The Economic Impact, Location Choices and Assimilation of Immigrants

Christoph Albert

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DIRECTOR DE LA TESI

Regis Barnichon i Albrecht Glitz

Departament d'Economia i Empresa

upf. Universitat Pompeu Fabra Barcelona

To Alex

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Abstract

This dissertation consists of three self-contained essays. In the first chapter, I study the labor market impact of documented and undocumented immigration in a search model with non-random hiring that is parameterized based on wage and job finding rate gaps I find in US data. The model predicts that native workers benefit from undocumented immigration due to its strong job creation effect. In the second chapter, we document that immigrants in the US concentrate in large, expensive cities, where their earnings gap to natives is higher, and that they consume less local goods than natives. To explain these facts, we develop a quantitative spatial equilibrium model, in which immigrants consume a fraction of their income at their origin. The model suggests that by moving economic activity to more productive cities, immigration has led to an expansion in output per worker by around 0.3%. In the third chapter, we propose a unified framework that combines the approaches of the wage assimilation and the labor market impact literature by allowing both the accumulation of host country specific skills and general equilibrium effects to affect the relative wages of immigrants. We show that the latter can explain between 31% and 63% of the decline in entry wages experienced by the immigrant cohorts arriving in the US between the 1970s and the 1990s.

Resum

Aquesta tesi consta de tres assajos separats. En el primer capítol, estudio l'impacte en el mercat de treball de la immigració documentada i no documentada en un model de cerca amb la contractació no aleatòria que es parametritza en funció de les diferències del tipus de salaris i les tases de búsqueda de feina que he trobat utilitzant dades dels EUA. El model prediu que els treballadors natius es beneficien de la immigració indocumentada a causa del seu fort efecte en la creació de llocs de treball. En el segon capítol, documentem que els immigrants als Estats Units es concentren en ciutats grans i costoses, on la diferència d'ingressos amb els natius és més alta i que consumeixen menys béns locals que aquests. Per explicar aquests fets, desenvolupem un model d'equilibri espacial quantitatiu, en què els immigrants consumeixen una fracció dels seus ingressos en el seu origen. El model suggereix que, pel movient de l'activitat econòmica cap a ciutats més productives, la immigració ha suposat una expansió de la producció per treballador de un 0,3%. En el tercer capítol, proposem un marc unificat que combina els enfocaments de l'assimilació salarial i la literatura d'impacte en el mercat de treball, ja que permet l'acumulació d'habilitats específiques en el país amfitrió i efectes d'equilibri general per afectar els salaris relatius dels immigrants. Mostrem que aquest últim pot explicar entre un 31% i un 63% del descens dels salaris d'ingressos experimentats per les generacions d'immigrants que arriben als EUA entre els anys 1970 i 1990.

Preface

This dissertation consists of three self-contained essays on immigrants' economic impact, location choices and wage assimilation in the US. Chapter 1 studies the labor market impact of low-skilled undocumented immigration in contrast to documented immigration; Chapter 2 investigates the location choices of immigrants and their consequences for the distribution of economic activity across cities; Chapter 3 proposes a novel framework that allows both skill accumulation and general equilibrium effects to account for changes in the wage assimilation patterns of immigrant arrival cohorts over time.

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

In the second chapter, co-authored with Joan Monras, we investigate the causes and effects of the spatial distribution of immigrants across US cities. We document that: a) immigrants concentrate in large, high-wage, expensive cities, b) the earnings gap between immigrants and natives is higher in larger, more expensive cities, and c) immigrants consume less locally than natives. In order to explain these findings, we develop a quantitative spatial equilibrium model in which immigrants consume a fraction of their income in their countries of origin. Thus, immigrants care not only about local prices, but also about price levels in their home countries. This gives them a comparative advantage relative to natives for living in high-wage, high-price, high-productivity cities, where they also accept lower wages than natives. These incentives are stronger for immigrants coming from lower-price index countries of origin. We rely on immigrant heterogeneity to estimate the model. With the estimated model, we show that current levels of immigration have reduced economic activity in smaller, less productive cities by around 5 percent, while they have expanded it in large, productive cities by around

6 percent. This has increased total aggregate output per worker by around 0.3 percent. We also discuss the welfare implications of these results.

In the third chapter, co-authored with Albrecht Glitz and Joan Llull, we propose a unified framework for the prediction of wage assimilation patterns that is based on the idea that earnings of immigrants not only depend on how close they are to natives with respect to their skills, but also on the amount of competition from workers offering similar skills. Thus, we combine the approaches of the literature on immigrant wage assimilation and the literature on the labor market impact of immigration by allowing for both the accumulation of host country specific skills and general equilibrium effects. Output is produced using imperfectly substitutable native and immigrant skill units, whereby immigrants can accumulate native units over time. The relative remuneration of the skill units depends on their total relative supply in the economy. Therefore, the wage gaps between natives and immigrants reflect both individual skills and the degree of labor market competition. After estimating the model using decennial US data from 1970 to 2010, from which we obtain an elasticity of substitution between native and immigrant labor around 13, we simulate counterfactual assimilation profiles by fixing the total skill supplies across arrival cohorts and compare them to the actual profiles. We find that 31% of the decline in entry wages experienced by the cohorts entering in the 1970s, 1980s and 63% of the decline experienced by the cohort entering in the 1990s can be explained by shifts in the relative supplies due to rising immigrant inflows in the US since the 1960s.

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Chapter 1

THE LABOR MARKET IMPACT OF UNDOCUMENTED IMMIGRANTS: JOB CREATION VS. JOB COMPETITION

1.1 Introduction

Is immigration beneficial for native workers because it leads to the creation of additional jobs or does it harm their labor market prospects through higher job competition? This question has been the subject of much debate as many developed countries saw rising immigrant inflows over the last few decades. In the United States, the share of foreign-born residents among the population has increased from around 5% in the 1970s to over 13% today, triggered by a change in immigration policy that facilitated the entry from Latin America and Asia and caused a shift in the skill composition towards less educated immigrants. Another major change in the nature of US immigration especially since the beginning of the 1990s is a pronounced shift towards undocumented immigration. While the number of all immigrants residing in the US doubled from around 20 million to 40 million between 1990 and 2013, the number of immigrants without legal status increased almost fourfold from 3 million to over 11 million during the same period.[1] Undocumented immigrants in the US actively participate in the labor market and make

[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.

up around 5% of the labor force.[2]

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

In order to quantify the differences in labor market outcomes by legal status, I perform a regression analysis using US survey data of low-skilled workers in the empirical part of this paper. I find that undocumented immigrants earn around 8% less and have a 7 percentage points higher job finding rate than documented immigrants. The latter earn around 4% less and have a 7 percentage points higher job finding rate than natives. After setting up the model, I parameterize it to match these estimates and use it to simulate documented and undocumented immigration. The simulations indicate that the job creation effect of undocumented immigration is large enough to dominate the job competition effect. Although its job creation effect is also positive, the opposite holds for documented immigration. Therefore, only undocumented immigration is unambiguously beneficial for natives as it raises both their employment rate and wages, whereas documented immigration decreases natives' employment. I test these predictions empirically using an early settlement instrument to account for endogeneity in the immigrant population shares. I find a positive effect of the undocumented immigrant share in the labor force on vacancy creation and wages among low-skilled workers at the city level, but I do not find a positive effect of the documented immigrant share. This supports the finding that undocumented immigration increases employment opportunities and wages of natives more than documented immigration.

Finally, I use the framework to study the impact of a counterfactual policy of stricter immigration enforcement, which I simulate by increasing the deportation ("removal")

[2] Borjas (2017a) 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.

rate for undocumented immigrants. I distinguish two cases: a rise in the removal rate that is the same independently of employment status and a rise in the removal rate only for employed workers, for example because of an intensified use of worksite raids by authorities. In the first case, the policy leads to a marginal increase in natives' and documented immigrants' unemployment rates because expected firm surplus and thus job creation are dampened weakly. In the second case, firms additionally have to pay a risk compensation in order to induce an undocumented job seeker to accept being hired and as a result wage costs rise and job creation is dampened more strongly. The group most affected by this policy are native workers, whose unemployment rate rises between 1.7 and 5.7 percentage points and wages fall between 0.5% and 1.7% when the removal rate increases by one percentage point. For documented immigrants, the effects on unemployment and wages are 0.5 to 1.5 percentage points and -1.1% to -3.7%, respectively.[3] I test these predictions using the state-wide implementation of omnibus immigration laws as a measure of stricter immigration enforcement and find that introducing these laws is associated with a lower job finding rate for all workers, which is evidence for muted vacancy creation. Moreover, I find a fall in wages for natives and higher wages for immigrants, which is consistent with a risk compensation in immigrants' wages.

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

The second contribution is the analysis of both documented and undocumented immigration in a search and matching model that is consistent with the empirical facts. The differences across workers in both wages and job finding rates generated by the model match their empirical counterparts. While a difference in wages between otherwise identical workers can also be generated in a standard job search model, the difference in job finding rates is a puzzle for a model with random matching between firms and workers. I therefore include a non-random hiring mechanism (following Barnichon and Zylberberg, 2017) in my framework, which implies that firms can receive multiple applications and choose their preferred candidate among them. This generates higher job

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

finding probabilities for cheaper workers and therefore implies that natives have the lowest and undocumented immigrants have the highest job finding rate as suggested by the data.

Previous studies on migration in the US often only distinguish immigrants according to their skill composition as measured by educational attainment and labor market experience (e.g. Borjas, 2003; Peri and Sparber, 2009; Ottaviano and Peri, 2012; Llull, 2017b). However, being undocumented has been shown to have a causal effect on immigrants' labor market outcomes,[4] and therefore legal status should not be neglected as an additional dimension of heterogeneity across immigrants.[5] A recent study that does differentiate between documented and undocumented immigrants is by Edwards and Ortega (2017). In contrast to my framework, the authors assume a frictionless labor market with wages equal to marginal productivity, which implies that the earnings differences between documented and undocumented workers are solely explained by their productivity differential. While productivity differences may play some role, there are various other explanations for lower earnings of undocumented workers that are unrelated to productivity. As undocumented immigrants have no work permission, firms are not bound to any minimum wage laws and might use the threat of being sanctioned for their hiring to justify paying them lower wages. Furthermore, the inability to receive unemployment benefits lowers the outside option to working and might additionally suppress the wages of undocumented workers. I therefore use a framework with search frictions that allows for wage differences across equally productive workers through heterogeneity in bargaining power and unemployment benefits across types for my analysis.

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

[4]Kossoudji and Cobb-Clark (2002) and Pan (2012) find that becoming legal is associated with an increase in wages. Amuedo-Dorantes and Bansak (2011) find that it additionally decreases the employment rate.

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

my model. This gives rise to the competition effect of immigration and implies that it depends on the size of the wage difference between natives and the immigrating worker type whether immigration is beneficial for natives or not.

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

The remainder of the paper is organized as follows. In section 1.2, I describe how undocumented immigrants are identified in the data and present some descriptive statistics. Section 1.3 analyzes wages and job finding rates of natives, documented and undocumented immigrants empirically. Section 1.4 sets up the search model with non-random hiring. Section 1.5 outlines the parameterization strategy. Section 1.6 examines the effect of documented and undocumented immigration in the model. Section 1.7 explores the impact of a rise in the removal risk. Section 1.8 tests some predictions derived from the model empirically. Section 1.9 concludes.

1.2 Data, Identification Method and Descriptives

In the following section, I describe the data and the method I use to identify undocumented immigrants. This method is first described in Borjas (2017a) and is based on demographic, social and economic characteristics of survey respondents. I show that the percentage of both documented and undocumented immigrants is by far the highest among workers without a high school degree. I further highlight the demographic differences between natives and immigrants and their concentration across industries by education level.

1.2.1 Data and Identification of Undocumented Immigrants

The data used in this section come from the March supplement of the Current Population Survey (CPS) obtained from IPUMS (Flood et al., 2017). My analysis is restricted to the period beginning in 1994 because information on the birthplace and citizenship status of a survey respondent was only included from that year on. I only consider prime age workers (age 25 to 65) in all samples. A respondent is defined as an immigrant, if born outside the United States and not American citizen by birth. In section 3.2, I further use the basic monthly files of the CPS with workers matched over two consecutive months following Shimer (2012) in order to examine transition rates between employment and unemployment.

Neither the CPS basic monthly files nor the March supplement allow to directly identify undocumented immigrants. However, as the US labor market surveys are address-based and designed to be representative of the whole population, they also include undocumented respondents. The CPS data are likely to offer the best coverage of undocumented immigrants because individuals are interviewed in person, whereas for the US Census and ACS data are collected by mail.[6] The government surveys are actually used by the US Department of Homeland Security (DHS) to estimate the size of the undocumented immigrant population via a so-called "residual method". The DHS obtains figures of legal immigrants in the US from administrative data of officially admitted individuals and subtracts them from the foreign-born non-citizen population estimated from the surveys. The resulting residual is the estimated number of unauthorized residents.

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

[6] 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.

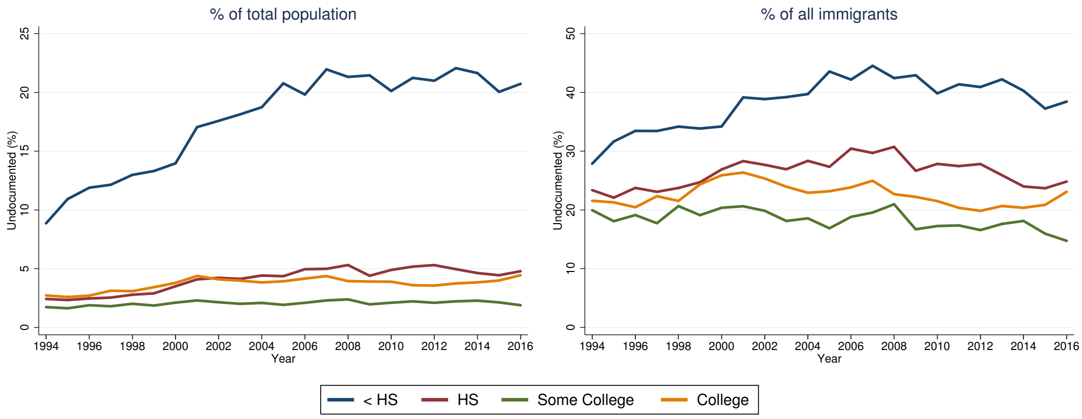
- being US citizen
- residing in the US since 1982 or before
- receiving social security benefits or public health insurance
- residing in public housing or receiving rental subsidies
- being veteran or currently in the Armed Forces
- working in the government sector or in occupations requiring licensing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

All remaining immigrants are then classified as undocumented. Thus, Borjas (2017a) does not apply a filter on the potentially undocumented immigrants to make their final count consistent with estimates from the residual method as Passel and Cohn (2014) do. In order to assess the accuracy of this simplified method without filtering, Borjas (2017a, Table 1) compares summary statistics for the undocumented immigrant population in his CPS sample with the corresponding summary statistics in a CPS sample including the undocumented identifier constructed by Passel and Cohn (2014), which he was granted access to by the authors. While the total share of undocumented immigrants in the population and most other statistics are very similar across the samples, their educational attainment is notably higher in the Borjas sample. This suggests that there might be an excess of immigrants classified as undocumented among the high-skilled.[7] In Appendix 1.A, I investigate this issue in more detail and show that applying Borjas' simplified method indeed leads to an excess of undocumented among immigrants with at least some college education in the CPS March and CPS basic data.

Figure 1.1 plots the share of undocumented immigrants identified with the method of Borjas (2017a) among the total prime age population and among all prime age immigrants since 1994 in the four groups commonly used for the classification of educational attainment: high school dropouts, high school graduates, workers with some college education and college graduates. Among high school dropouts, the percentage of undocumented immigrants is by far the highest and increased the strongest, from 9% in 1994 to over 22% in 2007, remaining relatively constant since then. In the higher education groups, which should be viewed with caution due to the mentioned overcounting of undocumented immigrants, the percentage has risen only moderately, reaching just around

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

Figure 1.1: Percentage of undocumented immigrants



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

5% for high school and college graduates.[8] Also among immigrants, the percentage of undocumented is the largest and increased the most in the group of high school dropouts. This suggests that on average undocumented have a lower education than documented immigrants and this difference has increased since 1994 (the percentage of high school dropouts is around 37% among the former and 19% among the latter in 2016).

Table 1.1 shows some descriptive statistics of the sample of prime age workers covering the most recent ten years (2007-2016) by education and status (native, documented immigrant or undocumented immigrant). Across all education levels, undocumented workers are six to seven years younger than both native and documented workers, who have around the same age. Moreover, depending on the education level, documented are 9 to 13 years longer in the US than undocumented immigrants. This is mainly because undocumented immigrants that entered the US in 1982 or before were granted amnesty by the Immigration Reform and Control Act of 1986 (IRCA) and thus the earliest entry year for an undocumented immigrant in the data is 1983. Irrespective of education, the percentage of men among documented immigrants is somewhat lower and among undocumented somewhat higher than among natives. The shares of hispanic and asian workers differ substantially by education. Among undocumented high school dropouts, 89% of workers are hispanic and this percentage decreases strongly with education. Among college graduates without documentation, only 18% are of hispanic origin. A similar pattern holds for documented immigrants, although their share of hispanic workers is lower than among undocumented immigrants. For the share of Asian workers, we observe the opposite pattern across education levels: the higher is

[8]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).

Table 1.1: Descriptive statistics

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

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

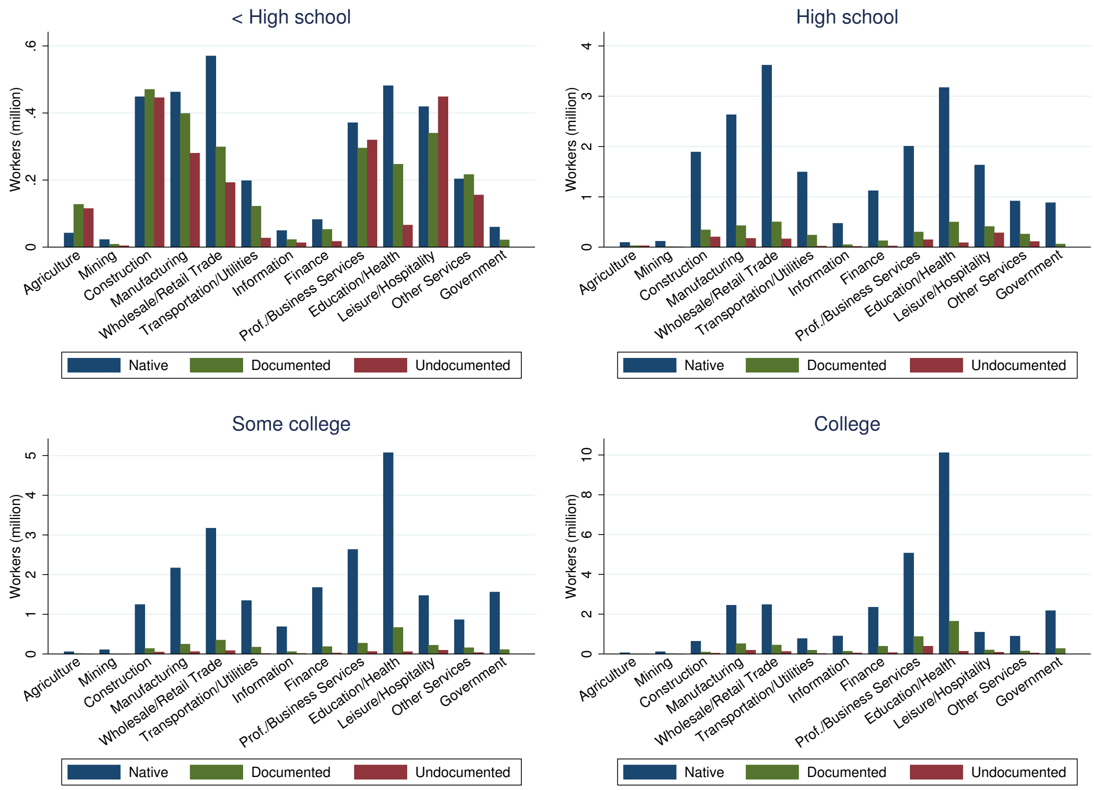
education, the higher is the share of asians among immigrants. Moreover, for workers with less than a college degree there are more asians among documented than among undocumented immigrants.

Figure 1.2 explores whether legal status is associated with a concentration in different industries. I identify 13 industries based on the one-digit level of the North American Industry Classification System (NAICS). The most salient feature of the figure are the high numbers of both documented and undocumented immigrant workers among high school dropouts, which in most industries are close to the number of native workers. Only Wholesale and Retail Trade, Transportation and Utilities, Education and Health as well as Government[9] are largely dominated by a native workforce. In Agriculture, native workers are even a small minority among workers without high school degree. Most undocumented high school dropouts work in the Construction and Leisure and Hospitality industry. In the latter, which includes for example cooks and waiters, they constitute even the largest share of the three worker types. The upper right and bottom panels suggest that among higher educated workers with at least a high school degree, the number of immigrants is small compared to the number of natives across all industries. Furthermore, the number of undocumented is always smaller than the number of documented immigrants.

Given the large size of the immigrant workforce relative to natives among high school dropouts, I choose to restrict my empirical analysis to this education level (for simplicity

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

Figure 1.2: Worker distribution across industries by education



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

henceforth referred to as "low-skilled"). Beside the large share of both documented and undocumented immigrant workers, there are three more reasons for focusing on this group. First, the identification method is more precise among low-skilled workers as shown in Appendix 1.A. Second, concentrating on workers that are homogenous in terms of their education level is likely to lead to a more precise estimation of the effect of legal status. Third, unobserved skill differences between natives, documented and undocumented immigrants play a rather small role in the low-skilled labor market.

1.3 Empirical Evidence

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

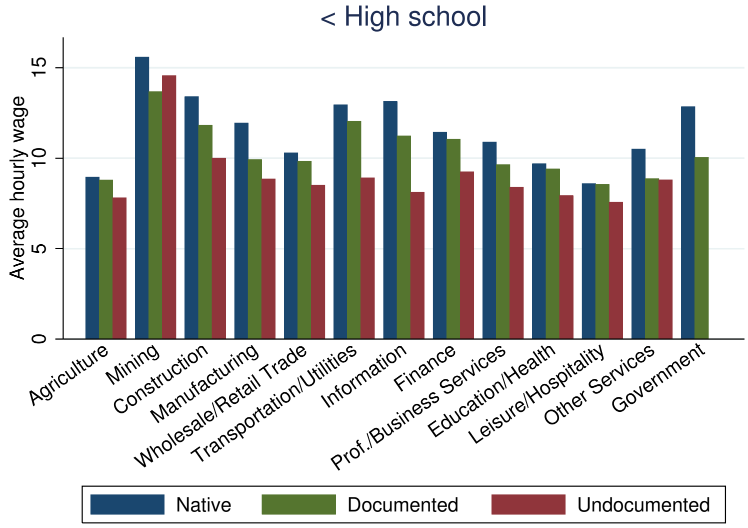
1.3.1 Wages

It has been well documented in the literature that immigrants are paid less than native workers even when controlling for observables in microdata. In order to find evidence for a wage difference among immigrants' because of their legal status, previous studies exploited the amnesty through the IRCA in 1986 as a quasi-experiment. Their estimates of the effect of legalization lie between 6% by Kossoudji and Cobb-Clark (2002) and 10% by Pan (2012). Borjas (2017a) introduces a novel, easily replicable strategy that does not rely on the IRCA and can be used to identify undocumented immigrants in more recent microdata. His estimates of the wage penalty of undocumented immigrants is around 12% (Borjas, 2017b).[10] I follow his strategy of using the CPS March supplement data with undocumented immigrants identified by the Borjas (2017a) algorithm to estimate differences in labor market outcomes. However, I use a sample of low-skilled workers only, in which the accuracy of the identification method is much higher, and add further controls to the regression model to account for different industry and occupation choices. As common in the literature (e.g. Borjas, 2003), I exclude the self-employed, those working without pay, those not working full-time (52 weeks per year, at least 35 hours per week) and individuals living in group quarters. I construct real hourly wages by dividing the total wage income of an employee by the number of hours worked per year, deflating the result to 1999 dollars with the CPI-U adjustment factor provided in the IPUMS database and controlling for outliers by dropping the 1st and 99th percentile of the distribution of the hourly wage.

Figure 1.3 reports the average hourly wages of workers without high school degree in each of the 13 industries during the period 2007-2016. As expected, natives earn the most in all industries. With the exception of Mining, documented immigrants have the second highest wages, while undocumented immigrants have the lowest. The worst-paying industries with earnings of under $10 for all types of workers are Leisure and Hospitality, Agriculture and Education and Health. Except for Mining and Construction, undocumented immigrants earn hourly wages well below $10 in all industries.

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

Figure 1.3: Hourly wages of low-skilled workers (1999 dollars)



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

However, these figures should be viewed with caution as Table 1.1 clearly suggests that the three worker types differ with respect to demographic characteristics, which certainly influence their earnings. Controlling for observables beyond education and industry is therefore crucial.

In order to test whether the wage differences between worker types also exist between otherwise comparable workers, I run a wage regression with an extensive set of demographic controls including age, age squared, sex, hispanic and asian origin. Additional to demographic factors and industry fixed effects, I control for workers' occupations, which relates to the specific technical function in a job. Indeed, several studies suggest that natives and immigrants are imperfect substitutes and tend to specialize in tasks they have a comparative advantage in, which are more communication-intensive for natives and more manual/physical for immigrants (Peri and Sparber, 2009). Thus, I include a dummy for each of the around 500 occupation codes attributed to workers in the CPS data. As a final robustness check, I include an interaction of industry and occupation fixed effects, i.e. a dummy for each industry-occupation combination instead of separate industry and occupation dummies. By doing so, I assume that only within each industry-occupation cell, natives, documented and undocumented immigrants are perfect substitutes. The regression specification has the following form:

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

where the dummies D_{it} and U_{it} are indicators for being a foreign-born documented or

Table 1.2: Legal status and hourly wage of low-skilled workers

	(1)	(2)	(3)	(4)	(5)
Documented	-0.118***	-0.071***	-0.094***	-0.044***	-0.043***
	(0.0047)	(0.0104)	(0.0085)	(0.0065)	(0.0067)
Undocumented	-0.272***	-0.207***	-0.237***	-0.128***	-0.126***
	(0.0051)	(0.0178)	(0.0151)	(0.0122)	(0.0123)
Demographics	No	Yes	Yes	Yes	Yes
Year/MSA FE	No	No	Yes	Yes	Yes
Ind/occ FE	No	No	No	Yes	No
Ind x occ FE	No	No	No	No	Yes
Observations	68563	68563	68563	68563	68563
R-squared	0.050	0.138	0.165	0.271	0.295

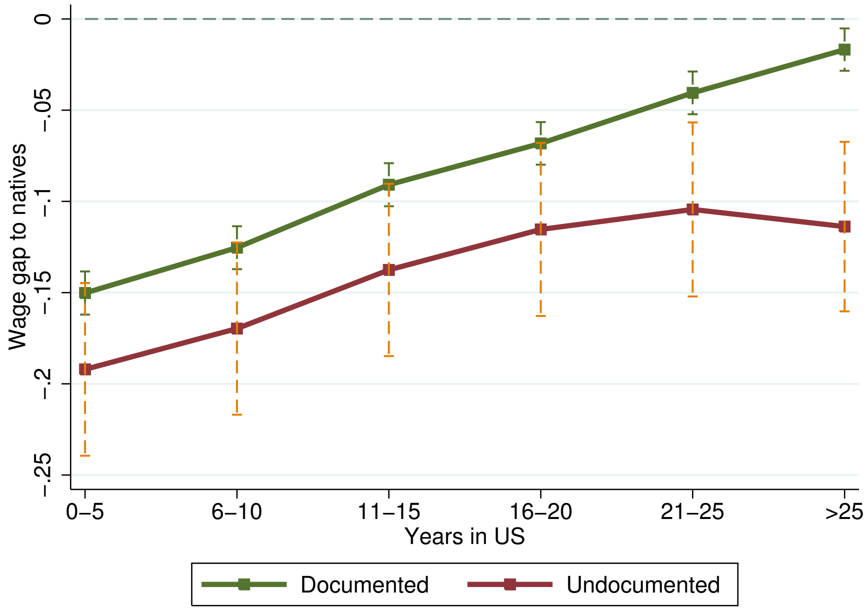
Notes: Dependent variable is the logarithm of the hourly wage. Data come from the CPS March supplement 1994-2016 and include high school dropouts aged 25-65. Demographic controls include sex, $race$, age and age^2. Standard errors are clustered at the metropolitan area level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

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 1.2. The baseline specification without controls suggests that documented immigrants earn around 12% and undocumented immigrants around 27% less than the native reference group. The inclusion of demographic controls shrinks the wage gaps to 7% and 21%, respectively. The results after additionally including year and MSA fixed effects in column (3) are in line with the results of a comparable specification in Borjas (2017b, Table 2), who finds very similar coefficients even though he uses a sample with all education groups and only the years 2012-2013.[11] Adding industry and occupation fixed effects shrinks both coefficients by around a half, which confirms the importance of controlling for the different distribution of workers across jobs even conditional on demographics. Coefficients remain virtually identical when including industry-occupation interactions. Column (5) indicates that documented immigrants earn only 4.3% less than natives and the undocumented status of an immigrant accounts for an additional wage gap of 8.3%. This result is well within the range of the results obtained by the studies estimating the wage gain from legalization through the 1986 IRCA.

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

Figure 1.4: Wage gap to natives



Notes: The wage gaps result from a regression with the same controls as in column (5) of Table 1.2 including workers with at most high school. Vertical dashed lines show 10% confidence intervals.

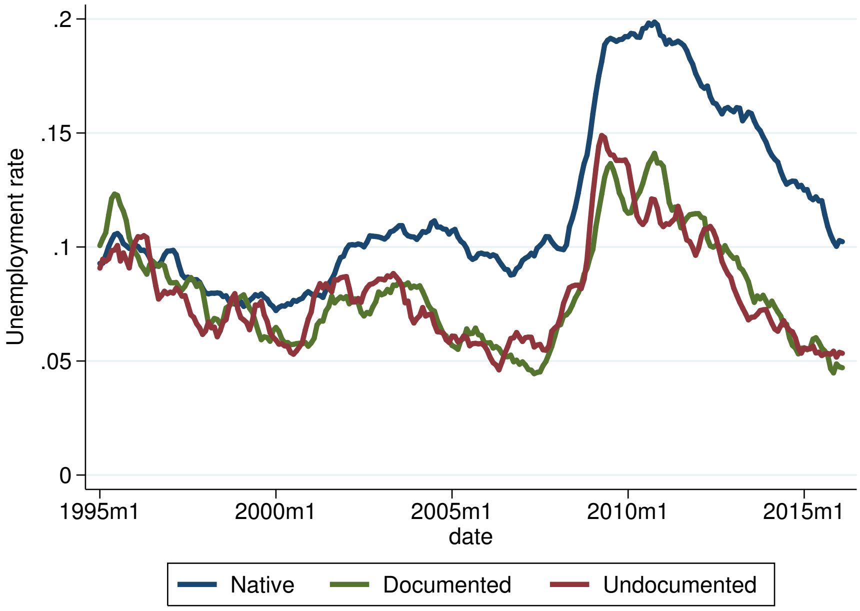
The regression model considered above still does not take into account the differences in time spent in the US between the immigrant types seen in Table 1.1. It is well known that immigrants assimilate into their host country over time and that this is associated with earnings growth (e.g. Borjas, 1985). In order to account for a potentially non-linear and immigrant-type specific growth in hourly wages over time, I augment the wage regression by an interaction between the documented and undocumented immigrant dummies and years in US, which I group in six 5-year intervals (1-5, 6-10, 11-15, 16-20, 20-25 and >25) denoted by $y = 1, ...6$. The equation for immigrants therefore takes the following form:

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

Figure 1.4 plots the wage gap to natives for both immigrant types for each interval of years in the US. To increase the number of immigrants observations per interval, I also include high school graduates in the regression underlying the figure and add a dummy indicating having completed high school as educational control.[12] The wage gaps of documented and undocumented immigrants residing in the US for at most 5 years are around 15% and 20% respectively. The speed of assimilation is almost identical for both types of immigrants during the first 20 years, however, after that the assimilation of

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

Figure 1.5: Unemployment rates of low-skilled workers



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

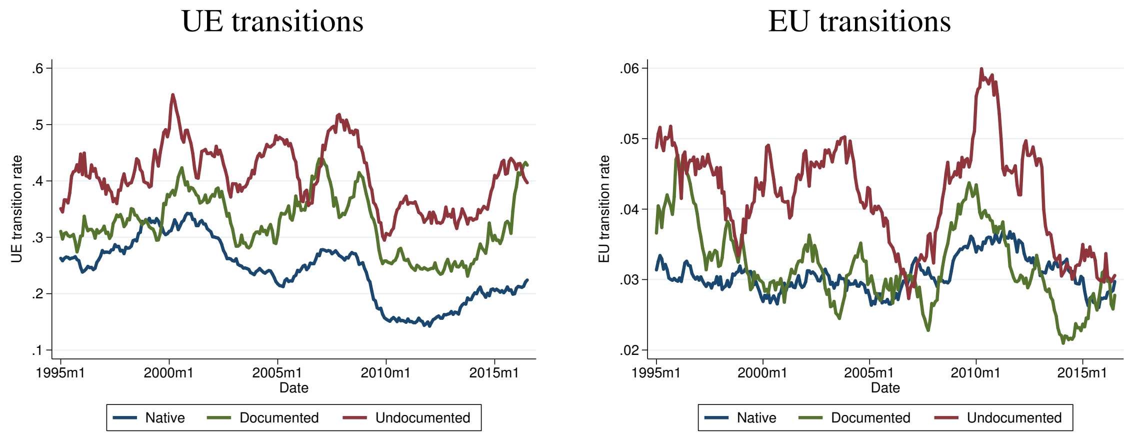
undocumented immigrants slows down. Earning only 2% less than natives, documented workers have almost fully assimilated after 25 years, at which point undocumented workers still earn around 12% less. Thus, there are two important take-aways from Figure 1.4. First, even accounting for the length of stay in the US, there is still a large wage gap between documented and undocumented immigrants. Second, the gap to natives is initially large and disappears through assimilation for the former but not for the latter.

1.3.2 Unemployment and Transition Rates

I now turn to the analysis of the difference in unemployment and transition rates between employment and unemployment. The data used in this subsection are the CPS basic monthly files, in which some of the variables for the identification of legal respondents, e.g. social security benefits or health insurance, are not available. Although this should lead to a lower precision of the undocumented immigrant identifier, I show in Appendix 1.A that there is no excess of undocumented immigrants among the low-skilled in the CPS basic data.

Figure 1.5 plots the seasonally adjusted unemployment rates of low-skilled workers. Both types of immigrants have virtually the same rate of unemployment, which is significantly lower than the one of natives, (except in the very beginning of the sample

Figure 1.6: Transition rates of low-skilled workers



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

period). Contrary to the findings for wages, this first evidence seems to suggest that only the status of being an immigrant but not the legal status matters for employment.

To determine 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 left panel of Figure 1.6 shows the series of job finding rates (UE transitions). Over most of the sample period, undocumented job searchers have the highest job finding rate of all workers with a gap of up to around 15 percentage points to documented job searchers. Only around 2007-2008 and at the end of the period, the latter have a similar rate. From 2000 on, natives permanently have the lowest job finding rate with the difference to undocumented immigrants being up to 25 percentage points. Given the similar level of the unemployment rate of documented and undocumented workers seen in Figure 1.5, we expect a higher separation for undocumented counteracting the higher job finding rate. This is confirmed by the right panel of Figure 1.6, which shows that the EU transition rate series of documented immigrants is close to the series of natives, while it is higher over most of the period for undocumented immigrants. Altogether, the decomposition in transition rates suggest that, although the unemployment rates of

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

Table 1.3: Legal status and UE transition of low-skilled workers

	(1)	(2)	(3)	(4)	(5)
Documented	0.069***	0.061***	0.071***	0.068***	0.069***
	(0.0047)	(0.0063)	(0.0078)	(0.0073)	(0.0072)
Undocumented	0.142***	0.126***	0.141***	0.139***	0.140***
	(0.0053)	(0.0084)	(0.0106)	(0.0116)	(0.0117)
Demographics	No	Yes	Yes	Yes	Yes
Year/State FE	No	No	Yes	Yes	Yes
Ind/occ FE	No	No	No	Yes	No
Ind x occ FE	No	No	No	No	Yes
Observations	75634	75634	75634	75634	75634
R-squared	0.016	0.029	0.044	0.057	0.079

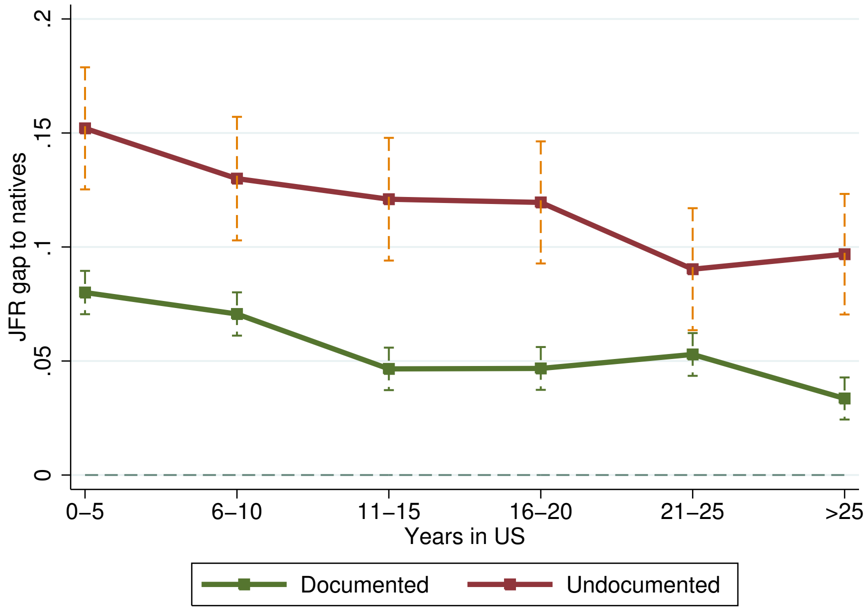
Notes: Dependent variable is the probability of a UE transition. Data come from the CPS basic files 1994-2016 and include high school dropouts aged 25-65. Demographic controls include sex, $race$, age and age^2. Standard errors are clustered at the state level. Significance levels: * p<0.1, ** p<0.05,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

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 (Shimer, 2012).

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

The regression results for job finding rates (UE transitions) are reported in Table 1.3 and confirm the patterns seen in Figure 1.6: both types of immigrants find jobs faster than natives and undocumented workers even faster than documented ones. Controlling for observables does not influence the results, which are almost identical across all specifications. With the average monthly job finding probability of all workers being around 23%, the coefficients suggest that documented workers find jobs with a probability that is around one third higher than the average and undocumented workers with

Figure 1.7: Job finding rate gap to natives



Notes: The wage gaps result from a regression with the same controls as in column (5) of Table 1.2 including workers with at most high school. Vertical dashed lines show 10% confidence intervals.

a probability that is even 60% higher than the average.

Analogously to Figure 1.4, Figure 1.7 plots the predicted difference in job finding rates of immigrants to natives depending on time in the US, resulting from a regression with an interaction between the immigrant dummies and 6 categories for years in the US. The results are robust to taking into account the duration of stay in the US as there is a permanent difference in job finding rates of 6 to 8 percentage points between the documented and undocumented immigrants. As for wages, the gap narrows over time for both types of immigrants, although it does not disappear completely after having spent more than 25 years in the US for neither type.

Table 1.4 shows the regression results with EU transitions as the dependent variable. In order to be consistent with the sample of the wage regressions, I only consider separations from full-time jobs. Further, I only consider transitions to unemployment, if the reason for unemployment is either "job loser" or "job leaver".[14] The coefficients in the model with the full set of controls suggest that documented immigrants have a 0.3 percentage points and undocumented immigrants a 0.6 percentage points lower separation probability than natives. Quantitatively, these differences between worker types are much smaller compared to the differences in job finding rates. This also holds when relating the differences to the smaller average separation probability, which is around 1.6%.

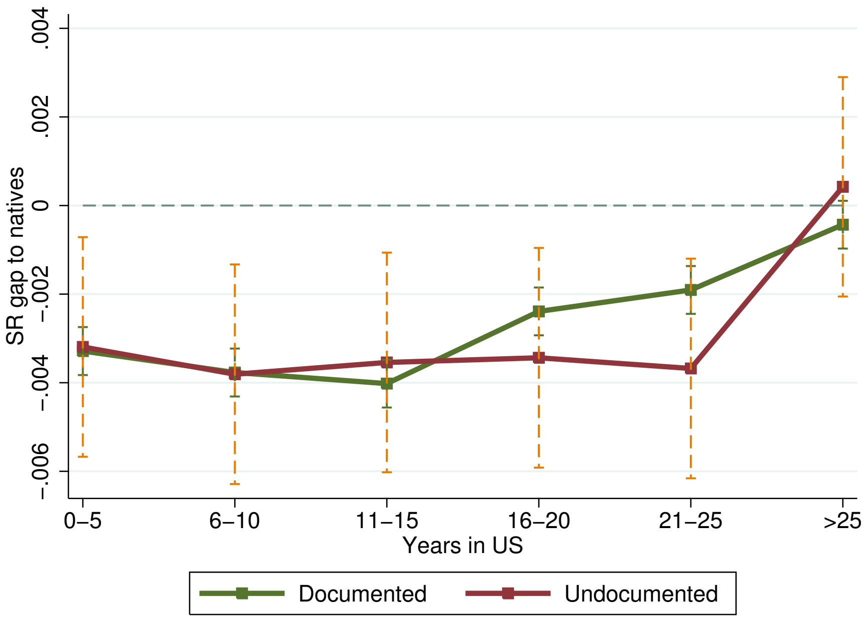
[14]The other unemployment reasons are: "temporary job ended", "re-entrant" and "new-entrant".

