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The Labor Market Impact of Undocumented Immigrants: Job Creation vs. Job Competition

Abstract

This paper studies the labor market impact of documented and undocumented immigration in a model with search frictions and non-random hiring. Since they accept lower wages, firms obtain a higher match surplus from hiring immigrants rather than natives. Therefore, immigration results in the creation of additional jobs but also generates more job competition. Whether job creation or competition is the dominating effect depends on the size of the induced fall in expected wages paid by firms. Using US data, I show in my empirical analysis that among low-skilled workers undocumented immigrants earn 8% less and have a 7 pp higher job finding rate than documented immigrants. Parameterizing the model based on these estimates, I find that the job creation effect of undocumented immigration dominates its job competition effect and leads to gains in terms of both employment and wages for native workers. In contrast, documented immigration leads to a fall in natives' employment due to its weaker job creation effect. A policy of stricter immigration enforcement, simulated by a rise in the deportation rate of undocumented workers, decreases firms' expected match surplus, mutes job creation and thus raises the unemployment rates of all workers.

JEL-Codes: J310, J610, J630, J640.

Keywords: wage gap, migrant workers, hiring, employment.

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1 Introduction

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% in the 1970s to over 13% today, triggered by a change in immigration policy that facilitated the entry from Latin America and Asia and caused a shift in the skill composition towards less educated immigrants. Another major change in the nature of US immigration especially since the beginning of the 1990s is a pronounced shift towards undocumented immigration. While the number of all immigrants residing in the US doubled from around 20 million to 40 million between 1990 and 2013, the number of immigrants without legal status increased almost fourfold from 3 million to over 11 million during the same period.[1] Undocumented immigrants in the US actively participate in the labor market and make up around 5% of the labor force.[2]

The goal of this paper is to shed new light on the labor market impact of both documented and undocumented immigration and on the question whether stricter immigration enforcement protects native workers. I first present novel evidence on the effects of legal status on workers' labor market outcomes among low-skilled workers and then analyze the impacts of both types of immigration in a labor market model featuring search frictions and non-random hiring. In this framework, the immigration of cheaper workers leads to an increase in job creation but also higher job competition. Job creation and job competition affect the unemployment rate of natives in opposite ways and which of the two effects dominates depends on the size of the difference in expected wages between natives and the immigrating worker type. The higher are the wage costs that firms can save by hiring an immigrant worker, the stronger is the job creation effect and the more beneficial is immigration. As undocumented immigrants earn the lowest wages, an increase in their share among job searchers results in a large decrease in expected labor costs of firms and therefore induces a strong job creation effect. In contrast, labor costs fall less or can even rise after an increase in the share of documented immigrant job searchers, resulting in a weak job creation effect.

In order to quantify the differences in labor market outcomes by legal status, I perform a regression analysis using US survey data of low-skilled workers in the empirical part of this paper. I find that undocumented immigrants earn around 8% less and have a 7 percentage points higher job finding rate than documented immigrants. The latter earn around 4% less and have a 7 percentage points higher job finding rate than natives. After setting up the model, I parameterize it to match these estimates and use it to simulate documented and undocumented

[1]There exist divergent figures of the number of undocumented immigrants in the US depending on the estimation method. The cited numbers are taken from the Pew Research Center, whose estimation relies on a "residual method". This method is based on a census count or survey estimate of the number of foreign-born residents who have not become U.S. citizens and subtracts estimated numbers of legally present individuals in various categories from administrative data. The resulting residual is an indirect estimate of the size of the undocumented immigrant population.

[2]Borjas (2016) for example finds that among the male population, the employment rate of undocumented immigrants is higher than both the employment rate of natives and legal immigrants.

immigration. The simulations indicate that the job creation effect of undocumented immigration is large enough to dominate the job competition effect. Although its job creation effect is also positive, the opposite holds for documented immigration. Therefore, only undocumented immigration is unambiguously beneficial for natives as it raises both their employment rate and wages, whereas documented immigration decreases natives' employment. I test these predictions empirically using an early settlement instrument to account for endogeneity in the immigrant population shares. I find a positive effect of the undocumented immigrant share in the labor force on vacancy creation and wages among low-skilled workers at the city level, but I do not find a positive effect of the documented immigrant share. This supports the finding that undocumented immigration increases employment opportunities and wages of natives more than documented immigration.

Finally, I use the framework to study the impact of a counterfactual policy of stricter immigration enforcement, which I simulate by increasing the deportation ("removal") rate for undocumented immigrants. I distinguish two cases: a rise in the removal rate that is the same independently of employment status and a rise in the removal rate only for 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 natives' and documented immigrants' unemployment rates because expected firm surplus and thus job creation are dampened weakly. In the second case, firms additionally have to pay a risk compensation in order to induce an undocumented job seeker to accept being hired and as a result wage costs rise and job creation is dampened more strongly. The group most affected by this policy are native workers, whose unemployment rate rises between 1.7 and 5.7 percentage points and wages fall between 0.5% and 1.7% when the removal rate increases by one percentage point. For documented immigrants, the effects on unemployment and wages are 0.5 to 1.5 percentage points and -1.1% to -3.7%, respectively.[3] I test these predictions using the state-wide 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 a fall in wages for natives and higher wages for immigrants, which is consistent with a risk compensation in immigrants' wages.

My first contribution to the literature consists in showing that legal status is an important driver of differences in labor market outcomes. In particular, I find that among low-skilled workers undocumented immigrants earn lower wages and have higher job finding rates than both natives and documented immigrants. Although the latter earn less and find jobs faster than natives as well, the differences are smaller and almost disappear for immigrants that have spent more than 25 years in the US. Having spent fewer years in the US is also associated with lower earnings and higher job finding rates (for both types of immigrants). These findings suggest a connection between the level of earnings and the speed of finding a job and are to the best of my knowledge novel in the literature.

[3]The exact values depend on the assumed disutility from removal, which affects how large the risk compensation and therefore the size of the impact of stricter immigration policy in the second case is. The ranges given correspond to a range of the removal disutility between 25% and 75% of an undocumented immigrant's lifetime utility.

The second contribution is the analysis of both documented and undocumented immigration in a search and matching model that is consistent with the empirical facts. The differences across workers in both wages and job finding rates generated by the model match their empirical counterparts. While a difference in wages between otherwise identical workers can also be generated in a standard job search model, the difference in job finding rates is a puzzle for a model with random matching between firms and workers. I therefore include a non-random hiring mechanism (following Barnichon and Zylberberg, 2016) in my framework, which implies that firms can receive multiple applications and choose their preferred candidate among them. This generates higher job finding probabilities for cheaper workers and therefore implies that natives have the lowest and undocumented immigrants have the highest job finding rate as suggested by the data.

Previous studies on migration in the US often only distinguish immigrants according to their skill composition as measured by educational attainment and labor market experience (e.g. Borjas, 2003, Peri and Sparber, 2009, Ottaviano and Peri, 2012, Llull, 2013). However, as being undocumented has been shown to have a causal effect on immigrants' labor market outcomes, in particular it increases wages (Kossoudji and Cobb-Clark, 2002, and Pan, 2002) and decreases employment (Amuedo-Dorantes and Bansak, 2011), legal status should not be neglected as an additional dimension of heterogeneity across immigrants.[4] An exception is a study by Edwards and Ortega (2016) who differentiate between documented and undocumented immigrants. In contrast to my framework, the authors assume a frictionless labor market with wages equal to marginal productivity, which implies that the earnings differences between documented and undocumented workers are solely explained by their productivity differential. While productivity differences may play some role, there are various other explanations for lower earnings of undocumented workers that are unrelated to productivity. As undocumented immigrants have no work permission, firms are not bound to any minimum wage laws and might use the threat of being sanctioned for their hiring to justify paying them lower wages. Furthermore, the inability to receive unemployment benefits lowers the outside option to working and might additionally suppress the wages of undocumented workers. I therefore use a framework with search frictions that allows for wage differences across equally productive workers through heterogeneity in bargaining power and unemployment benefits across types.

Other closely related work employing a model with search frictions to study employment and wage effects of immigration is by Chassamboulli and Peri (2015). They assume that all workers are equally productive but that immigrants, and even more so the subgroup of the undocumented, have lower reservation wages than natives due to higher job search costs. The prospect of hiring workers at a lower wage increases firms' profit and induces job creation, a mechanism also at work in this paper. However, their search model features random hiring, i.e. although firms can discriminate between natives and immigrants once they are matched, they cannot do so in their hiring. Hence, all workers always have the same job finding rate and therefore immigration unambiguously drives up wages and employment of natives. As the assumption of equal job finding rates across worker types is not supported by the data, I introduce non-random hiring in my model. This gives rise to the competition

[4] Most studies do not distinguish immigrants by legal status simply because the identification of undocumented immigrants in the data was not possible. A reliable method to identify them in US microdata has just become recently available (see section 2.1).

effect of immigration and implies that it depends on the size of the wage difference between natives and the immigrating worker type whether immigration is beneficial for natives or not.

The fact that many immigration studies stress the different skill distribution of immigrants and consider natives and immigrants as imperfect substitutes raises the question whether the assumption of perfect substitutability between natives, documented and undocumented immigrants made throughout the paper is too strong. To address this concern, I filter out skill differences as thorough as possible in my empirical investigation, which is why all results should be viewed as being conditional on having the same skills. In particular, I only focus on low-skilled workers and add an extensive set of demographic, occupation and industry controls in the regressions, including an interaction between industry and occupation fixed effects. Thus, I assume that worker types are perfect substitutes only within narrowly defined industry-occupation cells. I thereby control for imperfect substitutability within broader skill cells as emphasized by previous studies. This allows me to uncover legal status as an additional and so far neglected dimension of worker heterogeneity. In that sense, my work complements the literature focussing on skill heterogeneity.

The remainder of the paper is organized as follows. In section 2, I describe how undocumented immigrants are identified in the data and present some descriptive statistics. Section 3 analyzes wages and job finding rates of natives, documented and undocumented immigrants empirically. Section 4 sets up the search model with non-random hiring. Section 5 outlines the parameterization strategy. Section 6 examines the effect of documented and undocumented immigration in the model. Section 7 explores the impact of a rise in the removal risk. Section 8 tests some predictions derived from the model empirically. Section 9 concludes.

2 Data, Identification Method and Descriptives

In the following section, I describe the data and the method I use to identify undocumented immigrants. This method is first described in Borjas (2016) and is based on demographic, social and economic characteristics of survey respondents. I show that the percentage of both documented and undocumented immigrants is by far the highest among workers without a high school degree. I further highlight the demographic differences between natives and immigrants and their concentration across industries by education level.

2.1 Data and Identification of Undocumented Immigrants

The data used in this section come from the March supplement of the Current Population Survey (CPS) obtained from IPUMS (Flood et al., 2015). My analysis is restricted to the period beginning in 1994 because information on the birthplace and citizenship status of a survey respondent was only included from that year on. I only consider prime age workers (age 25 to 65) in all samples. A respondent is defined as an immigrant, if born outside the United States and not American citizen by birth. In section 3.2, I further use the basic monthly files of the CPS with workers matched over two consecutive months following Shimer (2012) in order to examine transition rates between employment and unemployment.

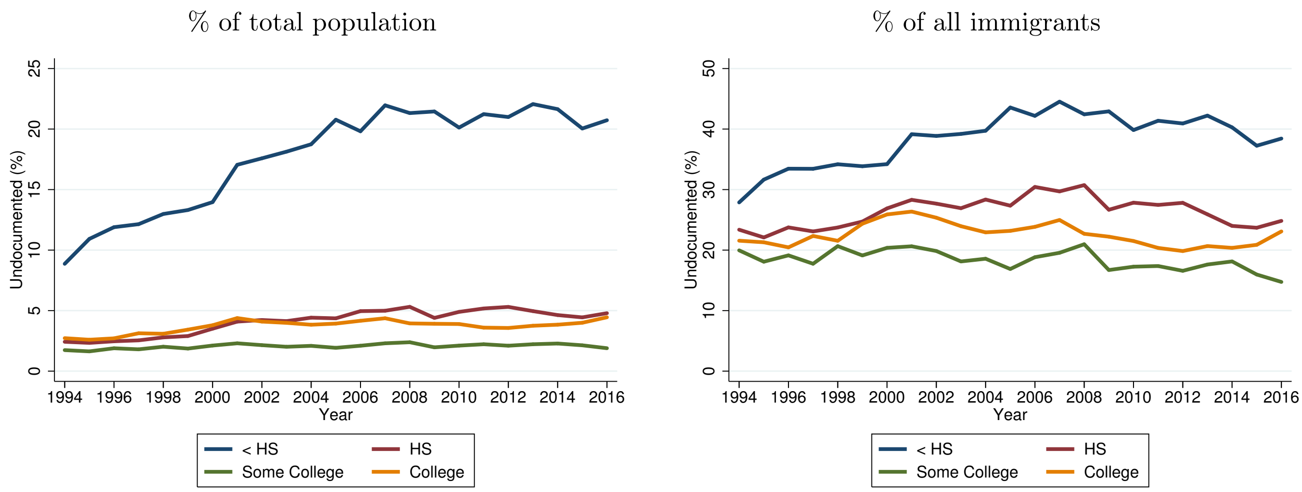
Neither the CPS basic monthly files nor the March supplement allow to directly identify undocumented immigrants. However, as the US labor market surveys are address-based and designed to be representative of the whole population, they also include undocumented respondents. The CPS data are likely to offer the best coverage of undocumented immigrants because individuals are interviewed in person, whereas for the US Census and ACS data are collected by mail.[5] The government surveys are actually used by the US Department of Homeland Security (DHS) to estimate the size of the undocumented immigrant population via a so-called "residual method". The DHS obtains figures of legal immigrants in the US from administrative data of officially admitted individuals and subtracts them from the foreign-born non-citizen 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 in the survey data 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 (2016) 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. His method consists in classifying every immigrant who fulfills at least one of the following conditions as documented:

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

[5] Only one third of those who do not respond to the ACS survey initially are randomly selected for in-person interviews, which could result in an underrepresentation of undocumented respondents, who might ignore the survey due to the fear of detection.

