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

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Abstract

This paper presents novel evidence on the effect of legal status on workers' labor market outcomes in the US and explores the impact of undocumented immigration in a labor market model featuring search frictions and non-random hiring. Firms receive applications from documented and undocumented workers and hire the worker they can extract the largest surplus from. As undocumented workers have a lower reservation wage due to their ineligibility for unemployment benefits, lower wage bargaining power and risk of being detected and removed, their wages are lower and job finding rates higher, which is consistent with the empirical evidence. An increase in the share of undocumented immigrants leads to the creation of additional jobs, but also more competition for documented job seekers. When calibrated to US data, the job creation effect dominates and undocumented immigration benefits documented workers. An increase in the removal rate mutes job creation and thus lowers the job finding rate of all workers. This detrimental effect is even larger if the removal rate increases more for employed workers (e.g. through worksite raids) because this leads to a risk premium in their wages. Using the introduction of statewide omnibus immigration laws as a measure of increased removal risk, I find evidence for muted job creation and a risk premium in immigrants' wages.

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

JEL: J31, J61, J63, J64.

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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 throughout the last few decades. In the United States, the share of foreign-born residents among the population has increased from around 5% in the 1970's to over 13% today, triggered by a change in immigration policy during the 1960s facilitating entry from Latin America and Asia and causing a shift in the skill composition towards less educated immigrants. A second major shift in the nature of US immigration especially since the beginning of the 1990s is 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 labor market, constituting around 5% of the labor force.[2]

The goal of this paper is to shed new light on the labor market impact of undocumented immigration and on the question whether stricter immigration enforcement protects documented workers. I first present novel evidence on the effect of documentation status on workers' labor market outcomes and then analyze the effects of undocumented immigration in a labor market model featuring search frictions and non-random hiring consistent with the empirical findings. In this framework, the immigration of undocumented workers leads to increased job creation but also poses higher job competition for documented workers. These effects are both induced by lower reservation wages of undocumented workers and have opposing effects on the employment of documented workers. Calibrated to US data, the model suggests that undocumented immigration is beneficial for documented workers because of a dominating job creation effect.

[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.

Stricter immigration enforcement that leads to a higher deportation (or "removal") probability mutes job creation, even more so if this policy targets rather employed than unemployed undocumented workers.

My first contribution to the literature consists in showing that documentation status is an important driver of labor market outcome differences across workers. In particular, I find that undocumented immigrants earn lower wages and have higher job finding rate 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 a higher job finding rate (for both types of immigrants). These findings suggest a connection between low wages and high job finding rates and are to the best of my knowledge novel in the literature. The second contribution is the analysis of the impact of undocumented immigration in a search and matching model featuring non-random hiring that is consistent with the empirical facts. I assume that workers are either documented or undocumented and that the latter have a lower reservation wage than the former. This explains the wage gap between the two worker types. 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, 2014) in my framework, which implies that firms can receive multiple applications and choose their preferred candidate among them (Barron et al. 1985, Barron and Bishop 1985). This generates higher job finding probabilities and employment rates for cheaper workers as suggested by the data.

The key characteristics implying a lower reservation wage for undocumented workers are ineligibility for unemployment benefits, a lower wage bargaining power and a risk of removal, whereby most of the reservation wage gap is driven by the bargaining power difference. Due to this gap, firms make a higher surplus by hiring undocumented job seekers and an increase in their share in the unemployed pool has two opposing effects: The job creation effect, which is the only effect present in the standard framework, induces firms to create more vacancies as expected wage costs fall and therefore leads to higher wages and job finding rates for all workers. The competition effect on the other hand, which is only present once we allow for non-random hiring, lowers documented workers' job finding as there is a higher probability of competing with an undocumented applicant. Which of the two effects dominates depends on the size of the reservation wage difference between the worker types. The higher are the wage costs that firms can save by hiring an undocumented instead of a documented worker, the stronger is the job creation effect and the more beneficial is undocumented immigration. After calibrating the model to match the data, I simulate an increase in the population share of undocumented immigrants and find that the job creation effect dominates the competition effect because the wage difference is large enough and expected wage costs of firms fall strongly. Hence, undocumented immigration is unambiguously beneficial for documented workers as it raises their job finding rates and wages.

Finally, I use the framework to simulate a policy of stricter immigration enforcement by increasing the removal risk. One effect of this is an increase in the break-up probability for matches with undocumented workers, which lowers job creation and depresses job finding rates and wages of all workers. A second effect arises, if the risk increases more strongly for employed than for unemployed undocumented workers. A higher removal rate for the employed implies that firms have to pay a risk compensation in order to induce an undocumented worker to accept a job. This compensation raises expected wage costs, decreases the expected profits from opening a vacancy and as a consequence depresses job creation and job finding rates of all workers further. This second effect is larger, the higher is the disutility associated with removal. Testing the model's predictions using the state-wide implementation of omnibus immigration laws as a measure of increased removal risk, I find that these laws are associated with a lower job finding rate for all workers, which is evidence for muted vacancy creation. Moreover, I find that they are associated with lower wages for natives and higher wages for immigrants, which is consistent with a risk compensation in immigrants' wages.

Previous studies on migration in the US often only considered the distinct skill composition or experience profiles of immigrants in their models (e.g. Borjas, 2003, Peri and Sparber, 2009, Ottaviano and Peri, 2012, Llull, 2013). However, as being undocumented is highly correlated with skills (on average undocumented immigrants have a lower education than documented ones) legal status as an additional dimension of immigrant heterogeneity should not be neglected.[3] An exception is a study by Edwards and Ortega (2016) who differentiate between documented and undocumented immigrants. Contrary 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 due to productivity differences. This is a questionable assumption as there are various other explanations for lower earnings of undocumented workers that are not related to productivity. Since the undocumented are not legally permitted to work, firms are not bound to any minimum wage laws and might use the threat of being sanctioned for hiring them to justify paying lower wages. Furthermore, the inability to receive unemployment benefits lowers the outside option to working and suppresses the wages of undocumented workers additionally. I therefore use a framework with search frictions that easily allows to consider these points by assuming differences in bargaining power and unemployment benefits across worker 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. The prospect of hiring workers at a lower cost 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 I find that the prediction of equal job finding rates across worker types is not supported by the data, I tackle the assumption of random hiring in this paper.

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

[3]Of course, most studies do not distinguish immigrants by legal status simply because an identifier to do so was not available. A reliable method to identify undocumented immigrants has just become recently available (see section 2.1).

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 natives, legal and undocumented immigrants are perfect substitutes only within each narrowly defined industry-occupation cell. I thereby control for imperfect substitutability within broader skill cells as emphasized by previous studies. This allows me to uncover documentation status as an additional and so far neglected dimension of 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 calibration strategy. Section 6 examines the effect of undocumented immigration of workers in the calibrated model. Section 7 explores the impact of a change 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 of identifying undocumented immigrants used. This method is first described in Borjas (2016) and 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. 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 include prime age workers (age 25 to 65) in all samples. A respondent is defined as an immigrant, if he is 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.[4] 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 the number 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). 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) based on the 2012-2013 CPS files they constructed, which he uses to identify undocumented respondents in all CPS March supplements since 1994. I follow his algorithm and replicate the undocumented status

[4] 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.

identifier in the CPS March supplement data. Borjas (2016) does not apply a filter to take care of the overcounting of undocumented immigrants in the microdata as the DHS residual method does but shows that his method yields an undocumented immigration population that is similar in terms of size and demographic characteristics to the one in Passel and Cohn (2014).

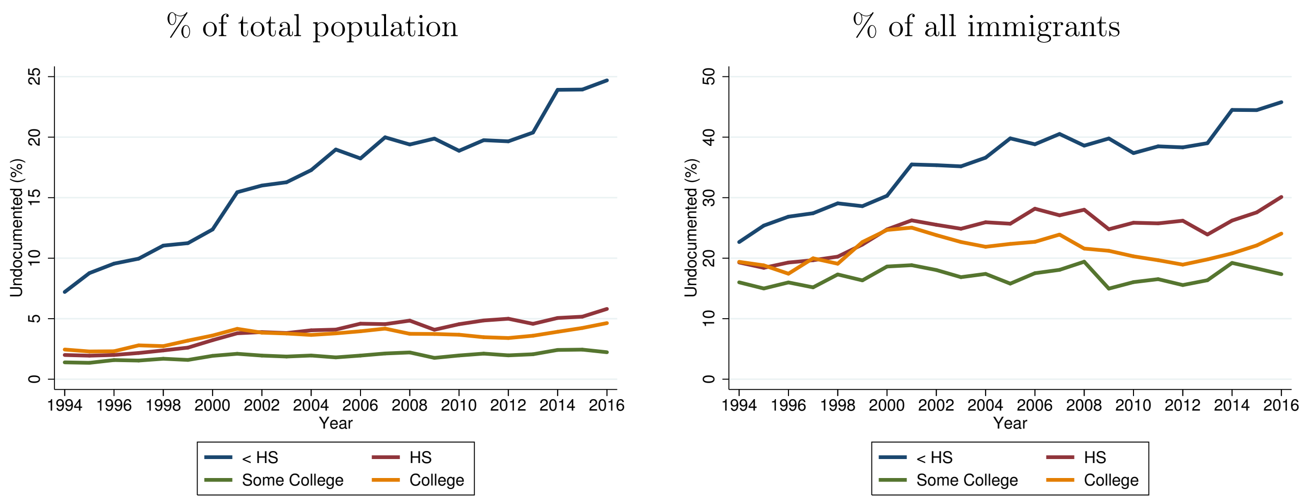
Borjas' simplified identification method consists in classifying every immigrant who does not fulfill at least one of the following condition as undocumented:

- being US citizen
- residing in the US since 1980 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

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 7% in 1994 to almost 25% in 2015. In the higher education groups, the percentage has risen only moderately, reaching just above 5% for high school and college graduates.[5] Also among immigrants, the percentage of undocumented is the largest and

[5] 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 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 1: Percentage of undocumented immigrants



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

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 is increasing over time (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. However, this is partially because all immigrants that reside in the US since 1980 or before are classified as legal.[6] 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 across the level of education education. Among undocumented high-school dropouts, 89% of workers are hispanic and this percentage decreases strongly with education. Among college

[6]This is due to the Immigration Reform and Control Act of 1986 (IRCA), which granted amnesty to all undocumented immigrants that had entered the US in 1980 or before.