Table 1.4: Legal status and EU transition of low-skilled workers

	(1)	(2)	(3)	(4)	(5)
Documented	-0.001**	-0.001	-0.001***	-0.003***	-0.003***
	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.0004)
Undocumented	0.001	-0.001	-0.002*	-0.006***	-0.006***
	(0.0005)	(0.0009)	(0.0009)	(0.0007)	(0.0007)
Demographics	No	Yes	Yes	Yes	Yes
Year/State FE	No	No	Yes	Yes	Yes
Ind/occ FE	No	No	No	Yes	No
Ind x occ FE	No	No	No	No	Yes
Observations	566368	566368	566368	566368	566368
R-squared	0.000	0.001	0.002	0.007	0.013

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

Figure 1.8: Separation rate gap to natives



Notes: The wage gaps result from a regression with the same controls as in column (5) of Table 1.2 including workers with at most high school. Vertical dashed lines show 10% confidence intervals.

Figure 1.8 plots the predicted difference in separation rates of immigrants depending on length of stay in the US. Conditional on time in the US, there is no significant difference in separation rates between immigrants. Both documented and undocumented workers have lower separation rates initially and fully catch up to natives after more than 25 years in the country.

1.3.3 Reservation Wages

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

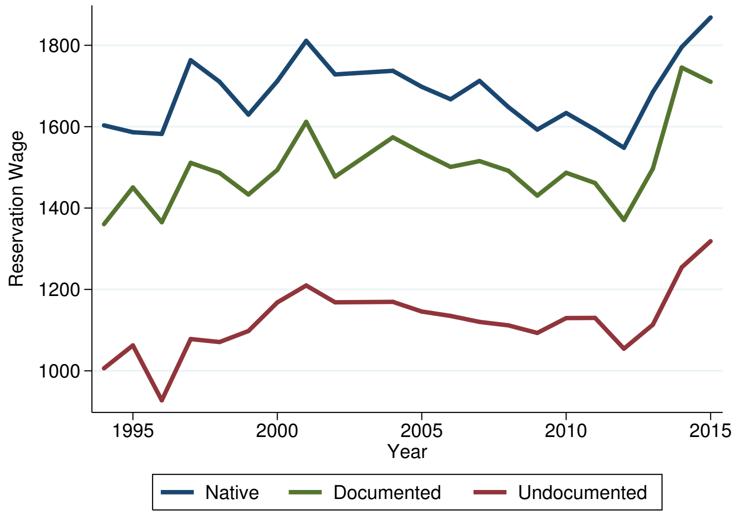
$$rU_i = z_i + f_i \frac{w_i - z_i}{r + s_i + f_i}.$$

The value depends positively on unemployment benefits z_i (which also include the value of leisure or home production and is net of job-search costs), job finding rate f_i and wage w_i (which depends on the bargaining power of a worker), and negatively on the interest rate r and the rate of job separation s_i. Being the opportunity costs to working, the flow value of being unemployed equals the reservation wage at which a worker is indifferent between staying unemployed and having a job, i.e. $\underline{w_i} = rU_i = rW(\underline{w_i})$. This equation shows how changes in the exogenous variables z_i, r and s_i affect the endogenous variables f_i and w_i through the equilibrium mechanism. A fall of the reservation wage, e.g. because of a decrease in z_i or an increase in s_i, lowers the threat point of a worker and therefore decreases his negotiated wage. This induces job creation due to higher firm profits, which increases job finding and therefore counteracts the reservation wage decline.

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

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

Figure 1.9: Reservation wages of low-skilled workers



Notes: The gaps underlying the calculation result from a regression with the full set of controls as in the final column of Table 1.2.

I obtain the series of wages and transition rates by first calculating the average for natives in each year and then running regressions corresponding to the final columns of Tables 1.2-1.4, in which the coefficients of D_{it} and U_{it} are allowed to vary by year. I compute the hourly wages and monthly transition rates f_i and s_i of documented and undocumented immigrants for each year by applying the gap given by the time-varying coefficients of the respective dummies to the corresponding series calculated for natives. In order to convert hourly wage to monthly income w_i , I assume 40 hours worked per week. For simplicity, the unemployment flow payment is computed as $z_i = 0.4w_i$. The monthly interest rate is set to 0.004 as in Shimer (2005).

Figure 1.9 displays the resulting series of reservation wages $\underline{w_N}$, $\underline{w_D}$ and $\underline{w_U}$. Despite having the highest job finding and lowest separation rate, undocumented immigrants have by far the lowest reservation wage, which is around \$600 below the reservation wage of natives throughout the whole period. Documented immigrants on the other are only around \$200 below natives. This confirms that the negative effect of a lower wage overcompensates the positive effect of a higher job finding and lower separation rate on the reservation wage of immigrants.

While lower reservation wages can account for the observed wage differences between worker types in a standard search 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.

1.4 Model

This section presents a labor market model that extends the canonical search and matching framework (Mortensen and Pissarides, 1994) with a non-random hiring mechanism based on the ranking assumption of Blanchard and Diamond (1994). They depart from the assumption that matching is strictly random and instead allow firms to gather and rank several applications. This is not only intuitive, but also consistent with evidence concluding that firms usually interview many applicants at once (Barron et al., 1985; Barron and Bishop, 1985). The ranking as well as the wage bargaining mechanisms are adopted from Barnichon and Zylberberg (2017). They assume that applicant types are ranked according to the surplus firms can extract by hiring them and when bargaining for the wage with the best type, a firm can threaten to hire the second-best applicant at his reservation wage.[16]

1.4.1 Basics, Matching Mechanism and Wage Bargaining

There is a continuum of measure one of risk-neutral, infinitely lived workers in the economy, who are either natives, documented immigrants or undocumented immigrants. Their type is denoted by $i \in \{N, D, U\}$ and each represents an exogenous share ω_i of the total work force P. A worker of a given type is either employed and inelastically supplies one unit of labor earning wage w_i, or unemployed, receiving a flow payment z_i. I assume that the flow payment consists of unemployment benefits z^{UI} and home production z_i^H for natives and documented immigrants, whereas undocumented immigrants are not eligible for unemployment benefits. Therefore, we have $z^{UI} + z_N^H \geq z^{UI} + z_D^H > z_U^H = z_U$. I also allow the bargaining powers β_i to differ between worker types, accounting for the fact that hiring an unauthorized worker is unlawful and thus undocumented immigrants are likely to have a lower bargaining power in negotiating wages.[17] Moreover, I introduce the possibility for an undocumented worker to be detected and removed. I allow the probability of detection to be potentially different for an employed and an unemployed worker.[18] I denote the rate of removal for

[16] In Barnichon and Zylberberg (2017), firm surplus depends on the applicant type because of differing productivity levels.

[17] Although there is no obvious intuition behind it, I also allow the bargaining power of documented immigrants to be different from the one of natives in order to replicate their wage difference found in the data. Chassamboulli and Peri (2015) take an alternative route and allow the unemployment flow payments to differ, arguing that documented immigrants have higher job search costs than natives. For the results of this paper it is not essential whether the wage gaps between worker types arise because of differences in z_i, β_i or a combination of both.

[18] This is motivated by evidence that under the presidency of George W. Bush, conducting worksite raids and arresting undocumented workers (with subsequent deportation in many cases) was the prevalent method to take action against illegal hiring. Under the presidency of Barack Obama, this policy changed towards targeting employers, which often led to undocumented workers being fired, but in few cases deported.

an employed worker by λ_i^W and for an unemployed worker by λ_i^U, both being strictly positive only for $i = U$. Removal not only implies job loss (in case of being employed), but also the loss of an utility amount $R > 0$, which captures the disutility associated with being removed.

There is a large measure of risk-neutral firms, which enter the economy by posting vacancies at a cost $c > 0$. A firm paired with a worker produces output y, which is independent of the worker type. I assume that workers can apply at most to one job and that their application is randomly allocated to a vacancy by an urn-ball matching function (Butters, 1977). Hence, due to coordination frictions, some firms will receive multiple applications while others will receive none. With a large number of vacancies v and a large number of homogeneous applicants, the probability for a firm to be matched with exactly k applicants can be approximated by a Poisson distribution $P(k) = \frac{q^k}{k!}e^{-q}$, where $q = u/v$ is the candidate to vacancy ratio ("queue length").[19] To fit the model to the data, I introduce a matching efficiency parameter μ, thereby proceeding as Blanchard and Diamond (1994) and Barnichon and Zylberberg (2017). This implies that every period, a worker sends out an application with probability μ. Denoting $q_i = u_i/v$ the queue length for type i, the probability to be matched with k_N natives, k_D documented and k_U undocumented workers is given by:

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

I implement the wage bargaining mechanism between firm and worker described in Barnichon and Zylberberg (2017). Job finding rate and bargaining position of an applicant will depend on the labor market tightness, i.e. the total number of candidates to vacancies (capturing the degree of job creation), as well as the composition of the candidate pool (capturing the degree of competition by better types). Whenever a firm receives one or more applications, the firm makes a take-it-or-leave-it offer to its highest ranked candidate with probability $(1 - \beta_i)$, capturing all the surplus by offering a wage making the candidate indifferent between taking the job and staying unemployed. With a probability β_i, the highest ranked applicant sends an offer to the firm demanding a wage that makes the firm indifferent between her and the second-best candidate. Hence, if a firm is only matched with one applicant, the expected payoffs are as in the standard Nash bargaining game and in expectation the worker receives a share β_i of the surplus S_i. With the ranking $S_U > S_D > S_N$, which will hold throughout, the following six cases are to be distinguished for the determination of the worker surplus S^W when a firm faces more than one applicant:

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

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

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

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

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

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

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

Thus, this form of wage bargaining implies that a worker can only extract any surplus from a match, if he is either the only candidate or a strictly better candidate than any other candidate applying to the same firm.

1.4.2 Workers

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

$$rW_i = w_i + s_i(U_i - W_i(w)) + \lambda_i^W(U_i - R - W_i(w)). \tag{1.1}$$

As implied by equation 1.1, I assume that undocumented workers still receive their unemployment value after removal, which is not essential for the results but improves

Table 1.5: Wage distribution

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

the tractability of the model.[20] The flow value of being unemployed is given by

$$rU_i = z_i + \int max(W_i(w) - U_i, 0) dF_i(w) - \lambda_i^U R, \tag{1.2}$$

where F denotes the distribution of the negotiated wages, which depends on the number and type of candidates applying for the same job. To find the reservation wage $\underline{w}_i$, note that when earning the reservation wage a worker is indifferent between employment and unemployment, so that we get $rU_i = rW(\underline{w}_i) = \underline{w}_i - \lambda_i^W R$. Combining this with 1.1 and 1.2 yields

$$\underline{w}_i = z_i + \frac{1}{r + s_i + \lambda_i^W} \int_{\underline{w}_i}^{\infty} (w - \underline{w}_i) dF_i(w) + \underbrace{(\lambda_i^W - \lambda_i^U)}_{\Delta\lambda_i} R. \tag{1.3}$$

The wage distribution F, which can be derived from the above described matching probabilities and wage bargaining mechanism, is summarized in Table 1.5.[21] Combining the distribution of wages with 1.3, defining $\tilde{r}_i \equiv r + s_i + \lambda_i^W$ and imposing $\lambda_N^W = \lambda_N^U = \lambda_D^W = \lambda_N^U = 0$, we get the reservation wages as

$$\underline{w}_N = \frac{z_N + \frac{\beta_N}{\tilde{r}_N} f_1 y}{1 + \frac{\beta_N}{\tilde{r}_N} f_1} \tag{1.4}$$

$$\underline{w}_D = \frac{z_D + \frac{\beta_D}{\tilde{r}_D}(f_1 y + f_2(\frac{\tilde{r}_D}{\tilde{r}_N}\underline{w}_N + (1 - \frac{\tilde{r}_D}{\tilde{r}_N})y))}{1 + \frac{\beta_D}{\tilde{r}_D} e^{-\mu q_D} e^{-\mu q_U}} \tag{1.5}$$

$$\underline{w}_U = \frac{z_U + \frac{\beta_U}{\tilde{r}_U}(f_1 y + f_2(\frac{\tilde{r}_U}{\tilde{r}_N}\underline{w}_N + (1 - \frac{\tilde{r}_U}{\tilde{r}_N})y) + f_3(\frac{\tilde{r}_U}{\tilde{r}_D}\underline{w}_D + (1 - \frac{\tilde{r}_U}{\tilde{r}_D})y)) + \Delta\lambda R}{1 + \frac{\beta_U}{\tilde{r}_U} e^{-\mu q_U}} \tag{1.6}$$

[20]This can be rationalized by defining $R = \tilde{R} + U_U - U_H$, where U_H is the (exogenous) unemployment value a removed worker receives in his home country after deportation and $\tilde{R}$ is the disutility directly received from being removed (e.g. temporary arrest, moving costs, family separation etc.). Being an endogenous variable, U_i cancels out in the term in the last bracket in equation 1.1. 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.

[21]The wage of a documented immigrant in case 2) is derived from $(y - w_D)/(r + s_D + \lambda_D^W) = (y - \underline{w}_N/(r + s_N + \lambda_N^W)$, i.e. equating the firm surplus when hiring a documented immigrant with the firm surplus when hiring a native paying his reservation wage. The derivation is analogous for undocumented immigrants' wages in cases 2) and 3). In order to save space I define $\tilde{r}_i \equiv r + s_i + \lambda_i^W$.

If all workers were identical, i.e. $z_N = z_D = z_U$, $\beta_N = \beta_D = \beta_U$ and λ_U^W=λ_U^U=0, the reservation wages of all types would be equal. A decrease in either z_i or β_i leads to a decline in the reservation wage for worker type i, which can be easily verified using equations 1.4-1.6. As I assume $z_N \geq z_D > z_U$, a sufficient condition for $\underline{w}_N > \underline{w}_D > \underline{w}_U$ is $\beta_N > \beta_D > \beta_U$. This condition is also sufficient if $\Delta\lambda R$ is close to zero, as then λ^W just acts as a separation rate differential between documented and undocumented workers and a rise in this differential decreases $\underline{w}_U$ relative to $\underline{w}_N$ and $\underline{w}_D$. If $\Delta\lambda R$ is large enough, we could have $\underline{w}_D < \underline{w}_U$. However, as this implies higher wages for undocumented immigrants than for documented immigrants, which is not consistent with the data, all model parameter constellations used throughout the paper will ensure that $\underline{w}_N > \underline{w}_D > \underline{w}_U$ is satisfied. Given that this ranking holds, the wage distribution implies that firms prefer to hire undocumented over documented immigrants and documented immigrants over natives.

The job finding rates for each worker type can be derived from $f_i = m_i/u_i$, where m_i denotes the number of vacancies filled by worker type i. The probabilities of a vacancy being filled by a native, documented and undocumented immigrant are given by f_2, f_3 and f_4, respectively. Thus, the job finding rates are:

$$f_N = f_2 V/u_N = \frac{(1-e^{-\mu q_N})e^{-\mu q_D}e^{-\mu q_U}}{q_N} \tag{1.7}$$

$$f_D = f_3 V/u_D = \frac{(1-e^{-\mu q_D})e^{-\mu q_U}}{q_D} \tag{1.8}$$

$$f_U = f_4 V/u_U = \frac{1-e^{-\mu q_U}}{q_U} \tag{1.9}$$

1.4.3 Firms

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

$$rJ_i(\pi) = \pi + (s_i + \lambda_i^W)(V - J_i(\pi)) \tag{1.10}$$

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

$$rV = -c + \int max(J_i(\pi) - V, 0)dG(\pi, i). \tag{1.11}$$

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

$$c = \int_0^\infty J_i(\pi)dG(\pi, i) \tag{1.12}$$

The distribution of profits shown in Table 1.6 can again be derived for every case con-

Table 1.6: Profit distribution

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

sidering the wages paid and the respective probabilities.

1.4.4 Static Equilibrium

As in the standard search framework, the ratio of job seekers to vacancies for each worker type is independent of the size of the total unemployment pool $u = u_N + u_D + u_U$. What determines the equilibrium is the composition of the pool, i.e. the shares of documented and undocumented immigrants among the unemployed u_D/u and u_U/u. The higher is u_U/u, the higher is the probability of a match with an undocumented applicant and the higher are expected firm profits. Hence, an increase in u_U with u_N and u_D being constant leads to an increase in vacancies that is overproportional to the increase of the total unemployment pool and thus a higher labor market tightness. It is less obvious what the effect of a relative increase of u_D on the equilibrium is. If documented immigrants' wages are relatively close to natives' wages, expected firm profits decrease and labor market tightness falls. If on the contrary documented immigrants' wages are relatively close to undocumented immigrants' wages, labor market tightness goes up.
In order to close the model, we need to consider the laws of motion of the number of unemployed workers and the work force given by:[22]

$$\dot{u}_N = s_N(\omega_N P - u_N) - f_N u_N, \tag{1.13}$$

$$\dot{u}_D = s_D(\omega_D P - u_D) - f_D u_D, \tag{1.14}$$

$$\dot{u}_U = s_U(\omega_U P - u_U) + u_{NU} - f_U u_U - \lambda^U u_U, \tag{1.15}$$

$$\dot{P} = u_{NU} - \lambda^W(\omega_U P - u_U) - \lambda^U u_U, \tag{1.16}$$

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

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

steady state of the number of unemployed workers of each type is given by:

$$u_N^* = \frac{\omega_N s_N}{s_N + f_N} \tag{1.17}$$

$$u_D^* = \frac{\omega_D s_D}{s_D + f_D} \tag{1.18}$$

$$u_U^* = \frac{\omega_U (s_U + \lambda^W)}{s_U + \lambda^W + f_U} \tag{1.19}$$

The static solution of the model is determined by equations 1.4, 1.5, 1.6, 1.10, 1.12, 1.17, 1.18, 1.19 and consists of the queue lengths q_N^*, q_D^* and q_U^*.

1.5 Parameterization

In the following, I describe the parameterization of the model, for which I use several methods. Some parameters are calibrated by setting them equal to their data equivalents or taking them from the literature, others are jointly estimated using the generalized method of moments. An overview of the parameter values can be found at the end of this section.

The level of productivity y and the native population ω_N are both normalized to 1. The annual interest rate is set to 4%, implying a monthly discount factor $\delta = 0.96^{1/12}$ and $r = (1 - \delta)/\delta = 0.0034$. Instead of fixing the population shares ω_D and ω_U and determining u_D/u and u_U/u from the steady state equation for unemployment, I set these ratios equal to their data equivalents of 0.19 and 0.16, respectively. I do so, because my targets for the job finding rate gaps are the coefficients of the immigrant dummies in the regression of Table 1.3 and these gaps will determine u_D/u and u_U/u in the model equilibrium. The empirical shares on the other hand are generated by the unconditional transition rates in the data and therefore inevitably different from the model result, if the population shares ω_i are set to their data equivalents. After fixing u_D/u and u_U/u, the population shares implied by the steady state of unemployment in the model can be computed by solving (20) for ω_D and (21) for ω_U.

Estimates of the flow payment of unemployment range between 0.4, the upper end of the range of income replacement rates in Shimer (2005), and 0.955 in Hagedorn and Manovskii (2008). I follow Hall and Milgrom (2008) and Pissarides (2009) and choose a value of 71% of the average wage $\overline{w}_i$ for documented workers, yielding $z_N = 0.70$ and $z_D = 0.67$. I assume that unemployment benefits are 40% of the average wage and thus the flow value of home production for natives is $z_N^H = z_N - z^{UI} = 0.31$, which I take as my value for $z_U^H = z_U$. After correction for time aggregation bias, I get an average separation rate for low-skilled native workers of 0.031. As Table 1.4 suggests that conditional on observables the separation rate is 0.003 lower for documented immigrants and 0.006 lower for undocumented immigrants, I set $s_D = 0.028$ and $s_U = 0.025$.

In order to obtain a value of the removal rate, I use yearly figures of unauthorized immigrants that are deported through so called "interior removals" from the Department of Homeland Security, which are available from 2008 through 2015. I convert these figures to a monthly frequency, divide them by the total number of undocumented immigrants residing in the US in the respective year and take the average across years. The resulting rate is 0.0013. Unfortunately, to the best of my knowledge there is no information on the employment status of deported immigrants available. I therefore assume $\lambda^W = \lambda^U = 0.0013$ in the baseline calibration and show how the predictions change when deviating from this assumption, i.e. $\Delta\lambda \neq 0$. The value of the disutility of deportation R only matters if $\Delta\lambda \neq 0$. I will check the robustness of the results to this case using values of R corresponding to 25% to 75% of an undocumented immigrants' lifetime utility.

Five parameters remain to be determined: β_N, β_D, β_U, c and the matching efficiency μ. As only the differences between these bargaining power parameters can be identified and actually matter for the model predictions, I get rid of one redundant parameter by assuming an average bargaining power in the economy of 0.5 (as many papers in the search literature). Hence, I impose the restriction $\frac{\omega_N}{\omega_N+\omega_D+\omega_U}\beta_D + \frac{\omega_D}{\omega_N+\omega_D+\omega_U}\beta_D + \frac{\omega_U}{\omega_N+\omega_D+\omega_U}\beta_U = 0.5$. This leaves four parameters to be estimated by matching five moments from the data: the average wages paid to immigrants relative to natives $\overline{w}_D/\overline{w}_N$ and $\overline{w}_U/\overline{w}_N$ and the job finding rates f_N, f_D and f_U. I obtain the targets for the relative wages from the last column of Table 1.2. I set the target for f_N equal to the mean of the job finding probability of natives, which equals 0.24, and obtain $f_D - f_N$ and $f_U - f_N$ from Table 1.3. The resulting data moments are $\overline{w}_D/\overline{w}_N = 0.957$, $\overline{w}_U/\overline{w}_N = 0.874$, $f_N = 0.24$, $f_D = 0.31$ and $f_U = 0.38$.

Let $\hat{g}$ denote the 5x1 vector of data moments. Let θ denote the 4x1 vector of model parameters to be estimated: β_D, β_U, c and μ. The corresponding moments generated by the model are a function of these parameters, denoted by $g(\theta)$. The GMM estimator is defined as the vector $\hat{\theta}$ that minimizes the distance between the model-generated and data moments $\Psi(\theta) = g(\theta) - \hat{g}$. Hence, it is given by $\hat{\theta} = \arg\underset{\theta\in R^5}{min}\Psi(\theta)'\Psi(\theta)$. To obtain the standard errors of the GMM estimator, note that the true data moments are a function of the true parameter vector, i.e. $g_0 = g(\theta_0)$. We then have $\sqrt{n}(\hat{\theta} - \theta_0) \xrightarrow{d} N(0, [D'V^{-1}D]^{-1})$, where $D = [\frac{\partial g(\theta_0)}{\partial \theta_0'}]$ and V is the covariance matrix of the data moments, i.e. $\sqrt{n}(\hat{g} - g_0) \xrightarrow{d} N(0, V)$ (Hansen, 1982). I obtain V by the Eicker-Huber-White sandwich covariance estimator and the matrix of derivatives by numerically differentiating the model at $\hat{\theta}$.[23] The resulting estimates with standard errors in parentheses and the calibrated parameters are shown in Table 1.7. While the wages can be matched exactly by estimating the bargaining powers of each worker type, this is not possible for the job finding rates as only two parameters are available to target three moments. The

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

Table 1.7: Baseline parameterization

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

moments yielded by the model are $f_N = 0.239$, $f_D = 0.325$ and $f_U = 0.370$, which are reasonably close to the targets. The estimates imply that the wage bargaining power of documented immigrants is 0.4 and therefore almost as low as the value of 0.28 for undocumented immigrants. The reason for this is that for the former the wage gap to natives is almost entirely generated by the difference in bargaining powers, while for the latter a significant part is generated by the assumed difference in the unemployment flow value. Whether the targeted wage gaps are matched by differences in the z_i or the β_i or a combination of both has no effect on the model equilibrium.[24]

1.6 The Effects of Immigration

1.6.1 Job Creation and Competition Effect

The model outlined in the previous section features two effects of a rise in the population share of undocumented immigrants that affect the job finding rate of natives in opposite ways. With a higher probability of receiving an application from an immigrant, expected wage costs of firms and thus the number of vacancies they post change. As explained

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

in section 4.4, expected wage cost fall when there are more undocumented immigrants in the pool of unemployed because this implies a higher probability of matching with the cheapest worker type and as a result there is a strong job creation effect. The effect of documented immigration on wage costs is ambiguous as they can drive the expected wage firms have to pay up or down, depending on the parameterization. The more similar documented immigrants are to natives, the more likely they drive expected wage costs up and thus the lower is the number of additional jobs.

While the strength and sign of job creation depends on the immigrant type and the parameters, the impact of the competition effect is unambiguous. Given a fixed number of vacancies, an increase in the share of either immigrant type decreases the job finding rate of natives as the probability of competing with a cheaper worker for a job, i.e. not being hired, rises. In particular, recalling the job finding rates given by 1.7-1.9 one can see that the job finding of a specific worker is affected by the queue length of all workers of the same type and the queue length of all workers that are ranked higher. Thus, undocumented immigrants are only affected by other undocumented immigrants, documented immigrants are affected by all immigrants and natives are affected by all types of workers. This can be shown analytically by taking the partial derivatives with respect to the queue lengths. For natives we have

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

For documented immigrants we have

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

And for undocumented immigrants we have

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

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

$$\frac{df_N}{du_D} = \underbrace{\underbrace{\frac{\partial f_N}{\partial q_N}}_{<0}\underbrace{\frac{dq_N}{dv}}_{<0}\underbrace{\frac{dv}{du_D}}_{>0}+\underbrace{\frac{\partial f_N}{\partial q_U}}_{<0}\underbrace{\frac{dq_U}{dv}}_{<0}\underbrace{\frac{dv}{du_D}}_{>0}}_{\text{job creation effect}} + \underbrace{\underbrace{\frac{\partial f_N}{\partial q_D}}_{<0}\underbrace{\frac{dq_D}{du_D}}_{>0}}_{\text{competition effect}} \lesseqgtr 0, \tag{1.20}$$

$$\frac{df_D}{du_D} = \underbrace{\underbrace{\frac{\partial f_D}{\partial q_U}}_{<0}\underbrace{\frac{dq_U}{dv}}_{<0}\underbrace{\frac{dv}{du_D}}_{>0}}_{\text{job creation effect}} + \underbrace{\underbrace{\frac{\partial f_D}{\partial q_D}}_{<0}\underbrace{\frac{dq_D}{du_D}}_{>0}}_{\text{competition effect}} \lesseqgtr 0, \tag{1.21}$$

$$\frac{df_U}{du_D} = \underbrace{\underbrace{\frac{\partial f_U}{\partial q_U}}_{<0}\underbrace{\frac{dq_U}{dv}}_{<0}\underbrace{\frac{dv}{du_D}}_{>0}}_{\text{job creation effect}} > 0. \tag{1.22}$$

The impact of undocumented immigration on job finding rates is

$$\frac{df_N}{du_U} = \underbrace{\underbrace{\frac{\partial f_N}{\partial q_N}}_{<0}\underbrace{\frac{dq_N}{dv}}_{<0}\underbrace{\frac{dv}{du_U}}_{>0}+\underbrace{\frac{\partial f_N}{\partial q_D}}_{<0}\underbrace{\frac{dq_D}{dv}}_{<0}\underbrace{\frac{dv}{du_U}}_{>0}}_{\text{job creation effect}} + \underbrace{\underbrace{\frac{\partial f_N}{\partial q_U}}_{<0}\underbrace{\frac{dq_U}{du_U}}_{>0}}_{\text{competition effect}} \lesseqgtr 0, \tag{1.23}$$

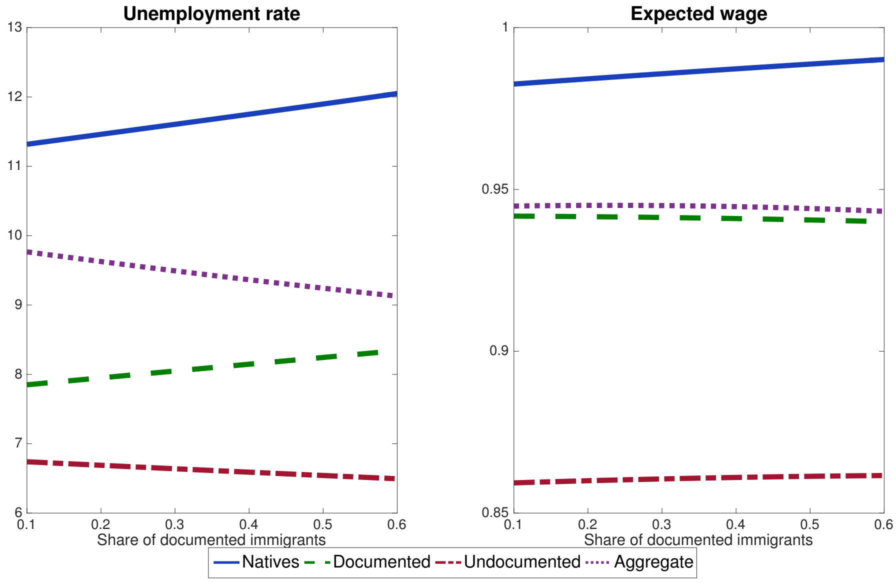
$$\frac{df_D}{du_U} = \underbrace{\underbrace{\frac{\partial f_D}{\partial q_D}}_{<0}\underbrace{\frac{dq_D}{dv}}_{<0}\underbrace{\frac{dv}{du_U}}_{>0}}_{\text{job creation effect}} + \underbrace{\underbrace{\frac{\partial f_D}{\partial q_U}}_{<0}\underbrace{\frac{dq_U}{du_U}}_{>0}}_{\text{competition effect}} \lesseqgtr 0, \tag{1.24}$$

$$\frac{df_U}{du_U} = \underbrace{\underbrace{\frac{\partial f_U}{\partial q_U}}_{<0}\underbrace{\frac{dq_U}{du_U}}_{>0}}_{\text{competition effect}} < 0. \tag{1.25}$$

Equations 1.20 and 1.23 suggest that the effect of both documented and undocumented immigration on natives' job finding (and thus their unemployment rate) is ambiguous. The larger is the difference in wages between natives and the type of immigrant entering the pool of the unemployed, the higher is the number of additional vacancies posted. Therefore, we know that $\frac{df_N}{du_U} > \frac{df_N}{du_D}$ must hold. However, only solving and simulating the model for different u_D and u_U will allow us to determine the signs of $\frac{df_N}{du_U}$ and $\frac{df_N}{du_D}$.

1.6.2 Simulating Documented Immigration

Figure 1.10: Unemployment (%) and wages depending on documented immig. share

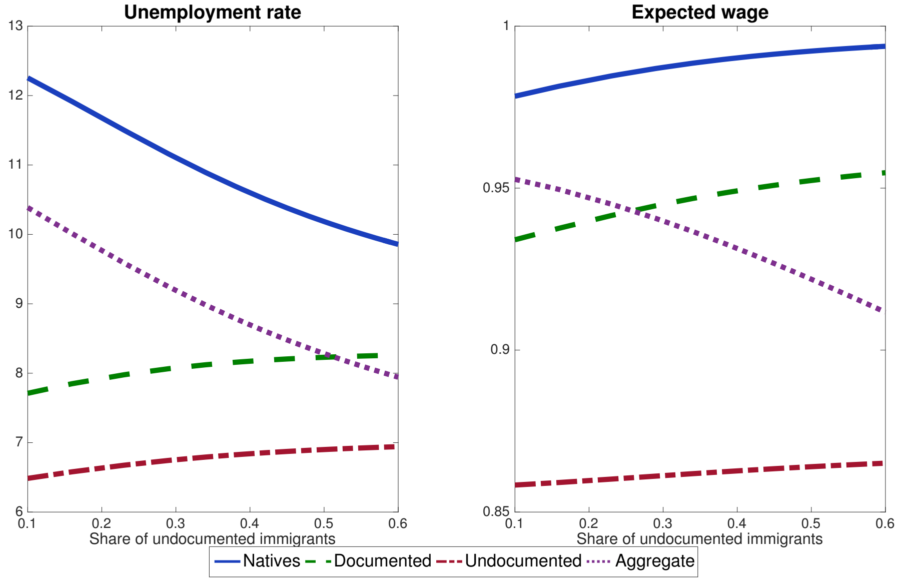


In order to find out whether the job creation or the competition effect in case of documented immigration dominates with the parameterization that replicates the data, I solve for the steady state equilibrium varying the population share ω_D. Figure 1.10 plots the resulting steady state unemployment rates, which are monotonic functions of the job finding rates according to equations 1.17-1.19, and expected wages by worker type and in the aggregate. As implied by equation 1.22, undocumented immigrants gain as documented immigrants pose no competition for them, which is indicated by a decreasing unemployment rate. However, the unemployment rate of both natives and documented immigrants increases, which suggests that the competition effect dominates the job creation effect. The latter is weak because the expected wage of documented immigrants is only slightly below the aggregate expected wage, implying only a small decline in wage costs when their population share rises. Therefore, only few additional vacancies are posted and this does not compensate for the higher degree of job competition for natives and documented immigrants.

Despite the fall in their job finding rate, the expected wage earned by natives increases. This result is due to the assumed wage bargaining mechanism, according to which a native worker receives a wage above the reservation wage, if and only if he is the only applicant for a firm. This happens with probability f_1 given in Table 1.5, which is the only variable affecting the reservation wage of natives (see equation (4)) and positively depends on the total queue length q.[25] As documented immigration leads to some job creation, q and f_1 increase. This implies a higher expected wage of natives for two

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

Figure 1.11: Unemployment (%) and wages depending on undocumented immig. share



reasons. First, the higher reservation wage implies higher wages paid to all natives in a job. Second, the higher probability of being matched to a firm without competitors implies that more natives find jobs in which they are paid above the reservation wage relative to jobs in which they are just paid the reservation wage. This is because if matched to a firm with other competitors, it is more likely that at least one of them is a documented immigrant. Hence, some natives that would have been hired at their reservation wage when there were less documented immigrants in the economy now remain unemployed without earning any wage.[26]

1.6.3 Simulating Undocumented Immigration

Figure 1.11 illustrates the effects of undocumented immigration by plotting the steady state equilibria depending on ω_U. The left panel shows that the unemployment rate of natives strongly declines with the share of undocumented immigrants. This result confirms that wages of undocumented workers are low enough so that their job creation dominates their competition effect. Firms post so many additional vacancies that the fall in the queue length of natives compensates the rise in the queue length of undocumented immigrants. On the other hand, the unemployment rate of documented immigrants increases, which indicates that the job creation effect is not dominant for them, although it is for natives. This suggests that in this kind of framework with three worker types, the competition through the type most preferred by firms affects the type in the middle

[26]Note that the result of an increase of natives' expected wage due to documented immigration does not hold, if natives receive a wage above the reservation wage also when there are other natives (but no immigrants) applying for the same job. This would be the case under the alternative assumption that wage bargaining takes place after the firm has committed to hire a worker.

stronger than the least preferred type. As established in 1.25, only the competition effect is present for undocumented workers and hence their unemployment rises. Expected wages of all worker types increase because the additional vacancies posted lead to a rise in reservation wages and this in turn leads to higher wages in all jobs. Moreover, the higher total queue length results in more workers matching with firms as single applicants and thus more workers enter high paying jobs. Because the share of workers earning the lowest wage goes up, the aggregate expected wage falls strongly, which is the reason behind the strong job creation effect. The combination of higher employment and higher earnings implies that the welfare of natives unambiguously increases through undocumented immigration.

1.6.4 Robustness to the Calibration of the Removal Disutility

The existence of two opposing forces whose magnitudes depend on the parameterization suggests that the findings might be sensitive to particular parameters, in particular the size of the surplus firms make by hiring undocumented workers. Therefore I next check whether the predictions of Figures 1.10 and 1.11 are robust to allowing $\Delta\lambda$ to be different from zero and to changes in the value of R. In particular, I consider the extreme case in which only employed undocumented workers can be detected and deported, i.e. $\lambda^U = 0$ and $\lambda^W = \Delta\lambda$. I recalibrate λ^W following the same method of calibration as described in section 5 but dividing monthly interior removals by the total number of employed undocumented immigrants instead of all undocumented immigrants. The resulting probability is 0.22%. As now $\Delta\lambda$ is strictly greater than zero, R always has a positive effect on $\underline{w}_U$. Thus, it affects undocumented immigrants' wages and as a consequence the wage gap between worker types. The value of R also affects job finding rates because a rise in $\underline{w}_U$ makes hiring undocumented workers more expensive, which mutes the vacancy creation effect. Therefore, it is necessary to re-estimate c, μ, β_D and β_U in order to match the moments from the data after a change in R. Figures B.1 and B.2 in the Appendix show the effects of immigration when setting R equal to 75% of an undocumented job seeker's lifetime utility U_U, which is the most extreme value I consider throughout the paper, and compare them to the benchmark calibration with $\Delta\lambda = 0$ (in light colors). Both unemployment rates and expected wages are virtually unaffected when choosing a high value for R. The unemployment rate of undocumented workers is somewhat elevated as their overall separation probability ($s_U + \lambda_W$) is now higher. Moreover, undocumented immigration has a weaker effect on vacancy creation, because the higher separation probability decreases their hiring surplus. This can be seen by a slightly less steep decline in the unemployment rate of natives in Figure B.2.

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

1.7 The Effects of Higher Removal Risk

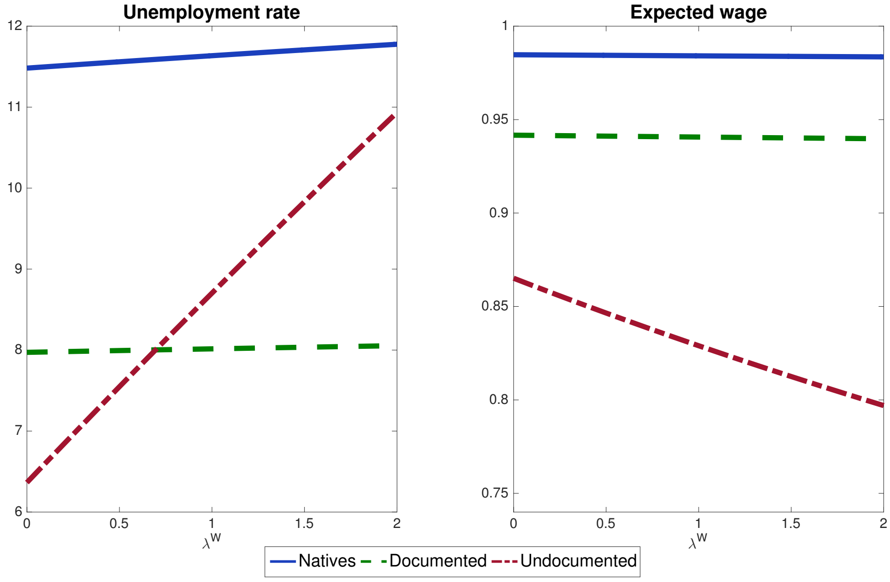
In what follows, I investigate how the equilibrium depends on the deportation risk parameters λ^W and λ^U and how their effect on the equilibrium changes with R. Recalling equation 1.6, we know that the effect of λ^W on undocumented workers' reservation wage is ambiguous. Given R is zero or sufficiently small, λ^W tends to decrease $\underline{w}_U$ acting like a rise in the job separation probability. However, if the disutility associated with deportation is high enough, a rise in λ^W increases $\underline{w}_U$ because $\Delta\lambda$, i.e. the risk of detection when employed relative to the risk when unemployed, rises and therefore the compensation needed to accept the risk of having a job goes up more strongly. Independently of the size of R, a higher λ^W will mute the job creation effect because the surplus firms expect to make by hiring an undocumented worker shrinks. If R>0, the job creation effect is additionally muted due to a higher risk compensation. This negative effect of λ^W on vacancy creation is increasing in R. A rise in λ^U, the risk of being deported when unemployed, unambiguously decreases the reservation wage because the opportunity cost to having a job falls and hence undocumented workers accept lower wages. As the aim is simulating an exogenous policy change by varying λ^W and λ^U, I use comparative statics and therefore keep the remaining parameters fixed.

Figures 1.12 shows the effect of an equal increase in both λ^W and λ^U (keeping the population share of undocumented immigrants constant).[27] As $\Delta\lambda$ remains zero, the rise in the removal rate only affects the match separation probability. An increase in this probability by one percentage points results in a rise of undocumented immigrants' unemployment rate by around 2.3 percentage points. At the same time, their wages fall by around 4% as the expected length of a match is now shorter and thus the surplus lower. This induces firms to create fewer vacancies, which also affects native and documented immigrant workers. However, the effect on them is moderate. A one percentage point increase in the removal rate leads to an increase in the unemployment rate by 0.14 percentage points for natives and 0.4 percentage points for documented immigrants, while their wages remain almost at the same level.