Figure 1: Percentage of undocumented immigrants



Source: CPS March supplement with Borjas (2016) identification, prime age workers only

All remaining immigrants are then classified as undocumented. Thus, Borjas (2016) does not apply a filter on the potentially undocumented immigrants to make their final count consistent with estimates from the residual method as Passel and Cohn (2014) do. In order to assess the accuracy of this simplified method without filtering, Borjas (2016, Table 1) compares summary statistics for the undocumented immigrant population in his CPS sample with the corresponding summary statistics in a CPS sample including the undocumented identifier constructed by Passel and Cohn (2014), which he was granted access to by the authors. While the total share of undocumented immigrants in the population and most other statistics are very similar across the samples, their educational attainment is notably higher in the Borjas sample. This suggests that there might be an excess of immigrants classified as undocumented among the high-skilled.[6] In Appendix A, I investigate this issue in more detail and show that applying Borjas' simplified method indeed leads to an excess of undocumented among immigrants with at least some college education in the CPS March and CPS basic data.

Figure 1 plots the share of undocumented immigrants identified with the method of Borjas (2016) among the total prime age population and among 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 strongest, from 9% in 1994 to over 22% 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 5% for high school and college graduates.[7] Also among immigrants, the percentage of undocumented is

[6]This could be explained by the fact that some variables for identification of documented immigrants are related to social security benefits, which high-skilled individuals receive in much fewer cases than low-skilled individuals.

[7]A part of the rise of the undocumented share among high school dropouts is due to the fact that education levels of natives and documented immigrants have improved more strongly than education levels of undocumented immigrants (between 1994 and

Table 1: Descriptive statistics

Education	*Status*	*Age*	*Years in US*	*% Men*	*% Hispanic*	*% Asian*
<HS	Native	45	-	52	23	3
	Documented	45	21	48	77	13
	Undocumented	39	12	57	89	7
HS	Native	45	-	50	11	2
	Documented	44	21	46	49	23
	Undocumented	38	11	54	69	15
SC	Native	44	-	45	10	3
	Documented	44	22	44	37	25
	Undocumented	38	11	51	51	19
C	Native	44	-	46	5	4
	Documented	44	20	45	18	44
	Undocumented	37	7	53	18	57

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

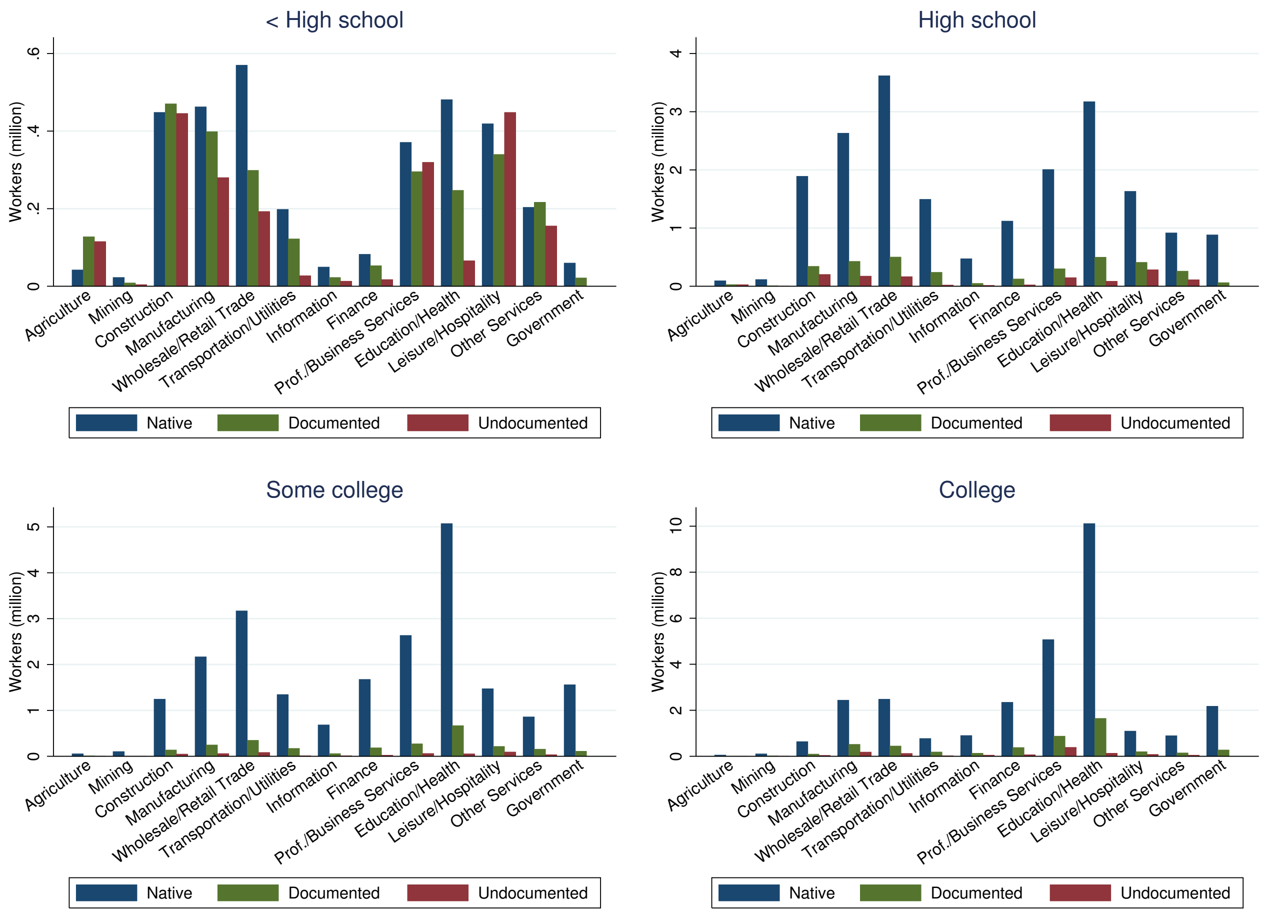
the largest and increased the most in the group of high school dropouts. This suggests that on average undocumented have a lower education than documented immigrants and this difference has increased since 1994 (the percentage of high school dropouts is around 37% among the former and 19% among the latter in 2016).

Table 1 shows some descriptive statistics of the sample of prime age workers covering the most recent ten years (2007-2016) by education and status (native, documented immigrant or undocumented immigrant). Across all education levels, undocumented workers are six to seven years younger than both native and documented workers, who have around the same age. Moreover, depending on the education level, documented are 9 to 13 years longer in the US than undocumented immigrants. This is mainly because undocumented immigrants that entered the US in 1982 or before were granted amnesty by the Immigration Reform and Control Act of 1986 (IRCA) and thus the earliest entry year for an undocumented immigrant in the data is 1983. Irrespective of education, the percentage of men among documented immigrants is somewhat lower and among undocumented somewhat higher than among natives. The shares of hispanic and asian workers differ substantially by education. Among undocumented high school dropouts, 89% of workers are hispanic and this percentage decreases strongly with education. Among college graduates without documentation, only 18% are of hispanic origin. A similar pattern holds for documented immigrants, although their share of hispanic workers is lower than among undocumented immigrants. For the the share of asian workers, we observe the opposite pattern across education levels: the higher is education, the higher is the share of asians among immigrants. Moreover, for workers with less than a college degree there are more asians among documented than among undocumented immigrants.

Figure 2 explores whether legal status is associated with a concentration in different industries. I identify 13

2016 the share of high school dropouts has fallen from 15% to 9% for the former and from 41% to 37% for the latter).

Figure 2: Worker distribution across industries by education



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

industries based on the one-digit level of the North American Industry Classification System (NAICS). The most salient feature of the figure are the high numbers of both documented and undocumented immigrant workers among high school dropouts, which in most industries are close to the number of native workers. Only Wholesale and Retail Trade, Transportation and Utilities, Education and Health as well as Government[8] are largely dominated by a native workforce. In Agriculture, native workers are even a small minority among workers without high school degree. Most undocumented high school dropouts work in the Construction and Leisure and Hospitality industry. In the latter, which includes for example cooks and waiters, they constitute even the largest share of the three worker types. The upper right and bottom panels suggest that among higher educated workers with at least a high school degree, the number of immigrants is small compared to the number of natives across all industries. Furthermore, the number of undocumented is always smaller than the number of documented immigrants.

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

Given the large size of the immigrant workforce relative to natives among high school dropouts, I choose to restrict my empirical analysis to this education level (for simplicity henceforth referred to as "low-skilled"). Beside the large share of both documented and undocumented immigrant workers, there are three more reasons for focusing on this group. First, the identification method is more precise among low-skilled workers as shown in 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, documented and undocumented immigrants play a rather small role in the low-skilled labor market.[9]

3 Empirical Evidence

Next, I present empirical evidence supporting the claim that the labor market performance of low-skilled workers is not only affected by being an immigrant or a native but also significantly by an immigrant's legal status. In particular, I show that low-skilled undocumented immigrants earn lower wages than both documented immigrants and natives. There is also a wage gap between the latter two types but it is much smaller in size. The wage gap to natives falls throughout an immigrant's stay in the US and disappears completely after 25 years for documented immigrants. Moreover, I find that immigrants find jobs faster than natives and that, analogously to wages, the gap is higher for undocumented immigrants and for both immigrant types falling in the length of stay in the country. I also find evidence of separation rate differences, although they are small and disappear for immigrants that are more than 25 years in the US. Finally, using a basic Mortensen-Pissarides framework, I show that the wage and transition rate gaps translate to a much lower reservation wage for undocumented immigrants relative to natives and documented immigrants.

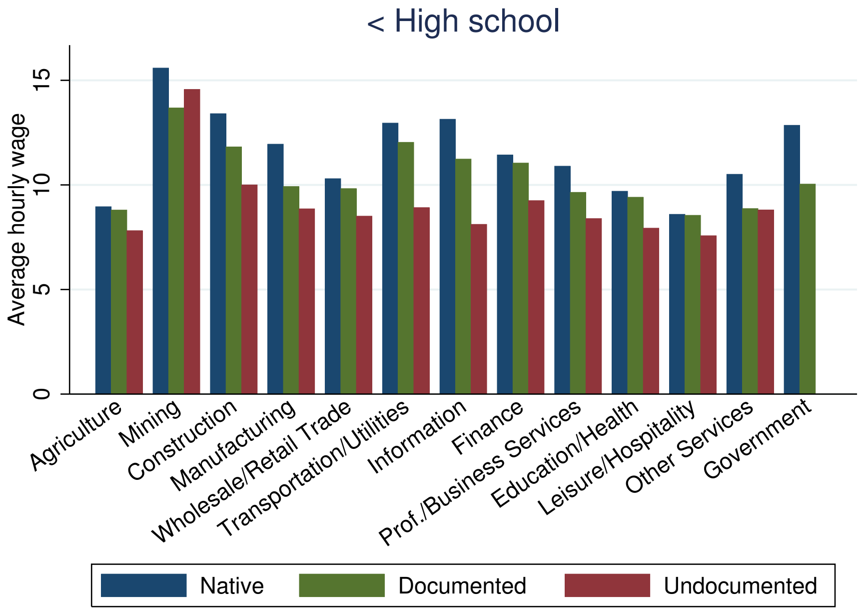
3.1 Wages

It has been well established by the literature that immigrants are paid less than native workers even when controlling for observables. However, until very recently there existed no extensive empirical research using microdata that also takes into account the effect of immigrants' legal status on earnings.[10] Borjas (2017) fills this gap by performing an analysis similar to the one I perform in this section. I follow his strategy in using the CPS March supplement data with undocumented immigrants identified by the Borjas (2016) algorithm but focus only on the low-skilled and add further controls to the regression model in order to account for different industry and occupation choices of undocumented immigrants. As common in the literature (e.g. Borjas, 2003), 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 people living in group quarters. I construct real hourly wages by dividing the total wage income of an employee by the number of hours worked per year, deflating the result to 1999 dollars with the CPI-U adjustment factor provided in the IPUMS database and controlling for outliers by dropping the 1st

[9] All empirical findings in this paper are quantitatively similar when using a sample of high school graduates or a pooled sample of workers with at most a high school degree.