Table 1: Descriptive statistics

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

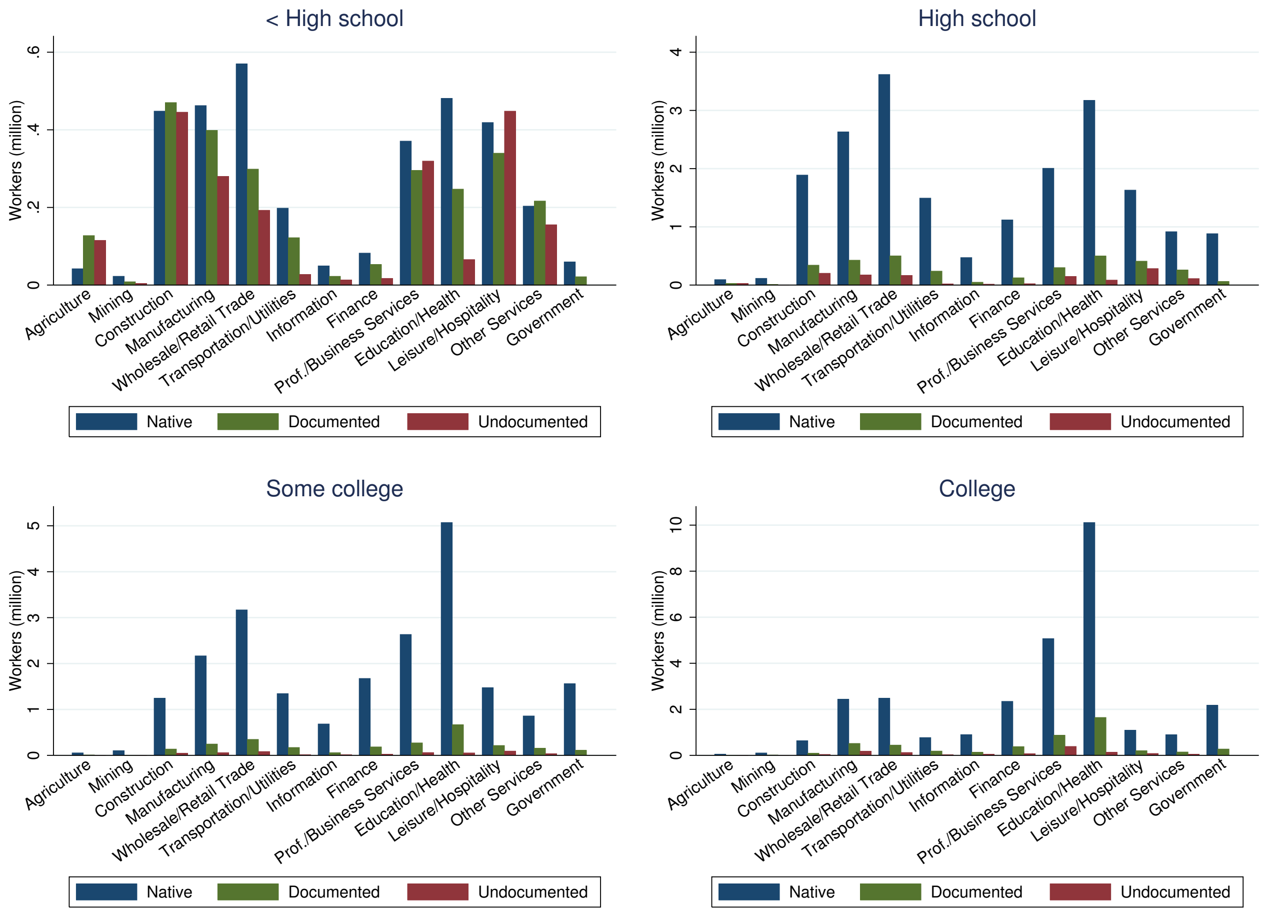
Note: The statistics are averages across the 2007-2016 CPS March supplement and drawn from the prime age worker sample described in the text.

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 worker status is associated with a concentration in different industries. I identify 13 different industries based on the one-digit level of the North American Industry Classification System (NAICS). The most salient feature of the figure is the high number of both documented and undocumented immigrant workers among high school dropouts, which is in most industries close to the number of native workers. Only Wholesale and Retail Trade, Transportation and Utilities, Education and Health as well as Government[7] 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

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

Figure 2: Worker distribution across industries by education



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

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.

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 only (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 because some of the variables used for identification like receiving social security benefits are less relevant for the high-skilled. In the Appendix I provide a back-of-the-envelope calculation of the percentage of correctly identified undocumented immigrants in each education group, which I find to be around 100% for low-skilled and only around 40%-50% for college educated workers. 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.[8]

3 Empirical Evidence

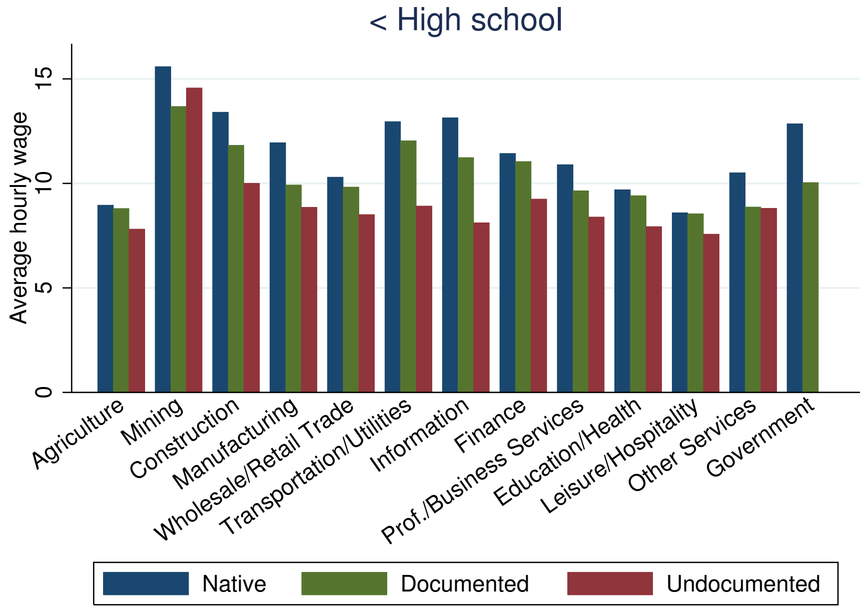
Next, I present empirical evidence supporting the claim that the labor market performance of low-skilled workers is not only affected by being an immigrant or a native but depends primarily on an immigrant's legal status. In particular, I show that low-skilled undocumented immigrants earn lower wages than both documented immigrants and natives. A wage gap between the latter two types is also existent but much smaller in size. The wage gap to natives falls throughout an immigrant's stay in the US and disappears completely after 25 years when being documented but not when being undocumented. 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 types falling in the length of stay in the country. I also find evidence of lower separation rates of immigrants, although the differences 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 differences 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, to my knowledge there exists no extensive

[8] All empirical findings in this paper also hold for high school graduates, workers with some college or using any pooled sample of workers having at most some college education.

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



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

empirical research using recent microdata that also takes into account the effect of legal status on earnings.[9] In order to fill this gap in the literature I use the CPS March supplement data with undocumented immigrants identified by the Borjas (2016) algorithm. Following previous studies (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.[10] 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 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 highest wages in all industries. With the only exception being Mining, documented immigrants have the second

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

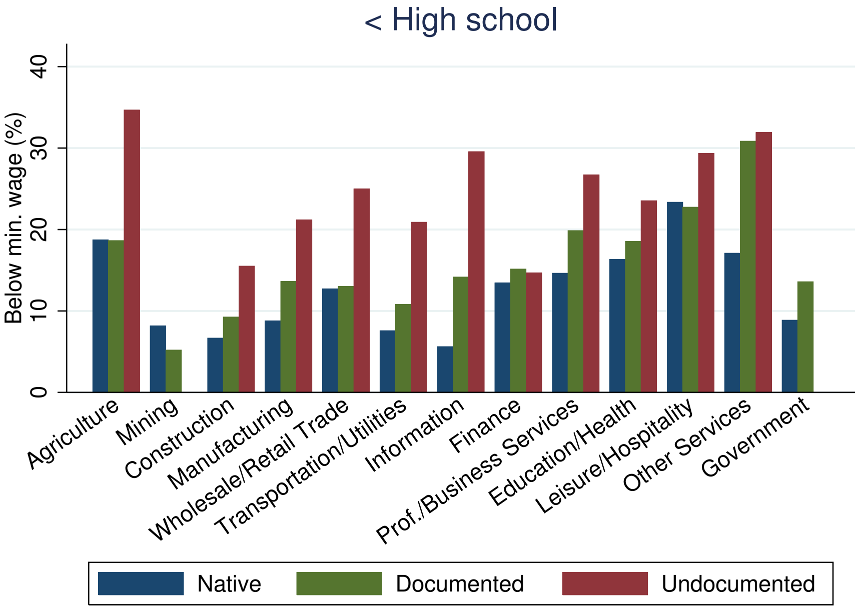
[10]Results are robust to keeping part-time workers.

highest wages, while undocumented immigrants earn the least. The lowest 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 samples differ with respect to demographic characteristics, which certainly influences their earnings. Controlling for observables beyond education and industry is therefore crucial.

Figure 4 shows the percentage of workers with hourly earnings below the minimum wage during the years 2007-2015. I define the minimum wage either as the one in force in the state a worker is residing in or as the federal minimum wage in case the latter is higher than the former in a given year. The figure suggests that 35% of undocumented workers working in Agriculture are paid below the minimum wage. In other industries with a high number of undocumented workers, the percentage lies between 20% and 30%, except in Construction. Pooling all industries, the percentage of workers earning below minimum wage is around 10 percentage points lower for documented than for undocumented immigrants and around 4 percentage points lower for documented immigrants than for natives.

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 the worker's occupation, 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, additional to industry dummies, I include a dummy for each of the around 500 occupation codes attributed to a worker 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

Figure 4: Low-skilled workers paid below minimum wage (%)



Note: The statistics are averages across the 2007-2015 CPS March supplement and drawn from the prime age worker sample described in the text.

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 earn around 12% and undocumented immigrants around 27% less than the native reference group. The inclusion of demographic controls and metropolitan area and year fixed effects shrinks the coefficients slightly. The wage differences indicated by 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] Additionally including industry and occupation fixed effects shrinks both

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

Table 2: Legal status and hourly wage of low-skilled workers

	(1)	(2)	(3)	(4)	(5)	(6)
Documented	-0.121***	-0.075***	-0.098***	-0.088***	-0.047***	-0.046***
	(0.0047)	(0.0099)	(0.0081)	(0.0075)	(0.0063)	(0.0064)
Undocumented	-0.267***	-0.206***	-0.235***	-0.204***	-0.128***	-0.125***
	(0.0051)	(0.0184)	(0.0158)	(0.0163)	(0.0131)	(0.0131)
Demographics	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
Metarea FE	No	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	No
Occupation FE	No	No	No	No	Yes	No
Industry x occupation	No	No	No	No	No	Yes
Observations	68505	68505	68505	68505	68505	68505
R-squared	0.048	0.136	0.161	0.194	0.264	0.288

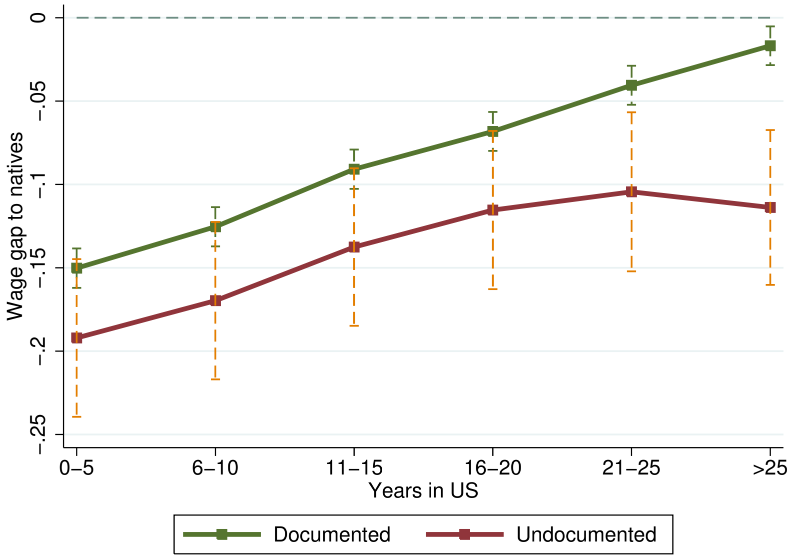
Note: Dependent variable is the logarithm of the hourly wage. Data come from the CPS March supplement 1994-2016 and include prime-age workers (25-65) without high school degree. Demographic controls include *sex*, *race*, *age* and age^2. Standard errors are clustered at the metropolitan area level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

coefficients by almost a half, which confirms that it is important to control for the different distribution of workers across jobs even conditional on demographics. Column (6) indicates that documented immigrants earn only 4.7% less than natives and the undocumented status of an immigrant accounts for an additional wage gap of 8%. Coefficients remain virtually identical when including industry-occupation interactions. This result 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

men and similar results among women.

Figure 5: Wage gap to natives



Note: The wage gaps result from a regression with the full set of controls as in column (6) of Table 2 including workers with at most a high school degree. Vertical dashed lines show 10% confidence intervals.