Figure 1.13 plots the case in which only the removal risk for employed undocumented immigrants λ^W rises. As mentioned above, the sizes of the effects depend on the calibration of the disutility from removal. The larger is R, the larger is the impact of an

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

Figure 1.12: Unemployment (%) and wages depending on λ^W with $\lambda^W = \lambda^U$

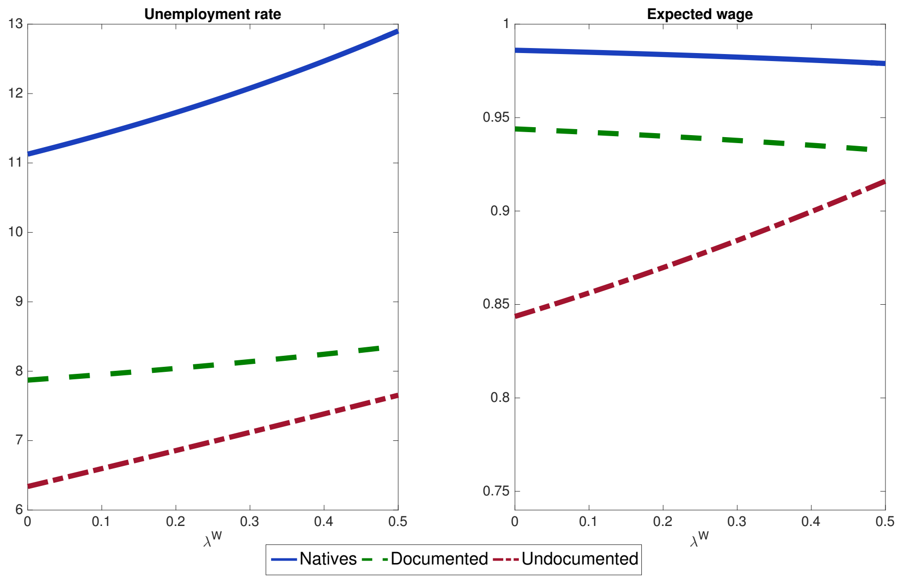


increase in the removal risk only affecting employed workers. For the plots, I assume an intermediate removal disutility of 50% of an undocumented immigrants' lifetime utility but in the following I give the ranges of the effects of a one percentage point increase in λ^W for a removal disutility between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

Altogether, the analysis in this section suggests that increased deportation efforts lower the welfare not only for undocumented, but also for documented workers. The negative impact on employment is especially large for natives, if efforts concentrate on worksite raids that make it more risky (but still worthwhile) for an undocumented immigrant to accept a job. The detrimental effect of worksite raids would be even larger, if the model also considered penalties for firms that hire workers illegally as this would mute vacancy creation further.[28]

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

Figure 1.13: Unemployment (%) and wages depending on λ^W with λ^U constant



1.8 Testing the Model Predictions

1.8.1 The Effects of Immigration

As suggested by the analysis in section 6, the model predicts that the job creation effect of undocumented immigration is stronger than the one of documented immigration. Quantitatively, the former should be large and the latter close to zero. Moreover, as a higher number of vacancies decreases the average time to find a job, which in turn increases the value of unemployment and thus the reservation wage, wages should rise more due to undocumented than documented immigration as shown in Figures 1.10 and 1.11. In the following, I test these predictions using an early settlement instrument inspired by the approach of Card (2001) as well as a refinement of this instrument suggested by Jaeger et al. (2018).

Data and Instrument Construction

For the following empirical analysis, I use decennial data between 1980 and 2010. I obtain the samples of the years 1980, 1990 and 2000 from the US Census. From 2001 onwards, the Census is replaced by the annual ACS, which has a smaller sample size. Therefore, I pool the ACS 2009-2011 to obtain the 2010 sample in order to get a similar number of observations as for the previous years.[29] All samples are downloaded from IPUMS (Ruggles et al. (2016)). I predict regional immigrant inflows by assigning the national inflows of documented and undocumented immigrants to an MSA using the

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

initial geographic distribution of immigrants with the same legal status in the respective base year. National inflows $I_{c,e,i,t}$ are defined as the difference in the number of immigrants from origin country c with status $i \in \{D, U\}$ and education e between period $t-1$ and t.[30] Let $\pi_{c,i,r,t}$ denote the share of immigrants from country c with status i and any education level that live in region r at time t. The inflows used to compute the instruments are given by the sum over the imputed inflows of immigrants to a specific region:

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

The predicted population levels of immigrants at time t are then

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

and the predicted population shares are

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

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

As first dependent variable I use the log change in the number of posted vacancies $\Delta \log v$ as a proxy for job creation. Annual data on vacancies at the MSA level are taken from the Conference Board Help Wanted OnLine (HWOL) data series. A version of the dataset is used in Barnichon and Figura (2015) and was provided in digital form ready for empirical analysis by courtesy of the authors.[31] The sample contains vacancies posted in 33 MSAs, which are listed together with their population shares of documented and undocumented immigrants in Appendix Table B.1. The other dependent variables are the log changes in the wages of low-skilled natives, documented and undocumented immigrants. In order to account for selectivity bias due to changes in the regional worker composition, I run a regression of the log hourly wages on demographics (sex, race, age, age squared) and occupation/industry controls using the 1980-2010 sample of low-skilled native workers. I then take the means of the residuals over MSAs and years to obtain the adjusted wages $\tilde{w}_{e,N,r,t}$, $\tilde{w}_{e,D,r,t}$ and $\tilde{w}_{e,U,r,t}$.

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

[31]Unfortunately, it is not possible to distinguish between vacancies that target low-skilled and high-skilled workers in these data. This is an important caveat as the population sample used is restricted to low-skilled workers. Therefore, parts of the effects on vacancies could potentially be due to spillovers to the high-skilled labor market, which the model abstracts from.

IV Estimation

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

$$\Delta \log y_{r,t} = \delta_0 + \delta_1 \Delta \hat{\eta}_{D,r,t} + \delta_2 \Delta \hat{\eta}_{U,r,t} + \phi_t + \varepsilon_{r,t}$$

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

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

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

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

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

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

First Stage Results

Table 1.8: First stage

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

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

Table 1.8 shows the results of the first stages for the conventional IV model and the model of Jaeger, Ruist and Stuhler (2018), henceforth called JRS IV. In both models, the instruments have positive and significant effects on the shares they are supposed to predict as indicated by the coefficients on the diagonals in the left-hand and the right-hand side of the table. Throughout all equations except the one in column (4), the F-statistics are above 10. The Sanderson-Windmeijer (SW) F-statistic is testing whether the effects of the endogenous variables can be separately identified in case of more than one endogenous variable. The values reported in the last row of the table indicate that indeed the endogenous regressors are identified, whereby the F-statistic is higher and hence the identification stronger for the (lagged) undocumented immigrant share.

Although the first-stage diagnostics ease potential concerns about identification, it is useful to directly inspect the serial correlations of the instrumented endogenous variables. Very high serial correlation of their predicted immigrant inflow rates in the decades after 1980 prevent Jaeger et al. (2018) from applying their IV strategy to these later periods. This does not necessarily need to be the case here. The focus on low-skilled workers and the distinction between documented and undocumented immigrants is likely to generate more time variation than in more aggregated data. Appendix Figure B.3 plots the regressors predicted by the first-stage, $\tilde{\eta}_{D,r,t}$ and $\tilde{\eta}_{U,r,t}$, against their respective lags. The figure suggests a high serial correlation for the changes in the documented immigrant share, especially in the upper left plot, where points almost lie on a $45°$ line.

The correlation coefficients are 0.94 in the decades 1980-2000 and 0.86 in 1990-2010. There is considerably more time variation in the change of the undocumented immigrant shares as seen in the bottom plots, for which the correlation coefficients are only 0.43 and 0.59, respectively. Thus, using the JRS IV strategy, I expect to obtain less precise estimates of the effects of documented immigrants.

Second Stage Results

Table 1.9 reports the second-stage results of the three different specifications, the OLS model (Panel A), the conventional IV approach (Panel B) and the JRS IV model (Panel C). The effect of undocumented immigrants on vacancies is positive and significant in the OLS and both the IV models. The coefficient in the preferred specification in Panel C indicates an increase in vacancies of around 2.1% due to a one percentage point increase in the population share of undocumented immigrants. This result is not only qualitatively in line with the model prediction, but also quantitatively close. Model simulations yield an effect that is around 1.7%.[32] The coefficient of the documented immigrant share in column (1) is strongly negative in the OLS and IV model and insignificant in the JRS IV model. This result, which deviates from the model prediction of a small but positive effect, might be caused by the imprecise estimation due to the high serial correlation in the share of documented immigrants, which causes very large standard errors.

The effect of undocumented immigrants on wages is positive and significant in all models and for all worker types except for immigrants' wages in the IV model. Being around 0.26% to 0.38% in Panel C, these wage effects are much stronger than the theoretical predictions, which are around 0.03%. The effect of documented immigrants on native wages is negative (but only significant at the 10% level), whereas the theory would predict a small positive effect of 0.01%. However, there is no significant effect on immigrants' wages, which is in line with the predictions (see Figure 1.10).

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

[32] The quantitative model predictions are generated by regressing the simulated series of steady-state logarithmic vacancies on the series of documented and undocumented immigrant shares (simulated between 0.1 to 0.6 while holding the other share constant)

Table 1.9: Second stage

	(1) Vacancies	(2) Native wage	(3) Doc. wage	(4) Undoc. wage
Panel A: OLS				
Doc. share	-4.834***	-0.291	-0.542*	-0.729**
	(1.068)	(0.2500)	(0.328)	(0.359)
Undoc. share	2.108***	0.578***	0.267*	0.267*
	(0.259)	(0.056)	(0.153)	(0.137)
Observations	99	99	99	97
R-squared	0.792	0.314	0.053	0.130
Panel B: IV				
Doc. share	-6.444***	-0.230	-0.128	-0.718*
	(1.497)	(0.305)	(0.376)	(0.422)
Undoc. share	2.490***	0.379***	-0.021	0.076
	(0.877)	(0.122)	(0.148)	(0.164)
Observations	99	99	99	97
R-squared	0.788	0.290	0.033	0.120
Panel C: JRS IV				
Doc. share	-0.424	-1.113*	0.130	-0.855
	(6.616)	(0.598)	(0.796)	(0.819)
Undoc. share	2.145***	0.336**	0.262*	0.377**
	(0.605)	(0.135)	(0.157)	(0.1500)
(Doc. share)$_{t-1}$	-6.097	0.830*	-0.158	0.305
	(3.872)	(0.456)	(0.585)	(0.676)
(Undoc. share)$_{t-1}$	0.763	-0.238***	-0.158	-0.145
	(1.025)	(0.080)	(0.153)	(0.165)
Observations	66	66	66	66
R-squared	0.887	0.500	0.089	0.110

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

responses, suggesting that there is no counteracting adjustment in vacancy posting over time.

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

Robustness checks

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

In order to check whether the results also hold using the traditional measurement of immigration, I repeat the regressions with the inflow rates $m_{i,r,t} = I_{i,r,t}/P_{r,t}$ as endogenous regressors and predicted inflow rates $m^Z_{i,r,t} = I^Z_{i,r,t}/P_{r,t}$ as instruments. If changes in the low-skilled populations do not systematically differ across MSAs, the differences between the measures $m_{i,r,t}$ and $\Delta\eta_{i,r,t}$ should be absorbed by the year fixed effects and the results be similar. The second stage results shown in Table 1.10 (first stage in Appendix Table B.2) are indeed consistent with the ones in Table 1.9. The only notable difference is that now undocumented immigration has no significant effect on vacancies using the conventional IV strategy in Panel B. Thus, also measuring immigration by the inflow rate yields supporting evidence for the model predictions.

As a second robustness check, I change the base period for the distribution of immigrants, according to which the national inflows are allocated to MSAs. Instead of taking the distribution in the initial year, I take the distribution in the year 1980 for the allocation of all national inflows in the periods 1980-1990, 1990-2000 and 2000-2010. Appendix Tables B.3 and B.4 show the estimation results for the first and second stages with the recalculated instruments. Now the effect of the share of undocumented immigrants on vacancies and immigrants' wages is not significant in Panel B. However, the coefficients in Panel C are qualitatively unchanged. Quantitatively, the response of vacancies is somewhat smaller and the response of wages somewhat larger compared to Table 1.9.

Table 1.10: Second stage with immigrant inflow rates as regressors

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

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

1.8.2 The Effects of Higher Removal Risk

Section 7 has shown that, at least qualitatively, the prediction that job finding rates of all workers fall when the removal risk increases does not depend on the assumption that this risk is the same for employed and unemployed workers nor on the assumption that there is a disutility from removal.[33] However, the prediction on wages does depend on these assumptions: if $\Delta\lambda = 0$, a higher removal risk decreases undocumented immigrants' wages, whereas if only λ^W (and thus $\Delta\lambda$) increases, their wages are predicted to rise. Finding a negative effect of an exogenous increase in the removal risk on the job finding

[33] Recall from equation 1.6 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 1.11: Legal status, omnibus laws and UE transition of low-skilled workers

	(1)	(2)	(3)	(4)	(5)
Omnibus law	-0.035***	-0.029***	-0.027***	-0.025***	-0.021***
	(0.0075)	(0.0072)	(0.0073)	(0.0062)	(0.0068)
Documented x omnibus	0.050*	0.034*	0.022	0.019**	0.007
	(0.0288)	(0.0199)	(0.0134)	(0.0091)	(0.0111)
Undocumented x omnibus	0.048*	0.043	0.014	0.012	0.005
	(0.0272)	(0.0379)	(0.0326)	(0.0299)	(0.0293)
Demographics	No	Yes	Yes	Yes	Yes
Year/State FE	No	No	Yes	Yes	Yes
Ind/occ FE	No	No	No	Yes	No
Ind x occ FE	No	No	No	No	Yes
Observations	75634	75634	75634	75634	75634
R-squared	0.016	0.029	0.044	0.057	0.079

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

rate of both workers types and on wages of documented workers would provide evidence that the job creation effect of undocumented immigration exists. Given the model is correct, finding a positive effect of a removal risk shock on the wages of undocumented immigrants would suggest that firms indeed have to pay them a risk compensation.

A possible source of variation in the deportation risk is provided by a change in state-wide immigration legislation. Good (2013) examines the impact of omnibus immigration laws (introduced in eleven US states since 2006) on population and employment of different demographic groups. These laws address several issues at a time including work authorization, document-carrying policy, public program benefits, human trafficking, local immigration law enforcement and determination of legal status when arrested.[34] Although it is to the best of my knowledge not verified whether these laws have an impact on the removal risk, RaphaelRonconi09 states that they have a nature of "in general creating an environment in which there is a constant threat of document verification and subsequent deportation." (Good, 2013, p. 4). Raphael and Ronconi (2009) and Good (2013) both provide evidence that the implementation of omnibus immigration laws is not endogenous to levels or changes in discriminatory attitudes or immigrant population size. I therefore assume that they are appropriate to capture an exogenous increase in the removal risk.

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

Table 1.12: Legal status, omnibus laws and hourly wage of low-skilled workers

	(1)	(2)	(3)	(4)	(5)
Omnibus law	-0.086***	-0.094***	-0.058***	-0.050***	-0.051***
	(0.0198)	(0.0179)	(0.0180)	(0.0155)	(0.0173)
Documented x omnibus	0.063**	0.070***	0.084***	0.073***	0.070***
	(0.0318)	(0.0244)	(0.0220)	(0.0182)	(0.0193)
Undocumented x omnibus	0.092***	0.097***	0.117***	0.104***	0.104***
	(0.0294)	(0.0272)	(0.0252)	(0.0238)	(0.0282)
Demographics	No	Yes	Yes	Yes	Yes
Year/MSA FE	No	No	Yes	Yes	Yes
Ind/occ FE	No	No	No	Yes	No
Ind x occ FE	No	No	No	No	Yes
Observations	68563	68563	68563	68563	68563
R-squared	0.051	0.137	0.165	0.271	0.295

Notes: Dependent variable is the logarithm of the hourly wage. Data come from the CPS March supplement 1994-2016 and include high school dropouts aged 25-65. Demographic controls include sex, $race$, age and age^2. Standard errors are clustered at the metropolitan area level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

In order to measure the effect of omnibus immigration laws on job finding, I rerun the regression with the job finding rate as dependent variable (see section 3.2) including a dummy indicating immigration omnibus laws to be in force in the state of residence of a survey respondent during the interview year. I interact this dummy additionally with the immigrant indicators in order to allow the effect of omnibus immigration legislation to vary across legal status. Table 1.11 presents the results. The coefficients in the third row capture the effect of the implementation of the laws on native workers. The preferred specification in the last column indicates that omnibus immigration legislation results in a decrease in the job finding rate of 2.1 percentage points for both natives, documented and undocumented workers. This is consistent with the model's prediction of a rise in the unemployment rates as seen in Figures 1.12 and 1.13.[35]

Finally, I rerun the wage regressions including the omnibus law indicator and interactions as regressors. The results in Table 1.12 suggest a drop in natives' wages of 5.1% due to the implementation of omnibus immigration laws. The coefficient of the undocumented-omnibus interaction of 0.104 implies that omnibus immigration legislation increased undocumented workers' wages by 5.3% (=0.104-0.051). This is consistent with the prediction of Figure 1.13 that a higher removal risk leads to higher wages

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

for undocumented workers. However, the coefficient of the documented-omnibus interaction, which indicates a wage increase of 1.9%, is not consistent with the model. If omnibus immigration laws only affect the removal risk of undocumented immigrants, this coefficient should be zero. One reason for a positive coefficient could be that even legal immigrants who are non-citizens can be subject to removal under certain circumstances and therefore might perceive the removal risk as higher even though omnibus immigration laws mostly target undocumented immigrants. This possibility is further backed up by a study by Arbona et al. (2010) who surveyed documented and undocumented Latin American immigrants living in Texas and find that the reported levels of deportation fear are similar for both groups.

1.9 Conclusion

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

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

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

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

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

Appendices

1.A Educational Attainment and Identification Accuracy

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

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

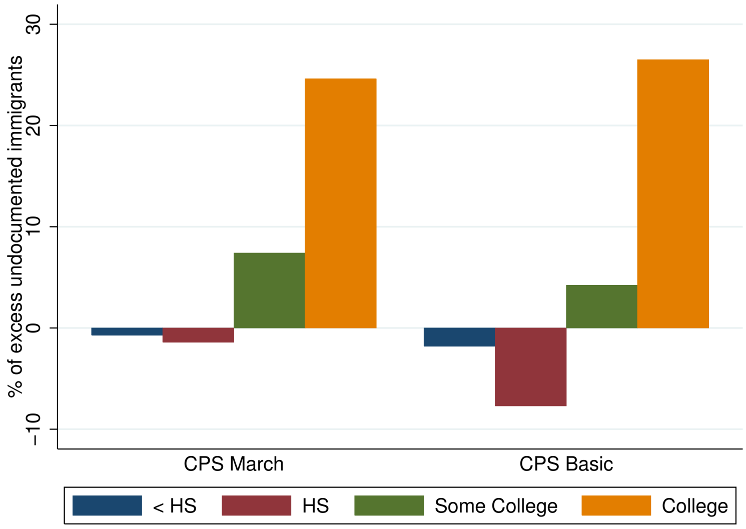
Notes: Following Borjas (2016) the statistics are calculated using a sample of individuals aged 20-64 from the years 2012-2013. The statistics from the Pew file are taken from Borjas (2017a, Table 1)

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

Table A.1 shows the distribution of undocumented immigrants across education levels and their total population share in the Pew CPS March, the Borjas CPS March and the CPS basic monthly files. In the CPS basic, I use all variables that are also used by the Borjas identification method except the ones related to social security benefits or health insurance, because these are exclusively available in the CPS March. Compared to the Pew CPS March, the education level of undocumented immigrants is higher in both the Borjas CPS March and the CPS basic. In particular, the share of college graduates is around 4 percentage points (or 25%) higher in the former and 5 percentage points (or 31%) higher in the latter, whereas the shares of both high school dropouts and high school graduates are lower. Moreover, in both datasets the total population share of undocumented immigrants, shown in the last row, is somewhat higher than in the Pew CPS March. This indicates that too many high-skilled immigrants are classified as undocumented by the simplified Borjas method.[36] In the CPS basic, the total population

[36]If I reclassify some undocumented immigrants with college degree to being documented in the Borjas

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



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

share is somewhat lower than in the CPS March, which is unexpected as the absence of some variables for the identification of documented immigrants should lead to an additional excess of immigrants classified as undocumented. The fact that there is no excess compared to the CPS March suggests that there is little difference in the accuracy of the identification method in the CPS basic data due to the missing variables.

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

Figure A.1 shows the analogously calculated percentages of excess undocumented immigrants for all education levels in the Borjas CPS March and the CPS basic data. For

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

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

1.B Additional Tables and Figures

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

MSA	Documented imm. (%)				Undocumented imm. (%)			
	1980	1990	2000	2010	1980	1990	2000	2010
Baltimore, MD	1.8	3.4	4.2	9.5	.6	.6	2.8	11
Birmingham, AL	.3	.6	2.1	4.2	.1	.4	3.5	14.1
Boston, MA/NH	12.9	20.9	22.1	24.4	5.9	6.4	13.4	23.4
Charlotte-Gastonia-Rock Hill, NC/SC	.7	1.9	6.4	11.5	.4	.6	12.2	21.2
Chicago, IL	10.4	24.5	25.1	28.5	7.9	5.5	17.9	25.3
Cleveland, OH	5.9	6.9	4.4	5.3	1.5	.6	1.4	3
Columbus, OH	1.6	2	4.5	7.7	.4	.5	4	9
Dallas-Fort Worth, TX	3.9	20.1	22.7	26.6	3.7	5.8	22.5	33.7
Denver-Boulder, CO	4.5	10.2	16	18.5	2.3	2.5	19	28.7
Detroit, MI	5.1	6.7	7.9	10.4	2	.5	4.1	6.1
Hartford-Bristol-Middleton- New Britain, CT	14.5	25.4	20.8	20.9	6.3	4.1	6.1	19
Houston-Brazoria, TX	7	28.1	28.3	31.6	6.9	5.9	20.9	33.7
Indianapolis, IN	.8	1.5	3.2	7.7	.3	.2	4.9	13.7
Kansas City, MO/KS	1.9	3.6	6.2	9.7	.7	.6	7.4	16.1
Los Angeles-Long Beach, CA	16.2	48.1	43.4	44.6	26.1	18.7	28.7	33.7
Louisville, KY/IN	.5	1.4	2.7	6.4	.1	.1	1.5	8.4
Memphis, TN/AR/MS	.6	1.2	3.7	7.5	.1	.3	4.6	13.3
Miami-Hialeah, FL	46.1	60.6	59.7	58.7	6.6	10.7	16.3	21.5
Minneapolis-St. Paul, MN	2.3	4.4	9	14.9	.6	1.1	9.3	17.7
Nashville, TN	.5	1.5	5.3	13.2	.2	.2	7.6	17.7
New York, NY-Northeastern NJ	21.3	35.8	36	36.9	10.2	9.1	21.9	30.9
Oklahoma City, OK	1.8	7.2	10.4	17.3	1	1.3	8.4	20.2
Philadelphia, PA/NJ	4.4	6	8	12.3	1.2	1.2	3.9	12.6
Phoenix, AZ	6.7	16.1	19.6	25.3	3.6	6.1	22.9	26.9
Pittsburgh, PA	2.8	3.3	2.5	3.4	.3	.1	.7	.7
Providence-Fall River-Pawtucket, MA/RI	12.1	29.2	22.6	26.1	10.5	5.1	9.4	17.5
Sacramento, CA	9	17.2	20.8	30.4	5.3	3.6	10.4	20.3
St. Louis, MO/IL	1.6	1.8	2.5	3.5	.2	.3	1.6	3.6
San Antonio, TX	10.4	20.8	20.6	24.3	4.8	2.5	8.3	15.9
San Diego, CA	14.3	34.3	35.3	38.1	11.3	11.8	20.8	29.5
San Francisco-Oakland-Vallejo, CA	15.8	33.5	34.3	39.6	10.3	11.2	22.9	32.8
Seattle-Everett, WA	6.2	10.1	16.2	27	2	2.8	9.9	20
Washington, DC/MD/VA	5.3	15.5	20.6	26.4	3.6	10	20.5	33.6

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

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

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

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

Table B.3: First stage with base period 1980

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

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

Table B.4: Second stage with base period 1980

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

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

Figure B.1: Documented immig. with $\lambda^W = 0.0022$, $\lambda^U = 0$ and $R = 0.75U_U$

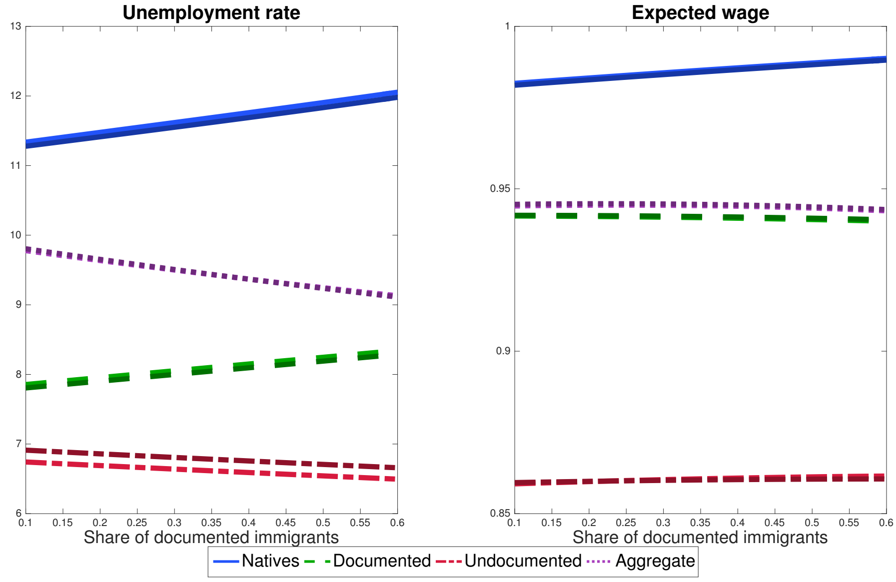


Figure B.2: Undocumented immig. with $\lambda^W = 0.0022$, $\lambda^U = 0$ and $R = 0.75U_U$

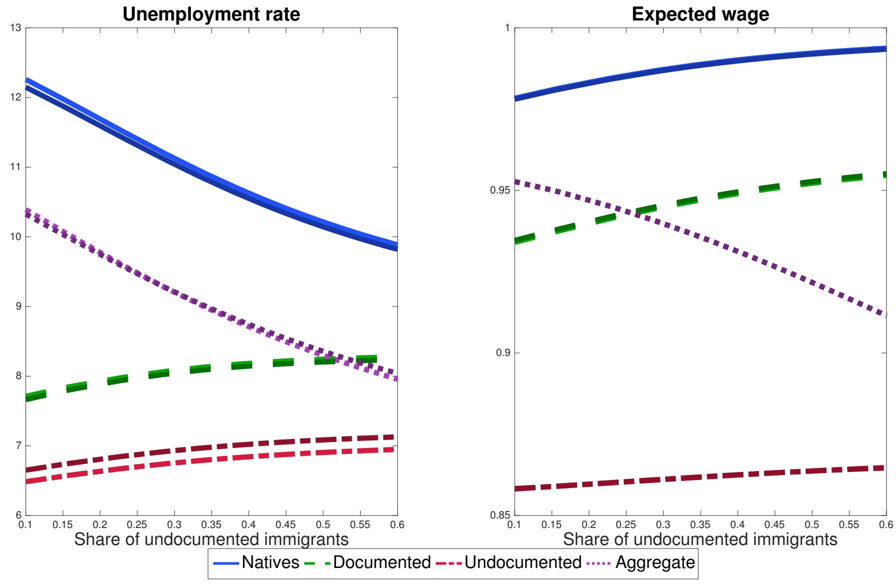
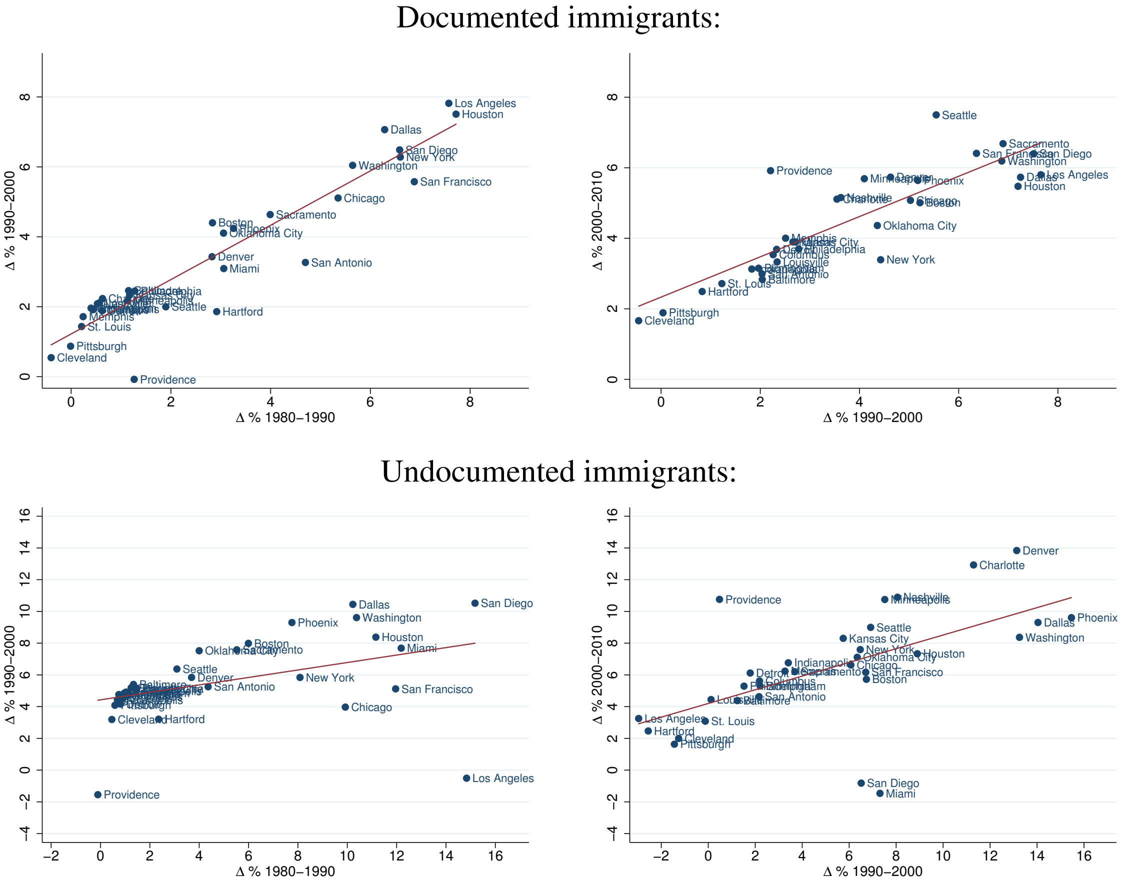


Figure B.3: Serial correlations of predicted changes in immigrant shares



Chapter 2

IMMIGRANTS' RESIDENTIAL CHOICES AND THEIR CONSEQUENCES

with Joan Monras*

2.1 Introduction

We consume mainly where we live; however, not all goods are produced locally. Both tradable and non-tradable local goods constitute the main elements of the price index that people face when living in a particular location. Since Krugman (1991) and the extensive literature that followed, this has constituted the basis for thinking about the distribution of people across space.

While this simplification of how people consume may be accurate for most of the population, immigrants spend a considerable portion of their income in their home countries. For example, using German data, Dustmann and Mestres (2010) estimate that immigrants send around 8 percent of their disposable income back to their home countries, and this share is even larger for immigrants that plan to return home. Thus, immigrants care not only about the local price index but also about the price index in their home countries.

Local price indices vary considerably between US cities. In New York City, for instance, they are around 20 percent higher than the national average–mainly due to housing.[1] At the same time, nominal incomes are also much higher in New York than in smaller, lower-price-index cities. These higher wages "compensate" for the higher living costs,

*CEMFI and CEPR. E-mail: monras@cemfi.es

[1]See Table 2.1. San Jose's local price index is around 50 percent above the national average. Local prices of tradable goods tend to be lower in large cities once the diversity of products available is taken into account (Handbury and Weinstein, 2015), though we do not take this into account in this paper.

as predicted in the Rosen (1974)-Roback (1982) spatial equilibrium model.

Given that immigrants care about both local prices and prices in their countries of origin while natives may be concerned solely with local ones, natives and immigrants potentially have different incentives for choosing which metropolitan area to live in.[2] For example, an immigrant may find it particularly advantageous to live in a city like New York. All else being equal, for immigrants in New York City, the income left after paying for local goods is likely to be higher than in a smaller, lower-wage, less expensive city.[3] In this paper, we show how this mechanism affects the residential choices of natives and immigrants in the United States both empirically and quantitatively through the lens of a model.

In the first part of the paper, we use a number of different data sets to document four novel and very strong empirical regularities in the United States. First, we report that in recent decades, immigrants have concentrated in large, expensive cities.[4] Second, the gap in earnings between natives and immigrants is *greatest* in these cities. Third, immigrants consume less than natives locally. And fourth, there is significant heterogeneity across different groups of immigrants. In particular, we show, using across *and* arguably exogenous within-origin variation, that these patterns in relative location choices and native-immigrant wage gaps are stronger for immigrants coming from lower-income, low-price-index countries.[5] We also obtain this result using higher frequency within-origin real exchange rate variation between Mexico and the United States. When the price of the peso is low relative to the dollar, i.e., when it is relatively cheaper to consume in Mexico, Mexicans concentrate more in large, expensive cities, and the native-immigrant earnings gap is higher.[6] We also show that these patterns are stronger for Mexicans closer to the US-Mexican border, in line with the idea that ties to the home country are stronger for immigrants physically closer to their home country (Hanson, 2001). Finally, in Appendix 2.B.1 we show that these patterns are attenuated in the case of immigrants that have spent a considerable amount of time in the United States and *cannot* be explained by immigrant networks, differences in human capital between

[2]A paper that also uses differences in preferences to understand differences between regions is Atkin (2013). Our focus is very different than Atkin's, however, since we study the spatial distribution of immigrants and natives based on their preferences for consuming in their country of origin, while Atkin (2013) studies how acquired local preferences affect migrants' nutrition and welfare.

[3]More generally, any neoclassical spatial equilibrium model where immigrants and natives have similar preferences but where immigrants have an extra normal good to consume–home country goods–would deliver this result. See the discussion at the beginning of Section 2.4.

[4]These cities, as is well known in the literature and we also document with our data, tend to pay higher nominal wages. See for example Combes and Gobillon (2014) and Glaeser (2008). We also document this fact in this paper.

[5]For this exercise we use Census, ACS and price levels at origin estimates by the World Bank for 1990, 2000, and 2010 and 89 different countries of origin and we rely in changes in the real exchange rate between the United States and the origin country in these 3 years.

[6]We focus on Mexicans because this is the largest immigrant group, and thus, there are enough movers so that we can estimate location choices across US cities for each year. See the exact details of this exercise in section 2.3.1.

natives and immigrants, or imperfect immigrant-native substitutability within narrowly defined education groups.

In the second part of the paper, we explain these strong empirical regularities with a quantitative spatial equilibrium model where preferences for locations depend on country of origin-specific price indexes. With this model we then investigate the role that immigration plays in shaping the distribution of economic activity across locations and, through this mechanism, its contribution to the general equilibrium. In the model, natives consume only locally, whereas immigrants also consume in their home country and therefore also care about price levels there.[7] Hence, an immigrant requires lower compensation in nominal wages in order to move to an expensive city. This implies that immigrants concentrate in expensive cities and that, if wages partly reflect the value of living in a city, the native-immigrant wage gap is higher in high local price index locations.[8] Some degree of substitutability between home and local goods allows this mechanism to be stronger for immigrants coming from poorer countries, which is in line with the data both when we compare location and wage patterns across countries of origin and when we relate these to exchange rate variation.

We estimate the key parameters of the model to match relative population and wage data across cities between natives and immigrants for each country of origin and we complement these estimates with parameters from the prior literature to perform quantitative exercises (specifically, we use Albouy (2016), Combes and Gobillon (2014), and Saiz (2010)). In particular, we find that the parameter governing immigrants' weight for the home country is around 10 percent. This means that the distribution of immigrants across locations and their wages relative to those of natives is consistent with immigrants consuming around 10 percent of their income in their country of origin. This aligns very well with the direct evidence provided using consumption data, which is not used when estimating the model. This magnitude suggests that the home country is economically important to immigrants and has a strong influence on where they decide to settle and their wages, which in turn has important consequences for the host country.

We use our estimated model to compute the counterfactual distribution of population, wages, and economic activity when immigrants do not care about consuming in their home country. This allows us to quantify how immigrant location choices may affect host countries. Our main finding is that there is a significant redistribution of economic activity from small, unproductive cities to large, productive ones as a consequence of

[7] Consumption at home can happen in various forms. It could be that immigrants spend a portion of their time in the home country, or that they send remittances to their relatives, or that they save for the future while intending to return to their country of origin. All these are equivalent from the point of view of the model. See Dustmann (1997) for savings decisions and return migration.

[8] In order to obtain this result, wage differences between workers cannot be competed away. This means that we depart from standard perfectly competitive models of the labor market and instead consider wage bargaining. See Becker (1957) and Black (1995).

immigrants' location choices.[9] With current levels of immigration, we show that low-productivity cities lose as much as 5 percent of output, while more productive ones gain as much as 6 percent. We also show that some natives who would otherwise live in these more productive cities are priced out of the housing market, and that the ones who stay have *higher* nominal incomes than they would without immigration. In sum, immigration contributes to increasing *nominal* inequalities across metropolitan areas. In aggregate, we estimate that current levels of immigration expand total output per capita by around 0.3 percent.[10]

We conclude our analysis by exploring how these changes in economic activity across space affect natives' welfare. There are essentially three groups of natives: workers, landowners, and firm owners. On the one hand, the model suggests that native workers in large, expensive cities lose in terms of welfare because immigrants' location choices put pressure on housing markets and this pressure is not compensated for by higher nominal incomes. On the other hand, landowners and firm owners in large cities benefit from immigration.

This paper extends the seminal work of Borjas (2001).[11] According to Borjas (2001), immigrants "grease the wheels" of the labor market by moving into the most favorable local labor markets. Within a spatial equilibrium framework, this means that they pick cities where wages are highest relative to living costs and amenity levels. Thus, in this context, immigrants do not necessarily choose the most productive cities, or those with the highest nominal wages. Instead, in our model, migrants prefer high-nominal-income cities because they care less than natives about local prices. This is a crucial difference that has important consequences for both the distribution of economic activity across space and the general equilibrium. Moreover, this insight also has important implications for empirical studies on immigration's effects on the labor market that rely on comparing metropolitan areas (see, among others, Card, 1990; Altonji and Card, 1991; Borjas et al., 1997; Card, 2005; Lewis, 2012; Llull, 2017a; Glitz, 2012; Borjas and Monras, 2017; Monras, 2015b; Dustmann et al., 2017; Jaeger et al., 2018).[12] In particular, it provides a strong explanation for why there is a positive correlation between wage levels and immigrant shares across metropolitan areas.

This paper is also related to a large body of recent work. Recent developments in quantitative spatial equilibrium models include Redding and Sturm (2008), Ahlfeldt et al. (2015), Redding (2014), Albouy (2009), Fajgelbaum et al. (2016), Notowidigdo (2013),

[9]Large, expensive cities are so, in the context of our model, because they are more productive. See Albouy (2016). In related work Hsieh and Moretti (2017), show how housing constraints are responsible in part for the smaller than optimal size of the most productive cities. This paper shows that immigrant location choices reduce these constraints. On optimal city size see also Eeckhout and Guner (2014).

[10]This estimate depends, to some extent, on the agglomeration forces assumed in the model.

[11]There are other papers with models that help to make arguments similar to the one made in Borjas (2001), for example, Bartel (1989) and Jaeger (2007).

[12]Dustmann et al. (2016) provide a recent review of this literature.

Diamond (2015), Monras (2015a), Caliendo et al. (2015), Caliendo et al. (Forthcoming), and Monte et al. (2015), among others, and have been used to explore neighborhoods within cities, the spatial consequences of taxation, local shocks, endogenous amenities, the dynamics of internal migration, international trade shocks, and commuting patterns.[13] However, only Monras (2015b), Piyapromdee (2017), and more recently Burstein et al. (2018), use a spatial equilibrium model to study immigration. Relative to these papers, we uncover novel facts that we use to understand general equilibrium effects of immigration that were unexplored until now. In fact, much of the literature on immigration ignores general equilibrium effects. Many studies in this literature compare different local labor markets–some that receive immigrants and some that do not (see Card, 2001)–or different skill groups see (Borjas, 2003). Neither of these papers, nor the numerous ones that followed them, are well suited to exploring the general equilibrium effects of immigration, and only a handful of papers use cross-country data to speak to some of those effects (see, for example, Di Giovanni et al., 2015). Within-country general equilibrium effects are, thus, completely under-explored in the immigration literature.

Finally, this paper also ties in with a significant amount of literature that investigates the effects of migrants on housing markets and local prices more generally. There is evidence that suggests that Hispanic migrants tend to settle in expensive metropolitan areas and that they exert pressure on housing prices (see Saiz, 2003, 2007; Saiz and Wachter, 2011). Relative to these papers, we document broader patterns in the data that are in line with this evidence and we provide a mechanism that can account for these facts and a quantitative spatial equilibrium model that highlights its importance. There is also some literature showing that immigration affects local prices (Lach, 2007; Cortes, 2008). This literature shows that price levels in high-immigrant locations may decrease relative to low-immigrant locations. This is usually explained by the impact that immigration has on the cost of producing some local goods. We abstract from this mechanism in this paper, but we could easily integrate it into the model and the results would be similar.

In what follows, we first describe our data. We then introduce a number of facts describing immigrants' residential choices, incomes, and consumption patterns. In Section 2.4, we build a model that rationalizes these facts. We estimate this model in Section 2.5, and we use these estimates to study the contribution of immigration to the spatial distribution of economic activity.

[13] Redding and Rossi-Hansberg (Forthcoming) provide a recent review of this literature.

