{D, U\}$ and education e between period $t-1$ and t. Thus, the inflows are net of outmigration. Let $\pi_{c,i,r,t}$ denote the share of immigrants from country c with status i and any education level that live in region r at time t. The inflows used to compute the instruments are given by the sum over the imputed inflows of immigrants to a specific region:

$$I^Z_{e,i,r,t} = \sum_c I^Z_{c,e,i,r,t} = \sum_c \pi_{c,i,r,t-1} I_{c,e,i,t}.$$

The predicted population levels of immigrants at time t are then

$$P^Z_{e,i,r,t} = P_{e,i,r,t-1} + I^Z_{e,i,r,t},$$

and the predicted population shares are

$$\eta^Z_{e,i,r,t} = P^Z_{e,i,r,t} / \Big(P_{e,N,r,t} + \sum_i P^Z_{e,i,r,t} \Big),$$

where $\big(P_{e,N,r,t} + \sum_i P^Z_{e,i,r,t}\big)$ is the total imputed population (natives and predicted number of immigrants) in a time-education-region cell. The final instruments are the changes in these shares between two periods $\eta^Z_{e,i,r,t} - \eta^Z_{e,i,r,t-1} = \Delta \eta^Z_{e,i,r,t}$, which are used to predict the part of the variation in the true change of the share $\Delta \eta_{e,i,r,t}$ that is exogenous to current labor market conditions.

As first dependent variable, I use the log change in the number of posted vacancies $\Delta \log v$ as a proxy for job creation. Annual data on vacancies at the MSA level are taken from the Conference Board Help-Wanted Index (HWI) and Help Wanted OnLine (HWOL) data series, which are combined following Barnichon (2010). A version of the dataset is used in Barnichon and Figura (2015) and was provided by courtesy of the authors. The sample contains vacancies posted in 33 MSAs, which are listed together with their population shares of documented and undocumented immigrants in online Appendix Table E.4. Unfortunately, it is not possible to distinguish in these data between vacancies that target low-skilled workers and those that target high-skilled workers. However, in case of the HWI, Anastasopoulos et al. (2018) argue that the index primarily includes vacancies in the low-skilled labor market. Nevertheless, especially in later years when the vacancy measure is based on online data, it cannot be ruled out that parts of the effects of immigration are due to spillovers to the high-skilled labor market, from which the model abstracts.

The other dependent variables are the log changes in the wages of low-skilled natives and documented and undocumented immigrants. To account for selectivity

[25] The final sample consists of prime-age workers living in the 33 MSAs covered by the vacancy data.

bias due to changes in regional worker composition, I run a regression of the log hourly wages on demographics (sex, race, age, age squared) and occupation/industry controls using the 1980–2010 sample of low-skilled native workers. I then take the means of the residuals over MSAs and years to obtain the adjusted wages $\tilde{w}_{e,N,r,t}$, $\tilde{w}_{e,D,r,t}$, and $\tilde{w}_{e,U,r,t}$.

IV Estimation.—As my final sample consists of low-skilled workers only, I drop the e subscript in the following. The specification of the OLS model is

$$\Delta \log y_{r,t} \;=\; \delta_0 + \delta_1 \Delta \eta_{D,r,t} + \delta_2 \Delta \eta_{U,r,t} + \phi_t + \varepsilon_{r,t},$$

where $\log y_{r,t}$ are either vacancies or wages of worker type $i \in \{N,D,U\}$ in region (MSA) r at time t, $\eta_{D,r,t}$ is the documented immigrant share, $\eta_{U,r,t}$ is the undocumented immigrant share, and ϕ_t is year fixed effects. The first-stage regressions are

$$\Delta \eta_{D,r,t} \;=\; \delta_{10} + \delta_{11} \Delta \eta^{Z}_{D,r,t} + \delta_{12} \Delta \eta^{Z}_{U,r,t} + \phi_{1,t} + \varepsilon_{D,r,t},$$

$$\Delta \eta_{U,r,t} \;=\; \delta_{20} + \delta_{21} \Delta \eta^{Z}_{D,r,t} + \delta_{22} \Delta \eta^{Z}_{U,r,t} + \phi_{2,t} + \varepsilon_{U,r,t}.$$