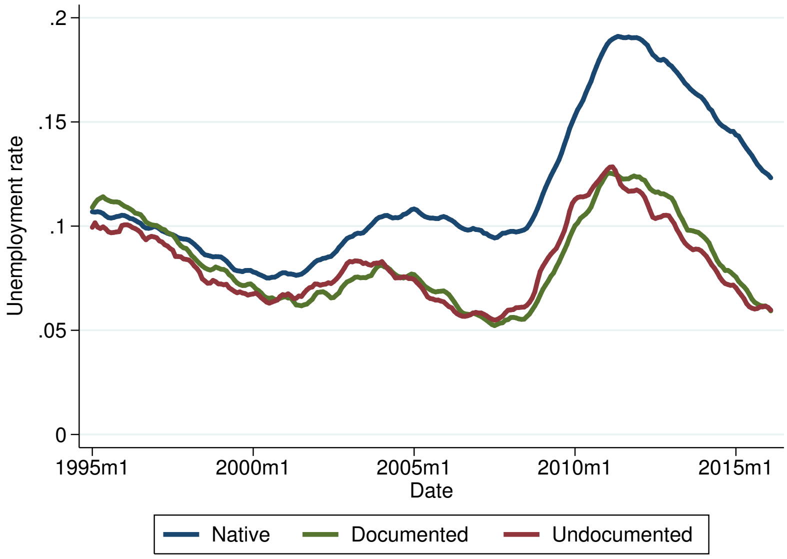
growth in hourly wages over time, I augment the wage regression by an interaction between the documented and undocumented immigrant dummies and years in US, which I group in six 5-year intervals (1-5, 6-10, 11-15, 16-20, 20-25 and >25) denoted by $y = 1, ...6$. The equation for immigrants therefore takes the following form:

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

Figure 5 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 only 2% less than natives, documented workers have almost fully assimilated after 25

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

Figure 6: Unemployment rates of low-skilled workers



Note: The series are constructed from CPS basic monthly files.

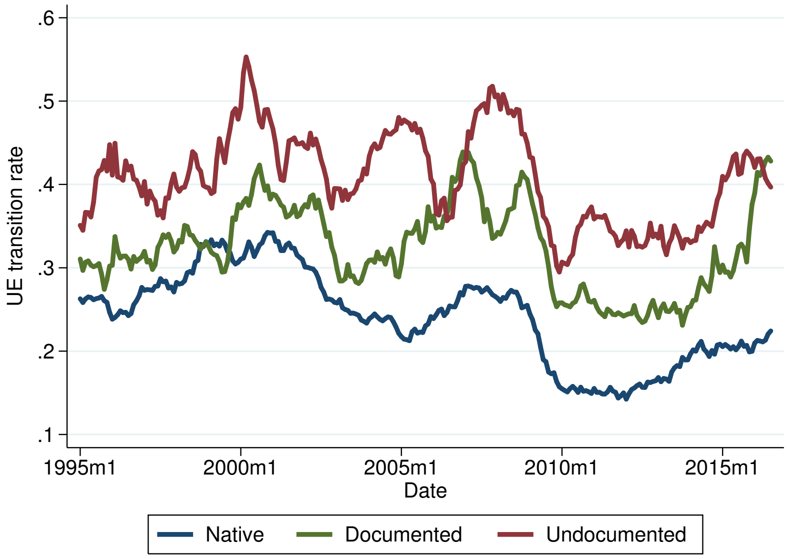
years, at which point undocumented workers still earn around 12% less. Thus, there are two important take-aways from Figure 5. First, even accounting for the length of stay in the US, there is still a large wage gap between documented and undocumented immigrants. Second, the gap to natives is initially 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. However, I show in the Appendix that in the monthly data still at least 90% of low-skilled illegal immigrants are correctly identified (see Appendix, Figure 18).

Figure 6 plots the 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

Figure 7: UE transition rates of low-skilled workers



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

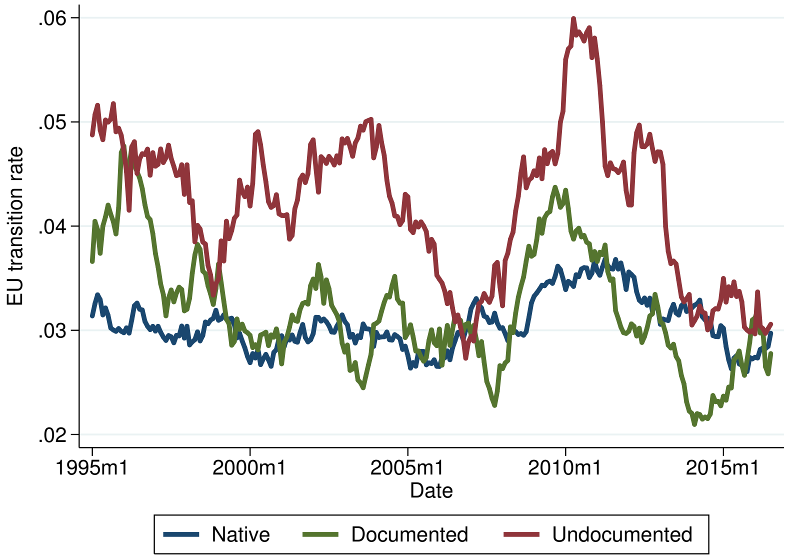
first evidence seems to suggest that only the status of being an immigrant but not the legal status matters for employment.

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 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 Figure 7. 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

[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.

Figure 8: EU transition rates of low-skilled workers



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

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 6, we expect a higher separation for undocumented counteracting the higher job finding rate. This is confirmed by Figure 8: the EU transition rate series of documented immigrants is close to the series of natives, while it over most of the period higher for undocumented.

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 unemployment over time

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

	(1)	(2)	(3)	(4)	(5)	(6)
Documented	0.074***	0.065***	0.075***	0.073***	0.071***	0.072***
	(0.0047)	(0.0067)	(0.0082)	(0.0076)	(0.0077)	(0.0076)
Undocumented	0.138***	0.122***	0.139***	0.136***	0.136***	0.137***
	(0.0054)	(0.0075)	(0.0097)	(0.0100)	(0.0107)	(0.0109)
Demographics	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
State FE	No	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	No
Occupation FE	No	No	No	No	Yes	No
Industry x occupation	No	No	No	No	No	Yes
Observations	75634	75634	75634	75634	75634	75634
R-squared	0.016	0.029	0.044	0.048	0.057	0.079

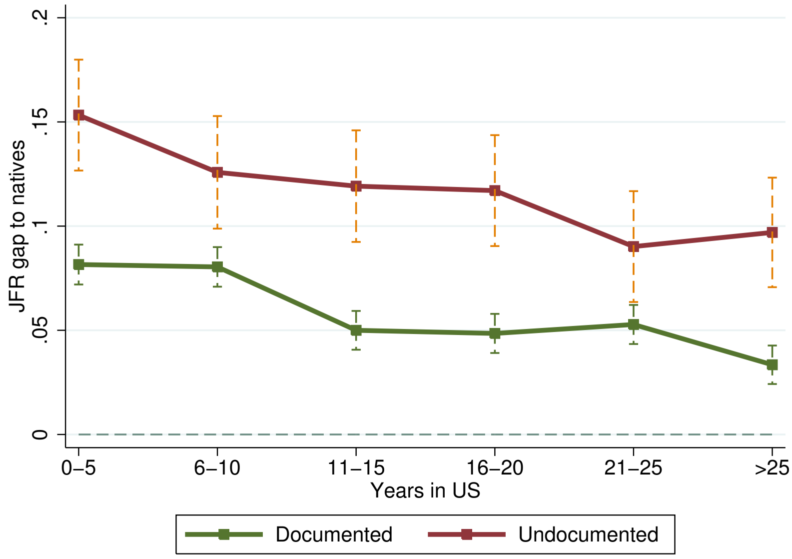
Note: Dependent variable is the probability of a UE transition. Data come from the CPS basic monthly files 1994-2014 and include prime-age workers (25-65) without high school degree matched over two consecutive months. Demographic controls include *sex*, *race*, *age* and age^2. Standard errors are clustered at the state level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

(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 including demographic, industry and occupational controls analogous to the wage regressions in the previous subsection. The dependent variable is a dummy indicating a transition from unemployment to employment or, respectively, employment to unemployment.

The regression results for job finding rates (UE transitions) are reported in Table 3. It confirms the pattern seen in Figure 7: 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

Figure 9: Job finding rate gap to natives



Note: The gaps result from a regression with the full set of controls as in column (6) of Table 2 including workers with at most a high school degree. Vertical dashed lines show 10% confidence intervals.

average and undocumented workers with a probability that is even 60% higher than the average.

Analogously to Figure 5, Figure 9 plots the predicted difference in job finding rates of immigrants to natives depending on time in the US as a result from regression specification (6) 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, although it does not disappear completely after having spent more than 25 years in the US for the documented.

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] Including demographic variables but no further controls, there is no significant difference in the separation rates between worker types. With the

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

Table 4: Legal status and EU transition of low-skilled workers

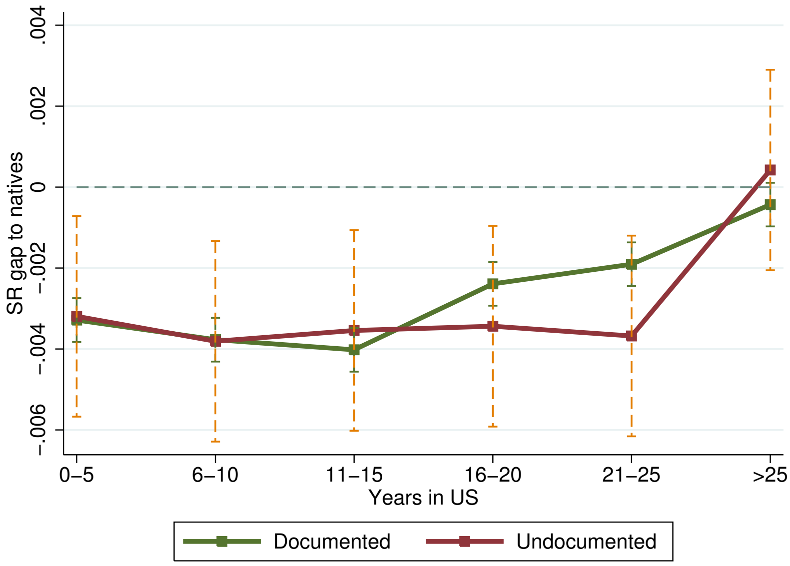
	(1)	(2)	(3)	(4)	(5)	(6)
Documented	-0.001*	-0.001	-0.001***	-0.002***	-0.003***	-0.003***
	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0004)
Undocumented	0.001	-0.001	-0.002**	-0.003***	-0.006***	-0.006***
	(0.0005)	(0.0008)	(0.0009)	(0.0007)	(0.0007)	(0.0007)
Demographics	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
State FE	No	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	No
Occupation FE	No	No	No	No	Yes	No
Industry x occupation	No	No	No	No	No	Yes
Observations	566368	566368	566368	566368	566368	566368
R-squared	0.000	0.001	0.002	0.005	0.007	0.013

Note: Dependent variable is the probability of an EU transition. Data come from the CPS basic monthly files 1994-2014 and include prime-age workers (25-65) without high school degree matched over two consecutive months. Demographic controls include *sex*, *race*, *age* and age^2. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

full set of controls, the coefficients 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 smaller compared to the differences in job finding rates. This also holds when relating the differences to the much smaller average separation probability, which is around 1.6%.

Figure 10 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.

Figure 10: Separation rate gap to natives



Note: The gaps result from a regression with the full set of controls as in column (6) of Table 2 including workers with at most a high school degree. Vertical dashed lines show 10% confidence intervals.