2.2 Data

For this paper, we rely on various publicly available data sets for the United States. For labor-market variables, we mainly use the US Censuses, the American Community Survey (ACS), and the Current Population Survey (CPS), all available on Ruggles et al. (2016) and widely used in previous work. For consumption, we combine a number of data sets that allow us to (partially) distinguish between natives' and immigrants' consumption patterns. These include the New Immigrant Survey and the Consumption Expenditure Survey. For country of origin data we use price levels estimated by the World Bank.[14] We describe these various data sets below.

2.2.1 Census, ACS, and CPS Data

First, we use CPS data to compute immigrant shares, city size, and average (composition-adjusted) wages at high frequency. The CPS data are gathered monthly, but the March files contain more detailed information on yearly incomes, country of birth, and other variables that we need. Thus, we use the March supplements of the CPS to construct yearly data. In particular, we use information on the current location–mainly metropolitan areas–in which the surveyed individual resides, the wage they received in the preceding year, the number of weeks that they worked in the preceding year, and their country of birth. We define immigrants as individuals born outside the United States with no American parents. This information is only available after 1994, and so we only use CPS data for the period 1994-2011. To construct composition-adjusted wages, we use Mincerian wage regressions where we include racial categories, marital status categories, four age categories, four educational categories, and occupation and metropolitan-area fixed effects. The four education categories are: high school dropouts, high school graduates, some college, and college graduation or more.

Second, we use the Census of population data for the years 1980, 1990, and 2000. These data are very similar to the CPS, except that the sample size is significantly larger–from a few tens of thousands of observations to a few million observations. After 2000, the US Census data are substituted on Ipums by the ACS. The ACS contains metropolitan-area information only after 2005 and so we use these data. Again, the structure of the data is very similar to the Census and CPS data. Our treatment of the variables is identical in each case.

We also use these data to compute local price indices. To do this, we follow Moretti (2013) and apply his code to ACS and Census data. From that, we obtain a local price index for each of the metropolitan areas in our sample. The CPS does not contain a number of variables that are used for this computation–particularly housing price

[14] We have also used per capita GDP from the Penn World Tables to check that our results are robust to using GDP per capita instead of price indices in the home country.

Table 2.1: List of top US cities by immigrant share in 2000

MSA	*Immig. (%)*	*Size rank*	*Population*	*Weekly wage*	*Price index*	*Wage gap (%)*
Miami-Hialeah, FL	64	23	1,056,504	332	1.13	-20
Los Angeles-Long Beach, CA	48	2	6,003,886	395	1.20	-24
McAllen-Edinburg-Pharr-Mission, TX	44	88	229,812	258	0.88	-16
San Jose, CA	44	25	888,632	563	1.52	-8
Salinas-Sea Side-Monterey, CA	40	146	120,699	355	1.22	0
El Paso, TX	40	70	291,665	300	0.92	-14
Brownsville-Harlingen-San Benito, TX	38	134	137,429	275	0.90	-17
New York, NY-Northeastern NJ	36	1	8,552,276	454	1.22	-19
Visalia-Tulare-Porterville, CA	33	125	155,595	306	0.95	-7
San Francisco-Oakland-Vallejo, CA	33	6	2,417,558	494	1.38	-10
Fort Lauderdale-Hollywood-Pompano Beach, FL	33	28	799,040	393	1.17	-12
Fresno, CA	30	56	396,336	327	0.98	-8
San Diego, CA	29	15	1,306,175	411	1.19	-13
Santa Barbara-Santa Maria-Lompoc, CA	29	112	176,133	390	1.25	-8
Riverside-San Bernardino, CA	28	14	1,428,397	388	1.07	-11
Ventura-Oxnard-Simi Valley, CA	28	61	362,488	460	1.23	-17
Stockton, CA	27	83	246,980	386	1.04	-14
Houston-Brazoria, TX	26	8	2,191,391	427	1.04	-18
Honolulu, HI	26	55	397,469	393	1.23	-4
Modesto, CA	25	102	203,134	372	1.03	-3

Notes: These statistics are based on the sample of prime-age workers (25-59) from the Census 2000. Weekly wages are computed from yearly wage income and weeks worked. Local price indices are computed following Moretti (2013). The wage gap is the gap in earnings between natives and immigrants, controlling for observable characteristics.

information–which explains why we cannot compute local price indices using CPS data. To give a sense of the metropolitan areas driving most of the variation in our analysis, Table 2.1 reports the metropolitan areas with the highest immigrant share in the United States in 2000, together with some of the main economic variables used in the analysis. As we can see in Table 2.1, most of the metropolitan areas with high levels of immigration are also large and expensive and pay high wages. The gap in earnings between natives and immigrants is also large in these cities. In this general description, there are a few notable outliers, which are mostly metropolitan areas in California and Texas relatively close to the US-Mexico border.

2.2.2 New Immigrant Survey and Consumer Expenditure Survey Data

To explore whether immigrants consume less locally than natives, we employ a number of different data sets. First, we use data from the New Immigrant Survey to document remittance behavior. While not a large data set, it is the only one to our knowledge that provides information on both the income and the amount remitted at the individual or household level for immigrants residing in the US.

The second data set that we use is the Consumer Expenditure Survey, which is maintained by the Bureau of Labor Statistics and has been widely employed to document consumption behavior in the US. It is a representative sample of US households and contains detailed information on consumption expenditure and household characteristics. Unfortunately, it contains no information on birthplace or citizen status, which is why it is impossible to directly identify immigrants. Instead, we rely on one of the Hispanic categories that identifies households of Mexican origin in the years 2003 to 2015. The data set contains around 30,000 households per year, of which around 7 percent are of Mexican origin.

2.2.3 Origin Country Price Index Data

The World Bank provides price indices of a large number of countries in the world relative to the United States in its International Comparison Program database from 1990.[15] These data expand the 89 countries of origin that we use in our estimation exercise.[16]

2.3 Stylized Facts

In this section, we start by documenting a series of facts about immigrants' location choices and wages. In particular, we show that immigrants concentrate much more than natives in large, expensive cities and that they tend to earn less than natives there. We also demonstrate that these patterns are stronger for immigrants coming from lower-income countries, and, within Mexican immigrants, for immigrants who moved to the US in high exchange-rate years. In the second part of this section, we document immigrants' consumption behavior, showing that immigrants tend to consume less than similar-looking natives at the local level.

2.3.1 Cities, Labor Market Outcomes, and Immigrants

Immigrants' location choices and city size

The first fact that we document in this paper is that immigrants tend to live in larger, more expensive cities in greater proportions than natives. This is something that was known to some extent in the literature (see, for example, Eeckhout et al., 2014; Davis and Dingel, 2012), but here we document it much more systematically: we use a much

[15] The exact title of the series is "Price level ratio of PPP conversion factor (GDP) to market exchange rate".

[16] An alternative source of similar information is provided by the OECD and the Penn World Tables. The OECD also estimates price levels of various countries. The number of countries that the OECD covers is smaller, which is why we report estimates in the paper using the World Bank data, although estimates for OECD countries may be more reliable. We obtain similar estimates using OECD data. We also obtain similar estimates using the GDP per capita in the country of origin, obtained from the Penn World Tables, to proxy for the price index.

larger number of data sets and we expand the existing literature by showing that there is also a strong relationship between immigrant shares and local price indices.

A simple way to document this fact is to regress the distribution of immigrants relative to the distribution of natives on city size or price level. In order to do this, we define the relative immigrant distribution as the share of immigrants living in city c divided by the share of natives living in city c and regress this measure (in logs) on the size or price level of city c. More specifically, we run the following regression:

$$\ln\left(\frac{\mathrm{Imm}_{c,t}}{\mathrm{Imm}_t}/\frac{\mathrm{Nat}_{c,t}}{\mathrm{Nat}_t}\right) = \alpha_t + \beta_t \ln P_{c,t} + \varepsilon_{c,t}, \tag{2.1}$$

where $\mathrm{Imm}_{c,t}$ is the number of immigrants and $\mathrm{Nat}_{c,t}$ is the number of natives in city c at time t. When the subscript c is omitted, the variables represent the total number of immigrants or natives living in cities in a particular time period. $P_{c,t}$ is either the total number of people in the city or its price level. We run separate regressions for each year.

Figure 2.1 shows these relationships using data from the Census 2000. In the left-hand panel, we observe that, even if there is some variance in the immigrant distribution across metropolitan areas, there is a clear positive relationship between immigrants and city size. This relationship is statistically significant. The relationship between immigrant share and price indices is even stronger and the linear fit better, as shown in the right-hand panel of Figure 2.1.[17] While there are some exceptions, mainly along the US-Mexico border, a city with a local price index that is 1 percent higher is associated with an increase of around 7 percent in the relative immigrant share as measured by the left-hand variable in Equation 2.1. In Appendix 2.B.4, we show that this relationship between the population level and the relative immigrant share also holds when using commuting zones instead of metropolitan areas.

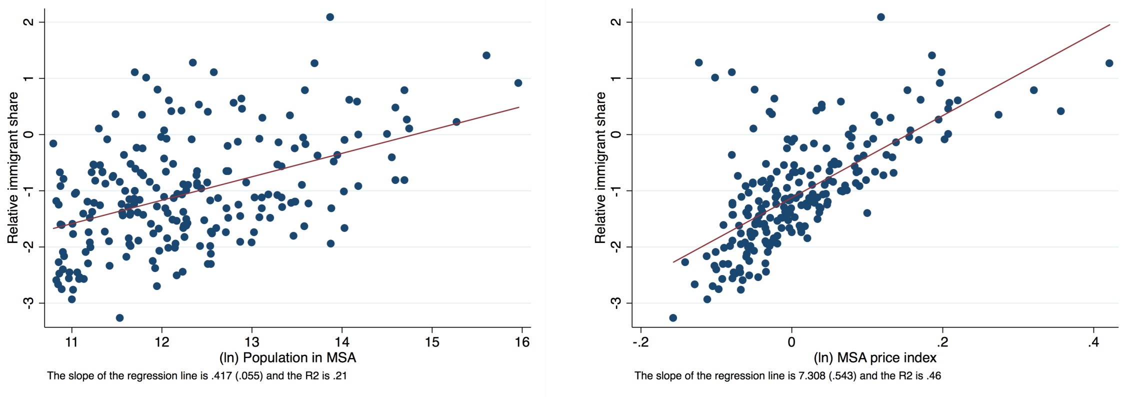
In Figure 2.2, we investigate how these relationships have evolved over time. To show this, we first run a linear regression following Equation 2.1 for each of the years displayed along the x-axis of the figure against the city size or the price index, and we then plot the various estimates and confidence intervals for these elasticities.

The left-hand panel in Figure 2.2 shows that the relationship between the relative immigrant share and city size has been positive since the 1980s. This relationship has become slightly stronger over time. While in 1980 the elasticity was around 0.3 percent, it has increased over the years to reach almost 0.5 percent when using the Census data. We observe a similar trend in the CPS data, but estimates are smaller and noisier, most likely because of measurement error. The elasticity of immigrant shares and local price indices first decreased from around 9 to 7 percent between 1980 and 1990 but has remained relatively stable since then.

We can summarize these two figures as follows:

[17] This is also the case when we include both city price and city size in a bivariate regression.

Figure 2.1: City size, price index, and relative immigrant share



Notes: The figure is based on the sample of prime-age workers (25-59) from the Census 2000. The MSA price indices are computed following Moretti (2013). Each dot represents a different MSA. There are 219 different metropolitan areas in our sample.

Figure 2.2: Evolution of the city size/price elasticity of the relative immigrant share

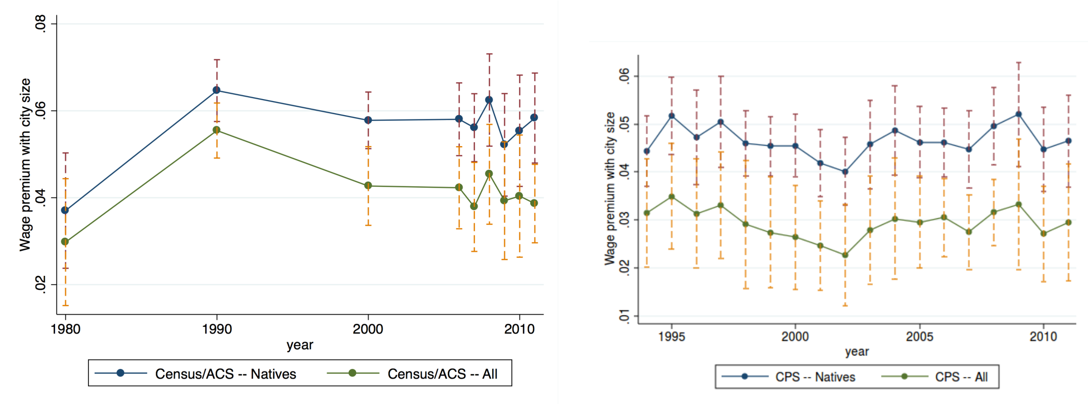
Notes: This figure uses Census/ACS and CPS data from 1980 to 2011 to estimate the relationship between the share of immigrants among all US immigrants relative to the share of natives among all US natives living in a city and its size and price. price indices can only be computed when Census/ACS data are available. Each dot represents the corresponding estimate of the elasticity of the relative immigrant distribution, city size, and city prices for each corresponding year. Vertical lines represent 95 percent confidence intervals.

Fact 1. *Immigrants concentrate in large, expensive cities much more than natives.*

Wages, city size, and local price indices

It is a well-known fact that wages are higher in larger cities (see, for example, Baum-Snow and Pavan, 2012). Moreover, this relationship has become stronger over time. In this section, we demonstrate this fact with our data. We show results using both the average (composition-adjusted) wages of natives alone and natives together with immigrants. To illustrate this fact, we again use various cross-sectional regressions and

Figure 2.3: Evolution of city size premium



Notes: This figure uses Census/ACS and CPS data from 1980 to 2011 to estimate the relationship between wage levels and city size. Each dot represents the corresponding estimate of the elasticity of immigrant shares, city size, and city prices for each corresponding year. CPS data start reporting place of birth only in 1994. Vertical lines represent 95 percent confidence intervals.

plot the estimates for each of the years. More specifically, we run regressions of the following type:

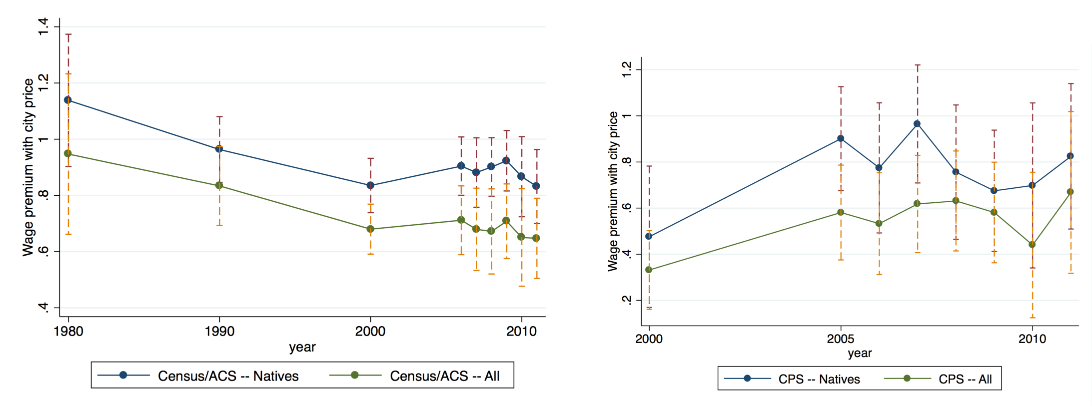
$$\ln w_{c,t} = \alpha_t + \beta_t \ln P_{c,t} + \varepsilon_{c,t} \tag{2.2}$$

where, as before, $P_{c,t}$ is either the total amount of people in the city or its price level and where $w_{c,t}$ is a measure of local wages.

In Figure 2.3, we show the evolution of the city size premium using Census data (left) and CPS data (right). We can compute this premium using natives and immigrants or focusing on native wages alone. In both cases, we always obtain positive and significant estimates. The city size wage premium has increased in the United States since 1980, although it has remained flat over the last 20 years or so (Baum-Snow and Pavan, 2012). Census estimates are slightly larger than CPS estimates–again, a consequence of measurement error in CPS data. A remarkable finding is that the city size premium is significantly smaller when combining both natives and immigrants for the computation of average (composition-adjusted) wages. We will come back to this point later.

In Figure 2.4, we repeat the exercise using price levels instead of city size. We obtain very similar patterns. The city price -wage premium is just less than 1. This means that an increase in the price level translates almost one for one to the wages paid in the city. If anything, this relationship has declined over the last 30 years or so. This is mainly due to the increase in price levels, as can be seen in Figure B.2 in the Appendix. Again, as was the case with the city size wage premium, when we also use immigrants to compute it, we see that the relationship is weaker than if we only use natives. This is true both when we use ACS/Census data and when we use CPS data.

Figure 2.4: Evolution of city price level premium



Notes: This figure uses Census/ACS and CPS data from 1980 to 2011 to estimate the relationship between wage levels and city prices. price indices can only be computed when Census/ACS data are available. Each dot represents the corresponding estimate of the elasticity of immigrant share, city size, and city prices for each corresponding year. CPS data start reporting the place of birth only in 1994. Vertical lines represent 95 percent confidence intervals.

We can summarize this fact as:

Fact 2. *Wages are higher in larger, more expensive cities. Both the city size wage premium and the city price wage premium are higher when wages are computed using the native population only.*

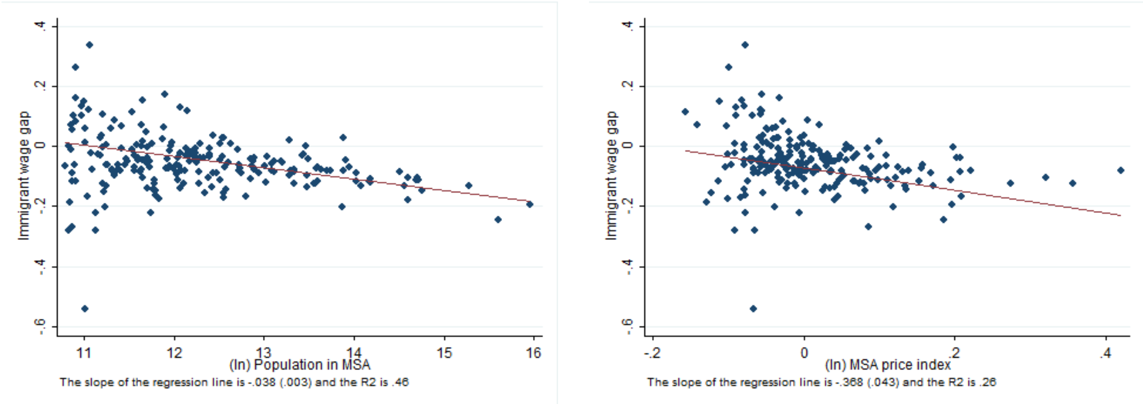
Immigrant wage gaps

In Figures 2.3 and 2.4, we observe that the city size and city price premiums seem to be significantly smaller when using immigrants to compute average (composition-adjusted) wages. In this subsection, we investigate this further. To that end, we compute the gap in wages between natives and immigrants as a function of city size and city prices.

As before, we show the results in two steps. In Figure 2.5, we show the estimates using data from the Census 2000. In the left-hand panel, we plot the difference in wages between natives and immigrants in our sample of metropolitan areas against the size of these cities. The relationship is negative and strong. The estimate is -0.038, meaning that if a city is 10 percent larger, the gap in wages between natives and immigrants is 0.38 percent larger. Again, in Appendix 2.B.4, we show that the relationship between the population level and the immigrant wage gap also holds when using commuting zones instead of MSAs.

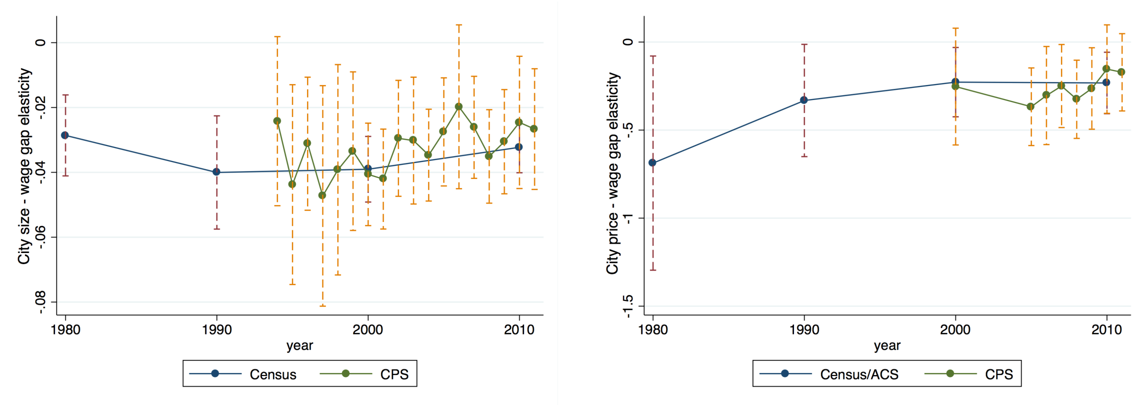
Moreover, the relationship between native-immigrant wage gaps and city size is very tight. The R squared is around 0.46, and the standard errors of the estimate are small. In fact, this relationship is extremely robust in the data. We run regressions of the type:

Figure 2.5: City size, price index, and wage gaps



Notes: This figure uses data from the Census 2000 to show the relationship between native-immigrant wage gaps and city sizes and prices. Each dot represents the gap in earnings between natives and immigrants in a metropolitan area. The red line is the fitted line of a linear regression.

Figure 2.6: Evolution of the city size/price elasticity of the wage gap



Notes: This figure uses Census and CPS data from 1980 to 2011 to estimate the relationship between native-immigrant wage gaps and city size and prices for each year. Each dot represents an estimate of the native-immigrant wage gap elasticity with city size and the city price index. The vertical lines represent 95 percent confidence intervals.

$$\ln w_{i,c,t} = \alpha_{1t} + \alpha_2 Imm_{i,c,t} + \beta Imm_{i,c,t} * \ln P_{c,t} + \gamma \ln P_{c,t} + \phi X_{i,c,t} + \varepsilon_{i,c,t} \quad (2.3)$$

where i indexes individuals, c indexes cities, t indexes years, Imm is an indicator variable for i being an immigrant, $\ln P$ indicates city size or city prices, and X contains observable individual characteristics as well as year and metropolitan ares (MSA) fixed effects.[18] In all our estimates, we obtain a negative β that remains highly statistically

[18]The individual controls are five dummies for race (white, black, American Indian/Aleut/Eskimo, Asian/Pacific Islander, other), five for marital status (married, separated, divorced, widowed, never

significant no matter what type of data or variation we use, as shown in Appendix 2.C.[19] One way to assess the stability of the relationship between native-immigrant wage gaps and city size over time is estimating the model for each year. The results are shown in Figure 2.6. As before, we show the estimates using both Census and CPS data over a number of years between 1980 and 2011. The relationship remains tight at around 0.035 through the entire period in both data sets. The right-hand panels of Figures 2.5 and 2.6 show the relationship between native-immigrant wage gaps and local price levels. We also observe a negative and tight negative relationship. If anything, it seems that over time, this relationship has become a little weaker, but remains at around -0.36.

To the best of our knowledge, this is the first paper to document this very strong feature of the data in the United States. It suggests that, for whatever reason, immigrants that live in larger, more expensive cities are paid less relative to natives than immigrants that live in smaller, less expensive cities.[20] This is not driven by immigrant legal status. In Appendix 2.B.3, we show that we obtain a similar relationship for documented and undocumented immigrants.[21] Nor is this driven by the composition of immigrants across US cities. In Figures 2.5 and 2.6, we control for observable characteristics, which include education, race, marital status, and occupation, etc. Furthermore, we check that this relationship prevails for each education group independently by running separate regressions by education category, and that it is robust to controlling for immigrant networks and for imperfect native-immigrant substitutability, as reported in Appendix 2.B.1.

We can summarize this fact as follows:

Fact 3. *The gap in wages between immigrants and natives increases with city size. Over time, this gap has been stable.*

Immigrant heterogeneity

Later in the model section, we argue that the results reported so far can be explained by the fact that part of what immigrants consume is related to home-country price indices instead of local ones. This implies that, if there is some degree of substitution between consuming locally or consuming in the country of origin, the patterns documented so far should be stronger for immigrants coming from countries of origin with lower price indices.

married/single), four age groups (three ten-year intervals from 25 to 54 and 55-59), four education categories (high school dropout, high school graduate, some college, college graduate or more), and 82 occupation categories, which are based on the grouping of the 1990 occupation codes from https://usa.ipums.org/usa/volii/occ1990.shtml.

[19]The regression results of the above baseline regression can be found in Table C.1.

[20]On average, immigrants earn less than natives, but this is driven mostly by immigrant wages from lower-income countries and by immigrants of all income levels in larger cities.

[21]To identify likely undocumented immigrants in the Census data, we apply the method described in Borjas (2017a).

To show that this is indeed the case, we carry out two alternative exercises in this subsection. First, we show that the relationships between relative location choices, wage gaps, and local price indices are stronger for immigrants coming from lower home-country price indices. We use both across and within country variation to document this fact. Second, we use arguably exogenous exchange rate fluctuations between Mexico and the US to show that these patterns are stronger for Mexicans that migrate to the US when the price of the Mexican peso is low relative to the dollar.

We also show in this section that the patterns in relative wages between immigrants and natives are stronger for Mexicans living closer to the border. We argue that this is in line with the idea that Mexicans closer to the border may have tighter ties to their country of origin.

All this evidence, together with the consumption patterns documented in Section 2.3.2, is key to highlighting the mechanism that generates a differential distribution of immigrants and natives across locations, as emphasized in the model that we introduce in Section 2.4.

Heterogeneity by country-of-origin price index

Our main hypothesis is that the relationships described in Facts 1 to 3 emerge because immigrants have more incentives than natives to live in large, more expensive cities that pay, on average, higher nominal wages if consumption in their home country is cheaper than local consumption. To explore whether the data are in line with this hypothesis, we rely on immigrant heterogeneity: some immigrants come from rich countries, with price levels similar to the ones in the US, which gives them fewer incentives to consume in their home countries. This should result in a flatter relationship between relative immigrant shares and immigrant-native wage gaps for immigrants coming from countries of origin with higher price levels. To explore this possibility we expand equations 2.1 and 2.3 as follows:

$$\ln(1+\frac{\text{Imm}_{c,o,t}}{\text{Imm}_{o,t}}/\frac{\text{Nat}_{c,t}}{\text{Nat}_t}) = \alpha_1 \ln P_{c,t} + \alpha_2 \ln P_{o,t} + \alpha_3 \ln P_{c,t} * \ln P_{o,t} + \delta_t + (\delta_o + \delta_c) + \varepsilon_{c,t} \tag{2.4}$$

$$\ln w_{i,c,t} = \beta_1 \ln P_{c,t} + \beta_2 \ln P_{o,t} + \beta_3 \ln P_{c,t} * \ln P_{o,t} + \delta_t + (\delta_o + \delta_c) + \phi X_{i,c,t} + \varepsilon_{i,c,t} \tag{2.5}$$

where as before $\ln P_{c,t}$ denotes the population or the price level of metropolitan area c, and where $\ln P_{o,t}$ denotes the price level of country of origin o relative to the US. It is is worth noting that we use $\ln(1+\frac{\text{Imm}_{c,o,t}}{\text{Imm}_{o,t}}/\frac{\text{Nat}_{c,t}}{\text{Nat}_t})$ instead of $\ln(\frac{\text{Imm}_{c,o,t}}{\text{Imm}_{o,t}}/\frac{\text{Nat}_{c,t}}{\text{Nat}_t})$ because this exercise is quite demanding in terms of data, and, thus, there are a few zeros. To

Table 2.2: Immigrant heterogeneity

Panel A: Location choices

VARIABLES	(1) Rel. Imm. share OLS	(2) Rel. Imm. share OLS	(3) Rel. Imm. share OLS	(4) Rel. Imm. share OLS
(ln) Population in MSA x (ln) Real xrate	-0.0418**		-0.0434***	
	(0.0207)		(0.0168)	
(ln) City price x (ln) Real xrate		-0.0326		-0.0461*
		(0.0309)		(0.0264)
Observations	26,700	26,700	26,700	26,700
R-squared	0.112	0.148	0.380	0.379
Year FE	yes	yes	yes	yes
MSA FE	no	no	yes	yes
Country origin FE	no	no	yes	yes

Panel B: Wage gaps

VARIABLES	(1) (ln) Wage OLS	(2) (ln) Wage OLS	(3) (ln) Wage OLS	(4) (ln) Wage OLS
(ln) Population in MSA x (ln) Real xrate	0.0531***		0.0485***	
	(0.0104)		(0.00393)	
(ln) City price x (ln) Real xrate		0.0491**		0.0431**
		(0.0236)		(0.0173)
Observations	3,083,257	3,083,257	3,083,257	3,083,257
R-squared	0.379	0.380	0.391	0.390
Xs	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
MSA FE	no	no	yes	yes
Country origin FE	no	no	yes	yes

Notes: This table shows regressions of relative immigrant shares and wages on population/city prices, exchange rates and the interaction between these two variables. A number of controls are added across columns. The regressions are limited to the top 100 metropolitan areas in size and 89 sending countries for the years 1990, 2000, and 2010. Standard errors clustered at the metropolitan area - country of origin level are reported. One star, two stars, and three stars represent statistical significance at 0.1, 0.05, and 0.01 confidence levels respectively.

avoid measurement error problems, we also restrict these regressions to the top 100 metropolitan areas in terms of size.[22]

In the wage regressions, $\ln P_{o,t}$ takes value 0 for individuals i that are born in the US. Thus, this is a difference-in-difference specification that captures the heterogeneity of our results with respect to the country of origin. The estimate of interest are α_3 and β_3. A negative estimate of α_3 means that when the price level of origin is lower, immigrants from this country of origin tend to concentrate more in larger, more expensive metropolitan. Similarly, a positive estimate of β_3 implies that the wage gaps of immigrants from these countries relative to natives are larger in these larger, more expensive metropolitan areas.

[22]Different selections of metropolitan areas lead to slightly different selections on the number of sending countries which result in small changes in the estimates. Expanding the number of metropolitan areas tends to introduce more measurement error. This tends to attenuate the estimates of the regressions with many fixed effects, something that is a normal consequence of estimating many fixed effects with measurement error. Reducing the number of metropolitan areas obviously reduces the number of observations which has small consequences on the point estimates and confidence intervals.

It is worth noting that we can estimate these equations using two different sources of variation. If we include country of origin fixed effects, α_3 and β_3 are identified through changes in the price level at origin across different years. If we do not include country of origin fixed effects, α_3 and β_3 are identified by comparing different countries of origin across metropolitan areas.

We present the results in Table 2.2, where we report only selected coefficients. Panel A show the results of estimating how relative immigrant shares change with the interaction of local sizes and prices with the price level of the country of origin while panel B repeats the exercise for wages. Columns (1) and (2) use across country of origin variation, while columns (3) and (4) use within country of origin variation. The results are clear. When price levels in the country of origin are low, immigrants tend to concentrate much more in larger metropolitan areas and they tend to receive lower wages. Moreover, the results do not depend on the type of variation that we use to estimate the heterogeneity of immigrant location choices and their wages and how this varies with city sizes and local price levels.

Heterogeneity within Mexican immigrants: real exchange rate fluctuations

To provide further evidence for our hypothesis, we use in this section high frequency fluctuations in real exchange rates. Exchange rate fluctuations are common and difficult to anticipate over short time horizons. Variation in exchange rates is likely to be a source of exogenous variation that can inform whether immigrants decide differently on their location choices as a function of price indices at origin and destination.[23]

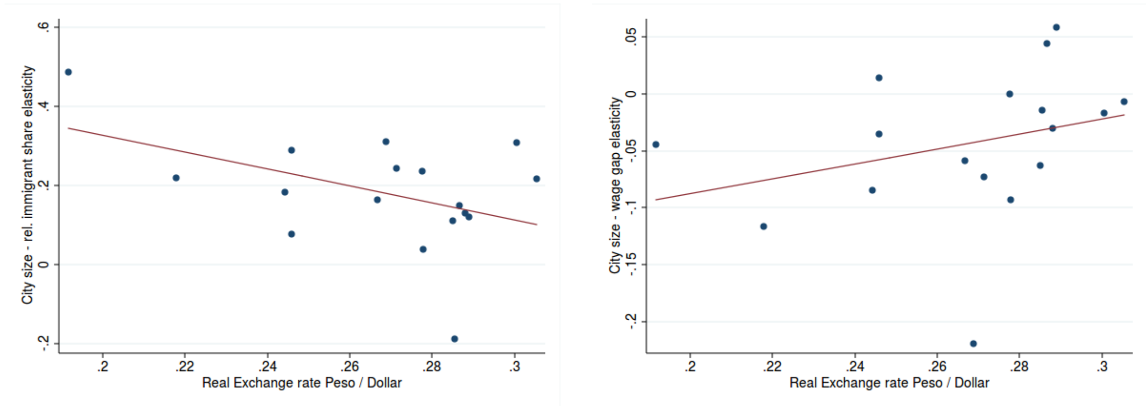
More concretely, we focus our analysis on migrants who change residences in a given year. We investigate whether these immigrant movers decide to concentrate more in large cities in years when prices in their home country are lower. For this exercise, we need the longest possible series of yearly data on a group of immigrants. For this reason, we use CPS data and concentrate on Mexican migrants: Mexicans are the largest immigrant group, and thus measurement error is likely smaller for this group.

Intuitively, the higher the real exchange rate between the dollar and the currency of the country of origin, in our case Mexico, the cheaper consumption at home is for immigrants. Given these cheaper home-country prices, immigrants have a greater incentive to live in large, expensive cities with high nominal wages and are willing to accept relatively lower wages in these locations. Thus, when home-country prices are lower, the elasticities of the relative immigrant share and the wage gap should be higher (in absolute terms).

We estimate Equations 2.1 and 2.3 using Mexican movers separately for each year and plot the β coefficients against the average real exchange rate of the Mexican peso to the

[23] In this paper, we complement the evidence shown in Nekoei (2013). Exchange rate fluctuations affect not only the intensive margin of immigrant labor supply decisions (i.e. hours worked) but also, and very importantly, the extensive margin (i.e. location choices).

Figure 2.7: City size elasticity of relative immigrant share and wage gap of Mexicans



Notes: This figure uses data from the CPS 1994-2011 to show the relationships between the city size elasticity of the relative immigrant share and the wage gap of Mexican immigrants that changed location during the year preceding the survey. We estimate the elasticity for each year and plot it against the average real exchange rate of the Mexican peso to the US dollar during that year. Each dot represents an estimate of the coefficient β for the particular year based on Equations 2.1 and 2.3.

US dollar during that year.[24] The two plots in Figure 2.7 show a linear fit that goes in the expected direction. The lower the prices in Mexico relative to the US, the more positive the elasticity of the relative share of Mexican immigrants and the more negative the elasticity of the wage gap with respect to city size. Note that the largest shock to the real exchange rate happened in 1995, which is the outmost point on the left, and persisted into 1996, whereas the rate was relatively stable at around .28 during the 2000s. Certainly, the small fluctuations in these years would go unnoticed for most Mexicans and therefore we see no clear pattern in the plots around this value. However, the significant depreciation of the Mexican peso at the end of 1994 was clearly an event of which many Mexicans were aware. Thus, the fact that the elasticities are especially high in 1995 and 1996 supports our notion that the relative affordability of home consumption influences immigrants' residential choices by changing their incentives to live in cities with high nominal wages.

Heterogeneity within Mexican immigrants: distance to the border

An alternative source of heterogeneity is potentially provided by Mexicans who live closer to or further away from the border. The former are likely to have stronger ties to Mexico. These ties may take various forms. When living closer to the border, it may be easier to spend longer periods of time in Mexico and to stay in closer touch with family members not in the United States, and thus the weight of their home country may be

[24]We do not take the log of the left-hand side of Equation 2.1 to avoid losing MSAs without Mexican immigrant movers. Further, the place of residence in the previous year is not available for the survey year of 1995. Thus, we cannot use the wage year of 1994 for our estimates.

Table 2.3: Mexican-native wage gaps and distance to Mexico

	Panel A			
	(1)	(2)	(3)	(4)
	Wage	Wage	Wage	Wage
	All workers	All workers	Low-skilled	Low-skilled
VARIABLES	OLS	OLS	OLS	OLS
Immigrant	-0.405***	-0.261***	-0.402***	-0.282***
(Mexican immigrants only)	(0.0417)	(0.0221)	(0.0400)	(0.0310)
Sample	Border states	Non-border states	Border states	Non-border states
Observations	62,784	245,634	28,375	91,648
R-squared	0.447	0.398	0.323	0.287

	Panel B			
	(1)	(2)	(3)	(4)
	Wage	Wage	Wage	Wage
	All workers	All workers	Low-skilled	Low-skilled
VARIABLES	OLS	OLS	OLS	OLS
(ln) Population in MSA	0.0274	0.0347**	0.0275	0.0166
	(0.0249)	(0.0143)	(0.0323)	(0.0236)
(ln) Population in MSA x Immigrant	-0.0410***	-0.0322***	-0.0303***	-0.0265***
(Mexican immigrants only)	(0.00797)	(0.00989)	(0.00875)	(0.00800)
Sample	Border states	Non-border states	Border states	Non-border states
Observations	62,784	245,634	28,375	91,648
R-squared	0.448	0.398	0.324	0.288

Notes: These regressions report only selected coefficients. The complete set of explanatory variables is specified in Equation 2.3, and is expanded by including the years that Mexicans have been in the US and a dummy for likely undocumented status (based on Borjas, 2017a). Metropolitan-area fixed effects and year fixed effects are also included in the regression. These regressions use CPS data for the years 1994-2011. Low-skilled is defined as having a college degree or less. Robust standard errors, clustered at the metropolitan area level, are reported. One star, two stars, and three stars represent statistical significance at 0.1, 0.05, and 0.01 confidence levels respectively.

greater. We can use this insight to see whether the wage gap between Mexicans and natives, and the relationship between this gap and city size, is stronger for Mexicans close to the border.[25] For this, we run the wage regressions with Mexican immigrants separately for people living in cities in border states and for people living in non-border states. In order to account for characteristics of Mexicans that might differ across these samples and are likely to influence wages, we include years in the US and a dummy for being undocumented as additional controls.

Panel A in Table 2.3 shows that Mexicans close to the Mexican border earn less relative to natives than Mexicans further away. Importantly, this relationship emerges even when we control for the number of years that Mexicans have been in the US and both when comparing Mexicans of all education groups to natives (Columns 1 and 2) and when concentrating on the sample of low-skilled workers (Columns 3 and 4). This could suggest that, given that a larger part of the consumption of Mexicans close to the

[25]Cities close to the Mexican border are defined as locations in California, Arizona, New Mexico, or Texas, which are the four states that share a border with Mexico.

border is likely to be related to prices in Mexico, this allows Mexicans close to the border to accept lower wages. There are also alternative explanations for these results, so it is worth emphasizing that we take them purely as suggestive evidence that the mechanism posited in this paper may be relevant for explaining these patterns in the wages of immigrants of the same country of origin.

Panel B in Table 2.3 shows that the gap in wages between Mexicans and natives decreases faster with city size in locations close to the Mexican border than in locations further away. This relationship is what we use in Section 2.5 to estimate the model and obtain the importance of the home country in host-country local consumption. It suggests, thus, not only that Mexicans earn less closer to the border than further away (Panel A), but also that the relationship between Mexican-native wage gaps and city size is stronger closer to the border than further away (Panel B).[26]

2.3.2 Immigrant Consumption and Return Migration Patterns

In this paper, we argue that one way to explain the distribution of immigrants across US cities and their wages relative to natives is that immigrants spend a part of their income in their host country. In this section, we show this importance of the home country by analyzing remittance behavior, housing expenditure, consumption expenditure, and return migration patterns. All of these are in line with the notion that part of the consumption of immigrants takes place in the country of origin.

Remittances

Dustmann and Mestres (2010) report that immigrants in Germany remit around 10 percent of their income. While data of the same quality do not exist for the US, we can use the New Immigrant Survey to document the remittance behavior of immigrants in the US. Table 2.4 reports the frequency, the share of income, and the share of income for those immigrants that remit for a number of different origins. There is quite some variation in the frequency of remitting across origins. For example, 20 percent of immigrants from Mexico and as much as 32 percent of immigrants from other Latin American countries seem to remit part of their income to their home countries. This number is significantly lower for immigrants from European countries.

For the entire population of immigrants, immigrant remittances represent approximately between 2 and 3 percent of income. For those who remit, this number logically increases to between 10 and 15 percent, which is closer to the estimate provided in Dustmann and Mestres (2010). All in all, the numbers for the US seem broadly consistent with this

[26]We carried out a similar exercise comparing large and small Mexican households to see whether these patterns are also stronger for smaller Mexican households, which are presumably more attached to Mexico, than for larger ones. The results indicate that this is indeed the case, in line with the idea of this paper.

Table 2.4: Remittances

Origin region	*Frequency (%)*	*Income share (%)*	*Income share for remit>0 (%)*
Latin America	32.54	2.35	8.86
Africa	30.31	2.57	12.17
Asia	25.31	2.81	12.8
Mexico	20.55	2.57	14.02
Europe	12.93	1.25	10.73
Total	24.73	2.24	10.98

Notes: Data come from the 2003 NIS, a representative sample of newly admitted legal permanent residents. Statistics are based on a subsample of immigrants with positive income (from wages, self-employment, assets, or real estate) and with a close relative (parent, spouse, or child) living in the country of origin. Income shares over 200% are dropped.

prior literature. The main drawback of New Immigrant Survey data is that it does not include undocumented immigrants. Including them would likely change the numbers significantly.