[10] Edwards and Ortega (2016) document wage differences between documented and undocumented immigrants within industries, but do not perform a more in-depth regression analysis.

Figure 3: Hourly wages of low-skilled workers (1999 dollars)



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

and 99th percentile of the distribution of the hourly wage.

Figure 3 reports the average hourly wages of workers without high school degree in each of the 13 industries during the period 2007-2016. Not surprisingly, natives earn the most in all industries. With the only exception being 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. However, these figures should be viewed with caution as Table 1 clearly suggests that the three worker types differ with respect to demographic characteristics, which certainly influences their earnings. Controlling for observables beyond education and industry is therefore crucial.

In order to test whether the wage differences between worker types also exist between otherwise comparable workers, I run a wage regression with an extensive set of demographic controls including age, age squared, sex, hispanic and asian origin. Additional to demographic factors and industry fixed effects, I control for workers' occupations, which relates to the specific technical function in a job. Indeed, several studies suggest that natives and immigrants are imperfect substitutes and tend to specialize in tasks they have a comparative advantage in, which are more communication-intensive for natives and more manual/physical for immigrants (Peri and Sparber, 2009, Rica et al., 2013). Thus, I include a dummy for each of the around 500 occupation codes

Table 2: 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 FE	No	No	Yes	Yes	Yes
Ind/occ FE	No	No	No	Yes	No
Ind x occ FE	No	No	No	No	Yes
Observations	68563	68563	68563	68563	68563
R-squared	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^2. Standard errors are clustered at the metropolitan area level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

attributed to workers in the CPS data. As a final robustness check, I include an interaction of industry and occupation fixed effects, i.e. a dummy for each industry-occupation combination instead of separate industry and occupation dummies. By doing so, I assume that only within each industry-occupation cell, natives, documented and undocumented immigrants are perfect substitutes. The regression specification has the following form:

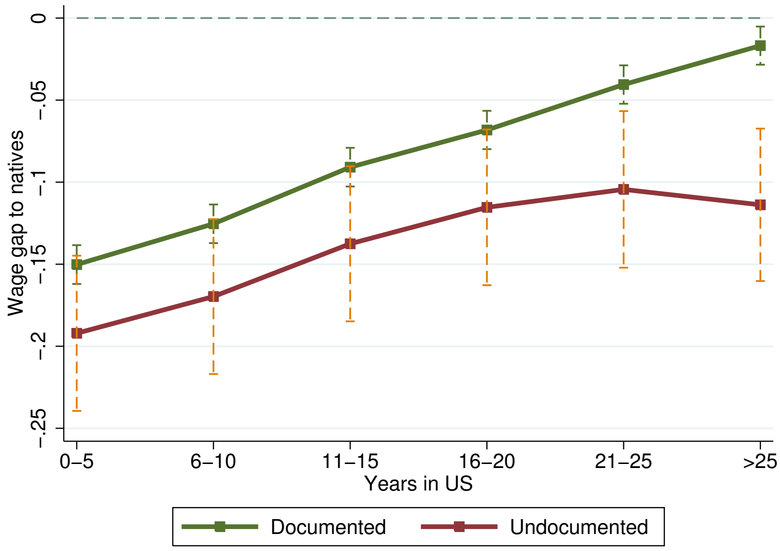
$$\ln w_{it} = \beta_0 + \beta_1 D_{it} + \beta_2 U_{it} + \phi_t + X'_{it}\gamma + \epsilon_{it},$$

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

The regression results are reported in Table 2. The baseline specification without controls suggests that documented immigrants earn around 12% and undocumented immigrants around 27% less than the native reference group. The inclusion of demographic controls shrinks the wage gaps to 7% and 21%, 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 Borjas (2017, Table 2), who finds very similar coefficients even though he uses a sample with all education groups and only the years 2012-2013.[11] Adding industry and occupation fixed effects shrinks both coefficients by around a half, which confirms the importance of controlling for the different distribution of workers across jobs even conditional on demographics. Coefficients remain virtually identical when including industry-occupation interactions. Column (5) indicates that documented immigrants earn only 4.3% less than natives and the undocumented status of an immigrant accounts for an additional wage gap of 8.3%. This result

[11] Borjas (2017) obtains a coefficient of -0.10 for documented and -0.224 for undocumented immigrants among men and similar results among women.

Figure 4: Wage gap to natives



Notes: The wage gaps result from a regression with the same controls as in column (5) of Table 2 including workers with at most high school. Vertical dashed lines show 10% confidence intervals.

is in line with previous studies that estimate the wage gain from legalization by comparing those immigrants who were granted amnesty via the 1986 IRCA and those who were not. Their estimates lie between 6% (Kossoudji and Cobb-Clark, 2002) and 10% (Pan, 2002).

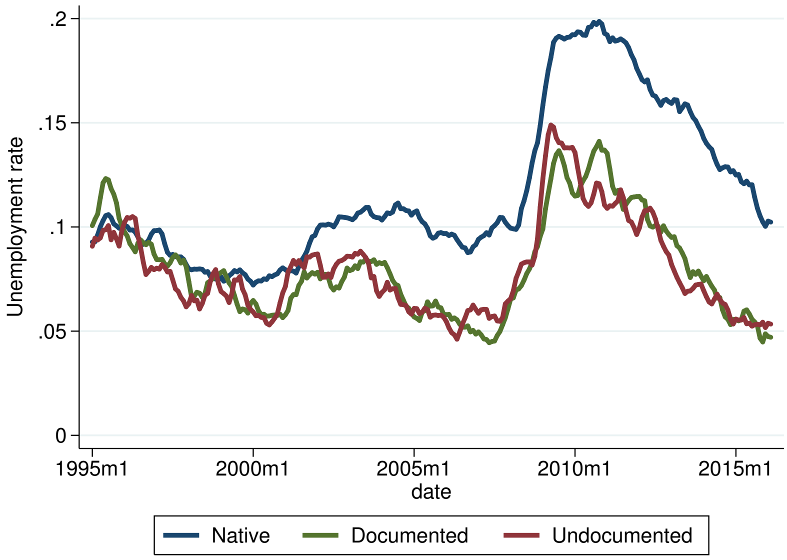
The regression model considered above still does not take into account the differences in time spent in the US between the immigrant types seen in Table 1. It is well known that immigrants assimilate into their host country over time and that this is associated with earnings growth (e.g. Borjas, 1985). In order to account for a potentially non-linear 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 US, which I group in six 5-year intervals (1-5, 6-10, 11-15, 16-20, 20-25 and >25) denoted by $y = 1, ...6$. The equation for immigrants therefore takes the following form:

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

Figure 4 plots the wage gap to natives for both immigrant types for each interval of years in the US. To increase the number of immigrants observations per interval, I also include high school graduates in the regression underlying the figure and add a dummy indicating having completed high school as educational control.[12] The wage gaps of documented and undocumented immigrants residing in the US for at most 5 years are around 15% and 20% respectively. The speed of assimilation is almost identical for both types of immigrants during the first 20 years, however, after that the assimilation of undocumented immigrants slows down. Earning

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

Figure 5: Unemployment rates of low-skilled workers



Notes: The series are constructed from CPS basic monthly files and seasonally adjusted using the X-12-ARIMA seasonal adjustment program provided by the U.S. Census Bureau.

only 2% less than natives, documented workers have almost fully assimilated after 25 years, at which point undocumented workers still earn around 12% less. Thus, there are two important take-aways from Figure 4. First, even accounting for the length of stay in the US, there is still a large wage gap between documented and undocumented immigrants. Second, the gap to natives is initially large and disappears through assimilation for the former but not for the latter.

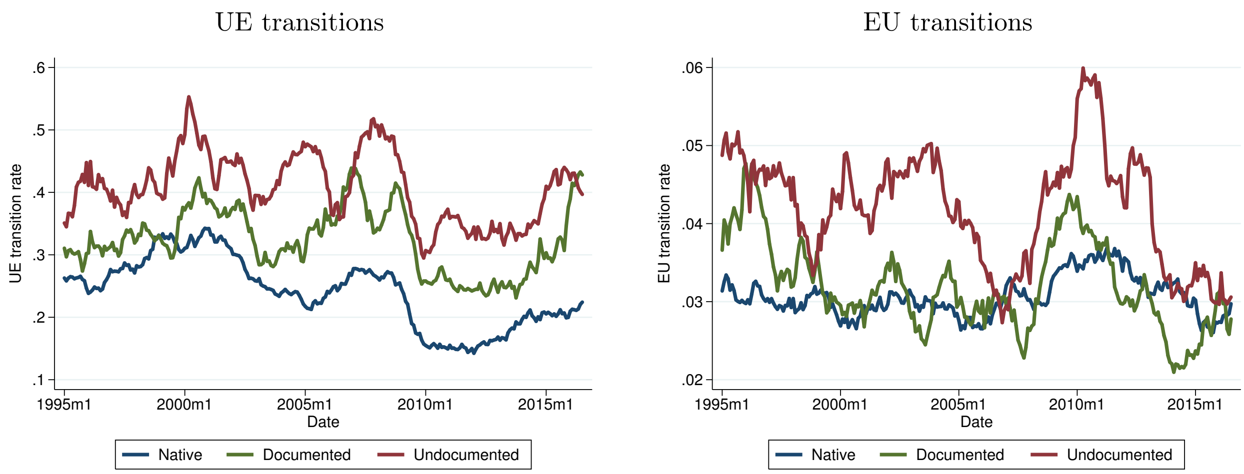
3.2 Unemployment and Transition Rates

I now turn to the analysis of the difference in unemployment and transition rates between employment and unemployment. The data used in this subsection are the CPS basic monthly files, in which some of the variables for the identification of legal respondents, e.g. social security benefits or health insurance, are not available. Although this should lead to a lower precision of the undocumented immigrant identifier, I show in Appendix A that there is no excess of undocumented immigrants among the low-skilled in the CPS basic data.

Figure 5 plots the seasonally adjusted unemployment rates of low-skilled workers. Both types of immigrants have virtually the same rate of unemployment, which is significantly lower than the one of natives, (except in the very beginning of the sample period). Contrary to the findings for wages, this first evidence seems to suggest that only the status of being an immigrant but not the legal status matters for employment.

In order to find out whether this unemployment gap is driven by unemployed immigrants finding jobs at a higher rate or employed immigrants separating from their job at a lower rate (or a combination of both), I

Figure 6: Transition rates of low-skilled workers



Notes: The figure shows 12-month moving averages, constructed from CPS basic monthly files and corrected for time-aggregation bias following Shimer (2012).

decompose the equilibrium unemployment rate into the underlying job finding and separation rates.[13] 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).

The series of job finding rates (UE transitions) are shown in the left panel of Figure 6. Over most of the sample period, undocumented job searchers have the highest job finding rate of all workers with a gap of up to around 15 percentage points to documented job searchers. Only around 2007-2008 and at the end of the period, the latter have a similar rate. From 2000 on, natives permanently have the lowest job finding rate with the difference to undocumented immigrants being up to 25 percentage points. Given the similar level of the unemployment rate of documented and undocumented workers seen in Figure 5, we expect a higher separation for undocumented counteracting the higher job finding rate. This is confirmed by the right panel of Figure 6, which shows that the EU transition rate series of documented immigrants is close to the series of natives, while it is higher over most of the period for undocumented immigrants. Altogether, the decomposition in transition rates suggest that, although the unemployment rates of documented and undocumented workers almost exactly coincide, the latter are characterized by much more frequent transitions in and out of employment. Moreover, the figures show that the unemployment gap between natives and immigrants is primarily driven by a differential in job finding rates. This is a surprising finding in the light of results of previous studies suggesting that the variation of unemployment rates across workers (e.g. skill types in Mincer, 1991) is almost solely driven by differing separation rates. Job finding on the other hand has been found to mainly account for cyclical fluctuations of

[13]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 $u_t/l_t = \frac{s_t}{s_t+f_t}$, which Shimer (2012) shows to almost exactly match the actual unemployment rate.