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]

$$rU_i = z_i + f_i \frac{w_i - z_i}{r + s_i + f_i}. \tag{1}$$

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

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

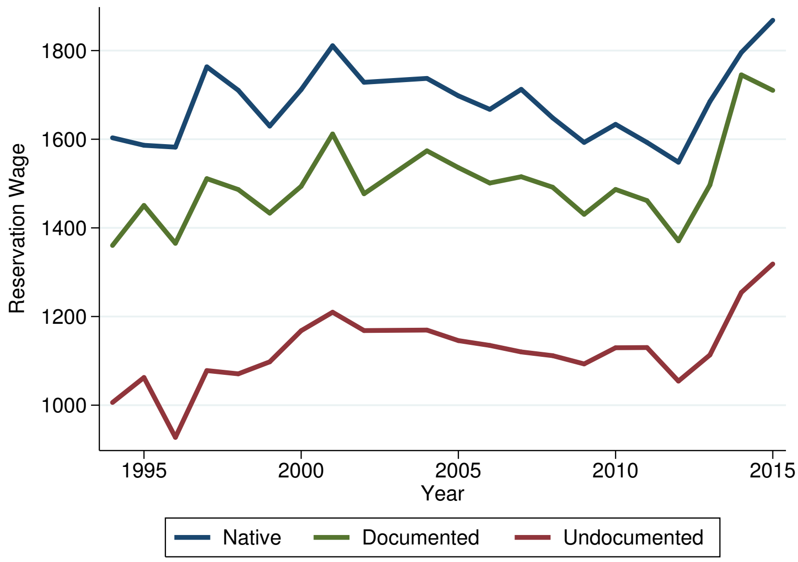
being unemployed equals the reservation wage at which a worker is indifferent between staying unemployed and having a job, i.e. $\underline{w_i} = rU_i = rW(\underline{w_i})$. Expression (1) shows how changes in the exogenous variables z_i, r and s_i affect the endogenous variables f_i and w_i. A fall 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 equation (1) 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 a model corresponding to specification (6) of the regression tables, in which the coefficients of D_{it} and U_{it} are allowed to vary over time by being interacted with the year dummies. 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 11 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

Figure 11: Reservation Wages



Note: The gaps underlying the calculation result from a regression with the full set of controls as in column (6) of Table 2.

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.

4 Model

This section presents a labor market model extending the canonical search and matching framework (Mortensen and Pissarides, 1994) with non-random hiring, whose implementation is based on the hiring mechanism in Barnichon and Zylberberg (2014). They depart from the assumption that matching is strictly random and instead allow firms to gather and rank several applications and hire the worker they receive the highest surplus from. This mechanism 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). For the sake of simplicity, I only distinguish two worker types: documented workers (including natives and documented immigrants) and undocumented immigrants.

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 can be either documented or undocumented. Their type is denoted by $i \in \{D, U\}$ 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^H. While home production is the same for both types, undocumented workers are not eligible for unemployment benefits and therefore we have $z_D = z^{UI} + z^H > z_U = z^H$. I also allow the bargaining powers β_D and β_U to differ between worker types, accounting for the fact that undocumented immigrants are likely to have a lower bargaining power in negotiating wages because hiring an unauthorized worker is unlawful. Moreover, I introduce the possibility for an unauthorized worker to be detected and removed. I allow the probability of detection to be potentially different for an employed and an unemployed worker.[16] I denote the rate of removal for an employed worker by λ^W and for an unemployed worker by λ^U. Removal not only implies job loss (in case of being employed), but also the loss of an utility amount $R > 0$,

[16]This is motivated by the fact 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 usually led to undocumented workers being fired, but in fewer cases being deported (see for example `http://www.nytimes.com/2010/07/10/us/10enforce.html?_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: $P(k) = \frac{q^k}{k!}e^{-q}$ with q being the candidate to vacancy ratio. To fit the model to the data, I introduce a matching efficiency parameter μ, thereby proceeding as Blanchard (1994). This implies that every period, a worker sends out an application with probability μ. Thus, the probability to be matched with k_D documented and k_U undocumented workers is given by:

$$P(k_D, k_U) = \frac{(\mu q_D)^{k_D}}{k_D!}e^{-\mu q_D} \; \frac{(\mu q_U)^{k_U}}{k_U!}e^{-\mu q_U} \tag{2}$$

where $q_i = u_i/V$, i.e. the ratio of candidates of type i to vacancies or "queue length".

I adopt the wage bargaining mechanism between firm and worker as described in Barnichon and Zylberberg (2014). 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, as well as the composition of the candidate pool. An increase in the share of workers in the pool that firms hire preferably will always decrease job finding of the workers already present, although it will increase average job finding of the total workforce (as it raises the share of the type with higher job finding). 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 to her outside option. With a probability β_i, the applicants send offers to the firm with the outcome that the best candidate demands a wage making 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. As undocumented have lower reservation wages than documented workers (for an expression of the reservation wages see below), we have that $S_U > S_D$. If a firm faces more than one applicant, there are three different cases to distinguish when determining the match surplus for the worker S^W:

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

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

Hence, a worker can only extract any surplus from a match when being the only candidate that is strictly better than the other candidates applying to the same firm.

4.2 Workers

In a continuous time setting, the flow values of being employed for legal and illegal workers are given by:

$$rW_D = w_D + s(U_D - W_D(w)) \tag{3}$$

$$rW_U = w_U + s(U_U - W_U(w)) + \lambda^W(U_U - R - W_U(w)). \tag{4}$$

As implied by equation (5), I assume that undocumented workers still receive their unemployment value after deportation, which is not essential for the results but improves the tractability

Table 5: Wage distribution

Case	Probability	Wage	
		Documented	Undocumented
1) No competitors	$f_1 = e^{-\mu q_D} e^{-\mu q_U}$	$\underline{w}_D + \beta_D(y - \underline{w}_D)$	$\underline{w}_U + \beta_U(y - \underline{w}_U)$
2) Only D competitors	$f_2 = (1 - e^{-\mu q_D}) e^{-\mu q_U}$	$\underline{w}_D$	$\underline{w}_U + \beta_U((1 + \frac{\lambda^W}{r+s})\underline{w}_D - \frac{\lambda^W}{r+s} y - \underline{w}_U)$
3) At least one U competitor	$f_3 = 1 - e^{-\mu q_U}$	$rU_D = \underline{w}_D$	$\underline{w}_U$

of the model.[17] The flow values of being unemployed rU_i are given by

$$rU_D = z_D + \int max(W_D(w) - U_D, 0) dF_D(w) \tag{5}$$

$$rU_U = z_U + \int max(W_U(w) - U_U, 0) dF_U(w) - \lambda^U R \tag{6}$$

with F denoting the distribution of the negotiated wages, which depends on the number 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 working and staying unemployed, so that we get $rU_D = rW(\underline{w}_D) = \underline{w}_D$ and $rU_U = rW(\underline{w}_U) = \underline{w}_U - \lambda^W D$. Hence, using this with (4) and (5), we get for legal workers:

$$\underline{w}_D = z_D + \frac{1}{r+s} \int_{\underline{w}_D}^{\infty} (w - \underline{w}_D) dF_D(w). \tag{7}$$

For undocumented workers we get:

$$\underline{w}_U = z_U + \frac{1}{r+s+\lambda^W} \int_{\underline{w}_U}^{\infty} (w - \underline{w}_U) dF_U(w) + \underbrace{(\lambda^W - \lambda^U)}_{\Delta\lambda} R. \tag{8}$$

The wage distribution F, which can be derived from the above described matching probabilities and wage bargaining mechanism, is summarized in Table 5.[18]

[17] 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.

[18] The undocumented wage in case 2) is derived from $(y - w_U)/(r + s + \lambda_W) = (y - \underline{w}_D)/(r + s)$, i.e. equating the firm surplus when hiring an undocumented with the firm surplus when hiring a documented worker.

Combining the distribution of wages with equations (7) and (8), we get the reservation wages as

$$\underline{w}_D = \frac{z_D + \frac{\beta_D}{r+s} f_1 y}{1 + \frac{\beta_D}{r+s} f_1} \tag{9}$$

$$\underline{w}_U = \frac{z_U + \frac{\beta_U}{r+s+\lambda^W}(f_1 y + f_2(\frac{\lambda^W}{r+s} y + (1 + \frac{\lambda^W}{r+s})\underline{w}_D) + \Delta\lambda R}{1 + \frac{\beta_U}{r+s+\lambda^W} e^{-\mu q_U}} \tag{10}$$

If all workers were identical, i.e. $z_D = z_U$, $\beta_D = \beta_U$ and λ^W=λ^U=0, the reservation wages of both 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 in equilibrium. As I assume $z_D > z_U$, a sufficient condition for $\underline{w}_D > \underline{w}_U$ is $\beta_D \geq \beta_U$. This condition is also sufficient if $R = 0$ or R is very small, 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 $\underline{w}_D$. If $\Delta\lambda R$ is large enough, i.e. the removal rate is much higher for the employed than for the unemployed, we could have $\underline{w}_D < \underline{w}_U$. However, as this is not consistent with the data, all model parameter constellations used throughout the paper will ensure that $\underline{w}_D > \underline{w}_U$ is satisfied. Given this inequality holds, the wage distribution implies that the expected wage of a undocumented workers is smaller than the expected wage of a documented worker and that firms always prefer to hire the former.

The job finding rates for each worker type can be derived from $f_i = m_i/u_i$, where m_i denotes the number of vacancies filled by worker type i. The probability of a vacancy being filled by a documented is given by f_2, while the probability of a vacancy being filled by an undocumented worker is given by f_3. Thus, the job finding rates are:

$$f_D = f_2 V/u_D = \frac{(1 - e^{-\mu q_D})e^{-\mu q_U}}{q_D} \tag{11}$$

$$f_U = f_3 V/u_U = \frac{1 - e^{-\mu q_U}}{q_U} > f_D \tag{12}$$

4.3 Firms

On the firm side, the flow values of hired documented and undocumented workers are given by

$$rJ_D(\pi) = \pi + s(V - J_D(w)) \tag{13}$$

$$rJ_U(\pi) = \pi + (s + \lambda^W)(V - J_U(w)) \tag{14}$$

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

$$rV = -c + \int max(J_i(\pi) - V, 0)dG(\pi, i). \tag{15}$$

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:

$$c = \int_0^\infty J_i(\pi)dG(\pi, i) \tag{16}$$

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 D, no U	$\mu q_D e^{-\mu q_D} e^{-\mu q_U}$	$(1 - \beta_D)(y - \underline{w}_D)$	D
2) One U, no D	$\mu q_U e^{-\mu q_D} e^{-\mu q_U}$	$(1 - \beta_U)(y - \underline{w}_U)$	U
3) > 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
4) > one U	$(1 - e^{-\mu q_U} - \mu q_U e^{-\mu q_U})$	$y - \underline{w}_U$	U
5) ≥ one D, one U	$\mu q_U e^{-\mu q_U}(1 - e^{-\mu q_D})$	$y - \underline{w}_U - \beta_U((1 + \frac{\lambda^W}{r+s})\underline{w}_D - \frac{\lambda^W}{r+s}y - \underline{w}_U)$	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 $u_D + u_U$. What determines the equilibrium is the ratio of documented to undocumented workers among the unemployed $u_U/u_D = q_U/q_D$. With the given distribution of profits, it can easily be verified that the higher is this ratio, the higher is the probability of having at least one undocumented applicant and therefore the higher are expected firm profits. Hence, while an increase in the unemployment pool that leaves u_U/u_D unchanged does not affect the equilibrium as vacancies will increase proportionally, a relative increase in u_U compared to u_D will lead to an increase in vacancies that is overproportional to the increase of the total unemployment pool and vice versa.

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:

$$\dot{u}_D = s(\frac{\omega_D}{P} - u_D) - f_D u_D, \tag{17}$$

$$\dot{u}_U = s(\frac{\omega_U}{P} - u_U) + u_{NU} - f_U u_U - \lambda^U u_U, \tag{18}$$

$$\dot{P} = u_{NU} - \lambda^W(\frac{\omega_U}{P} - u_U) - \lambda^U u_U, \tag{19}$$

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 $u_{NU} = \lambda^W(\frac{\omega_U}{P} - u_U) + \lambda^U u_U$. Thus, ouflows 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 therefore given by:

$$u_D^* = \frac{\omega_D s}{s + f_D} \tag{20}$$

$$u_U^* = \frac{\omega_U(s + \lambda^W)}{s + \lambda^W + f_U} \tag{21}$$

The static solution of the model is determined by equations (9), (10), (11), (12), (13), (14), (16), (20), (21), and consists of the equilibrium candidate-vacancy ratios q_D^* and q_U^*.

5 Calibration

In the following, I describe the calibration of the model, for which I use several methods. Some parameters are set equal to their data equivalents or are taken from the literature, others are chosen to jointly match some moments of the data. An overview of the calibrated parameter values can be found in Table 15 in the Appendix.