Expenditure on housing

One way to explore whether immigrants consume different local goods than natives is to investigate housing expenditure. If immigrants spend a portion of their income on home goods, they should (potentially) spend a lower share of their income on housing. This could be seen both in ownership rates and in rental prices paid.

First, if immigrants plan on returning home it is likely that ownership rates are lower among them. Ownership rates vary considerably by income and other characteristics. Thus, it may be useful to see if it is indeed the case that homeownership rates are lower among immigrants than *similar-looking* natives. This can be shown with the following regression:

$$\text{Owner}_i = \alpha + \beta \text{Immigrant}_i + \gamma \ln \text{HH Income}_i + \eta_c X_i + \varepsilon_i \tag{2.6}$$

where "Owner" indicates whether the head of household i is a homeowner or not, Immigrant_i is a dummy indicating that household i has at least one immigrant, and X_i denote various household characteristics, like the education level of the head of the household, marital status, the race of the head of the household, the size of the household, metropolitan-area fixed effects, occupation fixed effects, and time fixed effects. Thus, β identifies whether immigrants tend to rent rather than own the house in which they live relative to similar-looking natives.

The results are shown in Table 2.5, using Census and ACS data. It is apparent that immigrants are around 6 percentage points less likely to own the house in which they reside. This is true for a number of different subsamples. Column 1 uses only immigrant

Table 2.5: Immigrants' homeownership rates

VARIABLES	(1) Ownership OLS	(2) Ownership OLS	(3) Ownership OLS	(4) Ownership OLS
Immigrant	-0.0614***	-0.0624***	-0.0566***	-0.0539***
	(0.00567)	(0.00574)	(0.00648)	(0.00424)
(ln) Population in MSA x Immigrant				-0.000628
				(0.000465)
(ln) Population in MSA				0.00535
				(0.0116)
Total household income	0.175***	0.152***	0.121***	0.152***
	(0.00264)	(0.00220)	(0.00284)	(0.00219)
Observations	6,695,378	8,760,414	4,284,743	8,760,414
Sample	workers	all	income < p50	all
Controls	yes	yes	yes	yes

Notes: This table reports the regression of a homeownership dummy on an immigrant dummy and a number of observable characteristics as controls which include household income, race, occupation, metropolitan area of residence, family size, and marital status. Data from the US Census and ACS from 1980 to 2011 are used. Metropolitan-area and year fixed effects are included in all the regressions. Standard errors clustered at the metropolitan area level. One, two, and three stars denote 10, 5, and 1 percent significance levels respectively.

households where the head of the household works. Column 2 includes all households, irrespective of their labor-market status. Column 3 includes households in the bottom half of the income distribution. Column 4 investigates where there are significant differences in small relative to large cities, something that in this case does not seem to play an important role.

A second question is whether among renters immigrants consume less on local housing than similar-looking natives. Note that, again, differences in characteristics of the immigrant and native populations are going to translate into heterogeneity in housing expenditure that is not related to having a country of origin in which to consume. That is why it is important to control for personal characteristics and household income to make immigrants and natives "comparable". We use two alternative data sets to show that immigrants consume less on housing relative to "comparable", similar-looking natives.

The first piece of evidence comes from Census and ACS data, which can be used to compute "Monthly Rents" and total household income, and at the same time identify the country of birth of each individual. We can thus use the following regression equation:

$$\ln \text{Monthly Rents}_i = \alpha + \beta \text{Immigrant}_i + \gamma \ln \text{HH Income}_i + \eta_c X_i + \varepsilon_i \tag{2.7}$$

to investigate whether households with at least one immigrant consume less than natives once we control for household income. When the income measure is continuous, we could instead use as dependent variable "Monthly Rent / Income", which should lead to similar results, as we show below.

A different type of data that contain housing expenditure is the Consumer Expenditure Survey. The main drawback of these data is that they do not allow us to identify the country of birth of each individual. Instead, we need to rely on the identification of Hispanics from Mexico (which should be highly correlated with Mexican-born individuals, which, in turn, is one of the main immigrant groups). In these data, moreover, we do not have a continuous measure of household income. Instead, we have nine different income categories that we can use in our estimation. In particular, we run regressions of the following type:

$$\ln \text{Housing Exp}_i = \alpha + \beta \text{Mexican}_i + \sum_j \gamma_j \text{HH Income category } j_i + \eta_c X_i + \varepsilon_i \quad (2.8)$$

where "Housing Exp" is the reported expenditure on housing and "Mexican" identifies households of Mexican origin.

The results are reported in Panels A, B, and C in Table 2.6. In Panel A, we show that immigrants pay on average around 3 to 4 percent less in rental prices than similar-looking natives. In Column 1, we use the full sample of households where the head is working. Using this sample, we find that, once we control for personal characteristics and, very importantly, for household income, immigrant households pay monthly rents that are around 3 to 4 percent lower than native households. The estimates are similar when we use all households in the sample or households in the bottom half of the income distribution. In Column 4, we investigate whether these results vary with the size of the city. As with homeownership rates, this does not appear to be the case. Panel B reports the exact same results but using house expenditure as a share of income instead of (log) total housing expenditure as a dependent variable. Unsurprisingly, the results are in line with Panel A. Immigrant households consume around 1 to 2 percentage points less of their income on rents than similar-looking natives.

Panel C reports the results using Consumer Expenditure Survey data. These data do not identify metropolitan area, so all comparisons are within state. In Column 1, we show the regression of housing expenditure on a dummy indicating whether the household is of Mexican origin. The unconditional regression shows that it is indeed the case that households of Mexican origin consume less on housing. This, however, could simply reflect that they tend to earn less, or that their observable characteristics–like education or residential choices–are such that these types of household tend, on average, to consume less on housing. Column 2 controls for household income. This drops the estimate to a statistical zero. Column 3 shows that controlling for personal characteristics and for time and state fixed effects is important. Mexican-origin households tend

Table 2.6: Immigrants' expenditure on housing

Panel A: Census and ACS data

VARIABLES	(1) (ln) Monthly rent OLS	(2) (ln) Monthly rent OLS	(3) (ln) Monthly rent OLS	(4) (ln) Monthly rent OLS
Immigrant	-0.0379***	-0.0294**	-0.0258	-0.0235***
	(0.0125)	(0.0122)	(0.0164)	(0.00592)
(ln) Pop x Imm				-0.000434
				(0.00120)
(ln) Pop				0.0149
				(0.0364)
Total HH income	0.216***	0.271***	0.207***	0.271***
	(0.00491)	(0.00618)	(0.00496)	(0.00625)
Observations	2,060,237	2,697,707	1,939,684	2,697,707
Sample	workers	rent<income	income < p50	rent<income
Controls	yes	yes	yes	yes

Panel B: Census and ACS data, shares

VARIABLES	(1) Rent/Income OLS	(2) Rent/Income OLS	(3) Rent/Income OLS	(4) Rent/Income OLS
Immigrant	-0.0178***	-0.00856***	-0.0226***	-0.00555***
	(0.00390)	(0.00321)	(0.00687)	(0.00185)
(ln) Pop x Imm				-0.000220
				(0.000330)
(ln) Pop				0.00776
				(0.0100)
Total HH income	-0.279***	-0.218***	-0.410***	-0.218***
	(0.00181)	(0.00224)	(0.00332)	(0.00227)
Observations	2,060,237	2,697,707	1,939,684	2,697,707
Sample	workers	rent<income	income < p50	rent<income
Controls	yes	yes	yes	yes

Panel C: Consumption Expenditure Survey data

VARIABLES	(1) (ln) Housing Expenditure OLS	(2) (ln) Housing Expenditure OLS	(3) (ln) Housing Expenditure OLS	(4) (ln) Housing Expenditure OLS
Mexican	-0.222***	-0.012	-0.124***	-0.059***
	(0.009)	(0.008)	(0.010)	(0.009)
Observations	105,975	105,975	105,975	105,975
R-squared	0.006	0.184	0.218	0.278
Controls	none	income	pers. characteristics	all

Notes: Panels A and C in this table show regressions of (ln) monthly gross rents on an immigrant dummy, (ln) total household income and observable characteristics which include race, occupation, metropolitan area of residence, family size, and marital status. Panel B reports regressions of the share of income spent on monthly rents on the same controls. Year fixed effects are also included. Panel C uses household income bins fixed effects instead of a continuous measure of income. Panel B uses housing rents as a share of income as a dependent variable. The data for Panels A and B are taken from the US Census and ACS from 1980 to 2011. The data for Panel C are taken from the Consumer Expenditure Survey. Sample "all" uses all possible observations. Sample "workers" uses the observations where the head of the household is working. Sample "rent<income" restricts the sample to households whose total income is larger than the total rent (i.e. 12 times the monthly rent). Sample "income < p50" restricts the sample to workers in the bottom half of the earnings distribution (including homeowners and renters). Standard errors are clustered at the metropolitan area level in Panels A and B and at the state level in Panel C. One, two, and three stars denote 10, 5, and 1 percent significance levels respectively.

to be systematically different than native households in terms of education, residential choices, marital status, and, most importantly, family size. When in Column 4 we

Table 2.7: Immigrants' total expenditure, Consumer Expenditure Survey

VARIABLES	(1) (ln) Total Expenditure OLS	(2) (ln) Total Expenditure OLS	(3) (ln) Total Expenditure OLS	(4) (ln) Total Expenditure OLS
Mexican	-0.325***	-0.091***	-0.198***	-0.115***
	(0.027)	(0.018)	(0.017)	(0.013)
Observations	105,975	105,975	105,975	105,975
R-squared	0.015	0.285	0.220	0.342
Controls	none	income	pers. characteristics	all

Notes: This table shows regressions of (ln) total expenditure on a number of personal characteristics and an indicator for Mexican households. This first column does not control for any observables. Column 2 controls for personal characteristics and time and state fixed effects. Columns 3 and 4 include all the controls. Standard errors cluster at the state level. One, two, and three stars denote 10, 5, and 1 percent significance levels respectively.

control for both income and personal characteristics, we see that Mexican households consume less on housing than similar-looking native households, although the difference is not as large as the unconditional regression. This is our preferred estimate and aligns very well with the Census estimates. Given that we do not know the metropolitan area of residence, we cannot see whether households in larger metropolitan areas appear to consume differently in this data set or not.

Total expenditure

While it seems clear that immigrants spend less on housing than natives, it may be that they use this income on some other local goods, or rather that they save it for future consumption. To explore this, we can use the Consumption Expenditure Survey data and compare total local expenditure by Mexican households to that of all other households, following Panel C in Table 2.6.[27] More specifically, we can use the following specification:

$$\ln \text{Total Exp}_i = \alpha + \beta \text{Mexican}_i + \sum_j \gamma_j \text{HH Yearly Income category } j_i + \eta_c X_i + \varepsilon_i \quad (2.9)$$

where "Total Exp" is quarterly total expenditure at the household level, and where "Mexican" identifies Mexican households and where we also control for household income categories.

The results are reported in Table 2.7. Mimicking the results of Panel C in Table 2.6, we show that, unconditionally, Mexicans seem to consume around 27 percent less than other households. This may be because they earn less or because they have different

[27]For this section we use the variable "totexpcq" from the Consumer Expenditure Survey. This variable combines expenditures on all items.

characteristics than natives that explain consumption patterns. When controlling for both in Column 4, we see that Mexican households consume around 10 percent less than other households. This is consistent with the remittances sent to their home countries, or with them saving more for future consumption. We investigate whether future consumption in the home country is a potentially important channel in the following section.

Return migration

A final and very important reason why immigrants care about price indices in their home country is that many of them likely plan to return home at some point during their lifetime (Dustmann and Gorlach, 2016; Lessem, Forthcoming; Dustmann and Weiss, 2007; Dustmann, 2003, 1997).

To the best of our knowledge, there are no large, representative data sets directly documenting return migration patterns. This would require observations both in the destination country and in the home country over a certain period of time. While there are some data sets that make this possible, they are generally not very comprehensive.

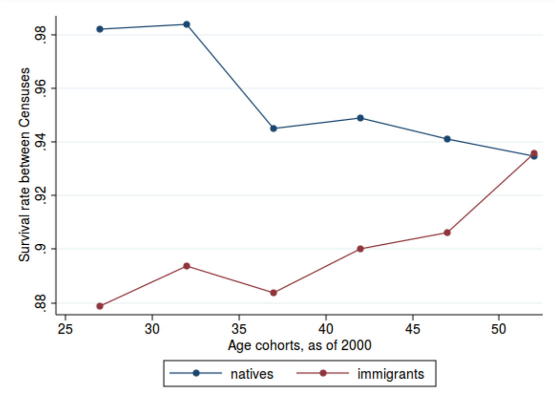
To obtain a better sense of general return migration patterns in the United States, we turn to Census data. In particular, we can track the size of cohorts of immigrants and natives across Censuses and use information on immigrants' year of arrival to see how many of them are "missing" in the following Census–and thus likely to have returned to their home countries.

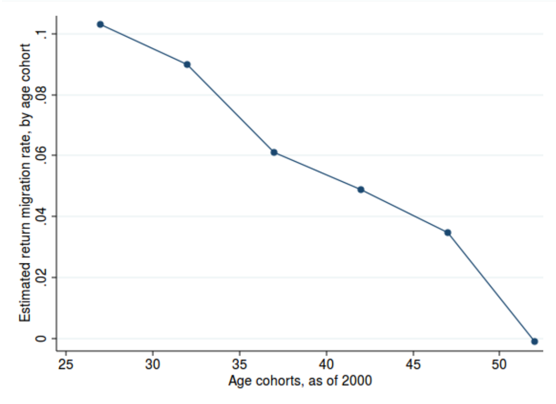
The left-hand graph in Figure 2.8 plots these survival rates by age cohort. For example, we observe that more than 98 percent of the natives aged between 25 and 30 in 2000 are still present in the 2010 ACS. This survival rate declines with age. For example, for the population that in 2000 was between 45 and 50 years old, the survival rate decreases to around 94 percent. When we carry out the same exercise for immigrants that arrived in the US before 2000, the survival rates decline substantially.[28]

In the graph on the right-hand side, we estimate return migration rates by taking the difference in survival rates between immigrants and natives. This is a good estimate if mortality rates for the same age cohort are similar in both immigrants and natives. In this graph in Figure 2.8, we observe that return migration is likely to be very high for younger cohorts and converges to 0 for older cohorts. That is, more than 10 percent of the immigrant population aged between 25 and 30 in 2000 are no longer in the United States by 2010. We begin the series at age 25, since these immigrants are already likely to be working in the US. Return migration rates are even higher for younger cohorts.

[28] We use the years 2000 and 2010 because there are strong reasons to suspect that there is some undercount of immigrants in Censuses prior to 2000. For example, the number of Mexican immigrants that claim to have arrived before 1990 in the Census 2000 is larger than the total number of Mexicans observed in the 1990 Census. See also Hanson (2006).

Figure 2.8: Return migration





Notes: This figure shows estimates of survival rates and return migration rates by age group. The graph on the left compares the size of natives and immigrants (who arrived before 2000) in Census years 2000 and ACS 2010 to estimate survival rates by age group. The graph on the right subtracts native survival rates from immigrant survival rates to obtain estimates of return migration rates by age group.

This means that for a large number of immigrants, future consumption takes place in a country other than the United States–possibly their home country. Thus, given that immigrants are likely to return and to care about future consumption, return migration patterns give additional support to the idea that immigrants partly take into account the price index in their country of origin when choosing their optimal location in the US.

2.4 Model

In this section, we introduce a quantitative model that can account for all the facts shown above and estimate it using US Census data for the years 1990, 2000, and 2010.

The two key aspects of the model are the differences in preferences between natives and immigrants and the modeling of the labor market. The only difference between natives and immigrants is that immigrants can consume in their countries of origin while natives consume only locally. We allow for some degree of substitution between consuming locally and in the country of origin, which is parametrized by a constant elasticity of substitution (CES) function. Second, labor markets are not perfectly competitive. Under perfect competition, differences in the wages of workers who are perfect substitutes in the production function would be competed away. This has been widely recognized in the discrimination literature since Becker (1957). Wage differences for similar workers can, instead, be sustained in equilibrium when there are frictions in the labor market (Black, 1995). We need this to be true in order to obtain the result that part of the value of living in a given location for the different groups of workers is reflected in wages.

It is worth emphasizing that while we take a stance on some functional forms to parametrize preferences and the labor market, the model could be made much more general. In essence, the conditions required to generate results that are in line with the evidence presented above are simply that a) immigrants have an extra normal good that they value and b) that part of the value of living in a location be observed in wages.[29]

Finally, it is also worth emphasizing that we have opted for the simplest quantitative version of the model that delivers results that are in-line with the data. Many other things that the literature has emphasized, like the role of migrant networks (see for example Munshi, 2003; Jaeger, 2007), can easily be incorporated into the model. We prefer not to incorporate them given the orthogonal role that they seem to play in the data, see Appendix 2.B.1 and the discussions in Section 2.3.

2.4.1 Location Choices

The utility function in location c for an individual i from country of origin j is given by:

$$\ln U_{ijc} = \rho + \ln A_c + \alpha_t \ln C^T_{jc} + (1-\alpha_t)\frac{\sigma}{\sigma-1}\ln\left(\frac{\alpha_l}{\alpha_l+\alpha_f}(C^{NT}_{jc})^{\frac{\sigma-1}{\sigma}} + \frac{\alpha_f}{\alpha_l+\alpha_f}(C^{NT}_{j})^{\frac{\sigma-1}{\sigma}}\right) + \varepsilon_{ijc}$$

where α_t denotes the share of consumption devoted to tradable goods, and where α_l and α_f denote the weight of consumption in local non-tradable and foreign non-tradable goods, respectively. Tradable goods are denoted by C^T and the basket of non-tradable goods is denoted by C^{NT}. Within non-tradable goods, σ is the elasticity of substitution between local and foreign non-tradables. Note that there are alternative interpretations for what C^{NT}_j really means. It could mean consumption in non-tradables in the home country, remittances sent to relatives, or future consumption in the home country. We do not explicitly model these different potential channels. We prefer to use a simpler formulation that encapsulates all of them, rather than attempting to model the specificities that each of these channels may exhibit.[30] C^{NT}_{jc} should be thought, in the context of the model, as consumption of housing and other non-tradable goods available in location c. Importantly, the various α_i govern the share of expenditure on the various types of goods. The difference between natives and immigrants is that for natives α_f is assumed to be zero, as stated more formally below. Besides this, ρ is a constant that ensures that there is no constant in the indirect utility function to be derived in what follows. ε is an extreme-value distributed idiosyncratic taste parameter for living in location c. A_c denotes local amenities.

[29]More concretely, the utility of consuming very small quantities in the home country should go to minus infinity.

[30]Moreover, it is very plausible that the importance of each of these channels differs from one type of immigrant to another. For instance, remittances may be more relevant for less skilled immigrants, while future consumption may be more relevant for more skilled immigrants. We do not attempt to address this heterogeneity in this paper.

Individuals maximize their utility subject to a standard budget constraint given by:

$$p^T C_{jc}^T + p_c C_{jc}^{NT} + p_j C_j^{NT} \leq w_{jc}.$$

We define $\alpha_t + \alpha_l + \alpha_f = 1$ and the auxiliary parameters $\bar{\alpha}_l = \frac{\alpha_l}{\alpha_l + \alpha_f}$ and $\bar{\alpha}_f = \frac{\alpha_f}{\alpha_l + \alpha_f}$. By utility maximization, we then obtain the following indirect utility of living in each location (derivation in Appendix 2.A.1):

$$\ln V_{ijc} = \ln V_{jc} + \varepsilon_{ijc} = \ln A_c + \ln w_{jc} - (1 - \alpha_t) \ln \bar{p}_{jc}(\bar{\alpha}_l, \bar{\alpha}_f) + \varepsilon_{ijc},$$

where

$$\bar{p}_{jc}(\bar{\alpha}_l, \bar{\alpha}_f) = (\bar{\alpha}_l^\sigma p_c^{1-\sigma} + \bar{\alpha}_f^\sigma p_j^{1-\sigma})^{\frac{1}{1-\sigma}}.$$

Given this indirect utility, workers decide where to live by selecting the location that delivers the highest level of indirect utility given the realization of the taste parameter. Given the distribution of ε, the outcome of this maximization gives:

$$\pi_{jc} = \frac{V_{jc}^{1/\lambda}}{\sum_k V_{jk}^{1/\lambda}} = \left(\frac{V_{jc}}{V_j}\right)^{1/\lambda}, \tag{2.1}$$

where λ is the parameter governing the variance of ε_{ijc} and $V_j = (\sum_k V_{jk}^{1/\lambda})^\lambda$. π_{jc} is the share of workers from country j that decide to live in city c as a function of indirect utilities. Note that indirect utility increases in wages and local amenities and decreases in local prices. Thus, locations with higher wages, higher amenity levels, and lower price indices will attract more people.

2.4.2 Firms' Technology

Firms' technology is given by the following linear production function for tradables:

$$Q_c^T = B_c L_c \tag{2.2}$$

where $L_c = \sum_i L_{icj}$ is the sum of all the workers that live in c and come from origin j. B_c is the technological level of the city c. If it depends on L_c, we have agglomeration externalities. In particular, we can assume that $B_c(L_c) = B_c L_c^a$ with $a \geq 0$. We will come back to this point in Section 2.5, but we ignore it in the presentation of the model to keep it simple.[31]

The marginal revenue of hiring an extra worker is given by B_c. The cost of hiring an additional worker, possibly from origin j, is the wage that they receive, which we

[31] For the model to have a solution, we need to make sure that $a < min\{\eta_c\}$, where η_c is the elasticity of housing supply that we introduce in Section 2.4.4.

denote by w_{jc}. Thus, the extra profit generated by hiring an additional worker is given by $B_c - w_{jc}$. The average cost of hiring workers across all the cities is given by $\bar{w}$. Note that we can choose to use this as the numeraire. Using this, we obtain that wages are relatively close to 1. Thus, using a Taylor expansion, we have that $(B_c - w_{jc}) \approx B_c - 1 - \ln w_{jc} = \ln \tilde{B}_c - \ln w_{jc} = S^F_{jc}$. This expression is the value of a new hire.

2.4.3 Labor Market

Labor markets are not competitive. Firms and workers meet and negotiate over the wage and split the total surplus of the match. A worker's surplus in matching with a firm is given by:

$$S^W_{jc} = \ln V_{jc}$$

Hence, we make the simplifying assumption that once located in a city, the worker's surplus no longer depends on the initial taste shock drawn and that his outside option to working is receiving an indirect utility of zero.[32] That is, a worker choosing city c will benefit from the local indirect utility.

The outcome of the negotiation between workers and firms is determined by Nash bargaining. Workers' weight in the negotiation is given by β. Thus, a share β of the total surplus generated by a match accrues to workers. Using this assumption, we can determine the wage levels of the various workers from country of origin j living in location c:

$$\ln w_{jc} = -(1-\beta) \ln A_c + \beta \ln \tilde{B}_c + (1-\beta)(1-\alpha_t) \ln \bar{p}_{jc} \qquad (2.3)$$

This equation shows standard results from the spatial economics literature. Higher wages in a city reflect either lower amenity levels, high local productivity, or high local price indices.

2.4.4 Housing Market

There are congestion forces because housing supply is inelastic. This gives the standard relationship between local prices and city size:

$$\ln p_c = \eta_c \ln L_c$$

This determines local price indices of non-tradable goods in the model. Note that we allow η_c to vary by city.

[32] The basic results of this paper are not sensitive to the exact specification of the worker surplus as long as it depends positively on local wages and amenities and negatively on local price levels.

2.4.5 Properties

Given these primitives of the model, in this subsection we derive a number of properties. These properties are the basis for the structural estimation described in Section 2.5.

The difference between natives and immigrants is the weight they give to local and foreign price indices:

Assumption 1. *Natives only care about local price indices so that $\alpha_f = 0$ and $\alpha_l = \alpha$. Immigrants care about local and foreign price indices so that $\alpha_f \neq 0$ and $\alpha_l + \alpha_f = \alpha$.*

Proposition 1. *Under the above assumption and the assumptions made on the modeling choices, there is a positive gap in wages between natives and immigrants. This gap increases in the local price index and the effect of the local price index is larger when p_j is low. The wage gap is given by the following expression:*

$$\ln w_{Nc} - \ln w_{jc} = (1-\beta)(1-\alpha_t)\ln p_c - (1-\beta)(1-\alpha_t)\ln \bar{p}_{jc} \tag{2.4}$$

Proof. Appendix 2.A.2 □

It is worth noting that in the model, differences in the price index of origin do not play a direct role in the special case of $\sigma = 1$ as then we have a Cobb-Douglas utility function that combines the consumption of local and foreign non-tradable goods. The result of this maximization problem is that the demand for each good is a constant portion of total income. If instead we assume that there is a high degree of substitutability between local and home consumption, we obtain the result that the immigrants' share of consumption in countries of origin with higher price indices is lower, hence the difference in the importance of local price indices for immigrants and natives decreases.

In Section 2.3, we also showed empirically that immigrants concentrate in higher proportions in larger, more expensive cities. This can be summarized in the following proposition:

Proposition 2. *Under assumption above, and the assumptions made on the modeling choices, immigrants concentrate in expensive cities. The spatial distribution of immigrants relative to natives is given by:*

$$\ln \frac{\pi_{jc}}{\pi_{Nc}} = \frac{1}{\lambda}\left(\beta(1-\alpha_t)\ln p_c - \beta(1-\alpha_t)\ln \bar{p}_{jc}\right) + \ln \frac{\sum_k \left(A_k \tilde{B}_k / L_k^{\eta_k(1-\alpha_t)}\right)^{\frac{\beta}{\lambda}}}{\sum_k \left(A_k \tilde{B}_k / \bar{p}_{jk}^{(1-\alpha_t)}\right)^{\frac{\beta}{\lambda}}} \tag{2.5}$$

Proof. Appendix 2.A.2 □

These two propositions are linked directly to the facts that we report in Section 2.3. They show the concentration of immigrants and the fact that immigrants receive lower wages than natives in expensive cities. If the relationship between local prices and population is positive (which is given by the inelastic supply of housing), these two propositions also show the relationship between city sizes and immigrants' location choices and wages. We can use the allocation of workers across locations to obtain the equilibrium size of the city. In particular, the following proposition characterizes the distribution of workers across cities given the total native and immigrant populations (L_N and L_j for each country of origin j).

Proposition 3. *The equilibrium size of the city increases in local productivity and amenities according to:*

$$L_c = (A_c\tilde{B}_c)^{\frac{\beta}{\lambda}} \sum_j \frac{L_j/\bar{p}_{jc}^{(1-\alpha_t)\frac{\beta}{\lambda}}}{\sum_k (A_k\tilde{B}_k/\bar{p}_{jk}^{(1-\alpha_t)})^{\frac{\beta}{\lambda}}} + \frac{(A_c\tilde{B}_c/L_c^{\eta_c(1-\alpha_t)})^{\frac{\beta}{\lambda}}}{\sum_k (A_k\tilde{B}_k/L_k^{\eta_k(1-\alpha_t)})^{\frac{\beta}{\lambda}}} L_N \tag{2.6}$$

Proof. Appendix 2.A.2 □

Note that this proposition also means that immigrants make large cities even larger. That is, because they care less than natives about the cost of large cities (i.e., congestion), they enable big cities to become larger. Moreover, it shows that cities are large because they are either productive (B_c) or pleasant to live in (A_c). Thus, conditional on amenity levels, immigration concentrates the population in more productive cities.
To see the aggregate effect of immigration on total output via their location choices, we can obtain an expression of total output per capita depending on the immigrant shares.

Proposition 4. *All else equal, the aggregate output per capita increases with the share of immigrants in the economy. Aggregate output per capita is given by the expression:*

$$q = \sum_c \left[(A_c\tilde{B}_c^{\frac{\beta+\lambda}{\beta}})^{\frac{\beta}{\lambda}} \sum_j \frac{\frac{L_j}{L}/\bar{p}_{jc}^{(1-\alpha_t)\frac{\beta}{\lambda}}}{\sum_k (A_k\tilde{B}_k/\bar{p}_{jk}^{(1-\alpha_t)})^{\frac{\beta}{\lambda}}} \right] + \frac{\sum_c (A_c\tilde{B}_c^{\frac{\beta+\lambda}{\beta}}/L_c^{\eta_c(1-\alpha_t)})^{\frac{\beta}{\lambda}}}{\sum_k (A_k\tilde{B}_k/L_k^{\eta_c(1-\alpha_t)})^{\frac{\beta}{\lambda}}} \frac{L_N}{L} \tag{2.7}$$

Proof. Appendix 2.A.2 □

What this proposition really means is that, holding total population constant, if there are more immigrants, total output is higher.

2.5 Model Estimation, Predictions and Welfare

In this section, we estimate the model presented in Section 2.4. For each country of origin, there are two key equations that the model generates, from which we can obtain the three key structural parameters (which we assume to be common across immigrants of different countries of origin).[33] The first key parameter is the weight of home-country goods in consumption ($\bar{\alpha}_f$), the second is the elasticity of substitution between home-country goods and local goods (σ), and the third is the sensitivity of migrant location choices to local conditions (λ).[34] We calibrate the rest of parameters using previous literature.

2.5.1 Model Estimation

To obtain the first two key parameters, we use the relationship between wage gaps and city prices across countries of origin. We estimate the model combining 1990, 2000 and 2010 Census and ACS data and World Bank price-level data. For this estimation we use the exact same data that we used for documenting immigrant heterogeneity in Section 2.3.1, see column (2) of Table 2.2.[35]

First, we use the relationship between wage gaps and local price indices that the model generates at the country of origin-metropolitan area level given by Equation 2.4 to estimate $\{\bar{\alpha}_f, \sigma\}$. More specifically, from this equation we obtain that:

$$\frac{\partial \ln \frac{w_{N,c}}{w_{j,c}}}{\partial \ln p_c} = (1-\beta)(1-\alpha_t)(1+\Omega_l)$$

And

$$\frac{\partial \ln \frac{w_{N,c}}{w_{j,c}}}{\partial \ln p_c \partial \ln p_j} = (1-\beta)(1-\alpha_t)\Omega_l(1-\Omega_l)$$

where $\Omega_l = \frac{\bar{\alpha}_l^\sigma p_c^{1-\sigma}}{\bar{\alpha}_l^\sigma p_c^{1-\sigma} + \bar{\alpha}_f^\sigma p_j^{1-\sigma}}$ is the share of consumption on local goods and is a function that depends on the two parameters of interest $\bar{\alpha}_f$ and σ and on the relative price index of foreign to local goods. We evaluate this equation at the average city and country of origin. In particular, we use the fact that on average home country price indices are 84 percent of the price index in the average US city.

[33] We could obviously allow for some heterogeneity across countries of origin that is not related to economic incentives but rather to some idiosyncratic preferences. This would likely explain the data better, but would obscure the explanatory power of our model.

[34] An alternative strategy would have been to use the suggestive evidence of how much the home country matters for immigrants shown in Section 2.3.2 and estimate the model using this information in conjunction with the labor-market data. We prefer the alternative of estimating the model using exclusively labor-market data as we believe that it better highlights the economic importance of the mechanism that we study in this paper.

[35] Using column (4) in that Table would result in similar estimates. We use column (2) because we use the model to explain cross-sectional moments.

From column (2) of Table 2.2 we obtain that:[36]

$$(1-\beta)(1-\alpha_t)(1+\Omega_l) = 0.487$$

$$(1-\beta)(1-\alpha_t)\Omega_l(1-\Omega_l) = 0.0491$$

This is a (non-linear) system of two equations and four unknowns: $\{\bar{\alpha}_f, \sigma, \beta, \alpha_t\}$. We can reduce the dimensionality of the parameter space by assuming that $\beta = .3$ and $1 - \alpha_t = .65$. This means that we assume that the weight of workers when bargaining for wages is 30 percent, and that the share of consumption that goes to non-tradables is 65 percent. There are a number of estimates in the literature on the workers' bargaining weight. Recent work, however, suggests that an estimate of 30 percent is reasonable. For example, Lise et al. (2016) obtain an estimate of 30 percent for college graduates, and of around 20 percent for high school graduates or less. In our context, low estimates help us explain the data better, so using a workers' bargaining weight of 30 percent is a conservative strategy within our framework. Note that, an estimate of 30 percent means that firms can extract quite some value from worker's location decisions.[37] This means, in the context of our model, that wages reflect to a large extend the value of living in each location. Estimates of the weight of tradable goods in overall consumption are somewhat elusive in the literature. An estimate of 35 percent of consumption spent on tradables is in-line with the relative size of tradable and non-tradable sectors estimated in Mian et al. (2013).

Once we have assumed specific values for α_t and β we are left with a system of two equations and two unknowns. We solve this system (numerically) and obtain the values for $\bar{\alpha}_f = 0.16$ and $\sigma = 1.29$. This parameter estimates have clear economic meaning. The fact that $\bar{\alpha}_f$ is around 16 percent means that the distribution of immigrants across locations and their wages is consistent with the fact that, on average, immigrants consume around 16 percent of non-tradables in their country of origin. This represents around 10 percent of their total consumption (α_f in the utility function defined above), since 65 percent of income is spent, on average, on non-tradables. This number coincides with the number estimated in Table 2.7 using consumption data directly. The elasticity of substitution σ is identified from the heterogeneity across countries of origin. An elasticity larger than one means that immigrants substitute consuming locally for home country consumption. Thus, immigrants from poorer, lower price index countries consume relatively more in their country of origin than immigrants from richer

[36]In Table 2.2 we only report the interaction between local prices and prices at origin, since that is the focus of that table. The coefficient in the column on the local price index is the one indicated here. This is comparable to the coefficient reported in Figure 2.5.

[37]See also the survey article Manning (2011). In recent papers, the range of estimates moves from 5 percent to 34 percent.

Table 2.8: Model estimates

Variable	Estimate	Source
Share of consumption on tradable goods (α_t)	0.35	Mian et al. (2013)
Workers' bargaining weight (β)	0.3	Lise et al. (2016)
Share of home goods consumption (α_f)	0.10	Estimated
Sensitivity to local conditions (λ)	0.05	Estimated
Elasticity of substitution home-local goods (σ)	1.29	Estimated
Amenity levels (A_c)		Albouy (2016)
Productivity levels (B_c)		Albouy (2016)
House-price supply elasticity (η_c)		Saiz (2010)
Local agglomeration (a)	0.05	Combes and Gobillon (2014)

Notes: This table shows the estimates of the structural parameters of the model.

origins.

To obtain λ we only need to use equation 2.5 using the estimates of β, α_t, σ, and α_f. From these we can obtain the relevant price index for each country of origin, and estimate equation 2.5 with linear least squares. We obtain that $\frac{1}{\lambda}\beta(1-\alpha_t) = 4.04$ with a standard error of 0.07. From this we can back up $\lambda = 0.048 \approx 0.05$.[38]

For the productivity and amenity levels across cities, and the force of local agglomeration forces we rely on prior literature. For the productivity and amenity levels, we use Albouy (2016). In a model similar to ours, but where the role of immigrants is not taken into account, Albouy (2016) estimates productivities and amenity levels for 168 (consolidated) metropolitan areas in our sample; we too use these below.[39] For the housing-supply elasticities, we rely on Saiz (2010).[40] Finally, we use an estimate of local agglomeration forces that is consistent with the consensus in the literature (see Combes and Gobillon, 2014; Duranton and Puga, 2004).

Once we fix this set of parameters, we use the model to perform counterfactuals. Table 2.8 shows the main estimates.

2.5.2 Immigration and Economic Activity

Comparison model vs. data

Once we have all the parameters–those that we estimate ourselves and those that we borrow from the literature–we can compare the quantitative predictions of our model with the data. Using various moments of the data should serve to show that our model

[38]We use 2 digit approximations. Nothing changes if we use higher precision.

[39]An alternative would be to allow these underlying amenities to depend on migration networks. This may change the estimation of the model, and would probably make the model closer to the data as suggested by the evidence presented in Section 2.B.1. We abstract from this in the paper to highlight our mechanism.

[40]Saiz (2010) reports housing-supply elasticities at the primary metropolitan statistical area (PMSA), so we use Albouy (2016)'s crosswalk between PMSAs and consolidated metropolitan statistical areas (CMSAs).

Figure 2.9: Model and data, metropolitan area-level moments

Notes: This figure compares the data and the model. Each dot represents a city. We use the 168 consolidated metropolitan areas used in Albouy (2016). See the text for the details on the various parameters of the model. In this figure, we assume that the endogenous agglomeration forces are 5 percent (i.e., $a = 0.05$).

can quantitatively match some of the key features of metropolitan-level cross-sectional US data. We demonstrate this below.

At an aggregate level, the model estimated exclusively on labor market data delivers an estimate of the weight of the home country on overall consumption that is very similar to the direct estimates that we obtained using consumption expenditure survey data. In section 2.3.2 we showed that Mexican immigrants consume on average, 11.5 percent less on local goods than similarly looking natives. We can directly compare this estimate with the estimate $\alpha_f = \bar{\alpha}_f * (1 - \alpha_t) = 0.16 * 0.65 = 10.4\%$.

At a disaggregate, metropolitan-area, level, we can compare the predictions of the model against data. In Figure 2.9, we plot a number of variables against the underlying productivity levels in each city taken from Albouy (2016). Note that our estimation of the model is at the city-country of origin level, while the moments in Figure 2.9 are at the metropolitan area level. The underlying productivity is the primitive parameter that drives our results on both location and wage gaps. In general, we do a better job of explaining the wage data than the population data.

The top-left graph in Figure 2.9 shows that population distribution across US cities in the model is slightly less concentrated in large cities than in the data. In both cases, there is a positive relationship, but the positive relationship between city size and productivity is weaker in the model. Another difference between the model and the data is that there is more dispersion in the data than in the model. This is not surprising since the only source of dispersion in the model is the differences in amenities between locations of similar productivity, while in the data the sources of heterogeneity may come from other channels. Meanwhile, the model does a good job of obtaining the relationship between wages and productivity. This is shown in the top-right graph in Figure 2.9. Again, the relationship is similar even though there is more dispersion in the data than in the model. The model also explains slightly better native-immigrant wage gaps (aggregated at the city level), than immigrant shares. That is, the model, which is estimated at the country of origin-metropolitan area level, delivers a positive relationship between immigrant shares and productivity at the city level that mimics the relationship in the data. As before, though, the model delivers a somewhat weaker relationship than the data. It is interesting to see that there are some important outliers in terms of immigrant shares. These smaller metropolitan areas with a high share of immigrants are always close to the Mexican border. This is something that the model cannot match as we have already discussed in Section 2.2. Similarly, the model is capable of generating a negative relationship between native-immigrant wage gaps at the city level that is similar to the one observed in the data, and that is at the root of the main findings of this paper.

Overall, it seems that our estimated model is quantitatively similar to the data, and can thus be used to perform some counterfactual experiments that should help to shed light on the importance of immigrants in a number of outcomes.

The distribution of economic activity and general equilibrium

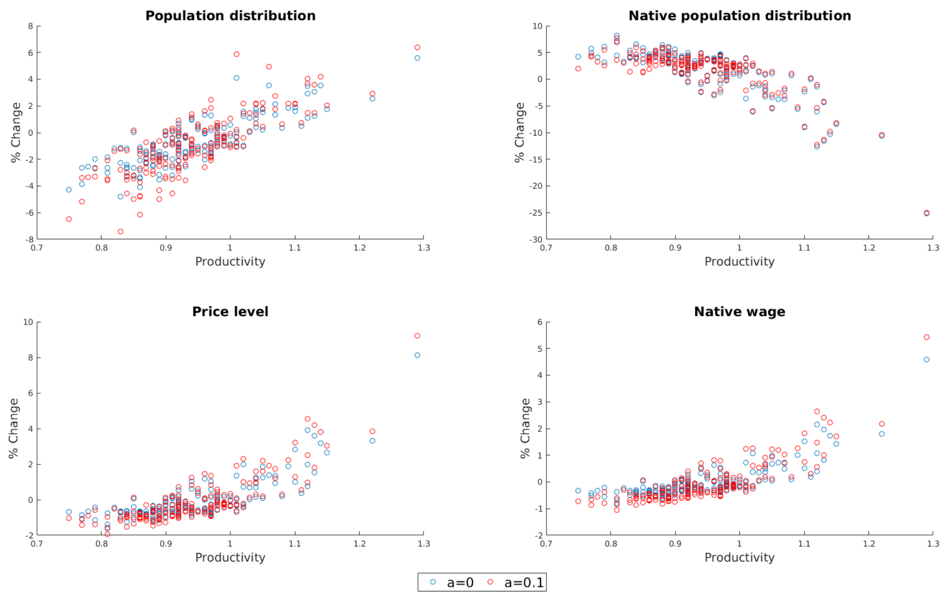
The main counterfactual exercise that we undertake is to examine what happens if, keeping total population constant, we increase the share of immigrants (holding constant the distribution of countries of origin). This uses Equation 2.5, previously introduced. That is, in this equation, we first compute the distribution of population across metropolitan areas assuming that there are no immigrants, and we then carry out the same exercise with current immigration levels of around 15 percent. We perform this exercise both with and without agglomeration forces (i.e., with $a = 0$ and $a > 0$ in equation 2.2).

In Figure 2.10, we plot the change in a number of outcome variables between the predictions of the model with and without immigrants. Effectively, this measures the role of migration on the economy through their residential choices.

It is apparent from Figure 2.10 that migration makes more productive cities larger. This is the basis of the output gains that come from the differential location choices of immigrants relative to natives. The graph shows how the most productive metropolitan areas in the United States are as much as between 4 and 8 percent larger as a result of current immigration levels than they would have been if immigrants had decided on residential locations in the way natives do. These gains are slightly larger in the presence of positive agglomeration forces.