By choosing MSAs as regional units, I implicitly assume that metropolitan areas are closed economies and that there are no spillover effects across them, e.g., through internal migration. However, as US workers are known to be geographically mobile, an immigration shock might be dampened in the long run by the movement of native workers. Furthermore, in the theory part, I only compare long-run steady states. If immigrants join the pool of the unemployed upon arrival, then their initial impact on vacancy creation will be much larger than their long-run impact, as the probability to match with a cheaper worker will be very high in the beginning and subsequently decrease to its new steady-state level as the initial unemployed immigrants are matched to firms. If there are long-lasting adjustment or transition processes and the origin composition and immigrant settlement patterns are correlated over time, then the coefficients of the above-outlined IV estimation are biased. This is because the short- and long-run responses to local immigration shocks are conflated, which has been shown by Jaeger, Ruist, and Stuhler (2018). I therefore follow their approach to account for long-run adjustment processes by additionally including the first lag of the immigrant shares in the model. Thus, the second stage becomes

$$\Delta \log y_{r,t} \;=\; \tilde{\delta}_0 + \tilde{\delta}_1 \Delta \hat{\eta}_{D,r,t} + \tilde{\delta}_2 \Delta \hat{\eta}_{U,r,t} + \tilde{\delta}_3 \Delta \hat{\eta}_{D,r,t-1} + \tilde{\delta}_4 \Delta \hat{\eta}_{U,r,t-1} + \tilde{\phi}_t + \varepsilon_{r,t},$$

where $\tilde{\delta}_1$ and $\tilde{\delta}_2$ capture the short-run responses and $\tilde{\delta}_3$ and $\tilde{\delta}_4$ capture the long-run responses to documented and undocumented immigration. The first-stage regressions are

$$\Delta \eta_{D,r,t} \;=\; \tilde{\delta}_{10} + \tilde{\delta}_{11} \Delta \eta^{Z}_{D,r,t} + \tilde{\delta}_{12} \Delta \eta^{Z}_{U,r,t} + \tilde{\delta}_{13} \Delta \eta^{Z}_{D,r,t-1}$$
$$+ \tilde{\delta}_{14} \Delta \eta^{Z}_{U,r,t-1} + \tilde{\phi}_{1,t} + \varepsilon_{D,r,t},$$

$$\Delta \eta_{U,r,t} = \tilde{\delta}_{20} + \tilde{\delta}_{21} \Delta \eta^{Z}_{D,r,t} + \tilde{\delta}_{22} \Delta \eta^{Z}_{U,r,t} + \tilde{\delta}_{23} \Delta \eta^{Z}_{D,r,t-1}$$

$$+ \tilde{\delta}_{24} \Delta \eta^{Z}_{U,r,t-1} + \tilde{\phi}_{2,t} + \varepsilon_{D,r,t},$$

$$\Delta \eta_{D,r,t-1} = \tilde{\delta}_{30} + \tilde{\delta}_{31} \Delta \eta^{Z}_{D,r,t} + \tilde{\delta}_{32} \Delta \eta^{Z}_{U,r,t} + \tilde{\delta}_{33} \Delta \eta^{Z}_{D,r,t-1}$$

$$+ \tilde{\delta}_{34} \Delta \eta^{Z}_{U,r,t-1} + \tilde{\phi}_{3,t} + \varepsilon_{U,r,t},$$

$$\Delta \eta_{U,r,t-1} = \tilde{\delta}_{40} + \tilde{\delta}_{41} \Delta \eta^{Z}_{D,r,t} + \tilde{\delta}_{42} \Delta \eta^{Z}_{U,r,t} + \tilde{\delta}_{43} \Delta \eta^{Z}_{D,r,t-1}$$

$$+ \tilde{\delta}_{44} \Delta \eta^{Z}_{U,r,t-1} + \tilde{\phi}_{4,t} + \varepsilon_{U,r,t}.$$

First-Stage Results.—Table 5 presents the results of the first stages for the conventional IV model and the model in Jaeger, Ruist, and Stuhler (2018), henceforth called JRS IV. In both models, the instruments have positive and significant effects on the shares that they are supposed to predict, as indicated by the coefficients on the diagonals on the left- and right-hand side of the table. Throughout all equations, except in column 4, the F-statistics are above ten. The Sanderson-Windmeijer (SW) F-statistic is testing whether the effects of the endogenous variables can be separately identified in cases of more than one endogenous variable. The values reported in the last row of the table indicate that the endogenous regressors are indeed identified, whereas the F-statistic is higher—and hence the identification is stronger—for the (lagged) undocumented immigrant share.