The level of productivity y and the documented population ω_D are both normalized to 1. The monthly discount factor δ is set equal to 0.9966, implying an annual interest rate of 4%. Instead of choosing the population shares ω_D and ω_U and determining the ratio u_U/u_D from the steady state equation for unemployment, I fix u_U/u_D at 0.27, which is the mean of this ratio over the period 1994-2014. I do so, because my target for the job finding rate gap is the coefficient of the illegal dummy in the regression of Table 3 and this gap will determine the equilibrium ratio u_U/u_D resulting from the model, given that ω_D and ω_U are fixed. The empirical ratio u_U/u_D on the other hand is generated by the unconditional transition rates in the data and therefore inevitably different to the model result, if the population ratio ω_U/ω_D is set to its data equivalent. After fixing u_U/u_D, the population ratio implied by the steady state of unemployment in the model can be computed by solving (15) for ω_i.[19]

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 choose an intermediate value of 0.71 for z_L as used in Hall and Milgrom (2008) and Pissarides (2009). Computing the unemployment benefits as $z^{UI} = 0.4\overline{w}_L$, where $\overline{w}_L$ is the average wage of legal workers, which is around 0.97, gives $z^{UI} = 0.39$. Hence, $z_D - z^{UI}$ yields $z^H = z_U = 0.32$. 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 documented immigrants have a separation rate that is 0.003 lower than the rate of natives and the immigrant share among documented workers is around 0.4, I set $s_D = 0.6 \cdot 0.031 + 0.4 \cdot 0.028 \approx 0.030$. The difference between the separation rates of undocumented immigrants and natives is 0.006 and thus I set $s_U = 0.031 - 0.006 = 0.025$.

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.[20] I convert these figures to a monthly frequency, divide them by the total number of undocumented immigrants residing in the US

[19] The model implies $\omega_U/\omega_D = 0.31$, which is very close to the ratio of 0.30 in the data

[20] "Interior removals" refer to deportations of immigrants that are not apprehended directly at the border. The figures are available at https://www.ice.gov/removal-statistics

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 $\Delta\lambda \neq 0$ and in this case I set $R = 100$. I will check robustness of the results to different choices of R.

This leaves four remaining parameters to be determined, c, β_D, β_U and the matching efficiency μ with three moments from the data to be matched. These are the ratio of the average wages paid to workers $\overline{w}_U/\overline{w}_D$ and the job finding rates f_D and f_U. In order to get rid of one parameter, I proceed as many papers in the search literature and assume an average bargaining power in the economy of 0.5. Hence, I restrict β_D and β_U to satisfy $\frac{\omega_D}{\omega_D+\omega_U}\beta_D + \frac{\omega_U}{\omega_D+\omega_U}\beta_U = 0.5$. This leaves the difference between β_D and β_U along with c and μ to be matched. According to the sixth column of Table 2, documented immigrants earn 4.6% less than natives. Taking natives as a reference group with a normalized wage of 1, I can then compute the wage level of all documented workers using the population proportions as $0.6 \cdot 1 + 0.4 \cdot 0.954 \approx 0.982$. With undocumented workers earning 12.5% less than natives, the wage ratio is then given by $\overline{w}_U/\overline{w}_D = 0.875/0.982 \approx 0.89$. In order to get the job finding rates, I proceed similarly as for the separation rates. The time aggregation bias corrected job finding rate of low-skilled natives is around 0.24. Considering the coefficients in the sixth column of Table 3, the job finding rates are $f_D = 0.6 \cdot 0.241 + 0.4 \cdot 0.312 \approx 0.27$ and $f_U = 0.241 + 0.137 \approx 0.38$. The resulting parameters are $\beta_L = 0.67$, $\beta_I = 0.15$, $\mu = 0.41$ and $c = 0.72$.

6 The Effect of Undocumented 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 workers that have opposing impacts on the job finding rate of documented workers. With a higher probability of receiving an application from an undocumented, expected wage costs of firms go down and therefore more vacancies are posted. This job creation effect increases documented workers' job finding and is also present in the standard framework with random hiring. The competition effect on the other hand decreases job finding rates of both worker types as the probability of competing with an undocumented for a job and thus not being hired rises. The two effects can be shown by recalling the expression for the job finding rate of documented workers (11). An increase in vacancies decreases the queue length q_D. By taking the partial derivative with respect to q_D we see that the marginal effect of an increase in q_D on f_D is negative:

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

Hence, the job creation effect is always positive. The competition effect can be demonstrated by taking the partial derivative with respect to q_U, which increases as a result of a rise in the undocumented population share:

$$\frac{\partial f_D}{\partial q_U} = -\mu \frac{(1 - e^{-\mu q_D})}{q_D} e^{-\mu q_U} < 0 \quad \forall\ q_U > 0,$$

$$\frac{\partial f_U}{\partial q_U} = \frac{e^{-\mu q_U}(1+\mu q_U) - 1}{q_U^2} < 0 \quad \forall\ q_U > 0.$$

Thus, the total effect of an increase in ω_U is ambiguous for documented and negative for undocumented workers:

$$\frac{df_D}{d\omega_U} = \underbrace{\underbrace{\frac{\partial f_D}{\partial q_D}}_{<0}\underbrace{\frac{dq_D}{d\omega_U}}_{<0}}_{job\ creation\ effect} + \underbrace{\underbrace{\frac{\partial f_D}{\partial q_U}}_{<0}\underbrace{\frac{dq_U}{d\omega_U}}_{>0}}_{competition\ effect} \lesseqgtr 0, \tag{22}$$

$$\tag{23}$$

$$\frac{df_U}{d\omega_U} = \underbrace{\underbrace{\frac{\partial f_U}{\partial q_U}}_{<0}\underbrace{\frac{dq_U}{d\omega_U}}_{>0}}_{competition\ +\ job\ creation\ effect} < 0. \tag{24}$$

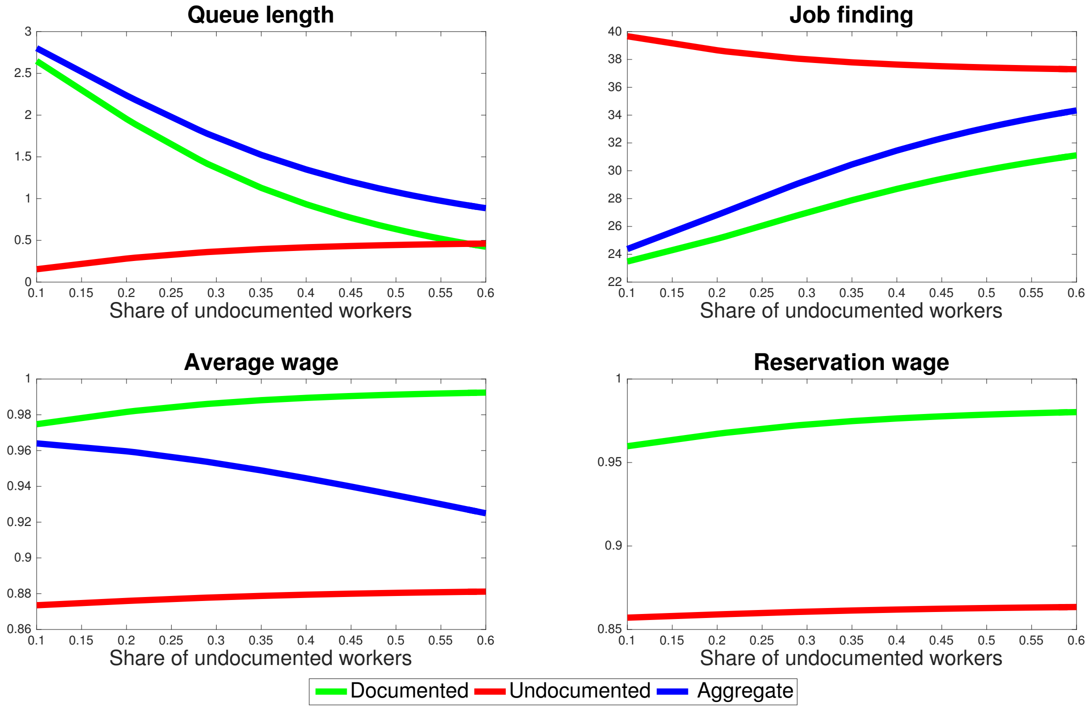
The larger is the difference between worker types, the larger is the difference in their reservation wages and therefore the higher is the increase in expected firm profits and the number of vacancies posted following an increase in ω_U. Hence, the job creation effect tends to zero when the worker types become identical and gets larger when increasing the difference between them, eventually letting $df_D/d\omega_U$ become positive.

6.2 Simulating Undocumented Immigration

In order to find out which of the two effects dominates with the calibration that replicates the data, I solve for the steady state equilibrium varying the undocumented population share $\omega_U/(\omega_D + \omega_U)$. Figure 12 plots the resulting steady state queue lengths, job finding rates, average wages and reservation wages by worker type and in the aggregate. The upper left panel shows a sharp decline in the queue length of documented workers, indicating a large increase in vacancies and hence a strong job creation effect. Accordingly, their job finding rate increases with the arrival of more undocumented workers, which confirms that the job creation effect is strong enough to dominate the competition effect. Average wages of both worker types increase as a result of a reservation wage increase induced by the additional vacancies posted. However, as the share of workers earning a lower wage goes up, the aggregate average wage paid drops. The reservation wage is equal to the value of unemployment for undocumented workers and therefore functions as a measure of welfare. The lower right panel suggests that the welfare of documented workers increases through undocumented immigration. For undocumented immigrants we have $\underline{w}_U = rU_U + \lambda^W R$. As $\lambda^W R$ is held fixed for now, the increase in undocumented workers' reservation wages also implies a rise in welfare for them.

Figure 13 shows the hypothetical effect of undocumented immigration under the assumption that there exists no bargaining power difference between the worker types. In this case, the wage gap only comes from the difference in unemployment benefits and the removal risk (the benchmark is plotted in dashed lines for comparison). The purpose of this figure is twofold. First, it illustrates that most of the reservation wage gap is generated by the bargaining power difference as under the assumption of equal bargaining powers there is only a gap of around 2% between the reservation wages of documented and undocumented workers. Second, it shows that with such a small reservation wage gap, the competition effect is the dominating one. Although there are still additional vacancies created as indicated by the decreasing aggregate

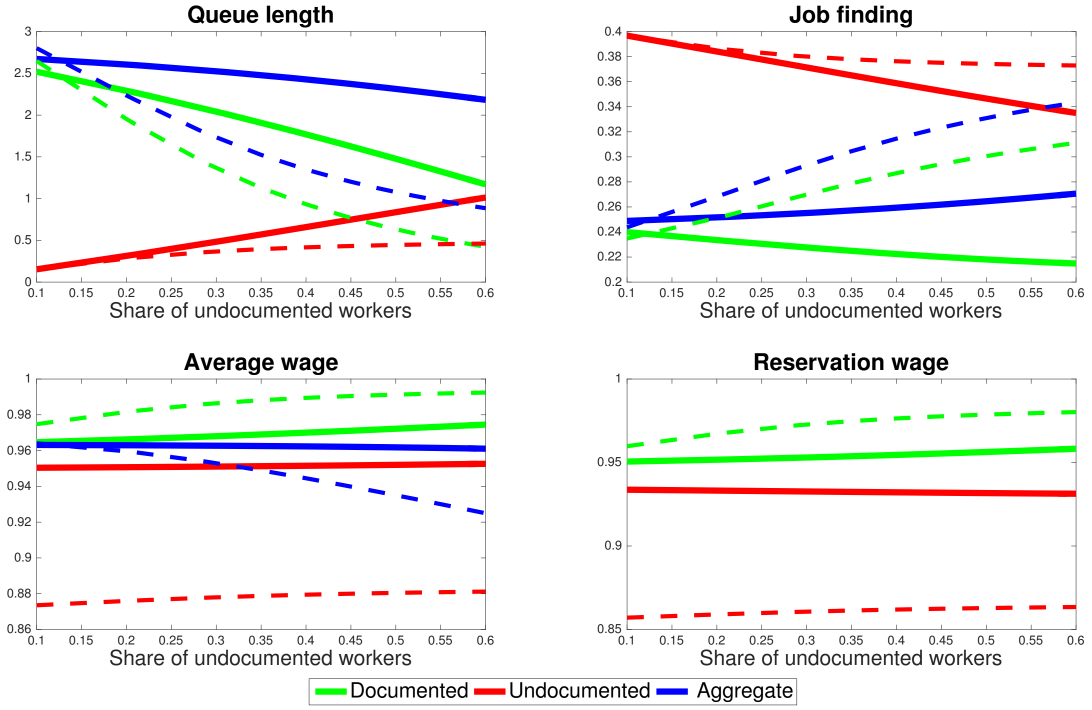
Figure 12: Equilibrium depending on undocumented share



queue length, the job finding rate curve of documented workers is now falling as job creation is not strong enough to counteract the increased job competition through undocumented workers.