Table 3: Legal status and UE transition of low-skilled workers

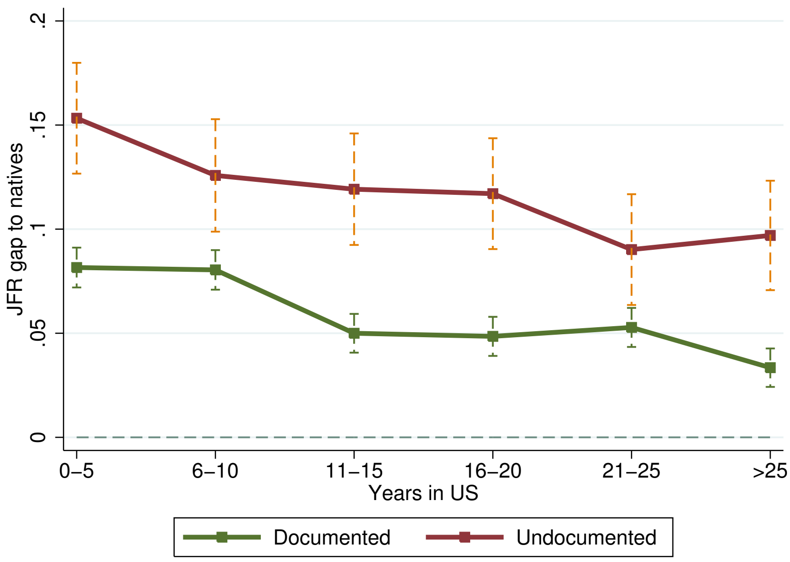
	(1)	(2)	(3)	(4)	(5)
Documented	0.069***	0.061***	0.071***	0.068***	0.069***
	(0.0047)	(0.0063)	(0.0078)	(0.0073)	(0.0072)
Undocumented	0.142***	0.126***	0.141***	0.139***	0.140***
	(0.0053)	(0.0084)	(0.0106)	(0.0116)	(0.0117)
Demographics	No	Yes	Yes	Yes	Yes
Year/State FE	No	No	Yes	Yes	Yes
Ind/occ FE	No	No	No	Yes	No
Ind x occ FE	No	No	No	No	Yes
Observations	75634	75634	75634	75634	75634
R-squared	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^2. Standard errors are clustered at the state level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

unemployment over time (Shimer, 2012).

The transition rate differences might be explained by the demographic or occupational heterogeneity between the worker types but not the type itself. I therefore estimate a linear probability model with the same controls as in the wage regressions in the previous subsection. The dependent variable is a dummy indicating a transition from unemployment to employment or a dummy indicating a transition from employment to unemployment.

Figure 7: Job finding rate gap to natives



Notes: The wage gaps result from a regression with the same controls as in column (5) of Table 2 including workers with at most high school. Vertical dashed lines show 10% confidence intervals.

Table 4: 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 FE	No	No	Yes	Yes	Yes
Ind/occ FE	No	No	No	Yes	No
Ind x occ FE	No	No	No	No	Yes
Observations	566368	566368	566368	566368	566368
R-squared	0.000	0.001	0.002	0.007	0.013

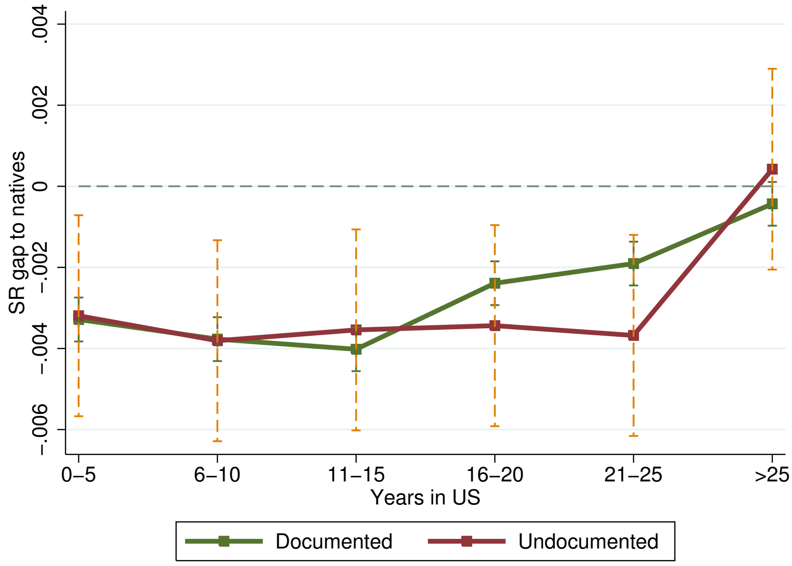
Notes: Dependent variable is the probability of a EU transition. Data come from the CPS basic files 1994-2016 and include high school dropouts aged 25-65. Demographic controls include *sex*, *race*, *age* and age^2. Standard errors are clustered at the state level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

The regression results for job finding rates (UE transitions) are reported in Table 3 and confirm the patterns seen in Figure 6: both types of immigrants find jobs faster than natives and undocumented workers even faster than documented ones. Controlling for observables does not influence the results, which are almost identical across all specifications. With the average monthly job finding probability of all workers being around 23%, the coefficients suggest that documented workers find jobs with a probability that is around one third higher than the average and undocumented workers with a probability that is even 60% higher than the average.
Analogously to Figure 4, Figure 7 plots the predicted difference in job finding rates of immigrants to natives depending on time in the US, resulting from a regression with an interaction between the immigrant dummies and 6 categories for years in the US. The results are robust to taking into account the duration of stay in the US as there is a permanent difference in job finding rates of 6 to 8 percentage points between the documented and undocumented immigrants. As for wages, the gap narrows over time for both types of immigrants, although it does not disappear completely after having spent more than 25 years in the US for neither type.

Table 4 shows the regression results with EU transitions as the dependent variable. In order 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 "job loser" or "job leaver".[14] The coefficients in the model with the full set of controls suggest that documented immigrants have a 0.3 percentage points and undocumented immigrants a 0.6 percentage points lower separation probability than natives. Quantitatively, these differences between worker types are much smaller compared to the differences in job finding rates. This also holds when relating the differences to the smaller average separation probability, which is around 1.6%.

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

Figure 8: Separation rate gap to natives



Notes: The wage gaps result from a regression with the same controls as in column (5) of Table 2 including workers with at most high school. Vertical dashed lines show 10% confidence intervals.

Figure 8 plots the predicted difference in separation rates of immigrants depending on length of stay in the US. Conditional on time in the US, there is no significant difference in separation rates between immigrants. Both documented and undocumented workers have lower separation rates initially and fully catch up to natives after more than 25 years in the country.

3.3 Reservation Wages

In the Mortensen-Pissarides search and matching model (Mortensen and Pissarides, 1994), the utility of a worker does not only depend on wage earnings but also on the probability of finding a job and the expected length of the job spell. Thus, besides wages, job finding and separation rates are crucial determinants of the values of working and searching for a job. Formally, this is summarized by the flow value for worker i of being unemployed, which in its basic form is given by:[15]

$$rU_i = z_i + f_i \frac{w_i - z_i}{r + s_i + f_i}.$$

The value depends positively on unemployment benefits z_i (which also include the value of leisure or home production and is net of job-search costs), job finding rate f_i and wage w_i (which depends on the bargaining power of a worker), and negatively on the interest rate r and the rate of job separation s_i. Being the opportunity costs to working, the flow value of being unemployed equals the reservation wage at which a worker is indifferent between staying unemployed and having a job, i.e. $\underline{w_i} = rU_i = rW(\underline{w_i})$. This equation shows how changes in the

[15]This follows from the flow value of working, given by $rW_i = w_i + s_i(U_i - W_i)$, combined with the flow value of unemployment, given by $rU_i = z_i + f_i(W_i - U_i)$.

exogenous variables z_i, r and s_i affect the endogenous variables f_i and w_i through the equilibrium mechanism. A fall of the reservation wage, e.g. because of a decrease in z_i or an increase in s_i, lowers the threat point of a worker and therefore decreases his negotiated wage. This induces job creation due to higher firm profits, which increases job finding and therefore counteracts the reservation wage decline.

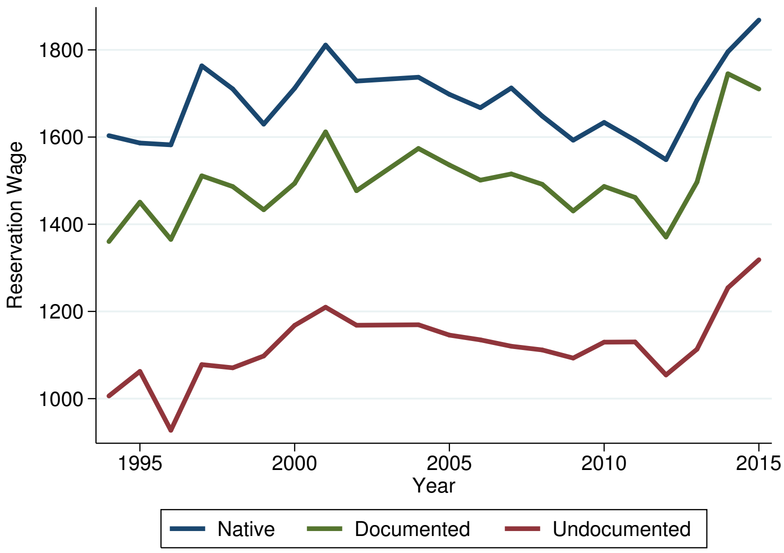
One explanation for the lower wages of undocumented compared to documented workers is that the former are characterized by a lower z_i. If low-skilled immigrants, and particularly undocumented ones, are disadvantaged relative to natives in terms of job search conditions and unemployment benefits, this lowers their reservation wage. However, as the reservation wage also depends on transition rates, it is not clear that a difference in paid wages automatically translates into a difference in reservation wages. As shown above, immigrants have higher job finding and lower separation rates, which tends to increase their reservation wages relative to natives. In order to provide some conclusive evidence on reservation wage differentials, I compute reservation wages according to the above expression for natives, documented and undocumented immigrants in each sample year.

I obtain the series of wages and transition rates by first calculating the average for natives in each year and then running regressions corresponding to the final columns of Tables 2-4, in which the coefficients of D_{it} and U_{it} are allowed to vary by year. I compute the hourly wages and monthly transition rates f_i and s_i of documented and undocumented immigrants for each year by applying the gap given by the time-varying coefficients of the respective dummies to the corresponding series calculated for natives. In order to convert hourly wage to monthly income w_i , I assume 40 hours worked per week. For simplicity, the unemployment flow payment is computed as $z_i = 0.4w_i$. The monthly interest rate is set to 0.004 as in Shimer (2005).

Figure 9 displays the resulting series of reservation wages $\underline{w_N}$, $\underline{w_D}$ and $\underline{w_U}$. Despite having the highest job finding and lowest separation rate, undocumented immigrants have by far the lowest reservation wage, which is around \$600 below the reservation wage of natives throughout the whole period. Documented immigrants on the other are only around \$200 below natives. This confirms that the negative effect of a lower wage overcompensates the positive effect of a higher job finding and lower separation rate on the reservation wage of immigrants.

While lower reservation wages can account for the observed wage differences between worker types in a standard search and matching model with random matching, it cannot account for the observed large differences in job finding rates, which are always equal across worker types. I therefore propose a model that incorporates non-random hiring in the search and matching framework in the next section. This model provides an intuitive explanation for why undocumented immigrants find jobs faster: when having the choice, firms prefer to hire undocumented workers because they can pay them lower wages.

Figure 9: Reservation Wages of low-skilled workers



Notes: The gaps underlying the calculation result from a regression with the full set of controls as in the final column of Table 2.

4 Model

This section presents a labor market model that extends the canonical search and matching framework (Mortensen and Pissarides, 1994) with a non-random hiring mechanism based on the ranking assumption of Blanchard and Diamond (1994). They depart from the assumption that matching is strictly random and instead allow 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 et al., 1985, Barron and Bishop, 1985). The ranking as well as the wage bargaining mechanisms are adopted from Barnichon and Zylberberg (2016). They assume that applicant types are ranked according to the surplus firms can extract by hiring them and when bargaining for the wage with the best type, a firm can threaten to hire the second-best applicant at his reservation wage.[16]

4.1 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 and inelastically supplies 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

[16]In Barnichon and Zylberberg (2016), firm surplus depends on the applicant type because of differing productivity levels.

are likely to have a lower bargaining power in negotiating wages.[17] Moreover, I introduce the possibility for an undocumented worker to be detected and removed. I allow the probability of detection to be potentially different for an employed and an unemployed worker.[18] I denote the rate of removal for an employed worker by λ_i^W and for an unemployed worker by λ_i^U, both being strictly positive only for $i = U$. Removal not only implies job loss (in case of being employed), but also the loss of an utility amount $R > 0$, which captures the disutility associated with being removed.

There is a large measure of risk-neutral firms, which enter the economy by posting vacancies at a cost $c > 0$. A firm paired with a worker produces output y, which is independent of the worker type. 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 $P(k) = \frac{q^k}{k!} e^{-q}$, where $q = u/v$ is the candidate to vacancy ratio ("queue length").[19] 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 (2016). 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 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 (2016). 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 making 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, 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. 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 the worker surplus S^W when a firm faces

[17] Although there is no obvious intuition behind it, I also allow the bargaining power of documented immigrants to be different from the one 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.