Although the first-stage diagnostics ease potential concerns about identification, it is useful to directly inspect the serial correlations of the instrumented endogenous variables. Very high serial correlation of its predicted immigrant inflow rates in the decades after 1980 prevents Jaeger, Ruist, and Stuhler (2018) from applying their IV strategy to these later periods. This does not necessarily need to be the case here. The focus on low-skilled workers and the distinction between documented and undocumented immigrants are likely to generate more time variation than is present in more aggregated data. Online Appendix Figure E.5 plots the regressors predicted by the first stage, $\tilde{\eta}_{D,r,t}$ and $\tilde{\eta}_{U,r,t}$, against their respective lags. The figure suggests a high serial correlation for the changes in the documented immigrant share, especially in the upper-left plot, where points lie on almost a 45-degree line. The correlation coefficients are 0.94 in the decades 1980–2000 and 0.86 in 1990–2010. There is considerably more time variation in the change of the undocumented immigrant shares as seen in the bottom plots, for which the correlation coefficients are only 0.43 and 0.59, respectively. Thus, using the JRS IV strategy, I expect to obtain less precise estimates of the effects of documented immigrants.

Second-Stage Results.—Table 6 reports the second-stage results of the three different specifications: the OLS model (panel A), the conventional IV approach (panel B), and the JRS IV model (panel C). The effect of undocumented immigrants on vacancies is positive and significant in the OLS and both IV models.

Table 5—First Stage

	IV		JRS IV			
	Doc. share (1)	Undoc. share (2)	Doc. share (3)	Undoc. share (4)	$(\text{Doc. share})_{t-1}$ (5)	$(\text{Undoc. share})_{t-1}$ (6)
$(\text{Doc. share})^Z$	0.598	0.061	0.490	0.352	0.455	0.023
	(0.071)	(0.276)	(0.065)	(0.183)	(0.128)	(0.104)
$(\text{Undoc. share})^Z$	0.109	0.555	0.012	0.468	−0.021	0.646
	(0.019)	(0.092)	(0.022)	(0.150)	(0.034)	(0.039)
$(\text{Doc. share})^Z_{t-1}$			0.069	0.356	0.438	−0.049
			(0.063)	(0.139)	(0.045)	(0.121)
$(\text{Undoc. share})^Z_{t-1}$			0.080	−0.538	0.073	0.582
			(0.043)	(0.118)	(0.038)	(0.108)
Observations	99	99	66	66	66	66
R^2	0.659	0.498	0.716	0.486	0.848	0.918
F-statistic	38.13	75.75	51.44	7.04	112.2	172.6
SW F-statistic	13.94	62.07	11.08	29.38	18.87	176.4

Notes: Population data are from the US Census Bureau 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 6—Second Stage

	Vacancies (1)	Native wage (2)	Doc. wage (3)	Undoc. wage (4)
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^2	0.792	0.314	0.053	0.130
Panel B. IV				
Doc. share	−6.444	−0.230	−0.128	−0.718
	(1.497)	(0.305)	(0.376)	(0.422)
Undoc. share	2.490	0.379	−0.021	0.076
	(0.877)	(0.122)	(0.148)	(0.164)
Observations	99	99	99	97
R^2	0.788	0.290	0.033	0.120
Panel C. JRS IV				
Doc. share	−0.424	−1.113	0.130	−0.855
	(6.616)	(0.598)	(0.796)	(0.819)
Undoc. share	2.145	0.336	0.262	0.377
	(0.605)	(0.135)	(0.157)	(0.1500)
$(\text{Doc. share})_{t-1}$	−6.097	0.8300	−0.158	0.305
	(3.872)	(0.456)	(0.585)	(0.676)
$(\text{Undoc. share})_{t-1}$	0.763	−0.238	−0.158	−0.145
	(1.025)	(0.080)	(0.153)	(0.165)
Observations	66	66	66	66
R^2	0.887	0.500	0.089	0.110

Notes: Population data are from the US Census Bureau 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.