This exercise confirms that the findings are sensitive to the parameters and therefore I next check whether the predictions of Figure 12 are robust to allowing $\Delta\lambda \neq 0$ and to the choice 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 0.0022. Since $\Delta\lambda$ 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 reestimate c, β_L and β_I in order to match the moments from the data after a change in R. Figures 19, 20 and 21 in the Appendix show the effect of undocumented immigration for the calibrations $R = 0$, $R = 100$ and $R = 200$ and compare it

Figure 13: Equilibrium depending on undocumented share with $\beta_D = \beta_U = 0.5$



Note: Benchmark from Figure 12 in dashed lines

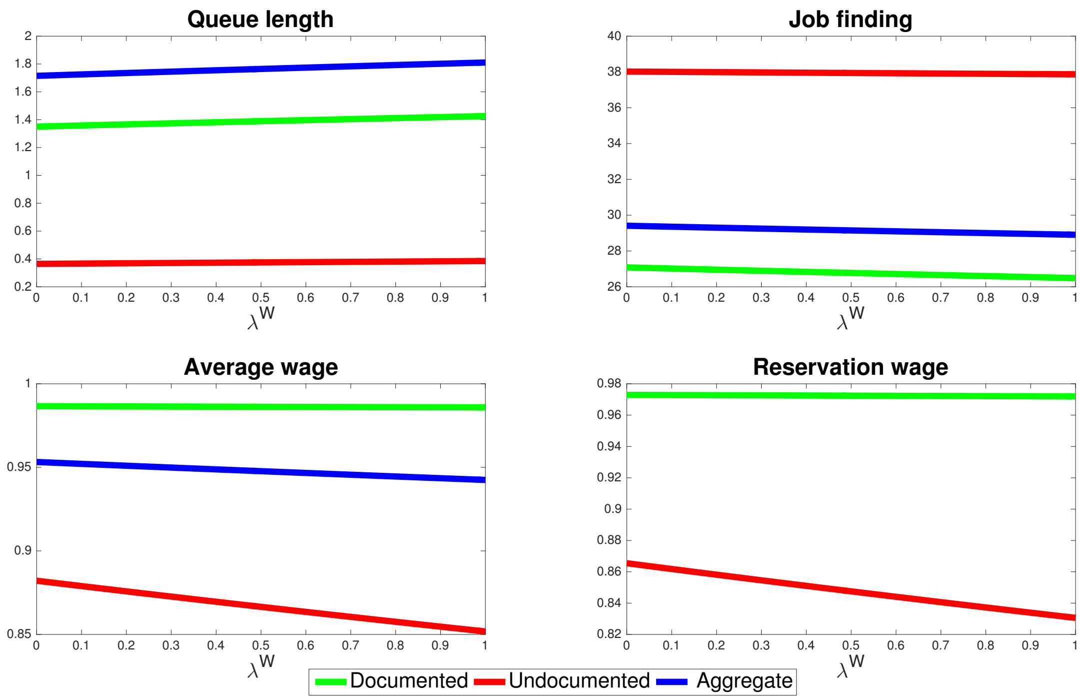
to the benchmark calibration with $\Delta\lambda = 0$ (dashed lines). Queue lengths, job finding rates and average wages are virtually unaffected by the choice of R after c, β_D and β_U are recalibrated. Only the reservation wage of undocumented workers changes, moving in the same direction as R.

In sum, undocumented immigration is unambiguously beneficial for documented workers. This is because the immigration of cheaper workers stimulates vacancy creation and this more than offsets the negative effect of increased competition on job finding for documented workers. Despite their fall in job finding, also undocumented workers' welfare increases through rising wages.

7 The Effect of 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.

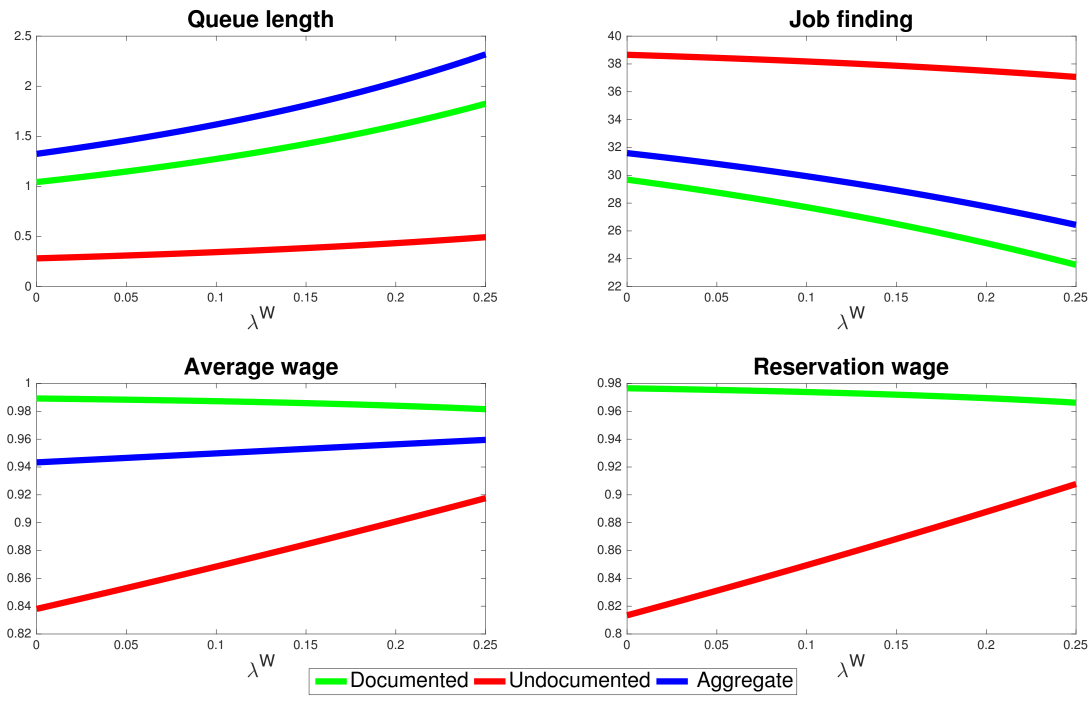
Figure 14: Equilibrium depending on λ^W with $\lambda^W = \lambda^U$



Recalling equation (10), 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 due to the larger separation risk. 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 do not recalibrate the remaining parameters.

Figures 14 shows the effect of an increase in both λ^W and λ^U on the equilibrium keeping the

Figure 15: Equilibrium depending on λ^W with $\lambda^U = 0.0013$



population share of undocumented immigrants fixed.[21] As $\Delta\lambda$ remains zero, the rise in the removal rate only affects undocumented workers' separation probability and hence the queue length rises slightly as the surplus from hiring undocumented workers falls and firms create less vacancies. This is reflected in a moderate fall in job finding rates of both worker types. While wages of documented workers remain almost flat, wages of undocumented workers fall sharply due to the direct effect of the lower match surplus on the reservation wage.

Figure 15 plots the equilibria for the case where only the removal risk when employed λ^W rises e.g. through more frequent worksite raids. Now, the negative impact on queue length and job finding is strongly enhanced because the surplus of hiring undocumented workers additionally falls due to the increase in the wage compensation for the higher deportation risk when employed, implying even less new vacancies posted. This is reflected by the strong rise in documented immigrants' reservation wages, which however do not reflect a higher welfare as the rise in $\underline{w}_U$ is counteracted by the rise in $\lambda^W R$.

[21] 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.

In sum, the analysis in this section suggests that increased deportation efforts by the authorities lower the welfare not only of the undocumented, but also of documented workers. This is even more so the case, if efforts concentrate on worksite raids making 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 hiring workers illegally as this would mute vacancy creation further.[22]

8 Testing the Model Predictions

In the previous section I have 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.[23] 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 change 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 or deter-

[22] I abstract from these penalties as there is no evidence that they are in fact large enough to play a significant role for firm decisions. Moreover, their addition to the model would bring no further insight beside enhancing the effect of a variation in λ^W.

[23] 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).

Table 7: Legal status, omnibus laws and UE transition of low-skilled workers

	(1)	(2)	(3)	(4)	(5)	(6)
Documented	0.071***	0.063***	0.075***	0.073***	0.071***	0.072***
	(0.0048)	(0.0070)	(0.0084)	(0.0078)	(0.0079)	(0.0077)
Undocumented	0.135***	0.120***	0.138***	0.135***	0.136***	0.137***
	(0.0055)	(0.0077)	(0.0098)	(0.0101)	(0.0109)	(0.0111)
Omnibus law	-0.035***	-0.029***	-0.027***	-0.025***	-0.025***	-0.021***
	(0.0075)	(0.0072)	(0.0073)	(0.0070)	(0.0062)	(0.0068)
Documented x omnibus	0.047	0.034*	0.020	0.017	0.017*	0.005
	(0.0288)	(0.0199)	(0.0134)	(0.0135)	(0.0094)	(0.0111)
Undocumented x omnibus	0.051*	0.043	0.015	0.013	0.013	0.006
	(0.0272)	(0.0379)	(0.0328)	(0.0326)	(0.0300)	(0.0294)
Demographics	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
State FE	No	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	No
Occupation FE	No	No	No	No	Yes	No
Industry x occupation	No	No	No	No	No	Yes
Observations	75634	75634	75634	75634	75634	75634
R-squared	0.016	0.029	0.044	0.048	0.057	0.079

Note: Dependent variable is the probability of a UE transition. Data come from the CPS basic monthly files 1994-2014 and include prime-age workers (25-65) without high school degree matched over two consecutive months. 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.

mination of legal status when arrested.[24] 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 conclude 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 including a dummy indicating immigration

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

Table 8: Legal status, omnibus laws and hourly wage of low-skilled workers

	(1)	(2)	(3)	(4)	(5)	(6)
Documented	-0.123***	-0.077***	-0.100***	-0.090***	-0.049***	-0.048***
	(0.0047)	(0.0100)	(0.0080)	(0.0075)	(0.0063)	(0.0064)
Undocumented	-0.269***	-0.208***	-0.238***	-0.206***	-0.131***	-0.128***
	(0.0052)	(0.0186)	(0.0158)	(0.0163)	(0.0130)	(0.0130)
Omnibus law	-0.089***	-0.097***	-0.062***	-0.056***	-0.052***	-0.052***
	(0.0193)	(0.0183)	(0.0182)	(0.0169)	(0.0157)	(0.0171)
Documented x omnibus	0.076**	0.090***	0.097***	0.092***	0.084***	0.081***
	(0.0309)	(0.0228)	(0.0212)	(0.0208)	(0.0184)	(0.0198)
Undocumented x omnibus	0.085***	0.095***	0.107***	0.100***	0.093***	0.092***
	(0.0300)	(0.0322)	(0.0300)	(0.0282)	(0.0259)	(0.0290)
Demographics	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
Metarea FE	No	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	No
Occupation FE	No	No	No	No	Yes	No
Industry x occupation	No	No	No	No	No	Yes
Observations	68505	68505	68505	68505	68505	68505
R-squared	0.049	0.136	0.162	0.194	0.264	0.288

Note: Dependent variable is the logarithm of the hourly wage. Data come from the CPS March supplement 1994-2016 and include prime-age workers (25-65) without high school degree. 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.