[18] This is motivated by evidence that under the presidency of George W. Bush, conducting worksite raids and arresting undocumented workers (with subsequent deportation in many cases) was the prevalent method to take action against illegal hiring. Under the presidency of Barack Obama, this policy changed towards targeting employers, which often led to undocumented workers being fired, but in few cases deported (see for example `http://www.nytimes.com/2010/07/10/us/10enforce.html?_r=0`).

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

more than one applicant:

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

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

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

d) *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: $S^W = \beta_D(S_D - S_N)$

e) *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: $S^W = \beta_U(S_U - S_N)$

f) *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.

4.2 Workers

Time is continuous and thus the flow value of being employed is given by:

$$rW_i = w_i + s(U_i - W_i(w)) + \lambda_i^W (U_i - R - W_i(w)). \tag{1}$$

As implied by equation (1), I assume that undocumented workers still receive their unemployment value after removal, which is not essential for the results but improves the tractability of the model.[20] The flow value of being unemployed is given by

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

[20] This can be rationalized by defining $R = \tilde{R} + U_U - U_H$, where U_H is the (exogenous) unemployment value 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_U cancels out in the term in the last bracket in equation (5). However, as this would complicate calculations, I instead assume $R = \tilde{R} + \overline{U}_U - U_H$, where $\overline{U}_U$ and therefore R are exogenous.

Table 5: Wage distribution

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

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 that we get $rU_i = rW(\underline{w}_i) = \underline{w}_i - \lambda_i^W R$. Combining this with (1) and (2) yields

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

The wage distribution F, which can be derived from the above described matching probabilities and wage bargaining mechanism, is summarized in Table 5.[21] Combining the distribution of wages with (3) and imposing $\lambda_N^W = \lambda_N^U = \lambda_D^W = \lambda_N^U = 0$, we get the reservation wages as[22]

$$\underline{w}_N = \frac{z_N + \frac{\beta_N}{r+s_N} f_1 y}{1 + \frac{\beta_N}{r+s_N} f_1} \tag{4}$$

$$\underline{w}_D = \frac{z_D + \frac{\beta_D}{r+s_D}(f_1 y + f_2(\frac{r+s_D}{r+s_N}\underline{w}_N + (1 - \frac{r+s_D}{r+s_N})y))}{1 + \frac{\beta_D}{r+s_D} e^{-\mu q_D} e^{-\mu q_U}} \tag{5}$$

$$\underline{w}_U = \frac{z_U + \frac{\beta_U}{r+s_U+\lambda^W}(f_1 y + f_2(\frac{r+s_U}{r+s_N}\underline{w}_N + (1 - \frac{r+s_U}{r+s_N})y) + f_3(\frac{r+s_U}{r+s_D}\underline{w}_D + (1 - \frac{r+s_U}{r+s_D})y)) + \Delta\lambda R}{1 + \frac{\beta_U}{r+s_U+\lambda^W} e^{-\mu q_U}} \tag{6}$$

If all workers were identical, i.e. $z_N = z_D = z_U$, $\beta_N = \beta_D = \beta_U$ and $\lambda^W = \lambda^U = 0$, 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, 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 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

[21] The wage of a documented immigrant in case 2) 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 firm surplus when hiring a documented immigrant with the firm surplus when hiring a native paying his reservation wage. The derivation is analogous for undocumented immigrants' wages in cases 2) and 3). In order to save space I define $\tilde{r}_i \equiv r + s_i + \lambda_i^W$.

[22] For the sake of simplicity, I drop the redundant subscripts of λ_U^W and λ_U^U.

of vacancies filled by worker type i. The probabilities of a vacancy being filled by a native, documented and undocumented immigrant are given by f_2, f_3 and f_4, respectively. Thus, the job finding rates are:

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

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

$$f_U = f_4 V/u_U = \frac{1 - e^{-\mu q_U}}{q_U} \tag{9}$$

4.3 Firms

The flow value of hiring a worker for a firm is given by

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

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

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

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 shown in Table 6 can again be derived for every case considering the wages paid and the respective probabilities.

Table 6: Profit distribution

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

4.4 Static 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 is u_U/u, the higher is the probability of a match with an undocumented applicant and the higher are expected firm profits. Hence, an increase in u_U with u_N and u_D being constant leads to an increase in vacancies that is overproportional to the increase of the total unemployment pool and thus a higher labor market tightness. It is less obvious what the effect of a relative increase of u_D on the equilibrium is. If documented immigrants' wages are relatively close to natives' wages, expected firm profits decrease and labor market tightness falls. If on the contrary documented immigrants' wages are relatively close to undocumented immigrants' wages, labor market tightness goes up.

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

$$\dot{u}_N = s_N(\frac{\omega_N}{P} - u_N) - f_N u_N, \tag{13}$$
$$\dot{u}_D = s_D(\frac{\omega_D}{P} - u_D) - f_D u_D, \tag{14}$$
$$\dot{u}_U = s_U(\frac{\omega_U}{P} - u_U) + u_{NU} - f_U u_U - \lambda^U u_U, \tag{15}$$
$$\dot{P} = u_{NU} - \lambda^W(\frac{\omega_U}{P} - u_U) - \lambda^U u_U, \tag{16}$$

where u_{NU} is the inflow of new undocumented immigrants, who I assume to be unemployed initially. In order to keep the population constant and obtain a static equilibrium, I set $u_{NU} = \lambda^W(\frac{\omega_U}{P} - u_U) + \lambda^U u_U$, which implies that outflows of deported immigrants are compensated by an equal amount of inflows. With the normalization $P = 1$, the steady state of the number of unemployed workers of each type is given by:

$$u_N^* = \frac{\omega_N s_N}{s_N + f_N} \tag{17}$$
$$u_D^* = \frac{\omega_D s_D}{s_D + f_D} \tag{18}$$
$$u_U^* = \frac{\omega_U(s_U + \lambda^W)}{s_U + \lambda^W + f_U} \tag{19}$$

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

5 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 a generalized method of moments. An overview of the parameter values can be found at the end of this section.

5.1 Calibration

The level of productivity y and the native population ω_N are both normalized to 1. The annual interest rate is set to 4%, implying a monthly discount factor $\delta = 0.96^{1/12}$ and $r = (1-\delta)/\delta = 0.0034$. Instead of fixing the population shares ω_D and ω_U and determining u_D/u and u_U/u from the steady state equation for unemployment, 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 the regression of Table 3 and these gaps will determine u_D/u and u_U/u in the model 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 of unemployment in the model can be computed by solving (20) for ω_D and (21) 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 in Hagedorn and Manovskii (2008). I follow Hall and Milgrom (2008) and Pissarides (2009) and choose a value of 71% of the average wage $\overline{w}_i$ for documented workers, yielding $z_N = 0.70$ and $z_D = 0.67$. I assume that unemployment benefits are 40% 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 my 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 4 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 $s_U = 0.025$.

In order to obtain a value of the removal rate, I use yearly figures of unauthorized immigrants that are deported through so called "interior removals" from 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 US 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 will check the robustness of the results to this case using values of R corresponding to 25% to 75% of an undocumented immigrants' lifetime utility.

5.2 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 many papers in the search literature). Hence, I impose the restriction $\frac{\omega_N}{\omega_N+\omega_D+\omega_U}\beta_D + \frac{\omega_D}{\omega_N+\omega_D+\omega_U}\beta_D + \frac{\omega_U}{\omega_N+\omega_D+\omega_U}\beta_U = 0.5$. This leaves four parameters to be estimated by matching five moments from the data: the average wages paid

Table 7: Baseline parameterization

Parameter	Definition	Value (SE)	Target
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	Unempl. flow payment	0.70	70% of wage
z_D		0.67	70% of wage
z_U		0.31	z^{UI} = 40% of native wage
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
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)	$f_N = 0.24$

to immigrants relative to natives $\overline{w}_D/\overline{w}_N$ and $\overline{w}_U/\overline{w}_N$ 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 2. 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 3. The resulting data moments are $\overline{w}_D/\overline{w}_N = 0.957$, $\overline{w}_U/\overline{w}_N = 0.874$, $f_N = 0.24$, $f_D = 0.31$ and $f_U = 0.38$.

Let $\hat{g}$ denote the 5x1 vector of data moments. Let θ denote the 4x1 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 $\hat{\theta} = \arg\min_{\theta \in R^5} \Psi(\theta)'\Psi(\theta)$. 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 $\sqrt{n}(\hat{\theta} - \theta_0) \xrightarrow{d} N(0, [D'V^{-1}D]^{-1})$, where $D = [\frac{\partial g(\theta_0)}{\partial \theta_0'}]$ and V is the covariance matrix of the data moments, i.e. $\sqrt{n}(\hat{g} - g_0) \xrightarrow{d} N(0, V)$ (Hansen, 1982). I obtain V by the Eicker-Huber-White sandwich covariance estimator and the matrix of derivatives by numerically differentiating the model at $\hat{\theta}$.[23] The resulting estimates with standard errors in parentheses and the calibrated parameters are shown in Table 7. While the wages can be matched exactly by estimating the bargaining powers 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

[23] I use the tool "Adaptive Robust Numerical Differentiation" written by John D'Errico for MATLAB: http://es.mathworks.com/matlabcentral/fileexchange/13490-adaptive-robust-numerical-differentiation

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. The reason for this is that 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 or the β_i or a combination of both has no effect on the model equilibrium.[24]

6 The Effects of Immigration

6.1 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, expected wage costs of firms and thus the number of vacancies they post change. As explained in section 4.4, expected wage cost 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 and as a result there is a strong job creation effect. The effect of documented immigration on wage costs is ambiguous as they can drive the expected wage firms have to pay up or down, depending on the parameterization. The more similar documented immigrants are to natives, the more likely they drive expected wage costs up and thus the lower is the number of additional jobs.

While the strength and sign of job creation depends on the immigrant type and the 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 a job, i.e. not being hired, rises. In particular, recalling the job finding rates given by (9)-(11) one can see that the job finding of a specific worker is affected by the queue length of all workers of the same type and the queue length 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. This can be shown analytically by taking the partial derivatives with respect to the queue lengths. For natives we have

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

[24]Chassambouli and Peri (2015) for example only allow for variation in the unemployment flow payments between worker types and have to set them to values below zero for both immigrant types in order to match the targeted wage gaps to natives. In order to avoid negative values, I allow for variation in both unemployment flow payments and wage bargaining powers.

For documented immigrants we have

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

And for undocumented immigrants we have

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

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

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

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

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

The impact of undocumented immigration on job finding rates is

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

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

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

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

6.2 Simulating Documented Immigration

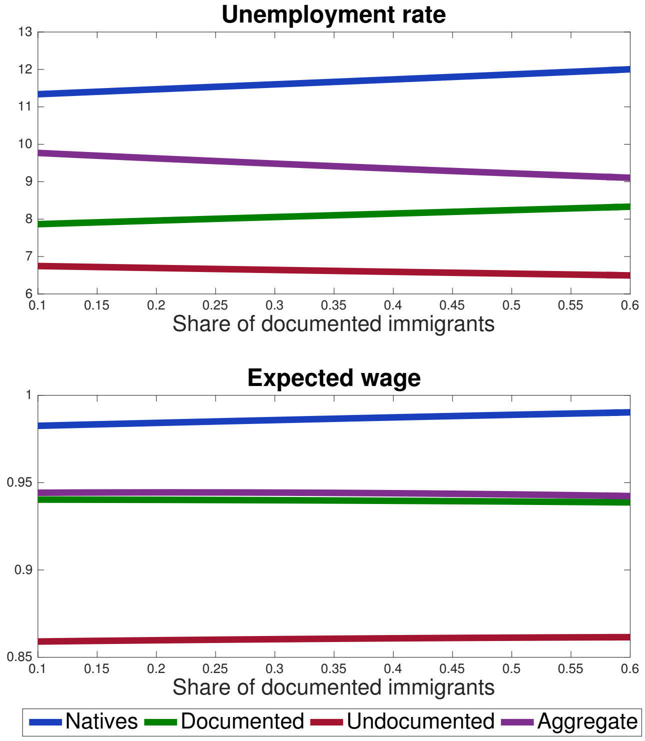
In order to find out whether the job creation or the competition effect in case of documented immigration dominates with the parameterization that replicates the data, I solve for the steady state equilibrium varying the population share ω_D. Figure 10 plots the resulting steady state unemployment rates, which are monotonic functions of the job finding rates according to equations (17)-(19), and expected wages by worker type and in the aggregate. As implied by equation (22), undocumented immigrants gain as documented immigrants pose no competition for them, which is indicated by a decreasing unemployment rate. However, the unemployment rate of both natives and documented immigrants increases, which suggests that the competition effect dominates the job creation effect. The latter is weak because the expected wage of documented immigrants is only slightly below the aggregate expected wage, implying only a small decline in wage costs when their population share rises. Therefore, only few additional vacancies are posted this does not compensate for the higher degree of job competition for natives and documented immigrants.