As a result of migrants' strong preference for more productive cities and the pressure

Figure 2.10: Effect of immigrants



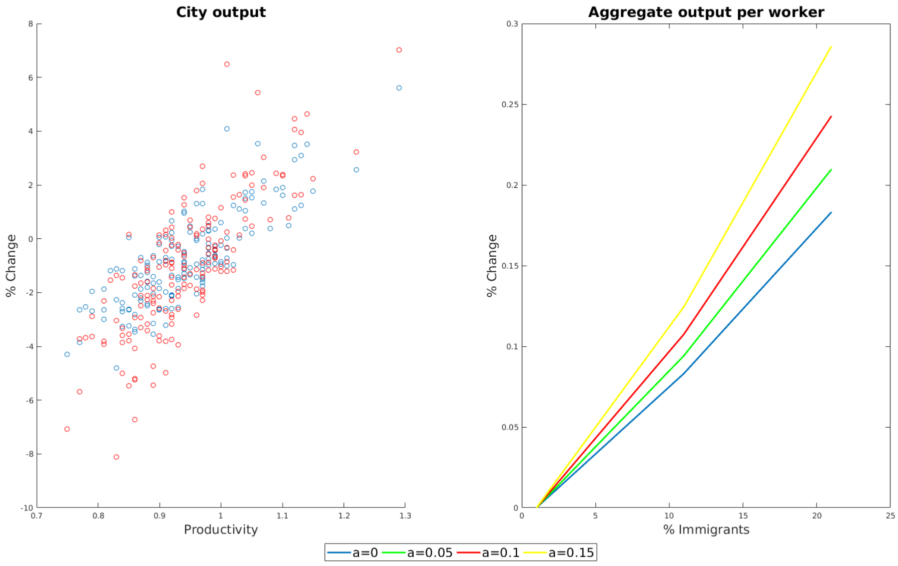
Notes: This figure compares the model with and without agglomeration forces. Each dot represents a city. We use the 168 consolidated metropolitan areas used in Albouy (2016). See the text for details of the various parameters of the model.

that this decision puts on local price indices, which can be seen in the bottom-left graph in Figure 2.10, natives are displaced from more productive cities into less productive ones, as can be seen in the top-right graph in Figure 2.10. In fact, current levels of migration can potentially account for a significant part of the increase in local price indices in more productive cities.

The bottom-right graph in Figure 2.10 shows what happens to natives' wages, which move in the same direction as the city price levels. With agglomeration forces, both positive and negative changes are more pronounced than the price-level changes because we see additional effects of population on wages through productivity. It is remarkable to note that immigrant location choices also help to explain the divergence in nominal incomes between metropolitan areas, in line with the evidence reported in Moretti (2013). In the context of the model, however, real-wage inequality between small and large locations does not increase as a result of immigration, as we explain in the following section.

In Figure 2.11, we investigate the effect of immigration on output. Two things stand out. First, immigration moves economic activity from low-productivity locations to high-productivity ones. These gains are even greater in the presence of agglomeration forces. These output gains in more productive cities are in the order of 4 to 8 percent. Second, immigration induces overall output gains. The gain in size of the most productive cities translates into output gains for the entire country, even if low-productivity places lose out.

Figure 2.11: Effect of immigrants on the distribution of output and on total output



Notes: This figure compares the model with and without agglomeration forces. Each dot in the graph on the left represents a city. We use the 168 consolidated metropolitan areas used in Albouy (2016). See the text for details of the various parameters of the model. The graph on the right shows the relationship between total output and aggregate immigrant share predicted by the model.

The magnitude of these overall gains depends crucially on agglomeration forces. We show this in the right-hand graph in Figure 2.11. Immigration shares, at around 20 percent, translate into total output gains per capita in the range of 0.2 to 0.3 percent. It is also interesting to note that the increase in aggregate output resulting from immigrant location choices is convex in the share of migrants. Thus, immigration results in overall gains and, perhaps more prominently, important distributional consequences, particularly between more and less productive locations.

Discussion of welfare consequences

While it is easy to talk about wages, local price indices, and the distribution of economic activity and populations across locations using the model, it is slightly more difficult to use the model to obtain clear results on the effect that migration has on welfare. These difficulties stem from the fact that there are essentially three different types of agent in the model and the consequences of immigration are heterogeneous among them.

The first type of agent in the model, which has been the focus for most of the paper, is workers. While native workers in larger, more productive cities benefit from immigration in terms of wages, they lose out in terms of welfare. This is a consequence of the fact that we are using a spatial equilibrium model and we need to have congestion forces dominate agglomeration forces. Higher levels of immigration result in higher nominal wages in more productive cities than in less productive ones, but the increase in local price indices is larger than the change in nominal wages. This ensures that a unique spatial equilibrium exists with both high and low levels of immigration, but it also implies that native workers in more productive cities lose out relative to native workers in less productive cities with higher levels of immigration.

However, this is not the case for firm owners and landowners. While we have not modeled these explicitly, it is quite clear that firms and landowners in more productive cities benefit more than those in less productive cities. This is because firms in the model do not pay land rents (something we could include) and because immigrants put pressure on housing costs.

Thus, whether immigration increases welfare in high- relative to low-productivity areas depends crucially on our assumptions about who owns the land and who owns the firms. Given that these are simply assumptions, we prefer not to make overall welfare calculations.[41]

2.6 Conclusion

This paper begins by documenting that immigrants concentrate in larger, more expensive cities and that their earnings relative to natives are lower there. These are very strong patterns in the US data. We obtain these results using a number of specifications, time periods, and data sets. They are also robust to controlling for immigration networks and only attenuate for immigrants whose countries of origin display similar levels of development as the United States or who have spent more time in the United States.

Taking all this evidence together, we posit that these patterns emerge because a share of immigrants' consumption is affected not by local price indices but rather by prices in their country of origin. That is, given that immigrants send remittances home and are more likely to spend time and consume in their countries of origin, they have a greater incentive to live in high-nominal-income locations than natives.

We build a quantitative spatial equilibrium model with frictions in the labor market to quantify the importance of this mechanism. We estimate the model and show that the differential location choices of immigrants relative to natives have two consequences. First, they move economic activity from low-productivity places to high-productivity places. Second, this shift in the patterns of production induces overall output gains. Relying on country of origin heterogeneity, we estimate these gains to be in the order of 0.3 percent of output per capita with current levels of immigration.

This paper extends some of the insights in the seminal contribution of Borjas (2001). Borjas' main argument is that immigrants choose the locations where demand for labor

[41] One possibility is to assign output to workers and firms according to aggregate, nation-wide, labor and capital shares. See Hsieh and Moretti (2017).

is higher, thus helping to dissipate arbitrage opportunities across local labor markets. We show in this paper that immigrants systematically choose not just locations with higher demand for labor but specifically more productive locations, and we quantify how much these choices contribute to overall production in the United States.

Appendices

2.A Proofs

2.A.1 Derivation of indirect utility

Consider the following utility in location c for an individual i from country of origin j:

$$U_{ijc} = \rho + \ln A_c + \alpha_t \ln C^T_{jc} + (1-\alpha_t)\frac{\sigma}{\sigma-1}\ln\left(\frac{\alpha_l}{\alpha_l+\alpha_f}(C^{NT}_{jc})^{\frac{\sigma-1}{\sigma}} + \frac{\alpha_f}{\alpha_l+\alpha_f}(C^{NT}_{j})^{\frac{\sigma-1}{\sigma}}\right) + \varepsilon_{ijc}$$
s.t. $C^T_{jc} + p_c C^{NT}_{jc} + p_j C^{NT}_j \leq w_{jc}$

Let

$$\begin{aligned}\bar{\alpha}_l =& \frac{\alpha_l}{\alpha_l+\alpha_f}\\ \bar{\alpha}_f =& \frac{\alpha_f}{\alpha_l+\alpha_f}\end{aligned}$$

We also take note of the following relationships:

$$\begin{aligned}\bar{\alpha}_l + \bar{\alpha}_f &= 1\\ \alpha_t + \alpha_l + \alpha_f &= 1\end{aligned}$$

Then, the utility in location c for an individual i from country of origin j can be written as:

$$U_{ijc} = \rho + \ln A_c + \alpha_t \ln C^T_{jc} + (1-\alpha_t)\frac{\sigma}{\sigma-1}\ln\left(\bar{\alpha}_l(C^{NT}_{jc})^{\frac{\sigma-1}{\sigma}} + \bar{\alpha}_f(C^{NT}_{j})^{\frac{\sigma-1}{\sigma}}\right) + \varepsilon_{ijc}$$
s.t. $C^T_{jc} + p_c C^{NT}_{jc} + p_j C^{NT}_j \leq w_{jc}$

Note that

$$\begin{aligned}&\lim_{\sigma\to 1}(1-\alpha_t)\frac{\sigma}{\sigma-1}\ln\left(\bar{\alpha}_l(C^{NT}_{jc})^{\frac{\sigma-1}{\sigma}} + \bar{\alpha}_f(C^{NT}_{j})^{\frac{\sigma-1}{\sigma}}\right) = \left[\frac{0}{0}\right]\\ =&(1-\alpha_t)\lim_{\sigma\to 1}\frac{\frac{\bar{\alpha}_l(C^{NT}_{jc})^{\frac{\sigma-1}{\sigma}}\ln C^{NT}_{jc}\frac{1}{\sigma^2} + \bar{\alpha}_f(C^{NT}_{j})^{\frac{\sigma-1}{\sigma}}\ln C^{NT}_{j}\frac{1}{\sigma^2}}{\bar{\alpha}_l(C^{NT}_{j})^{\frac{\sigma-1}{\sigma}} + \bar{\alpha}_f(C^{NT}_{j})^{\frac{\sigma-1}{\sigma}}}}{\frac{1}{\sigma^2}} \text{ by l'Hopital}\end{aligned}$$

$$
\begin{aligned}
=&(1-\alpha_t)\lim_{\sigma\to 1}\frac{\bar{\alpha}_l(C_{jc}^{NT})^{\frac{\sigma-1}{\sigma}}\ln C_{jc}^{NT}+\bar{\alpha}_f(C_j^{NT})^{\frac{\sigma-1}{\sigma}}\ln C_j^{NT}}{\bar{\alpha}_l(C_j^{NT})^{\frac{\sigma-1}{\sigma}}+\bar{\alpha}_f(C_j^{NT})^{\frac{\sigma-1}{\sigma}}}\\
=&(1-\alpha_t)\left(\bar{\alpha}_l\ln C_{jc}^{NT}+\bar{\alpha}_f\ln C_j^{NT}\right)\\
=&\alpha_l\ln C_{jc}^{NT}+\alpha_f\ln C_j^{NT}
\end{aligned}
$$

Thus,

$$
\lim_{\sigma\to 1}U_{ijc}=\rho+\ln A_c+\alpha_t\ln C_{jc}^T+\alpha_l\ln C_{jc}^{NT}+\alpha_f\ln C_j^{NT}+\varepsilon_{ijc}
$$

which is the utility function using the Cobb-Douglas aggregation, possibly with a different ρ. We solve the problem in two stages:

- **Stage 1**: Define an auxiliary variable E and find the optimal decisions $C_{jc}^{NT*}(p_c,p_j,E)$ and $C_j^{NT*}(p_c,p_j,E)$ to the following maximization problem

$$
\begin{aligned}
&\max\ (1-\alpha_t)\frac{\sigma}{\sigma-1}\ln\left(\bar{\alpha}_l(C_{jc}^{NT})^{\frac{\sigma-1}{\sigma}}+\bar{\alpha}_f(C_j^{NT})^{\frac{\sigma-1}{\sigma}}\right)\\
&\text{s.t. } p_cC_{jc}^{NT}+p_jC_j^{NT}=E
\end{aligned}
$$

  Let

$$
\tilde{V}(p_c,p_j,E)=(1-\alpha_t)\frac{\sigma}{\sigma-1}\ln\left(\bar{\alpha}_l(C_{jc}^{NT*})^{\frac{\sigma-1}{\sigma}}+\bar{\alpha}_f(C_j^{NT*})^{\frac{\sigma-1}{\sigma}}\right)
$$

- **Stage 2**: Solve for $C_j^{T*}(p_c,p_j,w_{jc})$ and $E^*(p_c,p_j,w_{jc})$ of the maximization problem

$$
\begin{aligned}
&\max\ \rho+\ln A_c+\alpha_t\ln C_{jc}^T+\tilde{V}(p_c,p_j,E)\\
&\text{s.t. } C_{jc}^T+E\le w_{jc}
\end{aligned}
$$

Stage 1

$$
\begin{aligned}
&\max\ (1-\alpha_t)\frac{\sigma}{\sigma-1}\ln\left(\bar{\alpha}_l(C_{jc}^{NT})^{\frac{\sigma-1}{\sigma}}+\bar{\alpha}_f(C_j^{NT})^{\frac{\sigma-1}{\sigma}}\right)\\
&\text{s.t. } p_cC_{jc}^{NT}+p_jC_j^{NT}=E
\end{aligned}
$$

The associated Lagrangian is

$$
\mathcal{L}=(1-\alpha_t)\frac{\sigma}{\sigma-1}\ln\left(\bar{\alpha}_l(C_{jc}^{NT})^{\frac{\sigma-1}{\sigma}}+\bar{\alpha}_f(C_j^{NT})^{\frac{\sigma-1}{\sigma}}\right)+\lambda(E-p_cC_{jc}^{NT}-p_jC_j^{NT})
$$

First-order conditions are given by

$$\frac{\partial \mathcal{L}}{\partial C_{jc}^{NT}}: \ \frac{(1-\alpha_t)\bar{\alpha}_l (C_{jc}^{NT})^{\frac{-1}{\sigma}}}{\bar{\alpha}_l (C_{jc}^{NT})^{\frac{\sigma-1}{\sigma}} + \bar{\alpha}_f (C_j^{NT})^{\frac{\sigma-1}{\sigma}}} - p_c\lambda = 0$$
$$\frac{\partial \mathcal{L}}{\partial C_{j}^{NT}}: \ \frac{(1-\alpha_t)\bar{\alpha}_f (C_{j}^{NT})^{\frac{-1}{\sigma}}}{\bar{\alpha}_l (C_{jc}^{NT})^{\frac{\sigma-1}{\sigma}} + \bar{\alpha}_f (C_j^{NT})^{\frac{\sigma-1}{\sigma}}} - p_j\lambda = 0$$

Dividing the two first-order conditions, we obtain the following relationship

$$\frac{\bar{\alpha}_l}{\bar{\alpha}_f}\left(\frac{C_{jc}^{NT}}{C_j^{NT}}\right)^{\frac{-1}{\sigma}} = \frac{p_c}{p_j} \Rightarrow C_{jc}^{NT} = \left(\frac{\bar{\alpha}_f p_c}{\bar{\alpha}_l p_j}\right)^{-\sigma} C_j^{NT}$$

Using this relationship and the budget constraint, we find

$$C_{jc}^{NT} = \frac{\left(\frac{p_c}{\bar{\alpha}_l}\right)^{-\sigma}}{p_c\left(\frac{p_c}{\bar{\alpha}_l}\right)^{-\sigma} + p_j\left(\frac{p_j}{\bar{\alpha}_f}\right)^{-\sigma}} E$$
$$C_{j}^{NT} = \frac{\left(\frac{p_j}{\bar{\alpha}_f}\right)^{-\sigma}}{p_c\left(\frac{p_c}{\bar{\alpha}_l}\right)^{-\sigma} + p_j\left(\frac{p_j}{\bar{\alpha}_f}\right)^{-\sigma}} E$$

Thus, the maximized objective function is

$$\tilde{V} = (1-\alpha_t)\frac{\sigma}{\sigma-1}\ln\left(\bar{\alpha}_l\left(\frac{\left(\frac{p_c}{\bar{\alpha}_l}\right)^{-\sigma}}{p_c\left(\frac{p_c}{\bar{\alpha}_l}\right)^{-\sigma} + p_j\left(\frac{p_j}{\bar{\alpha}_f}\right)^{-\sigma}} E\right)^{\frac{\sigma-1}{\sigma}} + \bar{\alpha}_f\left(\frac{\left(\frac{p_j}{\bar{\alpha}_f}\right)^{-\sigma}}{p_c\left(\frac{p_c}{\bar{\alpha}_l}\right)^{-\sigma} + p_j\left(\frac{p_j}{\bar{\alpha}_f}\right)^{-\sigma}} E\right)^{\frac{\sigma-1}{\sigma}}\right.$$
$$= (1-\alpha_t)\ln E + (1-\alpha_t)\frac{1}{\sigma-1}\ln\left(p_c\left(\frac{p_c}{\bar{\alpha}_l}\right)^{-\sigma} + p_j\left(\frac{p_j}{\bar{\alpha}_f}\right)^{-\sigma}\right)$$
$$= (1-\alpha_t)\ln E - (1-\alpha_t)\ln \bar{p}(\bar{\alpha}_l, \bar{\alpha}_f)$$

where $\bar{p}_{jc}(\bar{\alpha}_l, \bar{\alpha}_f) = (\bar{\alpha}_l^{\sigma} p_c^{1-\sigma} + \bar{\alpha}_f^{\sigma} p_j^{1-\sigma})^{\frac{1}{1-\sigma}}$

Stage 2

$$\max \rho + \ln A_c + \alpha_t \ln C_{jc}^T + (1-\alpha_t)\ln E + (1-\alpha_t)\frac{1}{\sigma-1}\ln \bar{p}(\bar{\alpha}_l, \bar{\alpha}_f)$$
$$\text{s.t. } C_{jc}^T + E \leq w_{jc}$$

The associated Lagrangian is

$$\mathcal{L} = \rho + \ln A_c + \alpha_t \ln C_{jc}^T + (1-\alpha_t)\ln E - (1-\alpha_t)\ln \bar{p}(\bar{\alpha}_l, \bar{\alpha}_f) + \lambda(w_{jc} - C_{jc}^T - E)$$

The first-order conditions are

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial C_{jc}^T} &: \frac{\alpha_t}{C_{jc}^T} - \lambda = 0 \\ \frac{\partial \mathcal{L}}{\partial E} &: \frac{(1-\alpha_t)}{E} - \lambda = 0\end{aligned}$$

Using these first-order conditions and budget constraints,

$$\begin{aligned}C_{jc}^T &= \alpha_t w_{jc} \\ E &= (1-\alpha_t) w_{jc}\end{aligned}$$

Thus, the optimal choices for consumption can be written as

$$\begin{aligned}C_{jc}^T &= \alpha_t w_{jc} \\ C_{jc}^{NT} &= \frac{\left(\frac{p_c}{\bar{\alpha}_l}\right)^{-\sigma}}{p_c\left(\frac{p_c}{\bar{\alpha}_l}\right)^{-\sigma} + p_j\left(\frac{p_j}{\bar{\alpha}_f}\right)^{-\sigma}}(1-\alpha_t) w_{jc} \\ C_{j}^{NT} &= \frac{\left(\frac{p_j}{\bar{\alpha}_f}\right)^{-\sigma}}{p_c\left(\frac{p_c}{\bar{\alpha}_l}\right)^{-\sigma} + p_j\left(\frac{p_j}{\bar{\alpha}_f}\right)^{-\sigma}}(1-\alpha_t) w_{jc}\end{aligned}$$

This solution can be shown to satisfy the first-order conditions of the original problem. If we let ρ be a constant such that the indirect utility function has no constant, the indirect utility function can be written as

$$\boxed{\ln V_{ijc} = \ln V_{jc} + \varepsilon_{ijc} = \ln A_c + \ln w_{jc} - (1-\alpha_t)\ln \bar{p}_{jc}(\bar{\alpha}_l, \bar{\alpha}_f) + \varepsilon_{ijc}}$$

where $\bar{p}_{jc}(\bar{\alpha}_l, \bar{\alpha}_f) = (\bar{\alpha}_l^{\sigma} p_c^{1-\sigma} + \bar{\alpha}_f^{\sigma} p_j^{1-\sigma})^{\frac{1}{1-\sigma}}$

2.A.2 Proofs of propositions

Assumption Natives only care about local price indices so that $\alpha_f = 0$ and $\alpha_l = \alpha$. Immigrants care about local and foreign price indices so that $\alpha_f \neq 0$ and $\alpha_l + \alpha_f = \alpha$.

Proof. **Proposition 1**

- $\ln w_{jc} = -(1-\beta)\ln A_c + \beta \ln \tilde{B}_c + (1-\beta)(1-\alpha_t)\ln p_{jc}$
- $\ln w_{Nc} = -(1-\beta)\ln A_c + \beta \ln \tilde{B}_c + (1-\beta)(1-\alpha_t)\ln p_c$

Thus,

$$\ln w_{Nc} - \ln w_{jc} =(1-\beta)(1-\alpha_t)\ln p_c - (1-\beta)(1-\alpha_t)\ln p_{jc}$$

Denote $W = \ln w_{Nc} - \ln w_{jc}$. We are interested in the sign of $\frac{\partial W}{\partial p_c}$.

$$\begin{aligned}
W =&(1-\beta)(1-\alpha_t)\ln p_c - (1-\beta)(1-\alpha_t)\frac{1}{1-\sigma}\ln\left(\frac{\bar{\alpha}_l^{\sigma}}{p_c^{\sigma-1}} + \frac{\bar{\alpha}_f^{\sigma}}{p_j^{\sigma-1}}\right)\\
\frac{\partial W}{\partial p_c} =&\frac{(1-\beta)(1-\alpha_t)}{p_c} - \frac{(1-\beta)(1-\alpha_t)\bar{\alpha}_l^{\sigma}p_c^{-\sigma}}{\frac{\bar{\alpha}_l^{\sigma}}{p_c^{\sigma-1}} + \frac{\bar{\alpha}_f^{\sigma}}{p_j^{\sigma-1}}}\\
=&(1-\beta)(1-\alpha_t)\frac{\frac{\bar{\alpha}_f^{\sigma}}{p_j^{\sigma-1}}}{\frac{\bar{\alpha}_l^{\sigma}}{p_c^{\sigma-1}} + \frac{\bar{\alpha}_f^{\sigma}}{p_j^{\sigma-1}}} > 0
\end{aligned}$$

Also,

$$\begin{aligned}
\frac{\partial^2 W}{\partial p_c \partial p_j} =&(1-\beta)(1-\alpha_t)\frac{\left(\frac{\bar{\alpha}_l^{\sigma}}{p_c^{\sigma-1}} + \frac{\bar{\alpha}_f^{\sigma}}{p_j^{\sigma-1}}\right)(1-\sigma)\frac{\bar{\alpha}_f^{\sigma}}{p_j^{\sigma}} - \frac{\bar{\alpha}_f^{\sigma}}{p_j^{\sigma-1}}(1-\sigma)\frac{\bar{\alpha}_f^{\sigma}}{p_j^{\sigma}}}{\frac{\bar{\alpha}_l^{\sigma}}{p_c^{\sigma-1}} + \frac{\bar{\alpha}_f^{\sigma}}{p_j^{\sigma-1}}}\\
=&(1-\beta)(1-\alpha_t)(1-\sigma)\frac{\bar{\alpha}_f^{\sigma}}{p_j^{\sigma}}\frac{\frac{\bar{\alpha}_l^{\sigma}}{p_c^{\sigma-1}}}{\frac{\bar{\alpha}_l^{\sigma}}{p_c^{\sigma-1}} + \frac{\bar{\alpha}_f^{\sigma}}{p_j^{\sigma-1}}} < 0
\end{aligned}$$

Thus, the gap in wages between natives and immigrants is increasing in the local price index. Furthermore, the effect of the local price index on the wage gap is larger for low p_j.

□

Proof. **Proposition 2**
Recall that

$$\pi_{jc} = \frac{V_{jc}^{1/\lambda}}{\sum_k V_{jk}^{1/\lambda}} = \left(\frac{V_{jc}}{V_j}\right)^{1/\lambda}$$

Thus,

$$\ln \pi_{jc} - \ln \pi_{Nc} = \frac{1}{\lambda}(\ln V_{jc} - \ln V_{Nc}) - \frac{1}{\lambda}(\ln V_j - \ln V_N)$$

Using the definition of $\ln V_{jc}$ and the expression for the wage gap obtained above, we have

$$\begin{aligned}
\ln V_{jc} - \ln V_{Nc} =&\ln w_{jc} - \ln w_{Nc} - (1-\alpha_t)\left(\ln \bar{p}_{jc} - \ln p_c\right)\\
=&-(1-\beta)(1-\alpha_t)\ln p_c + (1-\beta)(1-\alpha_t)\ln \bar{p}_{jc} - (1-\alpha_t)\left(\ln \bar{p}_{jc} - \ln p_c\right)\\
=&\beta(1-\alpha_t)\ln p_c + \beta(1-\alpha_t)\ln \bar{p}_{jc}
\end{aligned}$$

Note that

$$
\begin{aligned}
\ln V_{jc} =& \ln A_c + \ln w_{jc} - (1-\alpha_t)\ln \bar{p}_{jc} \\
=& \ln A_c + \left(-(1-\beta)\ln A_c + \beta \ln \tilde{B}_c + (1-\beta)(1-\alpha_t)\ln \bar{p}_{jc}\right) - (1-\alpha_t)\ln \bar{p}_{jc} \\
=& \beta \ln A_c + \beta \ln \tilde{B}_c - \beta(1-\alpha_t)\ln \bar{p}_{jc}
\end{aligned}
$$

Thus,

$$
V_{jc} = A_c^{\beta} \tilde{B}_c^{\beta} \bar{p}_{jc}^{\beta(\alpha_t - 1)}
$$

Then,

$$
V_j = \left(\sum_k \left(A_k \tilde{B}_k \bar{p}_{jk}^{(\alpha_t-1)}\right)^{\frac{\beta}{\lambda}}\right)^{\lambda}
$$

$$
V_N = \left(\sum_k \left(A_k \tilde{B}_k p_k^{(\alpha_t-1)}\right)^{\frac{\beta}{\lambda}}\right)^{\lambda} = \left(\sum_k \left(\frac{A_k \tilde{B}_k}{p_c^{1-\alpha_t}}\right)^{\frac{\beta}{\lambda}}\right)^{\lambda}
$$

In equilibrium, $p_c = L_c^{\eta_c}$. Thus,

$$
\ln V_j - \ln V_N = -\lambda \ln \frac{\sum_k \left(A_k \tilde{B}_k / L_k^{\eta_k(1-\alpha_t)}\right)^{\frac{\beta}{\lambda}}}{\sum_k \left(A_k \tilde{B}_k / \bar{p}_{jk}^{(1-\alpha_t)}\right)^{\frac{\beta}{\lambda}}}
$$

Hence,

$$
\ln \frac{\pi_{jc}}{\pi_{Nc}} = \frac{1}{\lambda}\left(\beta(1-\alpha_t)\ln p_c - \beta(1-\alpha_t)\ln \bar{p}_{jc}\right) + \ln \frac{\sum_k \left(A_k \tilde{B}_k / L_k^{\eta_k(1-\alpha_t)}\right)^{\frac{\beta}{\lambda}}}{\sum_k \left(A_k \tilde{B}_k / \bar{p}_{jk}^{(1-\alpha_t)}\right)^{\frac{\beta}{\lambda}}}
$$

Denote $M = \ln \frac{\pi_{jc}}{\pi_{Nc}}$. Then,

$$
\begin{aligned}
\frac{\partial M}{\partial p_c} =& \frac{1}{\lambda}\left(\frac{\beta(1-\alpha_t)}{p_c} - \frac{\beta(1-\alpha_t)\bar{\alpha}_l^{\sigma} p_c^{-\sigma}}{\frac{\bar{\alpha}_l^{\sigma}}{p_c^{\sigma-1}} + \frac{\bar{\alpha}_f^{\sigma}}{p_j^{\sigma-1}}}\right) \\
=& \frac{\beta(1-\alpha_t)}{\lambda} \frac{\frac{\bar{\alpha}_f^{\sigma}}{p_j^{\sigma-1}}}{\frac{\bar{\alpha}_l^{\sigma}}{p_c^{\sigma-1}} + \frac{\bar{\alpha}_f^{\sigma}}{p_j^{\sigma-1}}} > 0
\end{aligned}
$$

This tells us that the distribution of immigrants relative to natives is higher in more expensive cities.

□

Proof. **Proposition 3**
Note

$$\pi_{jc} = \frac{L_{jc}}{L_j} = \left(\frac{V_{jc}}{V_j}\right)^{\frac{1}{\lambda}} = \left(\frac{A_c^\beta \tilde{B}_c^\beta / \bar{p}_{jc}^{\beta(1-\alpha_t)}}{V_j}\right)^{\frac{1}{\lambda}}$$

Then, the total immigrant population in city c is

$$L_{Ic} = \sum_j L_{jc} = \sum_j L_j \frac{L_{jc}}{L_j} = \sum_j L_j \left(\frac{A_c^\beta \tilde{B}_c^\beta / \bar{p}_{jc}^{\beta(1-\alpha_t)}}{V_j}\right)^{\frac{1}{\lambda}}$$

Substituting the expression for V_j, we get

$$L_{Ic} = (A_c \tilde{B}_c)^{\frac{\beta}{\lambda}} \sum_j \frac{L_j / \bar{p}_{jc}^{(1-\alpha_t)\frac{\beta}{\lambda}}}{\sum_k (A_k \tilde{B}_k / \bar{p}_{jk}^{(1-\alpha_t)})^{\frac{\beta}{\lambda}}}$$

For natives,

$$L_{Nc} = \frac{(A_c \tilde{B}_c)^{\frac{\beta}{\lambda}}}{\sum_k (A_k \tilde{B}_k / p_k^{(1-\alpha_t)})^{\frac{\beta}{\lambda}}} L_N / p_c^{(1-\alpha_t)\frac{\beta}{\lambda}} = \frac{(A_c \tilde{B}_c / L_c^{\eta_c \alpha})^{\frac{\beta}{\lambda}}}{\sum_k (A_k \tilde{B}_k / L_k^{\eta_k \alpha})^{\frac{\beta}{\lambda}}} L_N$$

And $L_c = L_{Ic} + L_{Nc}$. □

Proof. **Proposition 4**
Note

$$q = \sum_c \frac{B_c L_c}{L}$$

Thus,

$$q = \sum_c \left[(A_c \tilde{B}_c^{\frac{\beta+\lambda}{\beta}})^{\frac{\beta}{\lambda}} \sum_j \frac{\frac{L_j}{L} / \bar{p}_{jc}^{(1-\alpha_t)\frac{\beta}{\lambda}}}{\sum_k (A_k \tilde{B}_k / \bar{p}_{jk}^{(1-\alpha_t)})^{\frac{\beta}{\lambda}}} \right] + \frac{\sum_c (A_c \tilde{B}_c^{\frac{\beta+\lambda}{\beta}} / L_c^{\eta_c \alpha})^{\frac{\beta}{\lambda}}}{\sum_k (A_k \tilde{B}_k / L_k^{\eta_k \alpha})^{\frac{\beta}{\lambda}}} \frac{L_N}{L}$$

□

2.B Supplementary evidence

2.B.1 Robustness to alternative hypotheses

In this subsection, we investigate a number of alternative hypotheses that can either reinforce our results or potentially explain them. As we show in this section, alternative stories cannot explain the patterns in the data that we document. Moreover, we show that for groups of immigrants that are probably less attached to their home countries, these results are attenuated.

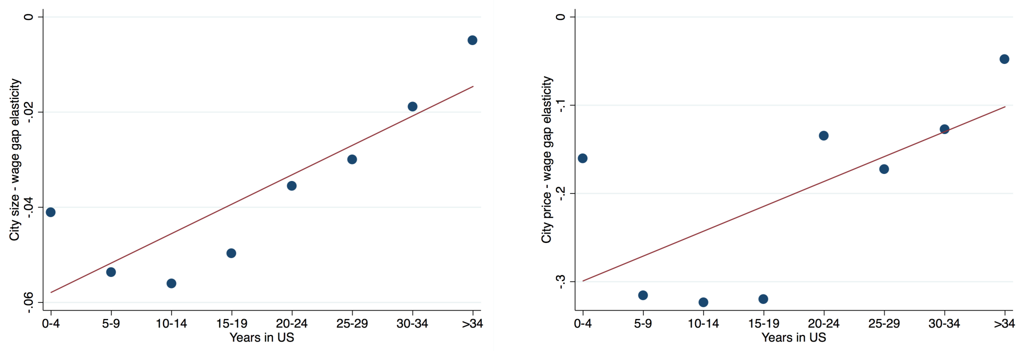
Immigration longevity in the US

According to Dustmann and Mestres (2010), immigrants that do not intend to return to their countries of origin remit a smaller share of their income. They are also less likely to spend time back home and thus are, in some way, more similar to natives. There is also a large body of literature starting with Chiswick (1978) that estimates the speed of assimilation into the receiving country. This literature has interpreted the early gap in wages between natives and immigrants as the lack of skills specific to the receiving country. While this is certainly a possibility, it does not explain why this gap is increasing in city size. However, we can use the insights from the immigrant assimilation literature to see whether the relationship between city size and city price level is stronger for newly arrived immigrants than for older ones. For this, we use the year of immigration taken from the Census data and divide immigrants into groups depending on their time spent in the US.

We plot the coefficients for different groups of immigrants by the years since arrival in Figure B.1. This shows that the elasticities are weaker for immigrants that have lived in the US for longer. The relationships between wage-gap elasticity and longevity seem to be non-linear for both city size and city price, initially becoming stronger with a peak for immigrants that have spent 10-14 years in the US and declining subsequently. A possible explanation for this is that the origin composition of immigrants varies depending on longevity, e.g. there is a disproportionately high number of recently arrived immigrants from countries with price levels similar to the US. If we repeat the estimation without immigrants from these countries, for whom we expect an elasticity of close to zero independently of longevity (see Fact 4), the relationships in Figure B.1 become more linear.[42] In particular, the estimates of the elasticity for immigrants that have spent 0-4 years in the US drop to around -0.05 in the left-hand plot and -0.3 in the right-hand plot, while the remaining estimates change little.

[42]We exclude immigrants from Europe, Canada, Australia, New Zealand, Japan, and South Korea.

Figure B.1: City size/price elasticity of wage gap by immigrant longevity



Notes: This figure uses data from the Census 2000 to show the relationships between the city size and city price elasticity of the native-immigrant wage gap depending on time spent in the US. Each dot represents an estimate of the coefficient β for the particular group based on Equation 2.3.

Immigrant networks

The results shown in the main text strongly suggest that immigrants earn less than natives in more expensive cities. In this paper, we argue that this is related to immigrants' share of consumption in their countries of origin. An alternative would be that immigrants earn less in large cities because there are large immigrant communities there. If immigrants perceive communities of their country of origin as a positive amenity, they could potentially accept lower wages in large, expensive cities because they are compensated through immigrant-network amenities. If this were the only mechanism at play, we would expect the relationship between wage gaps and city size to become stronger over time–which we do not see–but it is still worth investigating the importance of migrant networks in greater depth.

To investigate this alternative, we extend the basic regression framework introduced in Equation 2.3 to compute the estimates shown in Figures 2.5 and 2.6 to incorporate immigrant networks. Specifically, we estimate:

$$\begin{aligned}\ln w_{i,c,t} = \alpha_{1t} + \alpha_{2t} Imm_{i,c,t} + \beta_1 Imm_{i,c,t} * \ln Pop_{c,t} \\ + \gamma_1 \ln Pop_{c,t} + \beta_2 ImmigNetwork_{i,c,t} \\ + \gamma_1 ImmigNetwork_{i,c,t} * \ln Pop_{c,t} + \phi X_{i,c,t} + \delta_{ct} + \varepsilon_{i,c,t}\end{aligned} \tag{2.B.1}$$

where we measure the size of the network as $ImmigNetwork_{i,c,t} = \frac{Pop(i)_{c,t}}{Pop_{c,t}}$. That is, for each individual i, we compute the number of individuals from the same country of origin that at time t live in city c. For natives, this measure of immigrant networks takes a value of 0. Thus, β_2 measures the relative wages of immigrants and natives, given the various sizes of the network, while β_1 measures whether there is still a negative premium for immigrants in large cities, conditional on the role of migration networks.

Table B.1 shows the results. In Column 1, we only include the size of the migration network. As suggested in Borjas (2015b), migrant networks may be detrimental to

Table B.1: Wage gaps and immigrant networks

VARIABLES	(1) Wage OLS	(2) Wage OLS	(3) Wage OLS	(4) Wage OLS	(5) Wage OLS
Migrant network x (ln) Population in MSA		-0.252***			-0.0944**
		(0.0699)			(0.0384)
Migrant network in MSA	-0.976***	2.522***		-0.451***	0.865*
	(0.0802)	(0.884)		(0.0403)	(0.496)
(ln) Population in MSA	0.0306***	0.0342***	0.0423***	0.0397***	0.0399***
	(0.0117)	(0.0120)	(0.0156)	(0.0133)	(0.0132)
Immigrant			0.278***	0.356***	0.266***
			(0.102)	(0.0619)	(0.0731)
(ln) Population in MSA x Immigrant			-0.0310***	-0.0347***	-0.0283***
			(0.00770)	(0.00461)	(0.00548)
Observations	360,970	360,970	360,970	360,970	360,970
R-squared	0.413	0.414	0.417	0.418	0.418
Xs	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes
MSA FE	yes	yes	yes	yes	yes

Notes: This table shows estimates of the native-immigrant wage gap and how it changes with city size, controlling for immigration networks. Immigration networks are measured as the relative size of the immigrant population of each different country of origin with respect to the host metropolitan area. GDP origin is GDP per capita in the country of origin. These estimates use CPS data from 1994 to 2011.

immigrant wages. Our estimates suggest that a network that is 1 percent larger is associated with wages that are almost 1 percent lower. This negative relationship can be interpreted as evidence that immigrant networks are detrimental to immigrant assimilation into the labor market, or to the fact that migrant networks may be a positive amenity for immigrants, and thus, when living in larger networks, immigrants may be willing to work for a lower wage. In Column 2, we investigate whether the size of the network is more or less important in large cities. As the results show, it seems that immigrant networks are associated with lower immigrant wages, especially in larger cities.[43] In Column 3, we replicate the results already shown: immigrants' wages are lower than natives', especially in large cities. Columns 4 and 5 show that this negative premium of immigrants in large cities remains even when we control for immigration networks. In Column 4, we include in our baseline regression a control for the size of the network, while in Column 5 we also include the interaction of the size of the network and city size. In neither of these cases do these controls change our estimate of the relative wage gap between immigrants and natives, and city size.

Something that is potentially related to immigration networks and that may also help explain our results is the fact that the rate of learning may vary with city size (see the

[43]Note that the total effect of migrant networks on immigrants' wages in Column 2 is positive if the MSA population is above around 22,000. According to Column 3, immigrants have a lower wage than natives if the MSA population is above around 8,000. The population levels of all MSAs in our sample are above these thresholds at any point in time.

Table B.2: Immigrant-native wage gaps and human capital

VARIABLES	(1) Wage All	(2) Wage <HS	(3) Wage HS	(4) Wage SC	(5) Wage C
Immigrant	0.262*	0.115	0.239*	0.328***	0.186*
	(0.144)	(0.0765)	(0.128)	(0.0978)	(0.104)
(ln) Population in MSA	0.0438***	0.0371	0.0200	0.0338*	0.0644***
	(0.0167)	(0.0262)	(0.0235)	(0.0179)	(0.0180)
(ln) Population in MSA x Immigrant	-0.0337***	-0.0186***	-0.0305***	-0.0346***	-0.0201***
	(0.0110)	(0.00544)	(0.00949)	(0.00726)	(0.00745)
Observations	360,970	39,537	101,885	94,124	125,424
R-squared	0.382	0.224	0.262	0.269	0.310
Xs	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes
MSA FE	yes	yes	yes	yes	yes

Notes: These regressions report only selected coefficients. The complete set of explanatory variables is specified in Equation 2.3. Columns 2 to 5 show results by education group (high school dropout, high school graduate, some college, college). Column 1 shows the entire sample. Robust standard errors, clustered at the metropolitan area level, are reported. One star, two stars, and three stars represent statistical significance at 0.1, 0.05, and 0.01 confidence levels respectively.

important work by de la Roca and Puga, 2017). Perhaps wage gaps are greater in large cities because it takes time to learn the skills necessary to thrive there. If immigrants stayed in large cities for less time, this could generate the wage gap results that we obtain. To investigate this, we extend our baseline regression by including the (ln) years that immigrants have spent in the US and the interaction of this with city size. As shown in Column 5 in Table C.1 in Appendix 2.C.1, this does not explain our results either.

Thus, while immigrant networks seem to play a role in determining wage levels, it does not seem that they can account for the patterns in the data that we described above.

Immigrants' human capital and immigrant-native substitutability

A potential alternative story that could explain why the average immigrant-native wage gap is higher in larger cities may be that immigrants with lower levels of human capital concentrate there, at least relative to natives. To investigate this further, we separate our sample of immigrants and natives into four education groups and investigate whether within these education groups we obtain the same immigrant-native wage gaps that we have documented. Table B.2 reports these results. The interaction of city size and the immigrant dummy that identifies the elasticity of native-immigrant wage gaps and city size fluctuates from around 2 percent to around 3.5 percent for all education groups, even after controlling for other observable characteristics. Thus, the results reported so far suggest that there is a mechanism that is independent of human capital levels.