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 legal and illegal immigrant indicator in order to allow the effect of omnibus immigration legislation to vary across immigrant status. The results are shown in Table 7. 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 that in Figures 14 and 15, which suggest that the steepness of the fall in the job finding rates is almost identical for both worker types. In Figure 15, the fall corresponds to a rise in the deportation risk (for employed workers only) of around 0.05 to 0.1 percentage points. In 14, not even a rise in the deportation risk of 1 percentage point is enough to generate a fall in job finding rates of 2.1 percentage points. This indicates that either the deportation risk went up much more strongly than 1 percentage point or, more likely, that the risk went up more strongly for employed workers (as is the case in Figure 15).

Finally, I rerun the wage regressions including the omnibus law indicator and interactions as regressors. The results in Table 8 suggest a drop in natives' wages of 5.2% due to the implementation of omnibus immigration laws. The coefficient of the undocumented-omnibus interaction of 0.092 implies that omnibus immigration legislation increases undocumented workers' wages by 4% (=0.092-0.052). This is consistent with the prediction of Figure 15 that a higher removal risk leads to higher wages for undocumented workers. However, the coefficient of the documented-omnibus interaction, which is also positive and indicating that the wages of documented workers also increase, although only by 2.9%, is not consistent with the model. If omnibus immigration laws only affect the risk compensation of documented immigrants, this coefficient should be around zero. A possible reason for this coefficient being positive could be that immigrants who are legal residents but not citizens can still be subject to removal under certain circumstances and therefore might perceive the risk as being 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.

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 documentation status. This paper fills this gap by analyzing the labor market effects of documented as opposed to undocumented immigration in a model which generates results that are consistent with empirical findings presented.

I argue that legal status is key in understanding the impact of immigration by showing that immigrants earn lower wages and have higher job finding rates and that both gaps are much larger for undocumented than for documented immigrants. Moreover, the wage and job finding rate gaps to natives disappear almost completely for documented immigrants after more than 25 years in the US, while they remain large for the undocumented. As a differential job finding rate is at odds with a standard random matching mechanism, I propose a non-random hiring model with documented and undocumented workers to explain these findings. I assume that the latter have a lower unemployment value as well as a lower bargaining power than the former and that undocumented immigrant can be detected and removed. Due to their lower reservation wage, undocumented workers are cheaper for firms and thus always hired preferably, implying a higher job finding rate. An increase in the share of undocumented immigrants has two opposing effects on the job finding of documented workers. As average wage costs of firms are pushed downwards, they create additional vacancies, which tends to increase job finding. On the other hand, the increased competition for jobs tends to decrease documented workers' job finding. When fitting the model to the wage gap in the data, the job creation effect dominates the competition effect, implying that documented immigration is beneficial for documented workers.

A policy of stricter immigration enforcement, which I simulate by increasing the removal rate, dampens job creation due to a lower surplus of hiring undocumented immigrants, which in turn lowers job finding rates for all workers and wages for documented workers. The wage impact for undocumented workers is negative, if the rise in the removal rate is the same for employed and unemployed workers. If the rate increases more for employed workers (e.g. through worksite raids) the detrimental effect on vacancy creation is even larger as the risk premium in the wages of undocumented immigrants goes up. In order to provide empirical evidence for these predictions, I examine the effect of the introduction of state-wide omnibus immigration laws and find a decrease in the job finding rates for all workers, a decrease in wages for natives and an increase in wages for immigrants. This is consistent with muted vacancy creation due to lower firm profits and a risk premium in undocumented immigrants' wages. However, the finding that omnibus immigration laws have a positive effect on earnings of immigrants with legal status as well is in contradiction to the model and warrants further investigation.

The findings of this paper have important policy implications as stricter immigration enforcement is predicted to be detrimental for all workers and therefore fail its aim. To mitigate the negative effects, my analysis suggests that deportation policies should target unemployed rather than employed workers.

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Appendix

Education and Accuracy of the Identification Method

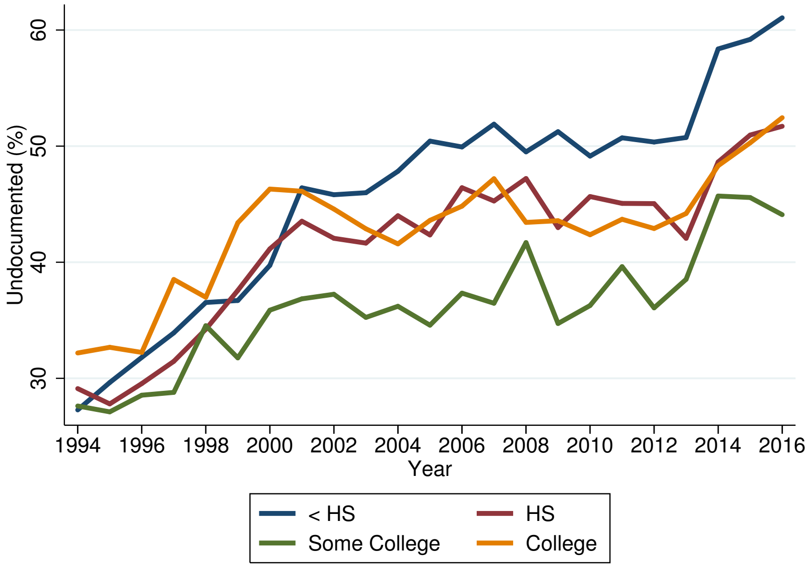
The most important indicator that allows to classify an immigrant as legal with certainty is holding US citizenship. Hence, the main driver behind the low undocumented immigrant share in the higher education groups could be a lower share of non-citizens. Indeed, in the whole sample, around 30% of high school dropouts are non-citizens, while this share is only 7% among high school and college graduates. Figure 16 plots the share of undocumented immigrants among individuals without US citizenship. It reveals that conditional on not having US citizenship, the shares of undocumented immigrants among high school dropouts, high school graduates and college educated workers are similar, with the latter even having the highest share before 2002. This hard to believe given the well-known fact that immigrants entering the United States illegally are usually poorly educated.

A potential explanation for the high share of undocumented immigrant among college educated non-citizens is that many of the variables used for the identification of legal immigrants are likely to classify more low-skilled than high-skilled individuals as legal because these variables are more relevant for the former. For example, almost 10% of citizen high school dropouts receive some form of Supplemental Security Income (SSI), whereas only 0.5% of citizens with college degree do. Also the percentages of citizens being publicly insured, residing in public housing or receiving rental subsidies from the government are much higher among high school dropouts than among college educated individuals.

Information on the educational attainment of undocumented immigrants provided by the Migration Policy Institute[25] allows me to check whether the accuracy of the simplified Borjas (2016) identification algorithm is dependent on the education level. According to the figures of the Migration Policy Institute, which are based on the ACS 2013, 50% of undocumented prime age workers did not have a high school degree (NHS), 24% had at most a high school degree (HS), 12% had some college education (SC) and 13% had a college degree (C). The equivalent percentages with undocumented immigrants being identified as in Borjas (2016) in the same

[25] http://www.migrationpolicy.org/data/unauthorized-immigrant-population/state/US

Figure 16: Share of undocumented among non-citizens with Borjas (2016) identification



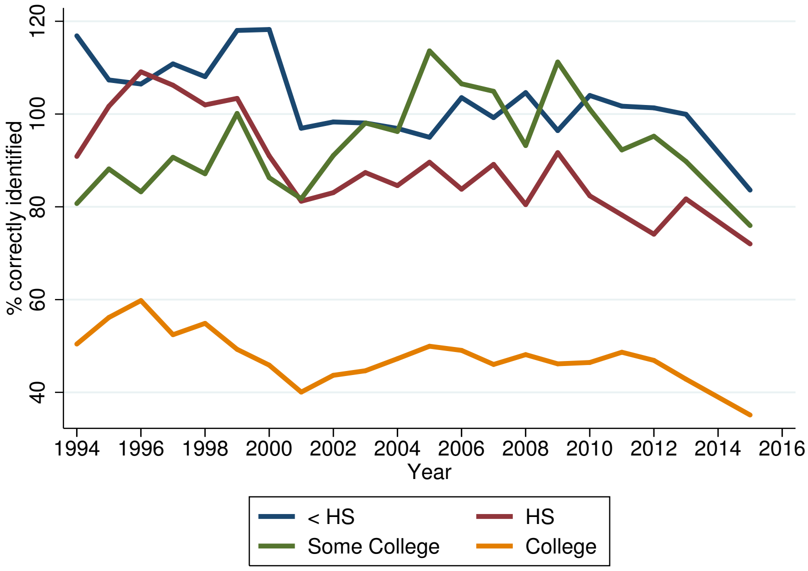
Source: CPS March supplement following Borjas (2016), prime age workers only

year are 39%[26] (NHS), 25% (HS), 11% (SC) and 25% (C). This indeed suggests that too many immigrants in the highest skill group are classified as undocumented. The information on educational attainment allows me to compute an estimate of the share of immigrants that are incorrectly identified as undocumented for each education group. In order to get a time series of this share, I assume that the education shares among unauthorized prime age workers and the share of prime age workers among all unauthorized immigrants stay constant over time because these figures are only available for 2013. I define the education shares of undocumented immigrants given by the Migration Policy Institute as the probabilities of having education $e \in \{NHS, HS, SC, C\}$ conditional on being undocumented, $p(e|I)$. I can then calculate the probability of being undocumented and having education level e as $p(I \cap e) = p(e|I) \cdot p(I)$, presuming that this the "true" share of undocumented immigrants.

In order to obtain a time series of $p(I)$, I take yearly data on the prime age population in the US from the St. Louis Fed[27] and yearly data on the total unauthorized population from the Pew Research Center.[28] Data on the undocumented prime age population are available for

[26]Borjas (2016) finds a percentage of 39.5%
[27]https://research.stlouisfed.org/fred2/
[28]http://www.pewhispanic.org/2014/12/11/unauthorized-trends/

Figure 17: Correctly identified undocumented immigrants in CPS March data (%)

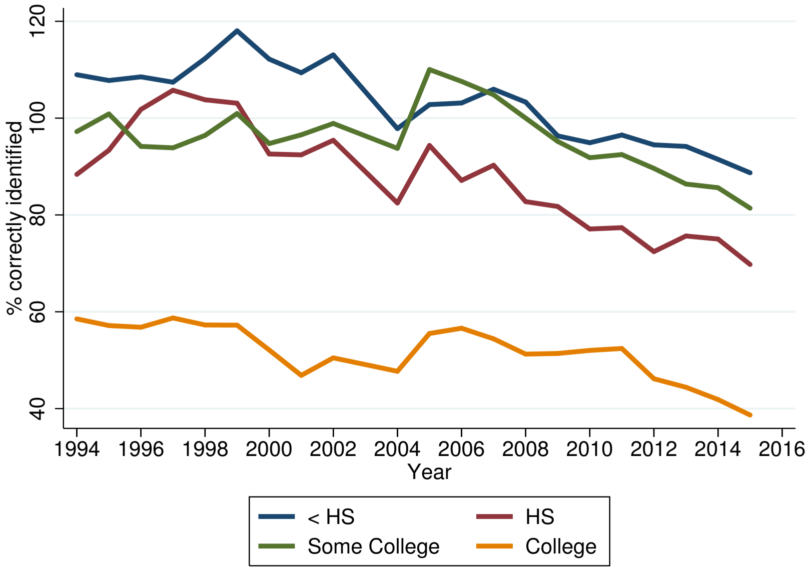


Source: Own calculations (see text), prime age workers only

2013 from the Migration Policy institute. Using this figure, I compute the share of prime age workers among undocumented immigrants of all ages in 2013. Assuming that this share stays constant over time, I calculate the undocumented prime age population for the remaining years by multiplying the share with the total undocumented population and obtain $p(I)$ by dividing through the total prime age population. Having constructed a time series of the true sample share $p(I \cap e)$, I then divide this series by the sample share of immigrants with education level e that I have classified as undocumented in the CPS March supplement using the Borjas (2016) algorithm and thus get the share of undocumented immigrants that are correctly identified.