The coefficient in the preferred specification in panel C indicates an increase in vacancies of around 2.1 percent due to a 1 percentage point increase in the share of undocumented immigrants. This result is not only qualitatively in line with the model prediction but also quantitatively close. Model simulations yield an effect that is around 1.7 percent.[26] The coefficient of the documented immigrant share in column 1 is strongly negative in the OLS and IV models and insignificant in the JRS IV model. This result deviates from the model prediction of a small positive effect, which might be caused by an imprecise estimation due to the high serial correlation in the share of documented immigrants.[27]

The effect of undocumented immigrants on wages is positive and significant in all models and for all worker types, except for immigrants' wages in the IV model. Being around 0.26 percent to 0.38 percent in panel C, these wage effects are much stronger than the predicted ones, which are around 0.03 percent in the baseline model. The effect of documented immigrants on native wages is negative and significant at the 10 percent level. This result is more consistent with the alternative bargaining model, which also predicts a negative effect (although not as large), than with the baseline model, which predicts a small positive effect. There is no significant effect on immigrants' wages, which is in line with the predictions of both model alternatives (see Figure 7 and online Appendix Figure D.4).

The coefficients of the lagged regressors in panel C, which capture long-run adjustments to immigration, suggest that the effects on native wages are smoothed out over time, as the coefficients are significant and their signs are opposite to the signs of the coefficients of the contemporaneous regressors. Adding up the respective coefficients in column 2, the long-run impact of undocumented immigration after adjustment is around 0.1 percent, and the long-run impact of documented immigration is around -0.3 percent. There seems to be a weak or no long-run adjustment of the wages of immigrants, as the lagged responses in columns 3 and 4 have opposite signs but are not significant. Also, for vacancies, the lagged responses are insignificant and have the same signs as the contemporaneous responses, suggesting that there is no counteracting adjustment in vacancy posting over time.

In Sections D.6 and D.7 in the online Appendix, I check the robustness of these results in two different ways. First, I use inflow rates instead of population shares to measure immigration shocks, as is common in the literature. Second, I consistently use 1980 as the base period for the distribution of immigrants that determines the allocation of future aggregate inflows across MSAs. Both robustness checks confirm the results.

In sum, the finding of positive effects of undocumented immigration on vacancies and wages, which hold using an OLS model as well as an IV strategy, is in line with the theory. Such positive effects are not found for documented immigration, which is consistent with the model predictions that documented immigration has a weaker impact on vacancy creation and wages than undocumented immigration

[26] The quantitative model predictions are generated by regressing the simulated series of steady-state logarithmic vacancies on the series of documented and undocumented immigrant shares (simulated between 0.1 and 0.6).

[27] Moreover, the predicted effect on vacancies is not as clear-cut in cases of documented immigration because a different parameterization that raises the wages of documented immigrants closer to the wages of natives can potentially lead to a sign switch of the effect.

does. The significant negative effect of documented immigration on native wages deviates from the predictions of the baseline model but is qualitatively supported by the model with the alternative bargaining mechanism. Altogether, the validity of the model and in particular the central result of this paper are supported by the data: low-skilled undocumented immigration has a stronger effect on job creation than documented immigration does and therefore benefits natives more in terms of both employment opportunities and wages.

B. *The Effects of Higher Deportation Risk*

Section VII has shown that qualitatively the prediction of lower job finding rates of all workers with a higher deportation risk does not depend on the assumption that the risk is the same for employed and unemployed workers or the assumption of a disutility from deportation.[28] However, the prediction on wages does depend on these assumptions: if $\Delta\lambda = 0$, then a higher deportation risk decreases undocumented immigrants' wages, whereas if only λ^W (and thus $\Delta\lambda$) increases, then their wages are predicted to rise. A negative effect of an exogenous increase in the deportation risk on the job finding rate of both workers types and on the wages of documented workers would be evidence of the existence of a job creation effect for undocumented immigration. If the model is accurate, then finding a positive effect of a deportation risk shock on the wages of undocumented immigrants would suggest that firms indeed pay them a risk compensation.

A possible source of variation in the deportation risk is provided by a change in statewide immigration legislation. Good (2013) examines the impact of omnibus immigration laws (introduced in 11 US states since 2006) on population and employment. These laws address several issues at a time, including work authorization, document-carrying policy, public program benefits, human trafficking, local immigration law enforcement, and determination of legal status when arrested.[29] Although, to the best of my knowledge, it is not verified whether these laws have an impact on actual deportations, they have a nature of generally creating an environment in which there is a constant threat of document verification and subsequent deportation (Good 2013, 4). Raphael and Ronconi (2009) and Good (2013) both provide evidence that the implementation of omnibus immigration laws is not endogenous to levels or changes in discriminatory attitudes or immigrant population size. I therefore assume that they are appropriate to capture an exogenous increase in the deportation risk.