An alternative explanation of these results is that immigrants and natives are imperfect substitutes (Ottaviano and Peri, 2012; Manacorda et al., 2012). This would generate

Table B.3: Wage gaps and imperfect native-immigrant substitutability

VARIABLES	(1) Wage OLS	(2) Wage OLS	(3) Wage OLS	(4) Wage OLS	(5) Wage OLS
Share of immigrants (by edcode) x (ln) Population in MSA		-0.0763***			-0.0386***
		(0.0106)			(0.00842)
Share of immigrants (by edcode)	-0.249***	0.805***		-0.108***	0.427***
	(0.0384)	(0.137)		(0.0260)	(0.114)
(ln) Population in MSA	0.0360***	0.0500***	0.0423***	0.0416***	0.0478***
	(0.0128)	(0.0149)	(0.0156)	(0.0137)	(0.0145)
Immigrant			0.278***	0.302***	0.226**
			(0.102)	(0.0982)	(0.0913)
(ln) Population in MSA x Immigrant			-0.0310***	-0.0323***	-0.0270***
			(0.00770)	(0.00735)	(0.00685)
Observations	360,970	360,970	360,970	360,970	360,970
R-squared	0.411	0.411	0.417	0.418	0.418
Xs	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes
MSA FE	yes	yes	yes	yes	yes

Notes: This table shows estimates of the native-immigrant wage gap and how it changes with city size, controlling for immigrant supply. Immigrant supply shocks are measured as the relative size of the immigrant population in each metropolitan area and each of the four education codes previously reported. These estimates use CPS data from 1994 to 2011.

a negative relationship between native-immigrant wage gaps and the number of immigrants (relative to natives) in a location. It is not clear why immigrants, in this alternative story, systematically cluster in larger, more expensive cities, but there could be an unknown factor that accounts for this. In order to investigate whether this is what is driving our results, we use Equation 2.B.1 but substitute the "migration network" variable by the share of immigrants within each education group in each metropolitan area.[44]

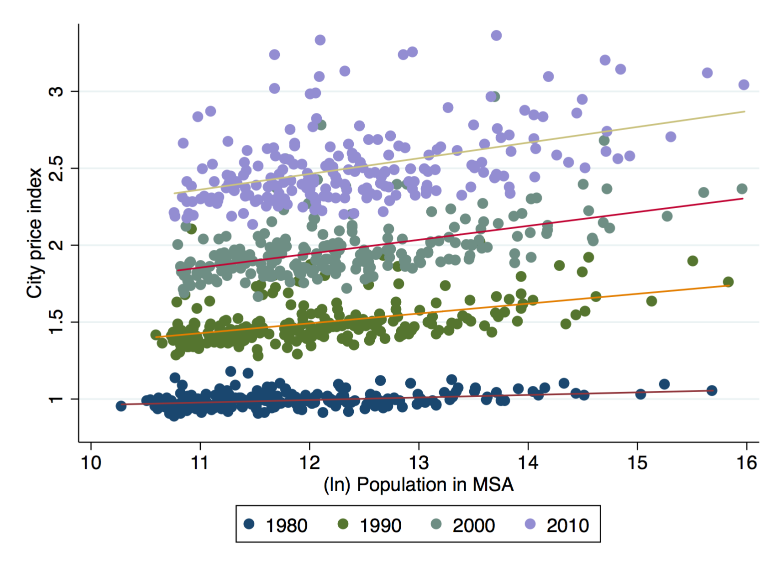
Table B.3 shows that when controlling for the relative supply of immigrants within education, we obtain the same relationship between immigrant-native wage gaps as with our baseline estimates. Column 1 in Table B.3 shows that there is a negative relationship between wage gaps and immigrant shares. This is consistent with immigrants and natives being imperfect substitutes within narrowly defined education groups. In Column 2, we show that this relationship seems to be stronger in larger cities, something that may explain our baseline results, shown in Column 3 for convenience. Columns 4 and 5 show that this is not the case. The interaction of the immigrant identifier and city size is unchanged by the inclusion of the share of immigrants in the metropolitan area within education groups, and, if anything, this regression suggests that an important part of the role that previous papers have attributed to imperfect native-immigrant substitutability may in fact be explained by immigrants' endogenous location choice.

[44] Alternatively, we can use the share of immigrants in the metropolitan area. This usually results in smaller estimates. See discussions in Card (2001), Borjas (2003), Card (2009), Borjas and Monras (2017), and Dustmann et al. (2016).

2.B.2 Price indices and city size

In this subsection, we show that city size and city price indices are strongly correlated in the data. We emphasize throughout the text that we obtain similar results when using city size or city price levels to differentiate the metropolitan areas. These two measures are indeed strongly correlated, as can be seen in Figure B.2. In fact, the relationship becomes steeper over time.

Figure B.2: City size and price index

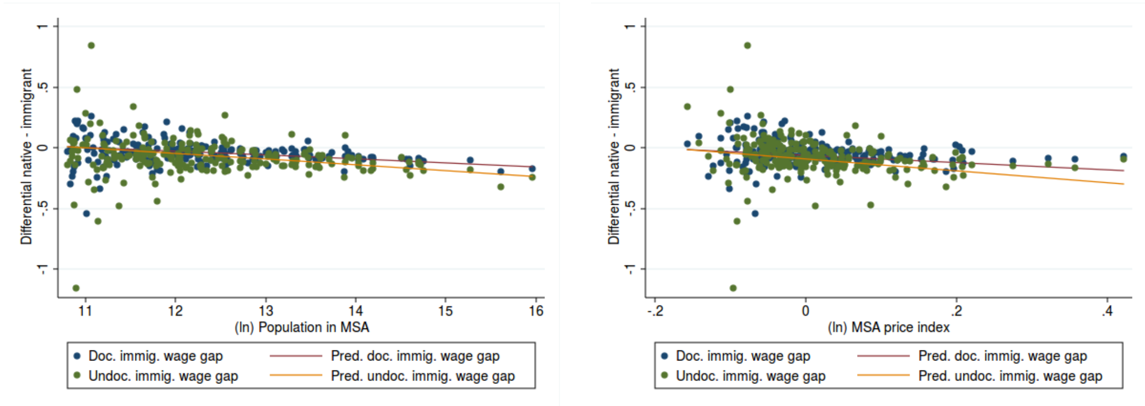


Notes: MSA populations are based on the sample of prime-age workers (25-59) from the Census 2000. The MSA price indices are computed following Moretti (2013). Each dot represents a different MSA-year combination. We have 219 different metropolitan areas in our sample.

2.B.3 Undocumented immigrants

In this subsection, we show that the wage results are not a consequence of undocumented workers. For this, we show that we obtain similar relationships between wage levels and city sizes and prices when we restrict the analysis to documented and to undocumented immigrants. We identify undocumented immigrants following Borjas (2017a). The two scatter plots of Figure B.3 show that the relationships are somewhat stronger for undocumented immigrants, which is intuitive as the expected time horizon of their stay in the US is likely to be shorter than for documented immigrants, and thus future expected consumption at origin has a higher weight relative to expected local consumption.

Figure B.3: Wage gaps, city size, and price indices (Census 2000)



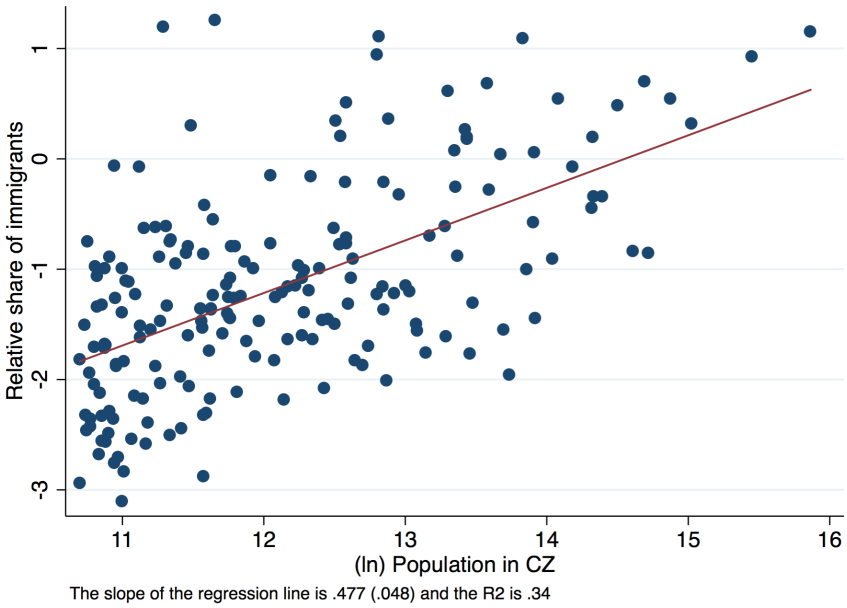
Notes: This figure uses data from the Census 2000 to show the relationship between the wage gaps of documented and undocumented immigrants to natives, city sizes, and prices. Each dot represents one of the 219 different metropolitan areas in our sample.

2.B.4 Commuting zones

This section shows that the main relationship between relative location choices and relative wages between natives and immigrants documented throughout the paper is independent of using metropolitan-area-level data or commuting zone data. While in our context it seems quite natural to think about metropolitan areas, some papers have emphasized the use of local labor markets which are typically measured by commuting zones. In our context, metropolitan areas may be a more natural unit of observation because in the monocentric city, Von-Thunen model we can think of a unique house-price index within them, something that is perhaps less natural for commuting zones (Von Thunen, 1826).

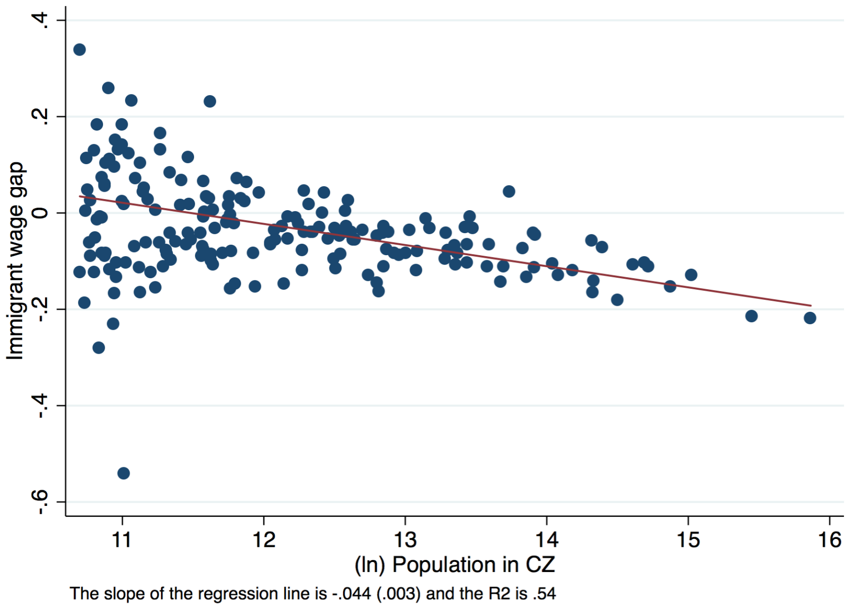
It is, however, worth checking that at least the main results reported in the paper do not depend in the geographic unit of analysis. Figures B.4 and B.5 show that immigrants concentrate in large commuting zones and their wages relative to natives are lower there. All other results that we have checked are unchanged when using commuting zones instead of metropolitan areas.

Figure B.4: Commuting zone size and immigrant distribution



Notes: The figure is based on the sample of prime-age workers (25-59) from the Census 2000. Each dot represents a different commuting zone. There are 191 different commuting zones in our sample. The red line is the fitted line of a linear regression.

Figure B.5: Commuting zone size and wage gaps



Notes: This figure uses data from the Census 2000 to show the relationship between native-immigrant wage gaps and city sizes and prices. Each dot represents the gap in earnings between immigrants and natives in a commuting zone. There are 191 different commuting zones in our sample. The red line is the fitted line of a linear regression.

2.C Regression tables

In this section, we present the regression tables mentioned in the main text.

2.C.1 Baseline wage regression

Table C.1: Baseline wage regression

VARIABLES	(1) Wage OLS	(2) Wage OLS	(3) Wage OLS	(4) Wage OLS	(5) Wage OLS
Immigrant	0.318	0.323**	0.320**	0.278***	0.344
	(0.249)	(0.144)	(0.145)	(0.102)	(0.256)
(ln) Population in MSA	0.0597***	0.0446***	0.0446***	0.0423***	0.0462***
	(0.00463)	(0.00308)	(0.00308)	(0.0156)	(0.0157)
(ln) Population in MSA x Immigrant	-0.0474**	-0.0340***	-0.0338***	-0.0310***	-0.0480**
	(0.0183)	(0.0106)	(0.0107)	(0.00770)	(0.0191)
Observations	360,970	360,970	360,970	360,970	356,143
R-squared	0.051	0.407	0.408	0.417	0.416
Xs	no	yes	yes	yes	yes + learn
Year FE	no	no	yes	yes	yes
MSA FE	no	no	no	yes	yes

Notes: Regressions are based on a CPS sample including male prime-age salaried workers (25-59). These regressions report only selected coefficients. The complete set of explanatory variables is specified in Equation 2.3. In Column 5, we include (ln) year in the US and its interaction with city size. We lose a few observations in this column because of lack of data and misrecording of the variable in CPS data. Robust standard errors, clustered at the metropolitan area level, are reported. One star, two stars, and three stars represent statistical significance at 0.1, 0.05, and 0.01 confidence levels respectively.

Chapter 3

LABOR MARKET COMPETITION AND THE ASSIMILATION OF IMMIGRANTS

with Albrecht Glitz* and Joan Llull†

3.1 Introduction

In this paper, we bring together two of the biggest strands of the migration literature by studying the interplay between the labor market impact of immigration and the wage assimilation of immigrants in a unified framework. Traditionally, assimilation studies attribute the initial gap between immigrants' and natives' wages to insufficient host country specific skills of immigrants. Over time in the host country, new skills are then acquired and existing home country specific skills are translated into productive host country specific skills through the acquisition of language proficiency and better knowledge of the institutional environment in the host country. However, as much of the labor market impact literature has shown, what matters for the relative wages of immigrants and natives is the relative supply of immigrants in the economy. If immigrants and natives are imperfect substitutes as suggested by Ottaviano and Peri (2012) in case of the US or Manacorda et al. (2012) in case of the UK, then a larger immigrant arrival cohort will lead to a larger initial wage gap relative to natives. In addition, if the initial arrival cohort is followed by another large cohort of highly substitutable immigrants, then wage growth of the initial cohort is bound to be slower than in the case where the initial inflow were to be followed by only a small subsequent arrival cohort. Relative wages between immigrants and natives and the way they evolve over time are thus driven by

*Universitat Pompeu Fabra and Barcelona GSE. E-mail: albrecht.glitz@upf.edu

†Universitat Autònoma de Barcelona, MOVE, and Barcelona GSE.
E-mail: joan.llull@movebarcelona.eu

differences in individual skill accumulation as emphasized in the assimilation literature on the one hand, and general equilibrium effects as emphasized in the impact literature on the other hand.

We model skill accumulation and general equilibrium effects jointly using a simple CES production function with imperfectly substitutable and accumulable native and immigrant labor units. In a competitive labor market equilibrium, the relative remuneration of these units depends on the relative aggregate quantities supplied in the economy. This framework allows us to assess the relative contribution of skill accumulation and equilibrium effects to observed relative wage profiles of immigrants and isolate the part of the initial wage gap and subsequent wage progression that can be purely attributed to initial endowment and accumulation of productive native skills.

We estimate the model by non-linear least squares using decennial US data of male workers from 1970 to 2010. We obtain an elasticity of substitution between native and immigrant labor units of around 13 in our preferred specification with aggregation of the total supplies at the state level. Consistent with the intuition, the elasticity is higher among low-skilled than among high-skilled workers. We simulate counterfactual assimilation profiles, for which we keep the evolution of total supplies faced by each cohort at the same level that is faced by the cohort arriving in the second half of the 1960s. The counterfactual profiles exhibit a decline in initial wages of immigrants between the 1960s and 1980s as documented in Borjas (1995). However, compared to the actual profiles, the drop is reduced by around 31% for the cohorts arriving in 1970s and 1980s and by 63% for the cohort arriving in the 1990s. While equilibrium effects still matter for the relative wage to natives ten years after arrival, the differences between the actual and counterfactual profiles fade away after 20 years. Moreover, our profiles show little evidence of a slowing down of wage assimilation for new arrival cohorts as emphasized by Borjas (2015a).

Estimating the model separately by education level suggests that equilibrium effects affect high-skilled immigrants' wages more because of the lower substitutability between their skills and natives' skills. Low-skilled immigrants' wages on the other hand rise relatively more after arrival due to skill accumulation over time.

Our framework builds on the large literature on economic assimilation starting with Chiswick (1978), who finds that immigrants outperform natives after 10-15 years in the country based on cross-sectional data. Subsequent work by Borjas (1985, 1995) shows that taking into account changing cohort quality leads to significantly flatter relative wage profiles. Duleep and Regets (1997), Duleep and Regets (2002) and Green and Worswick (2012) discuss the initial wage gap as a proxy for quality. Barth et al. (2004) study the relevance of the common time effects assumption. Lubotsky (2007) studies the role of selective out-migration for the estimation of immigrant earnings profiles. Kerr and Kerr (2011) and Borjas (2014) provide overviews over this strand of the literature.

Our paper is also related to the literature on the labor market impact of immigrants. An early work in a similar spirit is by LaLonde and Topel (1991). They assume that different immigrant arrival cohorts are imperfect substitutes and allow in their estimation for varying wage effects of these cohorts depending on how long the time between the arrival years is. Other studies employ spatial correlations (Card, 2001; Glitz, 2012; Monras, 2015c; Dustmann et al., 2017), skill cell correlations (Borjas, 2003; Mishra, 2007) or structural productions function approaches (Borjas, 2003; Ottaviano and Peri, 2012; Manacorda et al., 2012) to estimate the wage effects of immigration. Some recent work analyzes the labor market impact through the lens of equilibrium structural models (Llull, 2017b; Piyapromdee, 2017) or search and matching models (Chassamboulli and Peri, 2015; Albert, 2017).

The rest of the paper is organized as follows. Section 3.2 describes the data and presents some descriptive statistics as well as reduced form evidence for the relationship between wage assimilation and the size of immigrant inflows. Section 3.3 lays out the standard immigrant assimilation and labor market impact frameworks. Section 3.4 develops the unified framework on which we base our empirical estimation. Section 3.5 presents the results. Section 3.6 concludes.

3.2 Descriptive Facts and Reduced Form Evidence

3.2.1 Data and Descriptives

We use US Census data for the years 1970, 1980, 1990 and 2000 and pool the 2009-2011 ACS samples for the year 2010, which are all downloaded from IPUMS (Ruggles et al., 2010). Regarding variable definitions and the sample selection, which are described in detail in Appendix 3.A, we follow Borjas (1995), who keeps male wage and salary workers aged 25-64. Immigrants are grouped into the cohorts that can be identified by the varying intervals for the period of entry in all censuses. In particular, the first wave are pre-1950 arrivals, the second wave are 1950-59 arrivals and all following waves are defined by five year intervals.

Table 3.1 reports some descriptive statistics and reveals important changes in the demographic composition and earnings of immigrants compared to natives over time. Immigrants tend to be somewhat older than natives in 1970 and 1980, but younger in the later years. The share of high-skilled is higher among immigrants than among natives in the beginning of the sample, but immigrants fall behind natives in 1980. The gap further widens over time and reaches almost 20 percentage points in 2010. Relative more immigrants reside in metropolitan areas than natives and the share increases over time for both groups. While the two groups earn almost exactly the same hourly wage in 1970, similarly to the education level, immigrants fall behind over the sample period and earn

Table 3.1: Descriptive statistics by Census year

Census year	1970	1980	1990	2000	2010
Age					
Natives	42.0	40.7	39.8	41.5	43.1
Immigrants	44.3	41.0	39.6	39.6	41.2
High-skilled (%)					
Natives	26.5	39.6	51.8	58.0	62.2
Immigrants	28.4	37.1	42.1	44.1	42.4
Metro residents (%)					
Natives	65.2	70.1	70.1	58.0	75.9
Immigrants	88.7	90.8	92.6	93.1	92.9
Hourly wage (1999 USD)					
Natives	20.4	21.2	20.2	21.5	20.5
Immigrants	20.5	19.9	18.1	18.8	16.7
Population (million)					
Natives	24.95	26.20	30.50	33.31	34.06
Immigrants	0.70	2.01	3.34	5.63	8.87
Immigrants (%)	2.7	7.1	9.9	14.5	20.7

Notes: Statistics refer to a weighted sample of men aged 25-64 earning wage/salary income. High-skilled are individuals with at least some college education.

almost 19% less than natives in 2010. Finally, the most notable trend is the rise in the share of immigrants workers from less than 3% in 1970 to more than 20% in 2010.

Table 3.2 shows the previous statistics and the origin composition of immigrants by arrival cohort as observed in the first Census year after arrival.[1] While only 9% of the immigrants entering before 1970 are from Mexico, this share jumps to almost 24% ten years later, reflecting the change in US immigration policy during the 1960s, and reaches a peak of 32% for the 1990s cohort. The percentage of Asians among arrivals more than doubles between 1970 and 1980 and remains at a high level thereafter. On the other hand, the share of arrivals from Northwestern Europe and the Anglo-Saxon countries falls from 20.4% to 6.9% between 1970 and 2010. In total, more than 80% of immigrants arriving between 2005 and 2009 were either from Latin America or Asia, while they made up just above half of the arrivals 40 years earlier.

The time trends in demographic composition and earnings of immigrants seen in Table 3.1 are also reflected by the arrival cohorts. More recent cohorts are younger, have a higher percentage of high-skilled and earn less per hour. The inflows during the second half of the 1990s and 2000s correspond to 2.7% of the population in the year 2000 and 2010, respectively, while the inflow arriving during the second half of the 1960s corresponds to only 0.5% of the 1970 population.

[1] Here and in all the subsequent analysis, we consider only the cohorts that arrived during the five year interval before the survey is conducted in order to minimize distortions due to selective out-migration.

Table 3.2: Descriptive statistics by cohort in first year observed

Cohort	1965-69	1975-79	1985-89	1995-99	2005-09
Mexican (%)	9.0	23.9	24.8	32.0	29.1
Other Latin American (%)	29.0	16.6	23.8	18.0	24.6
NW European/Anglo-Saxon (%)	20.4	12.2	10.8	10.8	6.9
Asian (%)	13.9	31.3	28.8	24.1	27.5
Other (%)	27.7	16.0	11.8	15.1	11.8
Age	37.1	35.6	35.3	35.3	35.8
High-skilled (%)	35.0	39.5	42.1	46.6	46.2
Metro residents (%)	91.1	92.0	93.9	92.5	92.6
Hourly wage (1999 USD)	17.3	16.4	15.2	17.8	15.2
Size (million)	0.14	0.39	0.61	1.06	1.15
% of population	0.5	1.4	1.8	2.7	2.7

Notes: Statistics refer to a weighted sample of immigrant men aged 25-64 earning wage/salary income observed in the first Census after arrival. High-skilled are individuals with at least some college education. Anglo-Saxon countries are Canada, UK, Ireland, Australia and New Zealand.

3.2.2 Reduced Form Assimilation Patterns

As a first reduced form evidence for the effect of labor market competition on immigrants' wages, we show that there exists a negative relationship between the size of an immigrant cohort and the wage gap to natives. To obtain the wage gaps, we replicate the wage assimilation regression of Borjas (1995) using our 1970-2010 Census sample[2] and predict the native-immigrant wage difference at the time of entry for each cohort. The regression model takes the form:

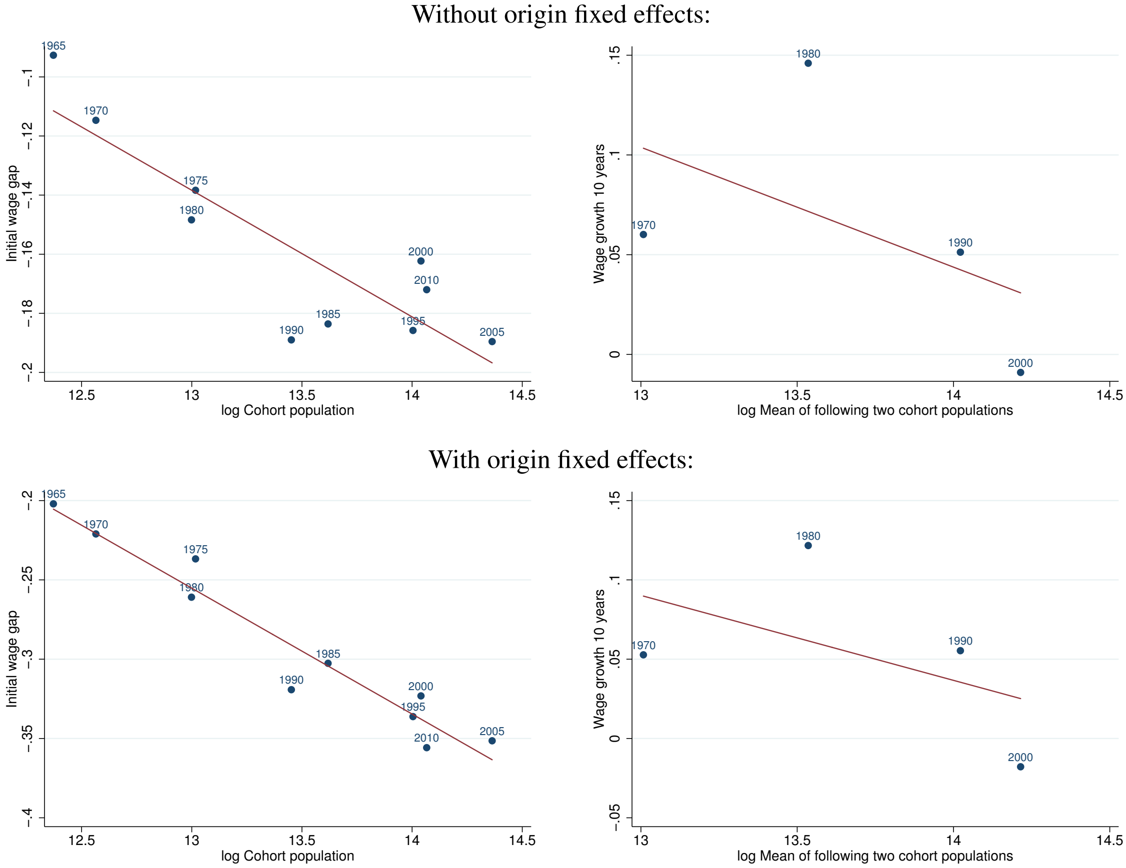
$$\log w_{ijt} = \beta_0 + \sum_k \beta_k C_k + X_{ijt}\phi_j + \delta_j AGE_{ijt} + \alpha YSM_{ijt} + \gamma_t + \varepsilon_{ijt}, \qquad (3.1)$$

where i indexes individuals, $j \in \{N, I\}$ is an index for being a native or an immigrant and t indexes time. C is a vector of dummies indicating the cohort of an immigrant, X is a vector of socioeconomic characteristics, AGE a cubic term in age, YSM a cubic term in years since migration (taking a value of zero for natives) and γ_t are year fixed effects. As also shown in Borjas (1995), the choice of the variables included in X has little effect on the cohort fixed effects β_k, which determine the native-immigrant wage differentials we are interested in. We choose Borjas' specification that includes years of education and a dummy for residence in a metropolitan area (both interacted with an immigrant and the year dummies).

The above regression model does not account for the changing origin composition of immigrant cohorts over time indicated in Table 3.2, which could provide an alternative explanation for the declining wages. We therefore also run regressions in which we add

[2]We find similar (in fact even stronger) results when restricting the sample to the same time period as Borjas, i.e. only 1970-1990.

Figure 3.1: Cohort size, wage gap and wage growth



Notes: The left graph uses Census data from 1970-1990 and plots the initial wage gap predicted by the regression model described in the text for each immigrant cohort against its population size. The right graph uses Census data from 1970-2000 and ACS data from 2010. The wage growth is calculated by taking the difference between the wage gap after 10 years in the US and the wage gap in the first year in the US. The assumed age of entry is 25.

a dummy for each origin interacted with the year dummies. We distinguish 17 origin regions (definition see Appendix 3.A). The omitted base origin country underlying the figures is Mexico.

In order to provide evidence not only for the effect of labor market competition on immigrants' initial wage gap, but also on their wage assimilation to natives over time, we next extend Borjas' regression model by allowing the effect of years in the US on the wage to vary by cohort. We then predict for each cohort the relative wage over time in the US, again for an immigrant entering at age 25. Thus, we estimate

$$\log w_{ijt} = \beta_0 + \sum_k \beta_k C_k + X_{ijt}\phi_j + \delta_j AGE_{ijt} + \sum_k \alpha_k C_k YSM_{ijt} + \gamma_t + \varepsilon_{ijt}. \quad (3.2)$$

Based on equation 3.1, the left-hand graphs of Figure 3.1 show for each cohort the predicted initial wage differential between an immigrant entering the US at age 25 and a native of the same age on the vertical axis and the log cohort population on the horizontal axis. There is a strong negative relationship between the two variables. A 10% increase in the population of an immigrant cohort decreases the wage gap relative to natives by around 0.88 percentage points. The linear fit becomes almost perfect when origin fixed effects are included in the regressions. Hence, the figure suggests that the rise in competition from similar immigrants can explain the declining entry wages of immigrants over the period 1960-1990 found in Borjas (1995). Also the further decline in entry wages in the subsequent 20 years can be related to rising competition.

Based on equation 3.2, the right-hand graphs of Figure 3.1 plot the wage growth during the first 10 years, i.e. the difference between the initial wage gap to natives and the wage gap after 10 years, against the average of the log population sizes of the following two cohorts (i.e the two cohorts entering during the 10 years after an immigrants' entry).[3] While the linear fit is not as good as for the initial wage gap, the graph also suggests a negative relationship between immigrants' wage growth and the size of subsequent immigrant waves, which is similar when including origin fixed effects.

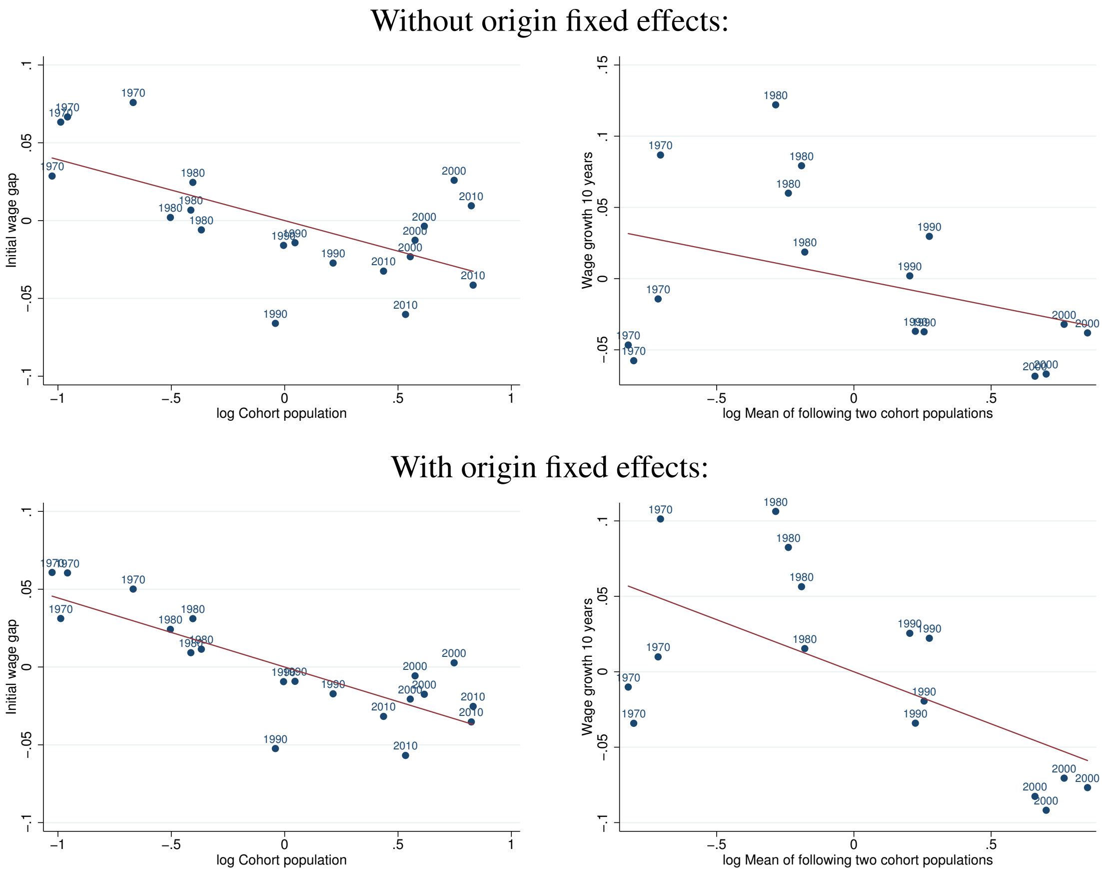
Workers from different education levels are imperfect substitutes in the majority of jobs and therefore competition might mainly come from immigrants of the same cohort *and* the same education level. We therefore allow for variation of assimilation profiles across education levels by including cohort-education-specific dummy variables. We distinguish between high school dropouts, high school graduates, some college and collage graduates. We also add a dummy indicating each education level for natives and therefore drop years of education from the controls. Indexing the education levels by e, the two models we estimate

$$\log w_{ijt} = \beta_0 + \sum_k \sum_e \beta_{ke} C_{ke} + X_{ijt}\phi_j + \delta_j AGE_{ijt} + \alpha YSM_{ijt} + \gamma_t + \varepsilon_{ijt}$$
$$\log w_{ijt} = \beta_0 + \sum_k \sum_e \beta_{ke} C_{ke} + X_{ijt}\phi_j + \delta_j AGE_{ijt} + \sum_k \sum_o \alpha_{ke} C_{ke} YSM_{ijt} + \gamma_t + \varepsilon_{ijt}.$$

Before plotting the cohort-education specific wage gap and wage growth against population, we subtract the means of each education group in order to obtain only within-education variation. Figure 3.2 shows the scatter plots. Now, there is a higher variance in the residuals compared to Figure 3.1, but still a strongly negative relationship both between the initial wage gap and cohort size and between wage growth and subsequent cohort size at the cohort-education level. The linear fit becomes somewhat better when

[3]We do not plot the 1965/1975/1985/1995 cohorts here because immigrants from these cohorts are for the first time observed five years after arrival. Thus, their assimilation profiles during the first five years are based on coefficients of time in the US that are estimated using only observations of immigrants being in the US longer than 5 years. The resulting initial wage gaps are therefore based on extrapolation and do not necessarily reflect the actual ones.

Figure 3.2: Cohort size, wage gap and wage growth, by education



Notes: The left graph uses Census data from 1970-1990 and plots the initial wage gap predicted by the regression model described in the text for each cohort-education group against its population size. The right graph uses Census data from 1970-2000. The wage growth is calculated by taking the difference between the wage gap after 10 years in the US and the wage gap in the first year in the US. The assumed age of entry is 25. Values are net of education fixed effects.

origin fixed effects are included.

Note that even with cohort-education-specific effects, which control for the trend in the educational gap between immigrants and natives, the evidence presented in this section is not yet conclusive of the effect of labor market competition on assimilation patterns. This is due to the time trend in the size of immigrant inflows, which makes it difficult to distinguish the effect of labor market competition from a potential time trend in assimilation patterns. After describing the two main empirical frameworks used in the literature to estimate the speed of assimilation and the wage impact of immigrants, we therefore propose a more structural approach in section 3.4, which combines these frameworks and allows us to identify the effect of labor market competition on wage assimilation.

3.3 Standard Empirical Frameworks

3.3.1 Assimilation Framework

The standard approach to estimate immigrant assimilation profiles proposed by Borjas (1995) is the basis for the regression model 3.1 in the previous section. For immigrants, the estimation equation is

$$\ln w_{it}^{M} = \beta_0 + \sum_{k} \beta_k C_k + X_{it}'\phi_M + \delta_M AGE_{it} + \alpha YSM_{it} + \gamma_t + \varepsilon_{it},$$

where β_k measures the wage gap upon arrival and is interpreted as a proxy for cohort quality, and $\alpha^* = (\delta_M + \alpha) - \delta_N$ measures the speed of assimilation.

For natives the equation is

$$\ln w_{it}^{N} = \beta_0 + X_{it}'\phi_N + \delta_N AGE_{it} + \gamma_t + \varepsilon_{it}.$$

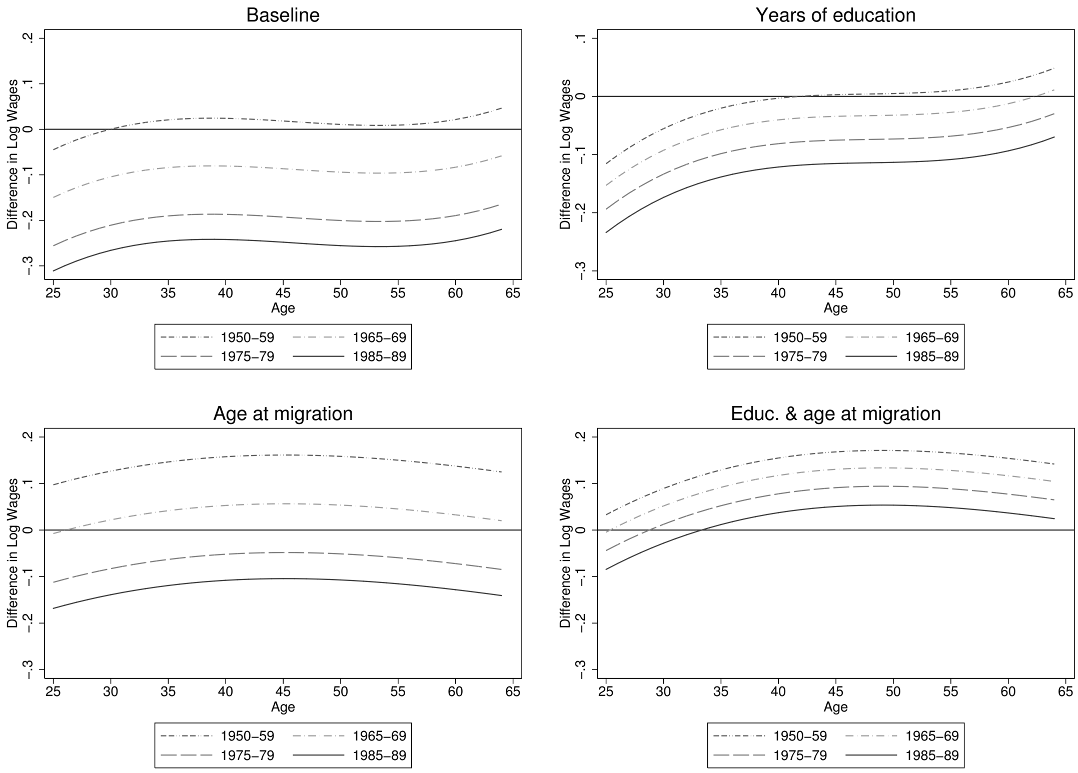
The year-fixed effects γ_t measure the impact of aggregate economic conditions, which are assumed to be the same for immigrants and natives.

In order to confirm his findings, we replicate the estimation conducted by Borjas (1995) using our 1970-1990 Census IPUMS extracts.[4] In particular, we estimate the specifications (1)-(4) of Table 5 in his paper and simulate the corresponding assimilation profiles similar to Figure 1 in Borjas (1995) based on these results. The first specification does not include any controls in the vector $X_{it}'\phi_N$, the second includes years of education and an indicator of living in a metropolitan area (both interacted with year-fixed effects), the third includes the age at migration for immigrants and the fourth includes both the controls of the second and the third specification. The estimates can be found in Table B.1 in Appendix 3.B.

Figure 3.3 shows the predicted profiles for an immigrant arriving in the US at age 25 with the average years of education in 1990 and residing in a metropolitan area. The profiles confirm the finding that the cohort-fixed effects, which measure “cohort quality", have steadily declined over time. While the upper two profiles of the figure are very precise replicates, we get around 10% higher intercepts than in the corresponding profiles of Borjas (1995) for all cohorts when age at migration is included. However, the differences in the intercepts between the cohorts, which are the only ones that matter for the point he is making, are almost identical to the ones in Borjas’ figures.

[4] The Census extracts used by Borjas (1995) contain around 900,000 observations and oversample immigrants relative to natives. Our IPUMS extracts with equal sampling of both groups contain around 3.3 million observations.

Figure 3.3: Replication of Borjas (1995)



Notes: Following Borjas (1995), the assimilation profiles are simulated for workers with the average years of education in 1990, residing in a metropolitan area and with 1990 period effects.