Despite the fall in their job finding rate, the expected wage earned by 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 he is the only applicant for a firm. This happens with probability f_1 given in Table 5, which is the only variable affecting the reservation wage of natives (see equation (4)) and positively depends on the total queue length q.[25] As documented immigration leads to some job creation, q and f_1 increase. This leads to a higher expected wage of 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. This is because if 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.[26]

[25] This can be seen from rewriting $f_1 = e^{-\mu(q_N+q_D+q_U)} \equiv e^{-\mu q}$.

[26] Note that the result of higher expected wages for natives may not hold, if natives receive a wage above the reservation wage also in case there are other natives applying for the same job. This is because the lower probability of being hired in a job that yields a surplus above staying unemployed drives down the reservation wage and thus wages paid in all jobs held by natives. This

Figure 10: Unemployment (%) and wages depending on documented immigrant share

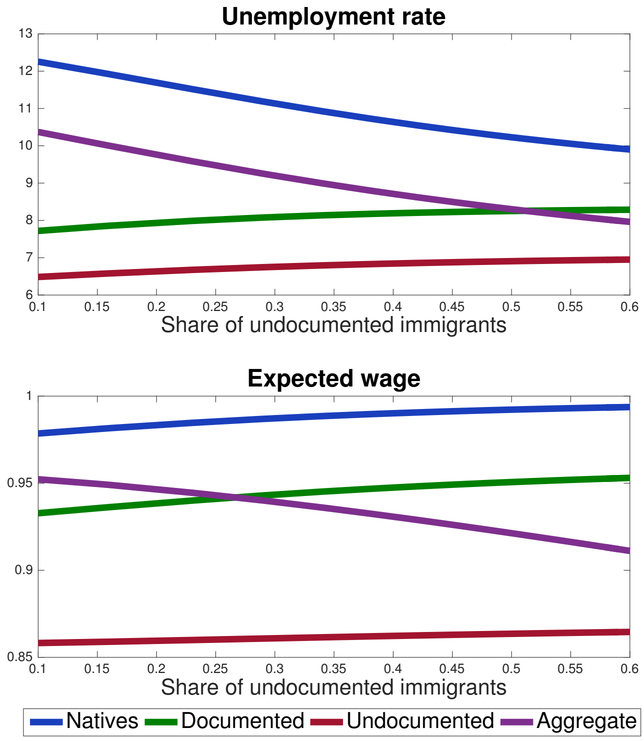


6.3 Simulating Undocumented Immigration

Figure 11 simulates the model for a varying population share of undocumented immigrants ω_U. The upper panel shows a decline in the unemployment rate of natives, which means that wages of undocumented workers are low enough so that the job creation effect dominates the competition effect. Firms post so many additional vacancies that the decline 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 immigrants increases, which indicates that the job creation effect is not dominant for them, although it is for natives. This result suggests that in this kind of framework with three worker types, the competition through the type most preferred by firms affects the type in the middle stronger than the least preferred type. As established in (25), only the competition effect is present for undocumented workers and hence their unemployment rises. Expected wages of all worker types increase because the additional vacancies posted lead to a rise in reservation wages, leading to higher wages in all jobs. Moreover, the higher total queue length results in more workers being matched to firms as only applicants and thus being in high paying jobs. As the share of workers earning the lowest wage goes up, the aggregate expected wage falls strongly, which is why the job creation effect is dominant. The combination of higher employment and higher earnings implies that the welfare of natives unambiguously increases through undocumented immigration.

result can be generated by simply assuming a minimum wage that lies above natives' reservation wage.

Figure 11: Unemployment (%) and wages depending on undocumented immigrant share



6.4 Robustness to the Calibration of R

The existence of two opposing forces whose magnitudes depend on the parameterization suggests that the findings might be sensitive to particular parameters, in particular the size of the surplus firms make by hiring undocumented workers. Therefore I next check whether the predictions of Figures 10 and 11 are robust to allowing $\Delta\lambda$ to be different from zero and to changes in the value of R. In particular, I consider the extreme case in which only employed undocumented workers can be detected and deported, i.e. $\lambda^U = 0$ and $\lambda^W = \Delta\lambda$. I recalibrate λ^W following the same method of calibration as described in section 5 but dividing monthly interior removals by the total number of employed undocumented immigrants instead of all undocumented immigrants. The resulting probability is 0.22%. As now $\Delta\lambda$ is strictly greater than zero, R always has a positive effect on $\underline{w}_U$. Thus, it affects undocumented immigrants' wages and as a consequence the wage gap between worker types. The value of R also affects job finding rates because a rise in $\underline{w}_U$ makes hiring undocumented workers more expensive, which mutes the vacancy creation effect. Therefore, it is necessary to re-estimate c, μ, β_D and β_U in order to match the moments from the data after a change in R. Figure B.1 in the Appendix shows the effects of immigration when setting R equal to 75% of an undocumented job seeker's lifetime utility U_U, which is the most extreme value I consider throughout the paper, and compares it to the benchmark calibration with $\Delta\lambda = 0$ (dashed lines). Both unemployment rates and expected wages are virtually unaffected by the choice of such a high value for R. The unemployment rate of undocumented workers is somewhat elevated as their overall separation probability $(s_U + \lambda_W)$ is now higher. Moreover, undocumented immigration has a weaker effect on vacancy creation, because the higher separation probability decreases their hiring surplus. This can be seen by a slightly flatter decrease in the unemployment rate of natives.

In sum, for any reasonable parameterization in line with the empirics, undocumented immigration is unambiguously beneficial for native workers. This is because the immigration of cheaper workers stimulates job creation and this more than offsets the negative effect of increased competition on the employment of natives. The opposite is true for documented immigration, whose job creation effect is small as expected wages paid by firms only decrease marginally.

7 The Effects of Higher Removal Risk

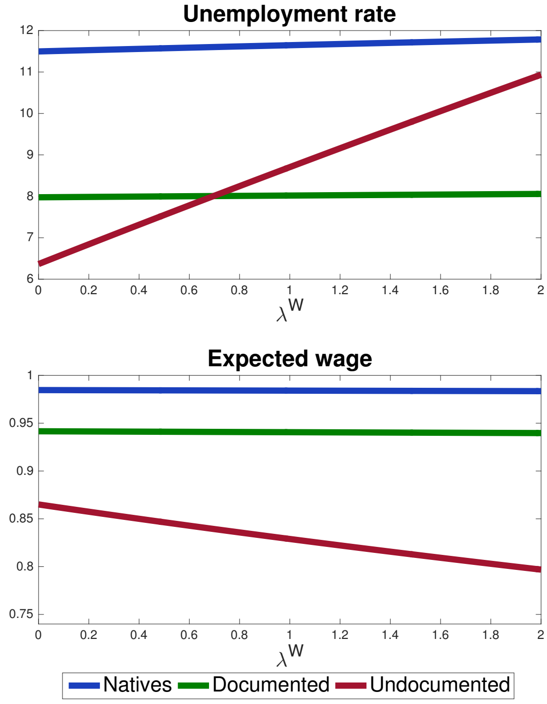
In what follows, I investigate how the equilibrium depends on the deportation risk parameters λ^W and λ^U and how their effect on the equilibrium changes with R. Recalling equation (8), we know that the effect of λ^W on undocumented workers' reservation wage is ambiguous. Given R is zero or sufficiently 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, 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 firms expect to make by hiring an undocumented worker shrinks. If $R>0$, 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.

Figures 12 shows the effect of an equal increase in both λ^W and λ^U (keeping the population share of undocumented immigrants constant).[27] As $\Delta\lambda$ remains zero, the rise in the removal rate only affects the match separation probability. An increase in this probability by one percentage points 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% 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 one percentage point increase in the removal 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 13 plots the case in which only the removal risk for employed undocumented immigrants λ^W rises. As

[27] 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 12: Unemployment (%) and wages depending on λ^W with $\lambda^W = \lambda^U$

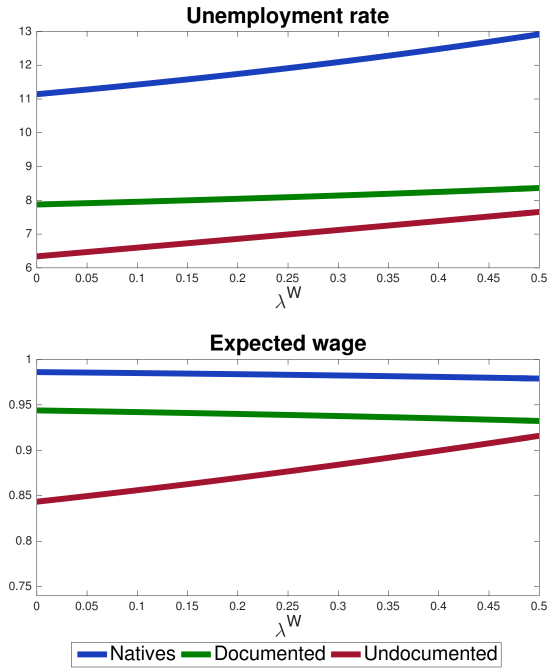


mentioned above, the sizes of the effects depend on the calibration of the disutility from removal. The larger is R, the larger is the impact of an increase in the removal risk only affecting employed workers. For the plots, I assume an intermediate removal disutility of 50% of an undocumented immigrants' lifetime utility but in the following I give the ranges of the effects of a one percentage point increase in λ^W for a removal disutility between 25% and 75% 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 and 2.5 to 2.8 percentage points for undocumented immigrants. Wages of the two former types decrease by 0.67% to 2.3% and 1.1% to 3.7%, 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. This is reflected in the rise of undocumented immigrants' wages, ranging from 5.3% to 23.7%.

Altogether, the analysis in this section suggests that increased deportation efforts lower the welfare not only for undocumented, but also for documented workers. 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.[28]

[28] I abstract from penalties because there is no evidence that they are large enough to play a significant role for firms' decisions in practice. Also, their addition to the model would bring no further insight besides enhancing the effect of a variation in λ^W.

Figure 13: Unemployment (%) and wages depending on λ^W with $\lambda^U = 0.0013$



8 Testing the Model Predictions

8.1 The Effects of Immigration

As suggested by the analysis in section 6, the model predicts that the job creation effect of undocumented immigration is stronger than the one of documented immigration. Quantitatively, the former should be large and the latter close to zero. Moreover, as a higher number of vacancies decreases the average time to find a job, which in turn increases the value of unemployment and thus the reservation wage, wages should rise more due to undocumented than documented immigration as shown in Figures 10 and 11. 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 et al. (2017).

8.1.1 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. From 2001 onwards, 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 in order to get a similar number of observations as for the previous years.[29] All samples are downloaded from IPUMS (Ruggles et al., 2010). 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

[29]The sample consists of prime-age workers living in MSAs that exist in all four time periods. The sample size is around 3 to 4 million persons in each year.

immigrants from origin country c with status $i \in \{D, U\}$ and education e between period $t-1$ and t.[30] 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

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

and the predicted population shares are

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

where $(P_{e,N,r,t} + \sum_i P^Z_{e,i,r,t})$ is the total imputed population (natives and predicted number of immigrants) in a time-education-region cell. The final instruments are the changes in theses 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 OnLine (HWOL) data series. A version of these data are used in Barnichon and Figura (2015) and were provided in digital form ready for empirical analysis 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 Appendix Table B.1. A caveat for using these data is that they pool together vacancies targeting workers of all education levels, while the predictions of my model as well as the population sample are restricted to low-skilled workers. The other dependent variables are the log changes in the wages of low-skilled natives, documented and undocumented immigrants. In order to account for selectivity bias due to changes in the 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 $\tilde{w}_{e,U,r,t}$.

[30]Thus, the inflows are net of out-migration.