To measure the effect of omnibus immigration laws on job finding, I rerun the regression with the job finding rate as dependent variable (see Section IIB), including a dummy indicating immigration omnibus laws to be in force in the state of residence of a survey respondent during the interview year. Additionally, I interact this dummy with the immigrant indicators to allow the effect of omnibus immigration

[28] Recall from equation (6) that the risk compensation only depends on $\Delta\lambda$, which is why assuming $\Delta\lambda = 0$ is equivalent to assuming $R = 0$.

[29] A full list of date of enactment by state and issues addressed can be found in Appendix 1 of Good (2013).

Table 7—Legal Status, Omnibus Laws, and UE Transition of Low-Skilled Workers

	(1)	(2)	(3)	(4)	(5)
Omnibus law	−0.035	−0.029	−0.027	−0.025	−0.021
	(0.0075)	(0.0072)	(0.0073)	(0.0062)	(0.0068)
Documented × omnibus	0.050	0.036	0.022	0.019	0.007
	(0.0288)	(0.0193)	(0.0134)	(0.0091)	(0.0111)
Undocumented × omnibus	0.048	0.042	0.014	0.012	0.005
	(0.0272)	(0.0379)	(0.0326)	(0.0299)	(0.0293)
Demographics	No	Yes	Yes	Yes	Yes
Year/state fixed effects	No	No	Yes	Yes	Yes
Ind/occ fixed effects	No	No	No	Yes	No
Ind × occ fixed effects	No	No	No	No	Yes
Observations	75,634	75,634	75,634	75,634	75,634
R^2	0.016	0.029	0.044	0.057	0.079

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.

legislation to vary across legal status. Table 7 presents the results.[30] The coefficients in the first row capture the effect of the implementation of the laws on native workers. The preferred specification in the last column indicates that omnibus immigration legislation results in a decrease in the job finding rate of 2.1 percentage points for both natives and documented and undocumented workers. This is consistent with the model's prediction of a rise in the unemployment rates as seen in Figures 9 and 10.[31]

Finally, I rerun the wage regressions, including the omnibus law indicator and interactions as regressors. The results in Table 8 suggest a drop in natives' wages of 5.1 percent due to the implementation of omnibus immigration laws. The coefficient of the undocumented-omnibus interaction of 0.104 implies that omnibus immigration legislation increased undocumented workers' wages by 5.3 percent ($= 0.104 - 0.051$). This is consistent with the prediction of Figure 10 that a higher deportation risk leads to higher wages for undocumented workers. However, the coefficient of the documented-omnibus interaction, which indicates a wage increase of 1.9 percent, is not consistent with the model. If omnibus immigration laws only affect the deportation risk of undocumented immigrants, then this coefficient should be zero. One reason for a positive coefficient could be that even legal immigrants who are noncitizens can be subject to deportation under certain circumstances and therefore might perceive the risk as higher even though omnibus immigration laws mostly target undocumented immigrants. This possibility is further backed up by Arbona et al. (2010), who survey documented and undocumented Latin American

[30] The coefficients of the noninteracted immigrant indicators are not shown to save space.

[31] Note that the larger steepness in the rise for undocumented immigrants is due to the direct effect of λ^W on the job separation probability, which additionally increases their unemployment rate. The drop in the job finding rates is almost identical for all worker types, which is consistent with the regression results.

Table 8—Legal Status, Omnibus Laws, and Hourly Wage of Low-Skilled Workers

	(1)	(2)	(3)	(4)	(5)
Omnibus law	−0.086	−0.094	−0.058	−0.050	−0.051
	(0.0198)	(0.0179)	(0.0180)	(0.0155)	(0.0173)
Documented × omnibus	0.063	0.077	0.084	0.073	0.070
	(0.0318)	(0.0242)	(0.0220)	(0.0182)	(0.0193)
Undocumented × omnibus	0.092	0.104	0.117	0.104	0.104
	(0.0294)	(0.0273)	(0.0252)	(0.0238)	(0.0282)
Demographics	No	Yes	Yes	Yes	Yes
Year/MSA fixed effects	No	No	Yes	Yes	Yes
Ind/occ fixed effects	No	No	No	Yes	No
Ind × occ fixed effects	No	No	No	No	Yes
Observations	68,563	68,563	68,563	68,563	68,563
R^2	0.051	0.139	0.165	0.271	0.295

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*. Standard errors are clustered at the metropolitan area level.

immigrants living in Texas and find that the reported levels of deportation fear are similar for both groups.