The resulting percentage ratios are shown in Figure 17. It suggests that only around 40% to 60% of undocumented immigrants with college degree are correctly identified as such. On the other hand, the ratio for high school dropouts lies around one, suggesting that there is a high accuracy in the identification algorithm in this education group. Undocumented immigrants with high school degree or some college are also relatively well identified with shares ranging from 75% to around 100%. In the beginning of the period $p(I \cap NHS)$ is even somewhat higher than the share of undocumented immigrants among high-school dropouts identified in the sample, which is probably owed to the fact that I have to use 2013 education levels but

Figure 18: Correctly identified undocumented immigrants in CPS monthly data (%)



Source : Own calculations (see text), prime age workers only

true education level changed over time. Hence, the values in Figure 17 far from the year 2013 should be viewed with caution.

Figure 18 shows the percentage of correctly identified undocumented immigrants in the CPS basic monthly files used for the analysis of transition rates. As the monthly data do not contain some of the variables for the identification (social security benefits, public health insurance, public housing and rental subsidies) a valid concern might be that the method is not sufficiently accurate even for the low-skilled using these data. However, the figures shows that the remaining identifiers variables have enough power to achieve a similar identification accuracy as in the CPS March supplement data.

Tables

Table 9: Legal status and hourly wage of low-skilled workers, men

	(1)	(2)	(3)	(4)	(5)	(6)
Documented	-0.141***	-0.078***	-0.095***	-0.083***	-0.053***	-0.053***
	(0.0058)	(0.0100)	(0.0087)	(0.0082)	(0.0076)	(0.0075)
Undocumented	-0.324***	-0.226***	-0.249***	-0.211***	-0.145***	-0.143***
	(0.0063)	(0.0182)	(0.0159)	(0.0167)	(0.0147)	(0.0146)
Demographics	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
Metarea FE	No	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	No
Occupation FE	No	No	No	No	Yes	No
Industry x occupation	No	No	No	No	No	Yes
Observations	44849	44849	44849	44849	44849	44849
R-squared	0.073	0.103	0.132	0.170	0.238	0.266

Note: Dependent variable is the logarithm of the hourly wage. Data come from the CPS March supplement 1994-2016 and include prime-age workers (25-65) without high school degree. 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.

Table 10: Legal status and hourly wage of low-skilled workers, women

	(1)	(2)	(3)	(4)	(5)	(6)
Documented	-0.121***	-0.074***	-0.108***	-0.092***	-0.035***	-0.035***
	(0.0071)	(0.0144)	(0.0120)	(0.0118)	(0.0100)	(0.0104)
Undocumented	-0.227***	-0.155***	-0.195***	-0.164***	-0.080***	-0.075***
	(0.0081)	(0.0220)	(0.0189)	(0.0183)	(0.0142)	(0.0149)
Demographics	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
Metarea FE	No	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	No
Occupation FE	No	No	No	No	Yes	No
Industry x occupation	No	No	No	No	No	Yes
Observations	23656	23656	23656	23656	23656	23656
R-squared	0.039	0.058	0.107	0.136	0.236	0.274

Note: Dependent variable is the logarithm of the hourly wage. Data come from the CPS March supplement 1994-2016 and include prime-age workers (25-65) without high school degree. 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.

Table 11: Legal status and UE transition of low-skilled workers, men

	(1)	(2)	(3)	(4)	(5)	(6)
Documented	0.101***	0.087***	0.100***	0.095***	0.093***	0.094***
	(0.0065)	(0.0106)	(0.0119)	(0.0107)	(0.0108)	(0.0112)
Undocumented	0.193***	0.166***	0.183***	0.178***	0.180***	0.180***
	(0.0075)	(0.0103)	(0.0128)	(0.0126)	(0.0126)	(0.0122)
Demographics	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
State FE	No	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	No
Occupation FE	No	No	No	No	Yes	No
Industry x occupation	No	No	No	No	No	Yes
Observations	43551	43551	43551	43551	43551	43551
R-squared	0.027	0.036	0.054	0.060	0.072	0.099

Note: Dependent variable is the probability of a UE transition. Data come from the CPS basic monthly files 1994-2014 and include prime-age workers (25-65) without high school degree matched over two consecutive months. 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.

Table 12: Legal status and UE transition of low-skilled workers, women

	(1)	(2)	(3)	(4)	(5)	(6)
Documented	0.034***	0.030***	0.036***	0.036***	0.034***	0.035***
	(0.0065)	(0.0086)	(0.0079)	(0.0083)	(0.0092)	(0.0095)
Undocumented	0.070***	0.065***	0.080***	0.078***	0.075***	0.075***
	(0.0073)	(0.0097)	(0.0096)	(0.0105)	(0.0128)	(0.0131)
Demographics	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
State FE	No	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	No
Occupation FE	No	No	No	No	Yes	No
Industry x occupation	No	No	No	No	No	Yes
Observations	32083	32083	32083	32083	32083	32083
R-squared	0.005	0.008	0.022	0.023	0.037	0.067

Note: Dependent variable is the probability of a UE transition. Data come from the CPS basic monthly files 1994-2014 and include prime-age workers (25-65) without high school degree matched over two consecutive months. 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.

Table 13: Legal status and EU transition of low-skilled workers, men

	(1)	(2)	(3)	(4)	(5)	(6)
Documented	-0.001**	-0.001	-0.002***	-0.003***	-0.004***	-0.004***
	(0.0006)	(0.0007)	(0.0006)	(0.0007)	(0.0006)	(0.0007)
Undocumented	-0.001**	-0.003***	-0.004***	-0.005***	-0.008***	-0.008***
	(0.0006)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0010)
Demographics	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
State FE	No	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	No
Occupation FE	No	No	No	No	Yes	No
Industry x occupation	No	No	No	No	No	Yes
Observations	371621	371621	371621	371621	371621	371621
R-squared	0.000	0.001	0.002	0.005	0.008	0.015

Note: Dependent variable is the probability of an EU transition. Data come from the CPS basic monthly files 1994-2014 and include prime-age workers (25-65) without high school degree matched over two consecutive months. Demographic controls include *sex*, *race*, *age* and age^2. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 14: Legal status and EU transition of low-skilled workers, women

	(1)	(2)	(3)	(4)	(5)	(6)
Documented	-0.001	0.001	-0.000	-0.001	-0.002**	-0.002**
	(0.0007)	(0.0009)	(0.0010)	(0.0010)	(0.0009)	(0.0009)
Undocumented	0.004***	0.003**	0.003*	0.000	-0.002**	-0.002**
	(0.0009)	(0.0013)	(0.0013)	(0.0009)	(0.0007)	(0.0007)
Demographics	No	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
State FE	No	No	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	No
Occupation FE	No	No	No	No	Yes	No
Industry x occupation	No	No	No	No	No	Yes
Observations	194747	194747	194747	194747	194747	194747
R-squared	0.000	0.001	0.003	0.006	0.011	0.023

Note: Dependent variable is the probability of an EU transition. Data come from the CPS basic monthly files 1994-2014 and include prime-age workers (25-65) without high school degree matched over two consecutive months. Demographic controls include *sex*, *race*, *age* and age^2. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 15: Baseline calibration

Parameter	Definition	Value	Target
y	Match productivity	1	Normalization
P	Size of population	1	Normalization
u_U/u_D	Ratio of unemployed	0.27	Data equivalent
z_D	Unemployment value	0.71	Hall and Milgrom (2008)
z_U	Unemployment value	0.32	$z^{UI} = 40\%$ of doc. workers wage
β_D	Bargaining power	0.67	Average bargaining power of 0.5
β_U	Bargaining power	0.15	Wage gap from regression
c	Vacancy cost	0.72	JFR gap from regression
μ	Matching efficiency	0.39	Documented workers' JFR of 0.27
δ	Discount rate	0.997	Annual interest rate of 4%
s_D	Separation rate	0.030	Data equivalent
s_U	Separation rate	0.025	SR gap from regression
λ^W	Removal rate	0.0013	Data equivalent
λ^U	Removal rate	0.0013	Data equivalent
R	Removal disutility	100	-

Figures

Figure 19: Equilibrium with $\lambda^W = 0.0022$, $\lambda^U = 0$ and $R = 0$

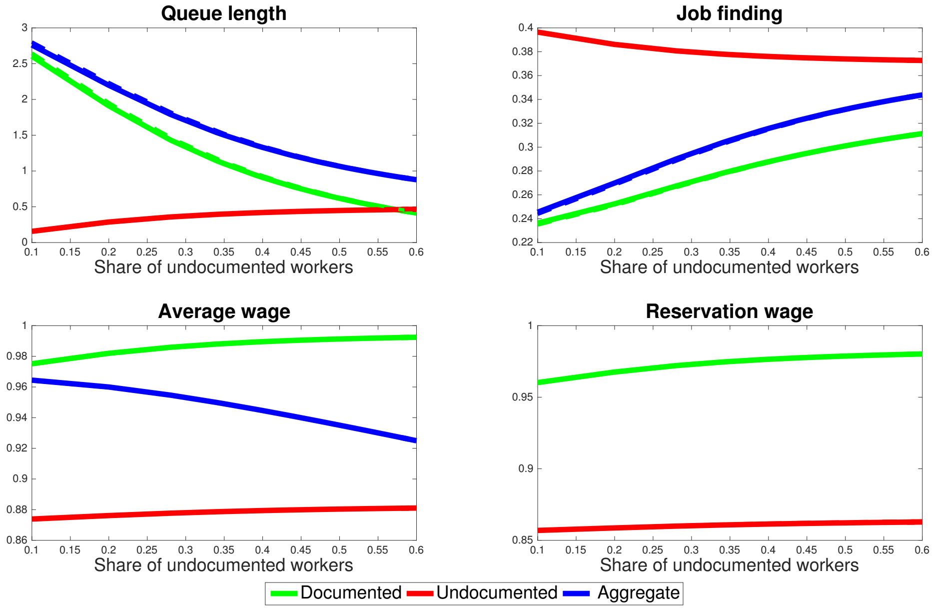


Figure 20: Equilibrium with $\lambda^W = 0.0022$, $\lambda^U = 0$ and $R = 100$

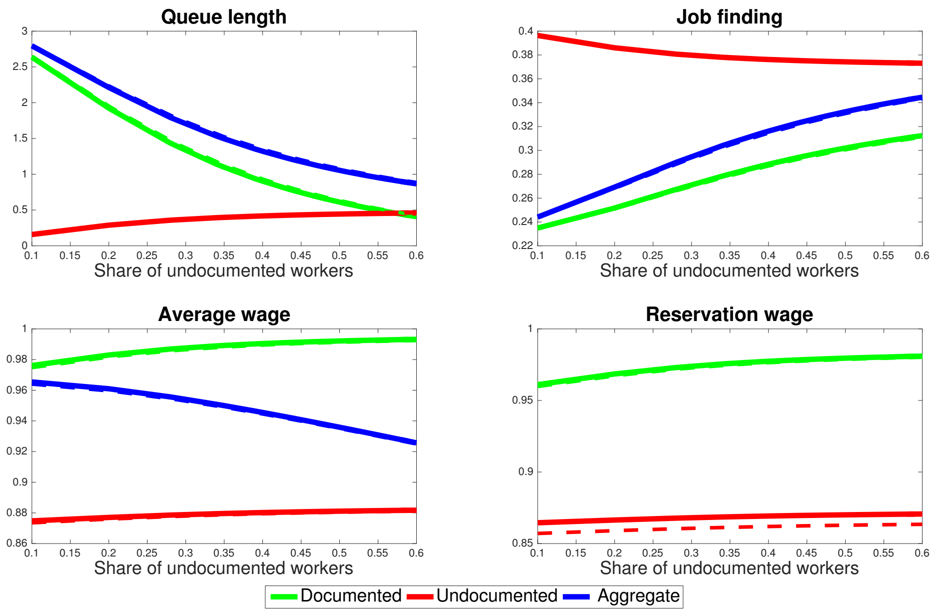


Figure 21: Equilibrium with $\lambda^W = 0.0022$, $\lambda^U = 0$ and $R = 200$