3.3.2 Labor Market Impact Framework

The standard equation for the estimation of the impact of immigration on wages is based on a nested-CES production function approach (Ottaviano and Peri, 2012; Manacorda et al., 2012). Output Q_t is produced using capital K_t and total labor L_t according to

$$Q_t = [\lambda_{Kt} K_t^v + \lambda_{Lt} L_t^v]^{1/v}.$$

L_t is an aggregate of labor of different skill types, whereby the skill cells are defined by education and experience and workers of different cells are imperfect substitutes to each other. If the first nest is defined by education i and the second by experience j, we get the labor aggregate as

$$L_t = \left[\sum_i \theta_{it} L_{it}^{\rho} \right]^{1/\rho} \qquad L_{it} = \left[\sum_j \alpha_{ij} L_{ijt}^{\eta} \right]^{1/\eta}.$$

where $\rho = 1 - 1/\sigma_E$ and $\eta = 1 - 1/\sigma_X$. Thus, σ_E is the elasticity of substitution across

education groups and σ_X is the elasticity of substitution across experience groups. θ_{it} and α_{ij} are time-variant technology parameters.
With nativity defining the last nest, the labor aggregate of the group with education i and experience j at time t is defined as

$$L_{ijt} = \left[\beta_{ijt}^N N_{ijt}^\delta + \beta_{ijt}^M M_{ijt}^\delta\right]^{1/\delta},$$

where $\delta = 1 - 1/\sigma_I$, with σ_I is the elasticity of substitution between native and immigrant workers. Estimates for σ_I within an education-experience cell range from 22 (Germany, D'Amuri et al., 2010) and 20 (US, Ottaviano and Peri, 2012) to 8 (UK, Manacorda et al., 2012). Equating native and immigrant wages to the appropriate marginal products of labor and denoting $S = N, M$, we get

$$\begin{aligned}
\ln w_{ijt}^S = {} & \ln \lambda_{Lt} + \frac{1}{\sigma_{KL}} \ln Q_t + \left(\frac{1}{\sigma_E} - \frac{1}{\sigma_{KL}}\right) \ln L_t + \ln \theta_{it} \\
& + \left(\frac{1}{\sigma_X} - \frac{1}{\sigma_E}\right) \ln L_{it} + \ln \alpha_{ij} \\
& + \left(\frac{1}{\sigma_I} - \frac{1}{\sigma_X}\right) \ln L_{ijt} + \ln \beta_{ijt}^S - \frac{1}{\sigma_I} \ln S_{ijt}
\end{aligned}$$

Absorbing all but the last two terms into d_{ijt} gives

$$\ln w_{ijt}^S = d_{ijt} + \ln \beta_{ijt}^S - \frac{1}{\sigma_I} \ln S_{ijt}.$$

The aggregate native-immigrant wage differential in each cell is thus given by

$$\ln\left(\frac{w_{ijt}^N}{w_{ijt}^M}\right) = \ln \beta_{ijt}^N - \ln \beta_{ijt}^M - \frac{1}{\sigma_I} \ln\left(\frac{N_{ijt}}{M_{ijt}}\right)$$

This implies that relative wages are a function of relative supplies as long as $\sigma_I < \infty$. Although the assimilation model presented in 3.3.1 aims to explain relative wages in a similar spirit as the model estimated on the skill cell level, it ignores the role of aggregate supply. Therefore, in the following section we provide a framework that allows to extend the result that relative supplies affect relative wages to individual level wage equations in the spirit of the assimilation literature.

3.4 Unified Framework

In the following, we set-up a framework, in which output is produced with a CES aggregate of immigrant and native efficiency labor units. The amount of efficiency units of each type that a worker owns depends on individual characteristics and can be accumulated over age and time in the US. The relative remuneration of these units depends on the aggregate native and immigrant skill supplies in the economy. Thus, wage differentials at any point in time reflect individual skills and the relative skill supply. As a consequence, wage assimilation profiles are affected by both skill accumulation and equilibrium effects. The latter could partially explain the documented cohort differences in initial wage gaps and in the speed of assimilation.

Let the aggregate production function be

$$Y_t = \left(\left(\sum_{i \in P_t} \alpha_{it} \right)^{\frac{\sigma-1}{\sigma}} + \left(\sum_{i \in P_t} \beta_{it} \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

where α_{it} denote immigrant efficiency units and β_{it} denote native efficiency units supplied by individual i. The accumulation of these efficiency units evolves according to the following processes

$$\begin{aligned}
\alpha_{it} &= \exp(\theta'_\alpha orig_i + \phi_\alpha YSM_{it} + \eta^M_\alpha edu_i) \\
\beta^I_{it} &= \exp(\gamma' coh_i + \theta'_\beta orig_i + \phi_\beta YSM_{it} + \delta^M AGE_{it} + \eta^M_\beta edu_i) \\
\beta^N_{it} &= \exp(c + \delta^N AGE_{it} + \eta^N edu_i).
\end{aligned}$$

Note that we assume that immigrants arrive with a given number of immigrant efficiency units α_i (which can depend on the country of origin, cohort, age etc.) and that the accumulation of native efficiency units β_{it} is allowed to differ between immigrants and natives. The marginal product of an additional efficiency unit is given by

$$\frac{\partial Y_t}{\partial \alpha} = Y_t^{\frac{1}{\sigma}} \left(\sum_{i \in P_t} \alpha_{it} \right)^{-\frac{1}{\sigma}} = \omega_{\alpha,t}$$

$$\frac{\partial Y_t}{\partial \beta} = Y_t^{\frac{1}{\sigma}} \left(\sum_{i \in P_t} \beta_{it} \right)^{-\frac{1}{\sigma}} = \omega_{\beta,t}$$

where ω^α_{it} and ω^β_{it} are equilibrium wages per immigrant and native efficiency unit. A worker's wage depends on the amount of immigrant and native efficiency units he supplies:

$$\begin{aligned}
w_{it} &= \omega_{\alpha,t}\alpha_{it} + \omega_{\beta,t}\beta_{it} \\
w_{it} &= Y_t^{\frac{1}{\sigma}} \left(\sum_{j \in P_t} \alpha_{jt} \right)^{-\frac{1}{\sigma}} \alpha_{it} + Y_t^{\frac{1}{\sigma}} \left(\sum_{j \in P_t} \beta_{jt} \right)^{-\frac{1}{\sigma}} \beta_{it}.
\end{aligned}$$

This can be written as

$$w_{it} = Y_t^{\frac{1}{\sigma}} \beta_{it} \frac{\alpha_{it}}{\beta_{it}} \left(\sum_{j \in P_t} \alpha_{jt} \right)^{-\frac{1}{\sigma}} + Y_t^{\frac{1}{\sigma}} \beta_{it} \left(\sum_{j \in P_t} \beta_{jt} \right)^{-\frac{1}{\sigma}}$$

$$w_{it} = Y_t^{\frac{1}{\sigma}} \beta_{it} \left(\left(\sum_{j \in P_t} \alpha_{jt} \right)^{-\frac{1}{\sigma}} \frac{\alpha_{it}}{\beta_{it}} + \left(\sum_{j \in P_t} \beta_{jt} \right)^{-\frac{1}{\sigma}} \right).$$

Taking logs yields

$$\begin{aligned} \ln w_{it} &= \frac{1}{\sigma} \ln Y_t + \ln \beta_{it} + \ln \left(\left(\sum_{j \in P_t} \alpha_{jt} \right)^{-\frac{1}{\sigma}} \frac{\alpha_{it}}{\beta_{it}} + \left(\sum_{j \in P_t} \beta_{jt} \right)^{-\frac{1}{\sigma}} \right) \\ &= \frac{1}{\sigma} \ln Y_t + \ln \beta_{it} - \underbrace{\frac{1}{\sigma} \ln \sum_{j \in P_t} \beta_{jt}}_{\substack{\text{native}\\ \text{aggregate}\\ \text{supply}}} + \ln \left(1 + \underbrace{\left(\frac{\sum_{j \in P_t} \alpha_{jt}}{\sum_{j \in P_t} \beta_{jt}} \right)}_{\substack{\text{relative}\\ \text{aggregate}\\ \text{supply}}}^{-\frac{1}{\sigma}} \underbrace{\left(\frac{\alpha_{it}}{\beta_{it}} \right)}_{\substack{\text{relative}\\ \text{individual}\\ \text{supply}}} \right). \end{aligned}$$

Substituting for α_{it} and β_{it}, we get for immigrant workers who have just arrived in the host country ($\beta_{it} = 0$)

$$\begin{aligned} \ln w_{it} &= \frac{1}{\sigma} \ln Y_t + \ln \alpha_{it} - \frac{1}{\sigma} \ln \left(\sum_{j \in P_t} \alpha_{jt} \right) \\ &= \frac{1}{\sigma} \ln Y_t + \theta'_\alpha orig_i + \phi_\alpha YSM_{it} + \eta_\alpha^M edu_i - \frac{1}{\sigma} \ln \left(\sum_{j \in P_t} \alpha_{jt} \right), \end{aligned}$$

for immigrant workers who have already accumulated some native efficiency units ($\alpha_{it} > 0$ and $\beta_{it} > 0$) we get

$$\begin{aligned} \ln w_{it} &= \frac{1}{\sigma} \ln Y_t + \gamma' coh_i + \theta'_\beta orig_i + \phi_\beta YSM_{it} + \delta^M AGE_{it} + \eta_\beta^M edu_i \\ &\quad + \ln \left(\left(\sum_{j \in P_t} \alpha_{jt} \right)^{-\frac{1}{\sigma}} \frac{\alpha_{it}}{\beta_{it}^I} + \left(\sum_{j \in P_t} \beta_{jt} \right)^{-\frac{1}{\sigma}} \right) \\ &= \frac{1}{\sigma} \ln Y_t + \gamma' coh_i + \theta'_\beta orig_i + \phi_\beta YSM_{it} + \delta^M AGE_{it} + \eta_\beta^M edu_i \\ &\quad - \frac{1}{\sigma} \ln \sum_{j \in P_t} \beta_{jt} + \ln \left(1 + \left(\frac{\sum_{j \in P_t} \alpha_{jt}}{\sum_{j \in P_t} \beta_{jt}} \right)^{-\frac{1}{\sigma}} \frac{\alpha_{it}}{\beta_{it}^I} \right) \end{aligned}$$

and for native workers ($\alpha_{it} = 0$) we get

$$\ln w_{it} = \frac{1}{\sigma} \ln Y_t + c + \delta^N AGE_{it} + \eta^N edu_i - \frac{1}{\sigma} \ln \left(\sum_{j \in P_t} \beta_{jt} \right).$$

Wages of immigrant and native workers thus depend both on their individual characteristics and on the aggregate native and immigrant skill supplies in the economy. Therefore, all contemporaneous, past and future inflows of immigrants and the composition of these inflows in terms of origins, education, age etc. affect entry wages and wage assimilation profiles.

Note that when ignoring the role of aggregate skill supplies, the set of equations above is precisely the set of wage equations estimated in a standard assimilation analysis following Borjas (1995). Also, with increasing accumulation of native efficiency units ($\beta_{it} \to \infty$), immigrant workers become more and more similar to native workers and their equations eventually become the same.

3.5 Results

3.5.1 Regression Results

We jointly estimate our wage equations using non-linear least squares. The term $\frac{1}{\sigma} \ln Y_t$ is absorbed by year-fixed effects in our first set of specifications, in which we aggregate the native and immigrant skill supplies at the national level. In our second set of specifications, we include year-state fixed effects and aggregate the supply terms at the state level, thus assuming that the geographic unit defining an economy is the state.

Table B.2 in the Appendix shows the results of the non-linear least squares estimation at the national level and at the state level for the full sample and separately by education group, whereby low-skilled workers are defined as having at most high school diploma and high-skilled as having at least some college education. The cohort-fixed effects, which are represented by the vector γ in equation (4), indicate how many native efficiency units β_{it}^I a cohort is endowed with at arrival compared to the omitted pre-1950 cohort, conditional on other observables. In the full sample and for high-skilled workers at both the national and the state level, immigrants arriving in later years have more native efficiency units compared to the omitted cohort. However, this does not seem to be true looking only at the low-skilled, for whom the coefficients decline over time at the national level and stay largely constant at the state level.

The elasticity of substitution σ is estimated at 7.4 at the national level and 13.8 at the state level in the full sample. In both cases the elasticity is lower for the high-skilled. This is in line with our intuition as high-skilled jobs usually involve less routine tasks and are more communication-intensive. Therefore, natives are less substitutable by immigrants due to their potentially lower language proficiency. Oddly, the elasticity is negative for the low-skilled at the national level, whereas it is positive and close to the value of the full sample at the state level.

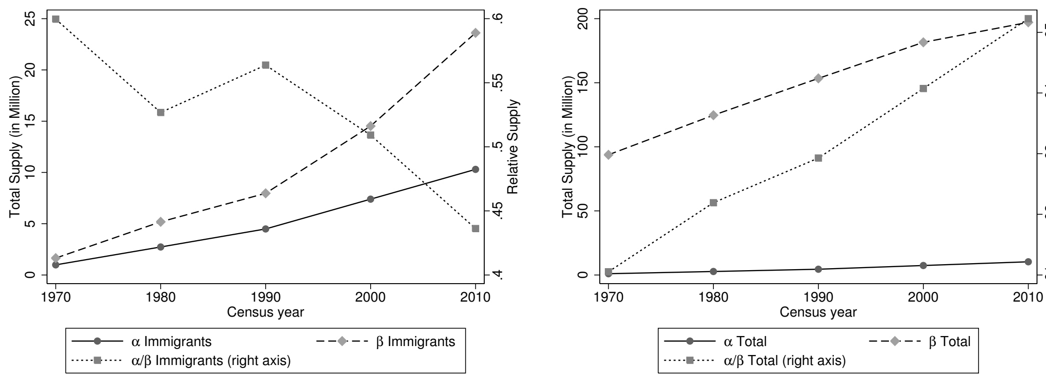
In order to investigate the cohort effects not only in terms of initial endowment, but also in terms of the speed of accumulation of native efficiency units, we finally extend our specification by allowing the cubic term of years since migration to differ across cohorts. Thus, we estimate cohort-specific vectors $\phi_{\beta,coh}$. The coefficients based on this specification at the state level are presented in Appendix Table B.3. Now, there is no clear pattern anymore in the cohort intercepts and they are insignificantly different from the base category in the full and the high-skilled sample. Likewise, there is also no clear pattern in the cohort-specific coefficients of years in the US (the quadratic and cubic terms are included in the regression but not reported in the table). Hence, at a first glance these results do not seem to confirm the finding of Borjas (1995) that the speed of assimilation of new arrival cohorts in the US has declined over time.

The estimates of the elasticity of substitution is 12.8 in the full sample and 8.7 in the high-skilled sample, values that are close to the previous estimates of 13.8 and 9 in Table B.2. However, the elasticity of substitution for the low-skilled is now 29 and therefore considerably higher than without cohort-specific effects of years since migration.

3.5.2 Aggregate Supplies of Immigrant and Native Labor

Using the estimates of the specification at the state level with cohort-specific cubic terms in years since migration, which is our preferred one, we can calculate the total supply of efficiency units of each type at every point in time by simply summing up the respective terms over all workers. In the left panel of Figure 3.4 we show the units of both types supplied by migrants and their ratio over time. While the immigrant supply of both native and immigrant units has risen strongly since 1970, the latter have seen an even stronger rise. As a result, the ratio of immigrant to native units has declined from around 0.6 to 0.44. However, when considering the total supplies by both natives and immigrants, the ratio has steadily increased between 1970-2010 as shown in the right panel. This is because, although much smaller in absolute value, the increase in total immigrant units is higher relative to its initial value in 1970 compared to the increase in native units relative to its initial value. Thus, the ratio of immigrant over native units supplied by all workers in the US has risen from around 1% in 1970 to more than 5% in 2010. Given expression (4), this change in the ratio decreases immigrants' wages relative to natives' wages, whereby the magnitude depends on the elasticity of substitution and the individual ratio of immigrant to natives units supplied. The lower is the elasticity of substitution and the higher is the ratio of individual supplies, the stronger is

Figure 3.4: Aggregate supplies of efficiency units



the wage effect of the increase in the ratio of aggregate supplies.

3.5.3 Predicted and Counterfactual Assimilation Profiles

In this section, we first use our estimates to predict the assimilation profiles of the cohorts arriving in 1965-69, 1975-79, 1985-89 and 1995-99 given the actual aggregate supplies observed. We then predict the counterfactual profiles for these cohorts keeping the time evolution of the aggregate supplies at the same level as the ones faced by the 1965-69 cohort. This means that in the first year of observation of each cohort, the aggregate supplies are as in 1970, in the following Census they are as in 1980 and so on. Thus, we are able to distinguish the true cohort effects from the equilibrium effects on initial wages and on the speed of assimilation.

Figure 3.5 plots the predicted assimilation profiles, i.e. the difference in the log wages between natives and immigrants depending on age assuming that the age at arrival is 25 years. This first figure is not conditional on education and MSA residence. Therefore, differences in the wage gaps are potentially driven by varying average education levels and MSA residence across cohorts. The left plot confirms the finding of Borjas (1995) that the cohort entry wages have declined from the 1960s to the 1980s. The fall in entry wage seems to have stopped in the 1990s as the corresponding cohort has a lower initial wage gap compared to the 1970s and 1980s cohorts. The right plot shows the counterfactual profiles under the assumption of equal aggregate supplies faced by each cohort. The differences in the initial wage gaps are now reduced by around 10 percentage points for each cohort after the 1970s. The gap is virtually zero for the 1990s cohort and around -9% and -11% for the 1970s and 1980s cohorts, respectively.

Next, we repeat the previous exercise, but condition on being low-skilled and residing in an MSA.[5] The conditional predicted assimilation profiles, which are shown in Figure

[5]Note that since the dummies for education and MSA residence are not interacted with the cohort effects, the particular value at which we fix these variables does not affect the differences in the wage gaps between cohorts.

Figure 3.5: Actual and counterfactual profiles, unconditional

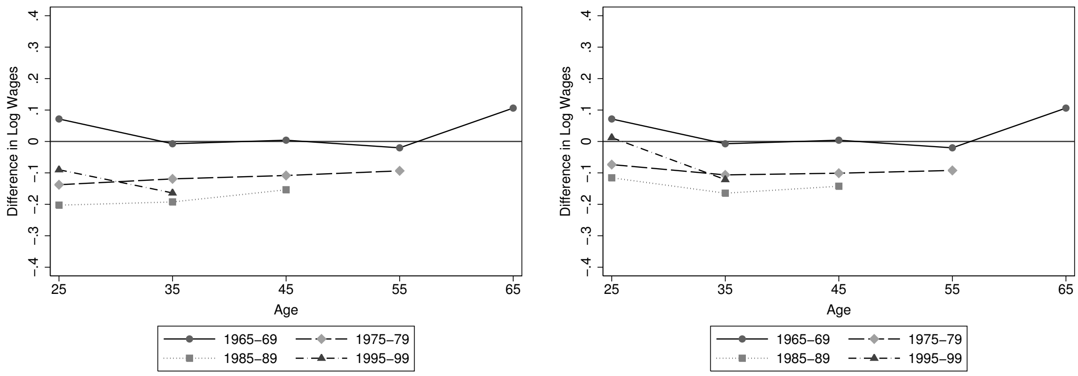
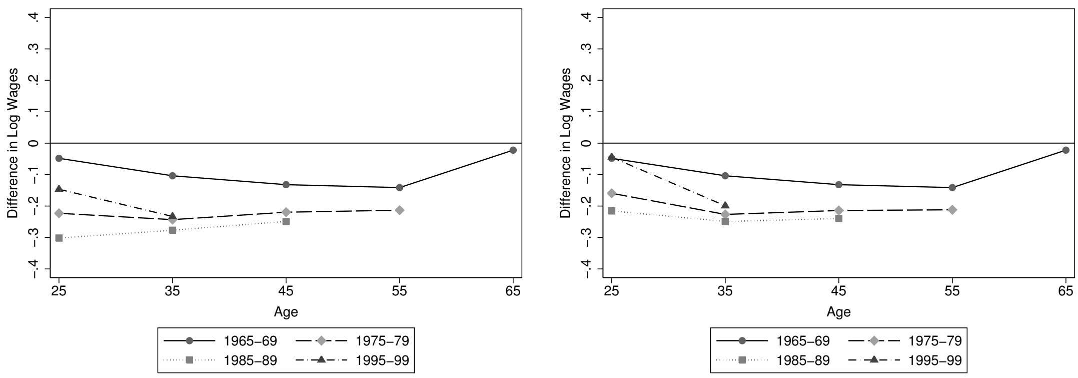


Figure 3.6: Actual and counterfactual profiles, conditional



3.6, are more directly comparable to the ones from the replication of Borjas (1995), where the covariates are also held fixed. Looking at the left panel, we find that conditioning on education and MSA residence increases the wage gaps for all cohorts and across all ages. Indeed, the gaps are now more similar to the ones in the upper right plot of Figure 3.3, whereby the wage gap of the 1960s cohort is somewhat smaller and the wage gap of the 1980s cohort is somewhat larger.[6] If we simulate the conditional profiles keeping the evolution of aggregate supplies at the level faced by the 1960s cohort, we again find that the initial wage gaps are significantly reduced and that there is no more difference in the initial wage between the 1960 and 1990s cohort. As before, the 1970s and 1980s cohorts have the largest wage gaps, however, they are reduced by around 6.5 percentage points for the former and 9 percentage points for the latter.

The exact actual and counterfactual wage gaps of the unconditional simulation in Figure 3.5 are shown in Table 3.3. In the last column, we calculate the fraction of the gap to the 1960s cohort that can be explained by the equilibrium effects arising from the evolution of aggregate supplies. This fraction amounts to around 31% for the 1970s and 1980s

[6] There are several possible sources for these differences. First, we use an extended sample including the years 2000 and 2010. Second, in our non-linear estimation we do not use the age-education deflator for the wage, control for two education groups instead of years of education and do not interact the cubic age term and MSA indicator with year-fixed effects.

Table 3.3: Explanatory power of the equilibrium effects

	Actual Initial Wage Gap G_I	Counterfactual Initial Wage Gap G_C	Explained Part $1 - \frac{G_C - G_{I,70}}{G_I - G_{I,70}}$
Cohort 1965-69	0.072	0.072	-
Cohort 1975-79	-0.138	-0.073	0.310
Cohort 1985-89	-0.203	-0.116	0.316
Cohort 1995-99	-0.090	0.012	0.630

cohorts and 63% for the 1990s cohort. Hence, we can conclude that equilibrium effects play an important role for wage assimilation profiles. However, they seem to fade away after 20 year in the US as in both the unconditional and the conditional plots there is no more visible difference between the actual and counterfactual relative wages at the age of 45 and beyond.

Another result arising from these figures is that there is no visible slowdown in wage assimilation over time, which seems to contradict the findings of Borjas (2015a). Across all cohorts, wages decline during the first ten years and then stay relatively constant. They only rise again after 30 years for the 1960s cohort, which is the only one for which we can observe aggregate supplies over such a long time horizon.

In order to investigate potential differences in the role of the equilibrium effects depending on the skill level, we simulate the conditional actual and counterfactual profiles separately by education. Due to the lower elasticity of substitution, we expect the aggregate supplies to affect high-skilled more than low-skilled workers. This is confirmed by Figures B.1 and B.2 shown in the Appendix. Keeping the supplies fixed for all cohorts reduces the initial wage gaps to natives with the same education by around 2 to 5 percentage points for the low-skilled cohorts and around 8 percentage points for the high-skilled cohorts of the 1970s and 1980s. High-skilled immigrants of the 1960s and 1990s cohorts on the other hand initially earn even more than natives, whereby the entry wages of the former seem to be unaffected by the equilibrium effects.

While except for the 1960s cohort thus the equilibrium effects play a larger role for the assimilation of the high-skilled, the plots also suggest that skill accumulation in turn plays a larger role for the assimilation of the low-skilled. Although the initial wage gaps are much higher in the low-skilled worker sample, they considerably decrease over time in the US, both in the actual and counterfactual profiles and across all cohorts. In contrast, the profiles of high-skilled immigrants are flat except for an increase after 30 years for the 1960s cohort. Thus, low-skilled immigrants seem to substantially accumulate native skills during their time in the US, whereas high-skilled immigrants are closer to natives with respect to their skills at arrival, but retain more of their less substitutable immigrant skills during their stay.

3.6 Conclusion

We provide a framework that allows to disentangle the contribution of skill accumulation to immigrants' economic assimilation from the contribution of labor market competition by combining the approaches of the wage assimilation and the labor market impact literature. Our non-linear estimation equation is based on a production function with imperfect substitutability between native and immigrant efficiency labor units and the possibility of the accumulation of these units over age and time in the host country. Estimating the model using US data of male workers from 1970 to 2010, we obtain an elasticity of substitution between native and immigrant labor that is around 13. The equilibrium effects arising due to the increasing immigrant inflows in the US since the 1960s together with the imperfect substitutability can explain between 31% and 63% of the difference in entry wages between immigrants arriving in the 1960s and more recent cohorts. Thus, the observed decline in entry wages over time in the actual assimilation profiles is partly accounted for by the higher competition through workers with similar skills. However, relative skill supplies have a negligible effect on relative wages for immigrants that are in the US 20 years or longer. Moreover, we find no evidence for systematic differences in the speed of wage assimilation across cohorts.

We also find that the elasticity of substitution between native and immigrant skills is lower among the high-skilled than among the low-skilled and therefore the former are relative more affected by equilibrium effects. On the other hand, skill accumulation is relatively more important for the latter. Their wage gap to natives substantially decreases with time in the US, whereas it stays relatively constant for the high-skilled.

Our easily replicable empirical framework opens many avenues for future research, e.g. a comparison of the case of the US with other countries' experiences. Further, it remains to explore the implications of selective out-migration or endogenous location choices for our estimates.

Appendices

3.A Sample Selection and Variable Definitions

Data are decennial and come from the Census 1970-2000 and the pooled ACS 2009-2011, which are all downloaded from IPUMS. We keep men aged 25 to 64 who are not self-employed, do not live in group quarters, are not enrolled in school and work in the civilian sector.

Immigrant definition

A person is defined as an immigrant if born in a foreign country and not American citizen by birth.

Wages

The hourly wage is computed by dividing the annual wage and salary income by annual hours worked. The latter are calculated by multiplying annual weeks worked with weekly hours worked. Wages are deflated to 1990 constant US$ using the CPI-U multiplier from the Bureau of Labor Statistics. Extreme observations with an hourly wage lower than $1 or larger than $250 are dropped. The hourly wage is adjusted for changes in the wage structure by the age-education deflator as described in Borjas (1995) for the reduced form evidence in sections 3.2 and the replication in 3.3.

Education level

We categorize individuals in four education groups: high school dropouts ($<$12 years of education), high school graduates (12), persons with some college (13-15), and college graduates (16+).

Immigrant cohorts

Given the intervals in which the year of immigration is available we distinguish the following twelve arrival periods to define immigrant cohorts: pre-1950, 1950-59, 1960-64, 1965-1969, 1970-1974,....,2005-09.

Region of origin

We consider two sets of birth regions. The first one consists of 17 regions, the second one is aggregated to five regions in order to have sufficient observations to estimate wages gaps and wage growth rates by origin. The disaggregated version distinguishes

the following regions: Mexico; Cuba; Other Caribbean; Central America; South America; Australia and New Zealand; Canada; United Kingdom, Ireland, Northwestern Europe and Central Europe & Israel; Southern Europe; Russia, Central Eastern Europe; Turkey, North Africa, & the Middle East; China, Hong Kong, & Singapore; Korea & Japan; Philippines; Burma, Laos, Thailand, Vietnam, Cambodia, Indonesia, Malaysia, & Brunei; India, Pakistan, & Central Asia; and Africa (excluding North Africa).
The aggregated version distinguishes the following regions: Mexico; Caribbean, Central and South America; Northwestern European and Anglo-Saxon countries (Australia, New Zealand, Canada, UK, Ireland); Asia; Rest of the world (Southern Europe, Africa and Middle East).

3.B Additional Tables and Figures

Table B.1: Replication of Borjas (1995)

	Baseline (1)	Years of education (2)	Age at migration (3)	Educ. & age at mig. (4)
Constant	0.518***	0.057	0.464***	0.028
	(0.0352)	(0.0338)	(0.0344)	(0.0330)
Age	0.141***	0.107***	0.145***	0.109***
	(0.0027)	(0.0025)	(0.0026)	(0.0025)
Age^2	-0.002***	-0.002***	-0.003***	-0.002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\text{Age}^3 \text{ x } 10^{-3}$	0.013***	0.009***	0.014***	0.010***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Immigrant	-0.718***	-0.211*	-0.168***	0.099***
	(0.0906)	(0.0863)	(0.0071)	(0.0081)
Age x immigrant	0.039***	0.021***		
	(0.0068)	(0.0064)		
Age^2 x immigrant	-0.001***	-0.001***		
	(0.0002)	(0.0002)		
Age^3 x immigrant x 10^{-3}	0.009***	0.007***		
	(0.0013)	(0.0012)		
YSM x immigrant	0.012***	0.019***	0.007***	0.013***
	(0.0010)	(0.0009)	(0.0010)	(0.0009)
YSM^2 x immigrant	-0.000***	-0.000***	-0.000***	-0.000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
YSM^3 x immigrant x 10^{-3}	0.001*	0.003***	0.001*	0.003***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Cohort Pre-1950	0.292***	0.097***	0.293***	0.099***
	(0.0117)	(0.0112)	(0.0117)	(0.0112)
Cohort 1950-59	0.266***	0.118***	0.266***	0.117***
	(0.0084)	(0.0081)	(0.0084)	(0.0081)
Cohort 1960-64	0.221***	0.097***	0.220***	0.096***
	(0.0081)	(0.0078)	(0.0081)	(0.0078)
Cohort 1965-69	0.161***	0.081***	0.161***	0.080***
	(0.0073)	(0.0071)	(0.0073)	(0.0071)
Cohort 1970-74	0.082***	0.056***	0.082***	0.055***
	(0.0069)	(0.0066)	(0.0069)	(0.0066)
Cohort 1975-79	0.055***	0.040***	0.056***	0.040***
	(0.0061)	(0.0058)	(0.0061)	(0.0058)
Cohort 1980-84	-0.001	-0.010	-0.001	-0.009
	(0.0066)	(0.0063)	(0.0066)	(0.0063)
1970 period effect	0.704***	0.142	0.716***	0.139
	(0.0846)	(0.0799)	(0.0846)	(0.0798)
1980 period effect	0.127**	0.136**	0.144**	0.144**
	(0.0478)	(0.0458)	(0.0478)	(0.0458)
Years of schooling		0.065***		0.065***
		(0.0002)		(0.0002)
Education x immigrant		-0.016***		-0.016***
		(0.0003)		(0.0003)
Age at migration			-0.005***	-0.006***
			(0.0001)	(0.0001)
R-squared	0.033	0.139	0.033	0.139
Observations	3324067	3324067	3324067	3324067

Notes: This table replicates the specifications (1) to (4) of Borjas (1995, Table 5) using a sample of male workers from the Censuses 1970-1990 dowloaded from IPUMS. The regressions of columns (2) and (4) include a dummy for residence in an MSA and its interaction with immigrant status. The cubic term in age, the years of schooling variable and the MSA residence indicator are also interacted with the year effects (coefficients of the year 1990 displayed).

Table B.2: Main results

	National level			State level		
	All	Low-skill	High-skill	All	Low-skill	High-skill
	(1)	(2)	(3)	(4)	(5)	(6)
β Variables						
Age x natives	0.101***	0.054***	0.152***	0.102***	0.056***	0.154***
	(0.0015)	(0.0019)	(0.0022)	(0.0015)	(0.0019)	(0.0022)
Age^2 x natives	-0.001***	-0.001***	-0.002***	-0.001***	-0.001***	-0.002***
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0001)
Age^3 x natives x 10^{-3}	0.005***	0.000	0.012***	0.006***	0.001	0.012***
	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0004)
Age x immigrant	0.426***	0.063***	0.309***	0.509***	0.107***	0.336***
	(0.0209)	(0.0080)	(0.0138)	(0.0253)	(0.0102)	(0.0144)
Age^2 x immigrant	-0.008***	-0.001***	-0.006***	-0.010***	-0.002***	-0.006***
	(0.0005)	(0.0002)	(0.0003)	(0.0006)	(0.0002)	(0.0003)
Age^3 x immigrant x 10^{-3}	0.048***	0.005***	0.035***	0.058***	0.012***	0.038***
	(0.0035)	(0.0014)	(0.0024)	(0.0042)	(0.0016)	(0.0025)
YSM	0.006**	0.013***	0.013***	0.004	0.081***	0.014***
	(0.0024)	(0.0031)	(0.0017)	(0.0027)	(0.0095)	(0.0017)
YSM^2	0.000**	-0.001***	-0.000***	0.000*	-0.001***	-0.000***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
YSM^3 x 10^{-3}	-0.002	0.009***	0.003**	-0.003	0.008***	0.005***
	(0.0016)	(0.0022)	(0.0009)	(0.0019)	(0.0022)	(0.0010)
Cohort 1950-59	0.345***	0.018	-0.018	0.265***	0.055***	-0.028*
	(0.0346)	(0.0124)	(0.0135)	(0.0399)	(0.0079)	(0.0133)
Cohort 1965-69	0.906***	-0.000	0.153***	0.871***	0.066***	0.119***
	(0.0435)	(0.0155)	(0.0160)	(0.0479)	(0.0088)	(0.0160)
Cohort 1975-79	0.935***	-0.074***	0.169***	0.861***	0.040***	0.124***
	(0.0444)	(0.0190)	(0.0166)	(0.0483)	(0.0094)	(0.0164)
Cohort 1985-89	1.032***	-0.099***	0.228***	0.906***	0.035***	0.150***
	(0.0461)	(0.0216)	(0.0173)	(0.0494)	(0.0100)	(0.0170)
Cohort 1995-99	1.353***	-0.086***	0.460***	1.273***	0.073***	0.391***
	(0.0504)	(0.0225)	(0.0182)	(0.0536)	(0.0115)	(0.0178)
High-skill x native	0.351***			0.344***		
	(0.0006)			(0.0006)		
High-skill x immigrant	1.470***			1.767***		
	(0.0334)			(0.0455)		

Table B.2 continued

	National level			State level		
	All	Low-skill	High-skill	All	Low-skill	High-skill
	(1)	(2)	(3)	(4)	(5)	(6)
α Variables						
YSM	0.025***	0.104***	0.025***	0.023***	-0.012**	0.019***
	(0.0009)	(0.0248)	(0.0024)	(0.0008)	(0.0050)	(0.0021)
YSM^2	-0.000***	-0.002***	0.000*	-0.000***	-0.001*	0.000***
	(0.0000)	(0.0006)	(0.0001)	(0.0000)	(0.0005)	(0.0001)
YSM^3 x 10^{-3}	-0.001	0.006	-0.006***	-0.000	-0.039**	-0.007***
	(0.0006)	(0.0046)	(0.0013)	(0.0005)	(0.0153)	(0.0012)
High-skill x immigrant	0.072***			0.111***		
	(0.0115)			(0.0107)		
Mexico	0.992***	-1.440***	1.008***	1.223***	-0.068	1.397***
	(0.0285)	(0.4582)	(0.0874)	(0.0219)	(0.1150)	(0.0522)
Other Latin America	1.060***	-1.315***	1.229***	1.298***	-0.007	1.649***
	(0.0295)	(0.4553)	(0.0870)	(0.0224)	(0.1210)	(0.0502)
NW Europe/Anglo-Saxon	1.198***	-1.998***	-6.566e+07	1.465***	0.677***	-613.892
	(0.0332)	(0.6873)	(.)	(0.0243)	(0.0894)	(.)
Asia	0.839***	-1.454***	0.873***	1.146***	0.017	1.454***
	(0.0360)	(0.4673)	(0.0939)	(0.0257)	(0.1128)	(0.0546)
Rest of the World	1.256***	-1.086**	1.264***	1.468***	0.147	1.624***
	(0.0302)	(0.4527)	(0.0903)	(0.0227)	(0.1222)	(0.0533)
Constant	0.582***	1.432***	0.027	0.511***	1.342***	-0.048
	(0.0199)	(0.0262)	(0.0300)	(0.0197)	(0.0259)	(0.0299)
σ	7.426***	-13.42***	5.569***	13.764***	12.459***	8.956***
	(.2269)	(3.6845)	(.3462)	(.3239)	(1.2291)	(.3747)
R-squared	0.168	0.116	0.097	0.186	0.141	0.117
Observations	6684810	3427580	3257230	6684810	3427580	3257230

Notes: The coefficients result from a non-linear least squares estimation of the model described in the text using a sample of male workers from the Censuses 1970-1990 and ACS 2000 and 2009-100 downloaded from IPUMS. The β variables also include origin fixed effects (five categories), which are not displayed. High-skilled are individuals with at least some college education.

Table B.3: Cohort-specific skill accumulation

	All	Low-skill	High-skill
β Variables			
Age x native	0.102***	0.054***	0.153***
	(0.0021)	(0.0027)	(0.0031)
Age^2 x native	-0.001***	-0.001***	-0.002***
	(0.0000)	(0.0001)	(0.0001)
Age^3 x native x 10^{-3}	0.005***	0.000	0.011***
	(0.0004)	(0.0005)	(0.0006)
Age x immigrant	0.252***	0.145***	0.311***
	(0.0151)	(0.0390)	(0.0204)
Age^2 x immigrant	-0.005***	-0.002**	-0.006***
	(0.0003)	(0.0009)	(0.0005)
Age^3 x immigrant x 10^{-3}	0.032***	0.010	0.038***
	(0.0024)	(0.0064)	(0.0033)
Cohort 1950-59	-0.374	6.776***	-1.628*
	(0.4286)	(0.7186)	(0.6530)
Cohort 1965-69	0.087	6.393***	-0.900
	(0.4267)	(0.6687)	(0.6349)
Cohort 1975-79	-0.385	6.122***	-1.063
	(0.4378)	(0.6958)	(0.6355)
Cohort 1985-89	-0.679	5.996***	-1.032
	(0.4445)	(0.7144)	(0.6342)
Cohort 1995-99	0.309	6.363***	-0.475
	(0.4264)	(0.6671)	(0.6336)
Cohort Pre-1950 x YSM	0.086*	-0.499***	-0.014
	(0.0352)	(0.0879)	(0.0529)
Cohort 1950-59 x YSM	0.126***	-0.053	0.120***
	(0.0135)	(0.0620)	(0.0189)
Cohort 1965-69 x YSM	0.088***	0.000	0.059***
	(0.0110)	(0.0115)	(0.0122)
Cohort 1975-79 x YSM	0.127***	-0.006	0.057***
	(0.0168)	(0.0184)	(0.0144)
Cohort 1985-89 x YSM	0.173***	-0.033	0.051*
	(0.0258)	(0.0263)	(0.0198)
Cohort 1995-99 x YSM	-0.001	-0.067*	0.000
	(0.0287)	(0.0275)	(0.0274)
High-skill x native	0.345***		
	(0.0009)		
High-skill x immigrant	0.441***		
	(0.0056)		

Table B.3 continued

	All	Low-skill	High-skill
α Variables			
YSM	0.009	0.036***	0.015
	(0.0071)	(0.0059)	(0.0168)
YSM^2	-0.002**	-0.000	-0.002
	(0.0007)	(0.0002)	(0.0017)
YSM^3 x 10^{-3}	-0.024	-0.002	-0.048
	(0.0216)	(0.0020)	(0.0481)
High-skill x immigrant	0.444***		
	(0.0079)		
Mexico	0.949***	0.072	1.102***
	(0.0531)	(0.1111)	(0.1367)
Other Latin America	0.985***	0.205*	1.224***
	(0.0561)	(0.1120)	(0.1429)
NW Europe/Anglo-Saxon	1.720***	0.296***	2.272***
	(0.0476)	(0.1099)	(0.1094)
Asia	1.222***	0.095	1.740***
	(0.0542)	(0.1119)	(0.1257)
Rest of the World	1.118***	0.334***	1.372***
	(0.0583)	(0.1112)	(0.1469)
Constant	0.393***	1.236***	-0.101**
	(0.0302)	(0.0391)	(0.0483)
σ	12.833***	29.22***	8.868***
	(.8395)	(2.8774)	(1.0429)
R-squared	0.187	0.146	0.117
Observations	3299723	1677289	1622434

Notes: The regression are based on the specification in Table B.2 at the state level with additionally included interactions between the cohort effects and the cubic term in year since migration in the β variables.

Figure B.1: Actual and counterfactual profiles of the low-skilled, conditional

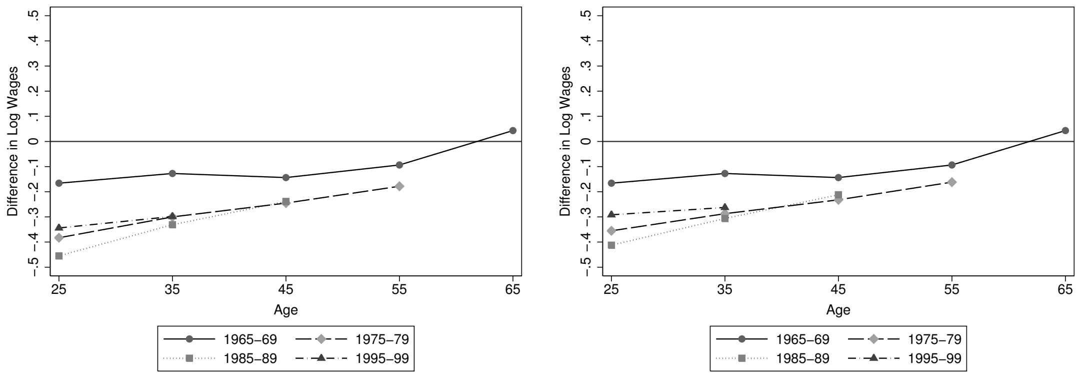
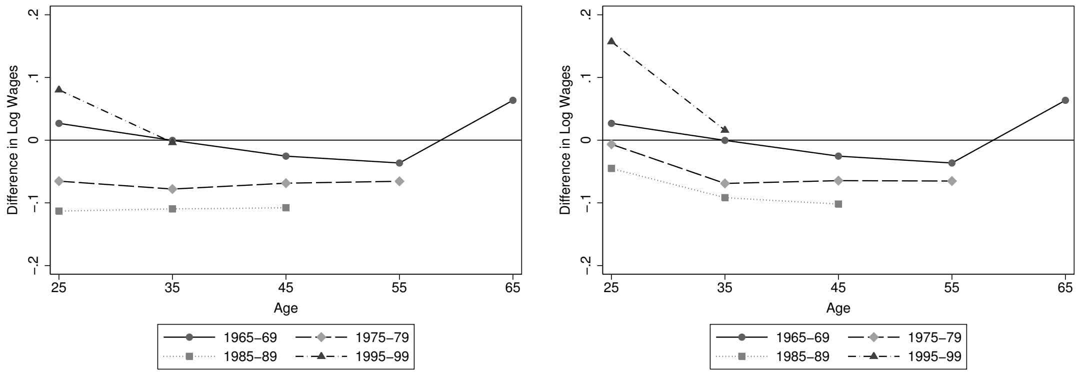


Figure B.2: Actual and counterfactual profiles of the high-skilled, conditional



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