VII. Discussion and Model Extensions

In this section, I discuss several simplifying assumptions made in the model and investigate the robustness of the predictions to extending the model by decreasing returns to labor, imperfect substitutability between natives and immigrants, and firm penalties.

A. *Constant Returns to Labor*

If there is a fixed production factor that is complementary to labor and whose supply is imperfectly elastic (e.g., capital), then the assumption of constant returns does not hold anymore, because an increase in labor supply due to immigration drives down labor productivity. However, previous papers analyzing the effects of immigration argue that capital is relatively flexible. Ottaviano and Peri (2012) shows that the detrended capital-labor ratio quickly reverts to its mean and that wages do not depend on labor supply at the aggregate level. Moreover, Lewis (2011) documents that low-skilled labor, which is the focus of this paper, and capital are close substitutes and that firms adjust by using less machinery in areas where the labor supply rises due to immigration. Nevertheless, there are also other complementary factors to low-skilled labor—for example, high-skilled labor, which might adjust more slowly to shocks.

In online Appendix C.1, I therefore relax the assumption of constant returns by extending the model with a final good sector using labor and a second factor for production, which I call capital but equivalently could be substituted by another labor type. I then simulate immigration under a range of different capital supply elasticities. This exercise shows that even in the limiting case of zero elasticity, the predictions of the model with respect to the effects on unemployment rates hold qualitatively. On the other hand, the wage effects of immigration become negative when the elasticity of capital supply is low enough.

B. *Perfect Substitutability between Natives and Immigrants*

Another assumption that warrants further discussion is that natives and both types of immigrants compete for the same jobs and are perfect substitutes. The data largely justifies this assumption. Despite somewhat different distributions across occupations, Table E.1 and Figure E.2 in the online Appendix suggest that the majority of low-skilled natives and immigrants are concentrated in similar occupations.

Furthermore, if immigrants and natives were competing for different jobs, then the gaps in job finding rates would need to be rationalized by other mechanisms besides the ranking by firms—for example, higher search frictions for native-dominated jobs, due to which vacancies take longer to fill, or a lower search effort by natives. It is hard to imagine that such alternative explanations could account for the large (and quantitatively very similar) job finding rate gaps both between natives and documented immigrants and between the latter and undocumented immigrants.[32]

Finally, several studies have shown that the elasticity of substitution between immigrants and natives with the same education is large: Card (2009) estimates an elasticity of 40 among low-skilled workers. In light of this finding, related papers, e.g., Chassamboulli and Peri (2015) and Colas (2018), also assume perfect substitutability between low-skilled natives and immigrants.

However, Ottaviano and Peri (2012) estimate the elasticity of substitution to be smaller, in particular among low-skilled workers (around 12.5 in the case of high school dropouts).[33] Therefore, it is important to establish that the predictions of the model are robust to allowing for imperfect substitution between natives and immigrants. I add this extension in online Appendix C.2. As relative marginal productivities are now negatively related to relative labor supplies, immigration decreases immigrants' wages and increases natives' wages more strongly than before. On the other hand, the effects on unemployment rates remain very similar to those in the baseline model.

C. *No Assimilation of Immigrants*

The theoretical predictions made in this paper are based on the comparison of purely static equilibria, which means that there is no scope for the assimilation of immigrants over time. Hence, new immigrants and those residing longer in the United States are identical. Yet, there exists ample evidence that immigrants economically assimilate during their stay in their host country. In my empirical analysis, I account for this by showing that the gaps in wages and job finding rates exist even conditional on years in the United States, as shown in Figures 3 and 5.

[32] In online Appendix D.2, I show that immigrants actually exhibit a lower search effort than natives do.

[33] One reason for the larger estimate of Card (2009) could be that he aggregates wages and labor supplies at the city level, whereas Ottaviano and Peri (2012) do so at the national level.

Nevertheless, these figures also suggest that the gaps are larger for immigrants that have arrived more recently, while the model parameters are matched to the average gaps for the total immigrant population. Hence, if newly arriving immigrants are very different from the average immigrant, then the model predictions might be inaccurate in the short run.