8.1.2 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, $\eta_{U,r,t}$ the undocumented immigrant share and ϕ_t year fixed effects. The first-stage regressions are

$$\begin{aligned}
\Delta\eta_{D,r,t} &= \delta_{10} + \delta_{11}\Delta\eta^Z_{D,r,t} + \delta_{12}\Delta\eta^Z_{U,r,t} + \phi_{1,t} + \varepsilon_{i,r,t}, \\
\Delta\eta_{e,U,r,t} &= \delta_{20} + \delta_{21}\Delta\eta^Z_{D,r,t} + \delta_{22}\Delta\eta^Z_{U,r,t} + \phi_{2,t} + \varepsilon_{i,r,t}.
\end{aligned}$$

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 the movement of natives workers. Furthermore, in the theory part I only compare long-run steady states. If immigrants join the pool of the unemployed upon arrival, 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 initially 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, 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 et al. (2017). 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 specification becomes

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

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 a change in the MSA population share of documented and undocumented immigrants, respectively. The first-stage regressions are

$$\begin{aligned}
\Delta\eta_{D,r,t} &= \tilde{\delta}_{10} + \tilde{\delta}_{11}\Delta\eta^Z_{D,r,t} + \tilde{\delta}_{12}\Delta\eta^Z_{U,r,t} + \tilde{\delta}_{13}\Delta\eta^Z_{D,r,t-1} + \tilde{\delta}_{14}\Delta\eta^Z_{U,r,t-1} + \tilde{\phi}_{1,t} + \varepsilon_{i,r,t}, \\
\Delta\eta_{U,r,t} &= \tilde{\delta}_{20} + \tilde{\delta}_{21}\Delta\eta^Z_{D,r,t} + \tilde{\delta}_{22}\Delta\eta^Z_{U,r,t} + \tilde{\delta}_{23}\Delta\eta^Z_{D,r,t-1} + \tilde{\delta}_{24}\Delta\eta^Z_{U,r,t-1} + \tilde{\phi}_{2,t} + \varepsilon_{i,r,t}, \\
\Delta\eta_{D,r,t-1} &= \tilde{\delta}_{30} + \tilde{\delta}_{31}\Delta\eta^Z_{D,r,t} + \tilde{\delta}_{32}\Delta\eta^Z_{U,r,t} + \tilde{\delta}_{33}\Delta\eta^Z_{D,r,t-1} + \tilde{\delta}_{34}\Delta\eta^Z_{U,r,t-1} + \tilde{\phi}_{3,t} + \varepsilon_{i,r,t}, \\
\Delta\eta_{U,r,t-1} &= \tilde{\delta}_{40} + \tilde{\delta}_{41}\Delta\eta^Z_{D,r,t} + \tilde{\delta}_{42}\Delta\eta^Z_{U,r,t} + \tilde{\delta}_{43}\Delta\eta^Z_{D,r,t-1} + \tilde{\delta}_{44}\Delta\eta^Z_{U,r,t-1} + \tilde{\phi}_{4,t} + \varepsilon_{i,r,t}.
\end{aligned}$$

8.1.3 First Stage Results

Table 8: First stage

	IV		JRS IV			
	(1)	(2)	(3)	(4)	(5)	(6)
	Doc. share	Undoc. share	Doc. share	Undoc. share	(Doc. share)$_{t-1}$	(Undoc. share)$_{t-1}$
(Doc. share)^Z	0.598***	0.061	0.490***	0.352*	0.455***	0.023
	(0.071)	(0.276)	(0.065)	(0.183)	(0.128)	(0.104)
(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)
(Doc. share)$^Z_{t-1}$			0.069	0.356**	0.438***	-0.049
			(0.063)	(0.139)	(0.045)	(0.121)
(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-squared	0.659	0.498	0.716	0.486	0.848	0.918
F-stat.	38.13	75.75	51.44	7.04	112.2	172.6
SW F-stat.	13.94	62.07	11.08	29.38	18.87	176.4

Notes: Population data are from the US Census 1980-2000 and ACS 2009-2011 and include high school dropouts participating in the labor force. The sample consists of 33 MSAs, for which data on job openings are available. Standard errors are clustered at the MSA level. The observations are weighted by MSA population. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 8 shows the results of the first stages for the conventional IV model and the model of Jaeger, Ruist and Stuhler (2017), henceforth called JRS IV. In both models, the instruments have positive and significant effects on the shares they are supposed to predict as indicated by the coefficients on the diagonals in the left-hand and the right-hand side of the table. Throughout all equations except the one in column (4), the F-statistics are above 10. The Sanderson-Windmeijer (SW) F-statistic is testing whether the effects of the endogenous variables can be separately identified in case of more than one endogenous variable. The values reported in the last row of the table indicate that indeed the endogenous regressors are identified.

8.1.4 Second Stage Results

Table 9 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 the IV models. The coefficient in the preferred specification in Panel C indicates an increase in vacancies of around 2.1% due to a one percentage point increase in the population 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%.[31] The coefficient of the documented immigrant share in column (1) is strongly negative in the OLS and IV model and insignificant in the JRS IV model. This result is a deviation from the model, which predicts that the impact of documented immigration on vacancies should be positive as well, albeit small (around 0.3%).

[31]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 to 0.6 while holding the other share constant)

Table 9: Second stage

	(1) Vacancies	(2) Native wage	(3) Doc. wage	(4) Undoc. wage
Panel A: OLS				
Doc. share	-4.834***	-0.291	-0.542*	-0.729**
	(1.068)	(0.2500)	(0.328)	(0.359)
Undoc. share	2.108***	0.578***	0.267*	0.267*
	(0.259)	(0.056)	(0.153)	(0.137)
Observations	99	99	99	97
R-squared	0.792	0.314	0.053	0.130
Panel B: IV				
Doc. share	-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-squared	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)
(Doc. share)$_{t-1}$	-6.097	0.830*	-0.158	0.305
	(3.872)	(0.456)	(0.585)	(0.676)
(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-squared	0.887	0.500	0.089	0.110

Notes: Population data are from the US Census 1980-2000 and ACS 2009-2011 and include high school dropouts participating in the labor force. The sample consists of 33 MSAs, for which data on job openings are available. Standard errors are clustered at the MSA level. The observations are weighted by average MSA population. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

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% to 0.38% in Panel C, these wage effects are much stronger than the theoretical predictions, which are around 0.03%. The effect of documented immigrants on native wages is negative (but only significant at the 10% level), whereas the theory would predict a small positive effect of 0.01%. However, there is no significant effect on immigrants' wages, which is in line with the predictions (see Figure 10).

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%

and the long-run impact of documented immigration around -0.3%. 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 even have the same signs as the contemporaneous responses, suggesting that there is no counteracting adjustment in vacancy posting over time.

In sum, the finding of a positive and significant effect of a rise in the undocumented immigrant population share on vacancies and wages, which holds using an OLS model as well as an IV strategy, is in line with the theory. Moreover, such positive effects are not found for the documented immigrants, which is consistent with the prediction that the impact of documented immigration on vacancy creation and wages is weak. Only the significant negative effect of documented immigration on native wages constitutes a qualitative deviation from the prediction of a small positive effect. However, this prediction from the theory is not as clear-cut as the prediction for the wage effect of undocumented immigration because a slightly different parameterization (that raises the wages of documented immigrants closer to the wages of natives) can potentially lead to a sign switch. Altogether, the validity of the model and in particular the central result of this paper is supported by the data: among low-skilled workers, undocumented immigration has a strong job creation effect and therefore benefits natives in terms of both employment opportunities and wages.

8.1.5 Robustness checks

The analysis conducted above differs from the extensive literature employing the previous settlement instrument with respect to the measurement of immigration. While most studies examine immigration in a perfect competition model, in which the increase in the mere supply of workers affects the equilibrium wage, I examine immigration in a model, in which only the change in the composition of the worker supply but not its size matters for the equilibrium. This is why my empirical measurement of immigration is the change in the population share and not the inflow rate, i.e. the change in the number of immigrants in a region divided by the initial population level. These two measure can be very different as the former takes into account changes in overall population. This is particularly important when concentrating on one skill-level only because in this case population levels not only change due to demographic factors but also due to skill upgrading over time.

In order to check whether the results also hold using the traditional measurement of immigration, I repeat the regressions with the inflow rates $m_{i,r,t} = I_{i,r,t}/P_{r,t}$ as endogenous regressors and predicted inflow rates $m^Z_{i,r,t} = I^Z_{i,r,t}/P_{r,t}$ as instruments. If changes in the low-skilled populations do not systematically differ across MSAs, the differences between the measures $m_{i,r,t}$ and $\Delta\eta_{i,r,t}$ should be absorbed by the year fixed effects and the results be similar. The second stage results shown in Table 10 (first stage in Appendix Table B.2) are indeed consistent with the ones in Table 9. The only notable difference is that now undocumented immigration has no significant effect on vacancies using the conventional IV strategy in Panel B. Thus, also measuring immigration by the inflow rate yields supporting evidence for the model predictions.

Table 10: Second stage with immigrant inflow rates as regressors

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

Notes: Population data are from the US Census 1980-2000 and ACS 2009-2011 and include high school dropouts participating in the labor force. The sample consists of 33 MSAs, for which data on job openings are available. Standard errors are clustered at the MSA level. The observations are weighted by average MSA population. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

As a second robustness check, I change the base period for the distribution of immigrants, according to which the national inflows are allocated to MSAs. Instead of taking the distribution in the initial year, I take the distribution in the year 1980 for the allocation of all national inflows in the periods 1980-1990, 1990-2000 and 2000-2010. The estimation results for the first and second stages with the recalculated instruments are shown in Appendix Tables B.3 and B.4. Now, in Panel B the effect of the share of undocumented immigrants on vacancies and immigrants' wages is not significant. However, the coefficients in Panel C are qualitatively unchanged. Quantitatively, the response of vacancies is somewhat smaller and the response of wages somewhat larger compared to Table 9.

8.2 The Effects of Higher Removal Risk

Section 7 has shown that, at least qualitatively, the prediction that job finding rates of all workers fall when the removal risk increases does not depend on the assumption that this risk is the same for employed and unemployed workers nor on the assumption that there is a disutility from removal.[32] However, the prediction on wages does depend on these assumptions: if $\Delta\lambda = 0$, a higher removal risk decreases undocumented immigrants' wages, whereas if only λ^W (and thus $\Delta\lambda$) increases, their wages are predicted to rise. Finding a negative effect of an exogenous increase in the removal risk on the job finding rate of both workers types and on wages of documented workers would provide evidence that the job creation effect of undocumented immigration exists. Given the model is correct, finding a positive effect of a removal risk shock on the wages of undocumented immigrants would suggest that firms indeed have to pay them a risk compensation.

A possible source of variation in the deportation risk is provided by a change in state-wide immigration legislation. Good (2013) examines the impact of omnibus immigration laws (introduced in eleven US states since 2006) on population and employment of different demographic groups. 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.[33] Although it is to the best of my knowledge not verified whether these laws have an impact on the removal risk, Good (2013) states that they have a nature of "in general creating an environment in which there is a constant threat of document verification and subsequent deportation." (Good, 2013, p. 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 removal risk.

In order 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 3.2) including a dummy indicating immigration omnibus laws to be in force in the state of residence of a survey respondent during the interview year. I interact this dummy additionally with the immigrant indicators in order to allow the effect of omnibus immigration legislation to vary across legal status. The results are shown in Table 11. The coefficients in the third 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, documented and undocumented workers. This is consistent with the model's prediction of a rise in the unemployment rates as seen in Figures 12 and 13.[34]

[32]Recall from equation (10) that the risk compensation only depends on $\Delta\lambda$, which is why assuming $\Delta\lambda = 0$ is equivalent to assuming $R = 0$ (apart from the welfare of undocumented workers, which varies with R but does not influence the equilibrium).

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

[34]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 consistent with the regression results.

Table 11: 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 x omnibus	0.050*	0.034*	0.022	0.019**	0.007
	(0.0288)	(0.0199)	(0.0134)	(0.0091)	(0.0111)
Undocumented x omnibus	0.048*	0.043	0.014	0.012	0.005
	(0.0272)	(0.0379)	(0.0326)	(0.0299)	(0.0293)
Demographics	No	Yes	Yes	Yes	Yes
Year/State FE	No	No	Yes	Yes	Yes
Ind/occ FE	No	No	No	Yes	No
Ind x occ FE	No	No	No	No	Yes
Observations	75634	75634	75634	75634	75634
R-squared	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^2. Standard errors are clustered at the state level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Finally, I rerun the wage regressions including the omnibus law indicator and interactions as regressors. The results in Table 12 suggest a drop in natives' wages of 5.1% 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% (=0.104-0.051). This is consistent with the prediction of Figure 13 that a higher removal risk leads to higher wages for undocumented workers. However, the coefficient of the documented-omnibus interaction, which indicates a wage increase of 1.9%, is not consistent with the model. If omnibus immigration laws only affect the removal risk of undocumented immigrants, this coefficient should be zero. One reason for a positive coefficient could be that even legal immigrants who are non-citizens can be subject to removal under certain circumstances and therefore might perceive the removal risk as higher even though omnibus immigration laws mostly target undocumented immigrants. This possibility is further backed up by a study by Arbona et al. (2010) who surveyed documented and undocumented Latin American immigrants living in Texas and find that the reported levels of deportation fear are similar for both groups.

Table 12: 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 x omnibus	0.063**	0.070***	0.084***	0.073***	0.070***
	(0.0318)	(0.0244)	(0.0220)	(0.0182)	(0.0193)
Undocumented x omnibus	0.092***	0.097***	0.117***	0.104***	0.104***
	(0.0294)	(0.0272)	(0.0252)	(0.0238)	(0.0282)
Demographics	No	Yes	Yes	Yes	Yes
Year/MSA FE	No	No	Yes	Yes	Yes
Ind/occ FE	No	No	No	Yes	No
Ind x occ FE	No	No	No	No	Yes
Observations	68563	68563	68563	68563	68563
R-squared	0.051	0.137	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^2. Standard errors are clustered at the metropolitan area level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

9 Conclusion

Three trends have characterized immigration into the US during the last few decades: a strong increase in the immigrant population share, a shift in the composition towards low-skilled immigrants and an increase in the share of undocumented immigrants. Previous literature has largely concentrated on the different skill composition of immigrants but thus far provided little evidence on the potential differential effects of immigrants on natives depending on their legal status. This paper fills this gap by analyzing the distinct labor market effects of documented and undocumented immigration in a unified framework, which generates predictions that are consistent with a number of key patterns documented in the data.