One explanation for the larger wage gaps of new immigrants could be that they have an even lower outside option to working (for example, because of lower savings) and/or an even lower bargaining power (for example, because of less information about the US labor market) than "older" immigrants do. In this case, new immigrants would be like an additional worker type that can underbid older immigrants in terms of wages and therefore has higher job finding rates, which would be consistent with the patterns seen in Figure 5.

Another reason for the lower earnings could be the lower host-country-specific skills (in particular, language) of new immigrants. However, it is less obvious how this alternative explanation could be consistent with higher job finding rates. One possibility is that new arrivals are more likely to work in traditional immigrant jobs that require few language skills and are hired at a greater rate than natives or older immigrants in these occupations are.[34] The census and ACS data contain a variable that indicates the level of English proficiency of respondents, which confirms that immigrants improve their English skills during their stay in the country.[35] Moreover, the occupational concentration of undocumented immigrants as measured by the Duncan dissimilarity index with respect to natives is somewhat higher for those that have arrived more recently.[36]

To investigate the extent to which the empirical results are driven by those occupations that require few language skills and have a highly disproportional share of undocumented immigrants, I rerun the regressions with wages and UE transitions as dependent variables after dropping *Cooks*, *Construction laborers*, *Carpenters*, *Gardeners*, and *Food prep workers*, which all have especially large shares of undocumented workers according to online Appendix Figure E.2. Online Appendix Tables D.3 and D.4 show that the wage gaps remain almost identical and the gaps in job finding rates for both types of immigrants decrease by just around 1 percentage point compared to the full sample results in Table 2.

In sum, the fact that a large part of the initial differences in wages and job finding rates persist even after many years in the United States speaks in favor of the mechanism suggested in this paper as the main driver. However, an initially higher concentration in traditional immigrant jobs, which likely arises due to inferior language skills, might be another possible channel that contributes to the gaps in wages

[34] Kossoudji and Cobb-Clark (1996), for example, find that undocumented immigrants are initially more concentrated in fewer occupations (especially food preparers, farm workers, and groundskeepers), but a majority eventually switches jobs, whereby the occupational mobility is related to improved English skills.

[35] I find that among those living for up to three years in the United States, 23 percent of legal and 37 percent of undocumented immigrants report not being able to speak English. These shares drop to 11 percent and 22 percent for those living for 10 to 15 years in the United States and finally to 7 percent and 17 percent for those who arrived more than 20 years ago.

[36] In particular, for those living for up to three years in the United States, the index is 0.50, which is somewhat higher than in the full sample. After 10 to 15 years, the index is 0.40, which is close to the full sample average. After 20 years, the index drops to 0.32.

and job finding rates, especially for recently arrived undocumented immigrants. This implies that if natives apply to these jobs to a lesser extent, then the competition effect of undocumented immigration might be smaller in the short run than the model predicts, which is an important caveat.

D. *No Penalties for Firms*

There is little evidence that penalties for hiring undocumented immigrants are large or frequent enough to play a significant role in firms' decisions. Both anecdotal evidence and the literature suggest that the risk of being fined or criminally prosecuted is small. The main reason is that authorities have to prove that a firm *knowingly* hired undocumented workers. This is very difficult in practice, as many have social security numbers that are either fake or belonging to other individuals, and therefore it needs to be proven that the employer not only checked but also recognized the fraudulent number.[37]

The finding of Brown, Hotchkiss, and Quispe-Agnoli (2013) that firms employing undocumented workers have a lower exit rate is further evidence that the additional surplus generated through lower wage cost more than compensates the risk of being fined. They also cite a report by the Congressional Budget Office stating that 91 percent of apprehensions of unauthorized immigrants occur at the border. Figure 1 in Lofstrom, Hill, and Hayes (2013) shows that in the whole United States, the number of fines given per year was at most 1,000 during the 1990s and declined to less than 100 from 2004 on. As they note, this suggests that only a very small fraction of employers using unauthorized labor are affected by fines. A recent analysis by the Transactional Records Access Clearinghouse (TRAC) at Syracuse University shows that criminal prosecutions of employers are even rarer and have almost never exceeded 20 individuals per year in the period from 2004 to 2019.[38]

Yet, there also exist cases where the firm's knowledge of illegal hiring practices could be proven and large sums were paid to avoid criminal prosecution.[39] It is therefore informative to check the robustness of the model to firm penalties. As there exists no information on the size of the undocumented workforce per given fine, it is difficult to use the number of fines per year to calibrate the corresponding parameter in the model. This is why I use official figures on "interior removals" to proxy for the risk of detection for an undocumented immigrant. Under the conservative assumption that all immigrants detected through interior removals were previously employed and that this always leads to a fine for the employer, this yields a monthly probability of being fined of 0.22 percent per undocumented worker. To check how the introduction of fines affects the model predictions, I solve the model for different values of the fine (from 0 to 50) and calculate the marginal effects of undocumented immigration (by increasing their population share by 1 percentage point) on natives' unemployment rates and wages. Online Appendix

[37] At the same time, the US antidiscrimination laws prohibit discrimination because of race or color, and a higher scrutiny when checking the social security numbers of seemingly undocumented immigrants could be viewed as such.

[38] See https://trac.syr.edu/immigration/reports/559/, accessed on August 20, 2019.

[39] A recent example is the case of Waste Management Inc. paying $5.5 million to avoid federal prosecution.

Figure E.6 plots these effects—i.e., the changes in the outcomes against the size of the fine. The higher the fine, the weaker the job creation effect of undocumented immigration, and therefore the negative effect on natives' unemployment rate and the positive effect on their wages are attenuated. However, the unemployment rate is still slightly decreasing (i.e., job creation dominating competition) when the fine is at the maximum of 50. As (monthly) productivity is normalized to one in the model, this would correspond to more than four years of labor output. However, actual fines for first offenders are between \$250 and \$2,000 per undocumented employee. The upper bound of this range roughly corresponds to the labor output of one month—thus, a fine equal to one, which would have negligible effects on the predictions. Therefore, it seems reasonable to abstract from firm penalties in the model. However, one should keep the implications of potential future policies that increase the risk of firm penalties in mind.

VIII. Conclusion

This paper analyzes the distinct labor market effects of documented and undocumented immigration in a framework that generates predictions consistent with a number of key data patterns, in particular large differences in job finding rates between natives and immigrants. As differentials in job finding rates are at odds with a standard random matching mechanism, I propose a job search model with nonrandom hiring and worker heterogeneity in bargaining power, unemployment benefits, and deportation risk. As immigrants accept lower wages than natives do, firms always prefer to hire the former when having the choice. Immigration has two opposing effects on natives. The creation of additional vacancies due to lower average wage costs decreases their unemployment rate, whereas the higher competition for jobs through cheaper workers increases it. Simulating the model shows that the job creation effect dominates the competition effect of undocumented immigration, implying employment gains and a strong rise in wages for natives. The opposite is the case for documented immigration, which drives down average wage costs only marginally and thus has a weak job creation effect. I test these predictions by estimating the impact of immigrant population shares on vacancies and wages among low-skilled workers and find qualitative support for the results.

A rise in the deportation rate for undocumented immigrants dampens job creation due to a lower expected firm surplus, which in turn lowers the job finding rates of all workers. In cases where the deportation rate rises more for employed undocumented workers—for example, through worksite raids—job finding rates and wages of legal workers fall more strongly, whereas wages of undocumented workers rise due to a risk premium for accepting a job.

The findings of this paper have important policy implications. Shielding the economy from low-skilled undocumented immigration or providing legal status to present undocumented immigrants has a negative impact on the employment opportunities and wages of low-skilled natives, at least in the short run. Therefore, such policies would achieve the exact opposite of what they are intended for. The same holds for stricter immigration enforcement through increased deportations, which is predicted to be detrimental for all workers. The negative impact on natives is especially large if deportation policies mainly target undocumented immigrants at their workplace.

The presented model abstracts from other relevant dimensions of heterogeneity between documented and undocumented immigrants, which might come more into effect in the long run. The higher prospect of a long-term stay in the United States, for example, could incentivize immigrants with legal status to invest in their education and host-country-specific skills, move to more productive jobs, or become entrepreneurs, all of which are likely to increase their productivity and have positive spillovers on natives. Moreover, the effects on high-skilled workers working in jobs complementary to low-skilled workers' jobs are not considered in this paper. This leaves many avenues for future research on undocumented immigration, which could be facilitated by improved data resources or new policy experiments.

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