I argue that legal status is an important factor for explaining differences in labor market outcomes by showing that low-skilled immigrants earn less and have higher job finding rates than low-skilled natives and that these differences are larger for undocumented than for documented immigrants. As differentials in the job finding rates are at odds with a standard random matching mechanism, I propose a job search model with non-random hiring that is consistent with these findings. I allow immigrants to have a lower wage bargaining power than natives and undocumented immigrants to further have a lower unemployment value as well as a risk of being removed. The model is parameterized by matching the wage and job finding rate gaps found in the data. As immigrants accept the lowest wages, firm always prefer to hire them when having the choice. An increase in the immigrant population share has two opposing effects on the speed of job finding. On the one hand, firms create additional vacancies because average wage costs are pushed downwards, which increases the job finding rates of all workers. On the other hand, the higher competition for jobs through cheaper workers decreases the job finding rates of all equally or more expensive workers. A model simulation shows that the job creation effect dominates the competition effect of undocumented immigration, implying overall gains 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 city population shares on vacancies and wages among low-skilled workers and find qualitative support for the results.

A policy of stricter immigration enforcement, simulated by a rise in the removal 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. With a one percentage point higher removal rate, the unemployment rate of natives increases by 0.14 percentage points in case the removal rate rise is the same for unemployed and employed undocumented immigrants. This effect augments to 1.7 to 5.7 percentage points in case the rate rises only for the employed, whereby the exact value depends on the assumed size of the disutility from removal. The change in natives' wages is virtually zero in the first case and around -0.67% to -2.3% in the second case. In the latter case, the impact is larger because undocumented immigrants' wages go up due to a risk premium for accepting a job and as a consequence job creation falls more. To test these predictions qualitatively, I examine the effect of the introduction of state-wide omnibus immigration laws and find a decrease in job finding rates for all workers, a decrease in wages for natives and an increase in wages for undocumented immigrants. This is consistent with muted vacancy creation and a risk premium in undocumented immigrants' wages. However, I find that omnibus immigration laws also have a small positive effect on the earnings of documented immigrants, which contradicts the model and warrants further investigation.

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 competing low-skilled natives. 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 certainly neglects other relevant dimensions of heterogeneity between documented and undocumented immigrants that might come into effect rather in the long run. The higher prospect of a long-term stay in the US for example could incentivize immigrants with legal status to invest in their education and country-specific skills, move to more productive jobs or become entrepreneurs, all of which is likely to increase their productivity and have positive spillovers on natives. Moreover, the potential effects on high-skilled workers are not considered in this paper. This leaves many avenues for future research on undocumented immigration, potentially facilitated by better data methods or new policy experiments of the US administration.

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Appendix

A Educational Attainment and Accuracy of the Identification Method

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

	Pew file	Borjas method	
	CPS March	CPS March	CPS Basic
< High school (%)	42.0	39.5	39.8
High school (%)	28.8	26.9	25.8
Some college (%)	13.2	13.5	13.3
College (%)	16.0	20.1	21.0
% of population	5.4	5.7	5.6

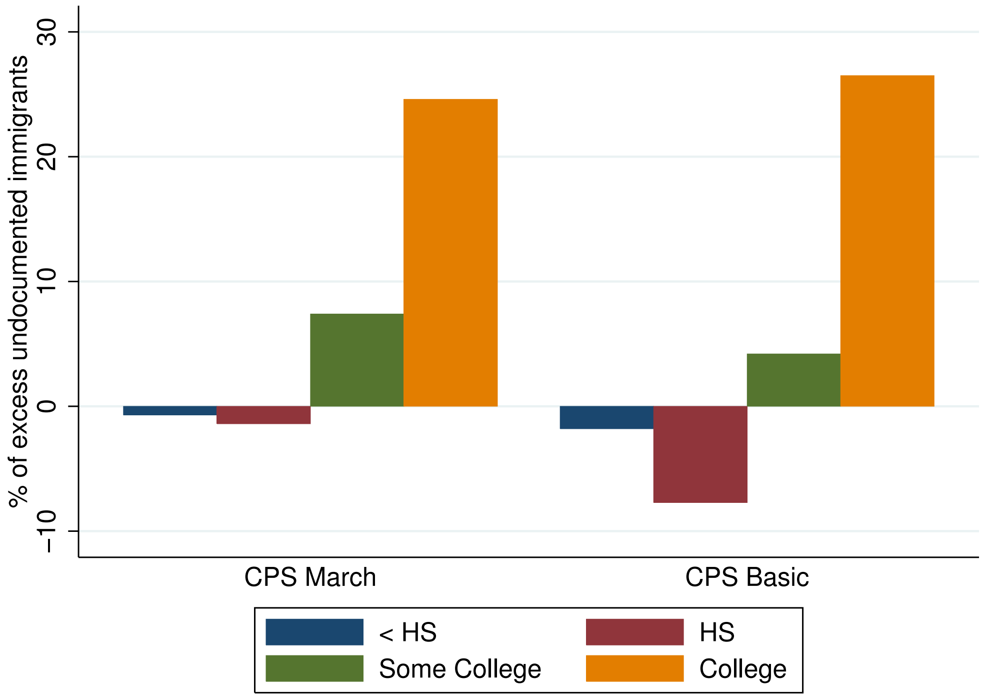
Notes: Following Borjas (2016) the statistics are calculated using a sample of individuals aged 20-64 from the years 2012-2013. The statistics from the Pew file are taken from Borjas (2016, Table 1)

In this Appendix section, I investigate how accurate Borjas' identification method is depending on the educational attainment of immigrants. The benchmark against which I make a comparison is the Pew CPS March file of the years 2012-2013, which includes the undocumented immigrant identifier developed by Passel and Cohn (2014). The description of its construction in Appendix C in their paper is not detailed enough to allow a replication of their method. However, Borjas was granted access to their datafile and presents some summary statistics based on it in Borjas (2016, Table 1).

Table A.1 shows the distribution of undocumented immigrants across education levels and their total population share in the Pew CPS March, the Borjas CPS March and the CPS basic monthly files. In the CPS basic, I use all variables that are also used by the Borjas identification method except the ones related to social security benefits or health insurance, because these are exclusively available in the CPS March. Compared to the Pew CPS March, the education level of undocumented immigrants is higher in both the Borjas CPS March and the CPS basic. In particular, the share of college graduates is around 4 percentage points (or 25%) higher in the former and 5 percentage points (or 31%) higher in the latter, whereas the shares of both high school dropouts and high school graduates are lower. Moreover, in both datasets the total population share of undocumented immigrants, shown in the last row, is somewhat higher than in the Pew CPS March. This indicates that too many high-skilled immigrants are classified as undocumented by the simplified Borjas method.[35] In the CPS basic, the total population share is somewhat lower than in the CPS March, which is unexpected as the absence of some variables for the identification of documented immigrants should lead to an additional excess of immigrants classified as undocumented. The fact that there is no excess compared to the CPS March suggests that there

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

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



Notes: The excess percentages are calculated by comparing the population shares of undocumented immigrants with a certain education levels in the CPS March and CPS Basic data using the simplified Borjas (2016) identification method against the corresponding shares in the Pew CPS March file, which are calculated with the figures shown in Table A.1 as described in the text.

is little difference in the accuracy of the identification method in the CPS basic data due to the missing variables.

The sample statistics in Table A.1 allow to quantify the difference between the sample size of undocumented immigrants classified by the Borjas method in the CPS March/basic and the sample size of undocumented immigrants classified by the Pew CPS March for each education level. The population share of undocumented immigrants with education level e can simply be calculated by multiplying their total population share with the share of undocumented immigrants having education level e. Thus, the population share of undocumented immigrants that hold a college degree is $0.054 \cdot 0.16 = 0.00864 = 0.864\%$. The corresponding value for the Borjas CPS March is around 1.15%. Hence, if we believe that the Pew CPS March file identifies all undocumented immigrants correctly, around 25% ($= (1.15 - 0.864)/1.15$) of college educated immigrants are falsely identified as undocumented in the Borjas CPS March.

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

B Tables and Figures

Table B.1: List of MSAs used in section 8.1 and immigrant population shares among low-skilled

MSA	Documented imm. (%)				Undocumented imm. (%)			
	1980	1990	2000	2010	1980	1990	2000	2010
Baltimore, MD	1.8	2.7	3.8	9	.6	1.3	3.2	11.6
Birmingham, AL	.3	.6	2	3.7	.1	.5	3.6	14.7
Boston, MA/NH	12.9	15.1	19.6	23.4	5.9	12.2	15.9	24.4
Charlotte-Gastonia-Rock Hill, NC/SC	.7	1.5	5.6	11.2	.4	1.1	12.9	21.5
Chicago, IL	10.4	14.9	19.7	24.6	7.9	15.1	23.3	29.2
Cleveland, OH	5.9	5.6	3.8	5	1.5	1.8	2	3.4
Columbus, OH	1.6	1.6	4	7.2	.4	.9	4.6	9.4
Dallas-Fort Worth, TX	3.9	12	17.4	23.4	3.7	13.9	27.8	37
Denver-Boulder, CO	4.5	7.4	13.4	16.4	2.3	5.3	21.6	30.9
Detroit, MI	5.1	5.2	6.8	9.9	2	2	5.2	6.6
Hartford-Bristol-Middleton- New Britain, CT	14.5	19.1	18.7	19.3	6.3	10.4	8.2	20.5
Houston-Brazoria, TX	7	15.8	22.2	27.7	6.9	18.2	27	37.6
Indianapolis, IN	.8	1.2	2.7	7.1	.3	.4	5.4	14.3
Kansas City, MO/KS	1.9	2.8	5.2	9.3	.7	1.3	8.3	16.5
Los Angeles-Long Beach, CA	16.2	24.2	32.4	38.3	26.1	42.6	39.7	40
Louisville, KY/IN	.5	1.2	2.5	6.1	.1	.3	1.7	8.8
Memphis, TN/AR/MS	.6	.7	3.3	6.5	.1	.8	5	14.3
Miami-Hialeah, FL	46.1	52.5	56.2	57.2	6.6	18.8	19.8	23
Minneapolis-St. Paul, MN	2.3	3.5	7.9	14.3	.6	2	10.3	18.3
Nashville, TN	.5	.9	4.6	12.6	.2	.8	8.3	18.4
New York, NY-Northeastern NJ	21.3	26.6	32.1	34.8	10.2	18.3	25.8	33
Oklahoma City, OK	1.8	4.7	8.1	15.3	1	3.9	10.6	22.2
Philadelphia, PA/NJ	4.4	5	7.2	11.7	1.2	2.1	4.7	13.3
Phoenix, AZ	6.7	10.8	15.5	21	3.6	11.4	27	31.2
Pittsburgh, PA	2.8	2.8	2.3	3.3	.3	.6	.8	.8
Providence-Fall River-Pawtucket, MA/RI	12.1	18.5	19.4	24.2	10.5	15.8	12.6	19.4
Sacramento, CA	9	11.7	18.5	27.5	5.3	9.1	12.7	23.1
St. Louis, MO/IL	1.6	1.5	2.3	3.2	.2	.6	1.8	3.8
San Antonio, TX	10.4	14.3	16.1	20.4	4.8	9	12.8	19.8
San Diego, CA	14.3	20.3	27	32.8	11.3	25.9	29.1	34.8
San Francisco-Oakland-Vallejo, CA	15.8	21.7	29.2	36.7	10.3	22.9	27.9	35.7
Seattle-Everett, WA	6.2	7.6	14.6	25.9	2	5.3	11.4	21.1
Washington, DC/MD/VA	5.3	10.8	18.1	25	3.6	14.8	23	35.1

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

Table B.2: First stage with immigrant inflow rates as regressors

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

Notes: Population data are from the US Census 1980-2000 and ACS 2009-2011 and include high school dropouts participating in the labor force. The sample consists of 33 MSAs, for which data on job openings are available. Standard errors are clustered at the MSA level. The observations are weighted by MSA population. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table B.3: First stage with base period 1980

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

Notes: Population data are from the US Census 1980-2000 and ACS 2009-2011 and include high school dropouts participating in the labor force. The sample consists of 33 MSAs, for which data on job openings are available. Standard errors are clustered at the MSA level. The observations are weighted by MSA population. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table B.4: Second stage with base period 1980

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

Notes: Population data are from the US Census 1980-2000 and ACS 2009-2011 and include high school dropouts participating in the labor force. The sample consists of 33 MSAs, for which data on job openings are available. Standard errors are clustered at the MSA level. The observations are weighted by average MSA population. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

B.1 Figures

Figure B.1: Equilibrium with $\lambda^W = 0.0022$, $\lambda^U = 0$ and $R = 75\%$ of U_U

Documented immigration: Undocumented immigration: