Decomposing the Native-Immigrant Wage Gap in the United States

Rebecca Lessem* and Carl Sanders‡

July 1, 2014

Abstract

Immigrant workers in the United States earn significantly lower wages than observably similar natives. We study the wage path of immigrants on order to understand this gap, focusing on the contributions of two mechanisms for wage growth. First, the value of labor market experience may differ for natives and immigrants. Second, it may take time for new immigrants to be matched with their optimal occupation after moving to the US. To separate these two forces, we create a parsimonious model of human capital accumulation and job search which we estimate using representative data on recent immigrants from the New Immigrant Survey. Data on each person's occupation in their home country, which is not available in datasets previously used to study immigrant wage assimilation, allows us to compare immigrants who come from similar occupations but have different career paths in the US. Reduced form evidence shows that both returns to experience and job search drive immigrant wage growth. Counterfactuals show that placing immigrants immediately in their long-run occupations reduces the initial native-immigrant wage gap by about 7%.

JEL Codes: J31, J15, J62

*Tepper School of Business, Carnegie Mellon University. rlessem@andrew.cmu.edu

†Department of Economics, Washington University in St. Louis and the Federal Reserve Bank of Saint Louis. carlsanders@wustl.edu

‡Thanks to Brian Kovak, Robert Miller, Carly Urban, and seminar participants at CMU, Kansas State University, Montana State University, NYU, Washington University in St. Louis, LSE, UCL, and the Society for Economics Dynamics, the Society of Labor Economics, Midwest Economics Association, the North American Summer Meeting of the Econometric Society, the Canadian Economics Association, the Southern Economics Association annual meetings for helpful comments. Financial support from the National Center for Border Security and Immigration at the University of Arizona is gratefully acknowledged.

1 Introduction

Immigrants in the United States earn lower wages than natives, even when comparing workers with the same education levels and work experience. But this is not simply lower-skilled immigrants entering the US labor force: there is evidence that the wage gap between immigrants and natives falls with time working in the US labor market.[1] In the short term, this income gap can lead to over-representation of immigrants on welfare rolls and government assistance programs. In the long run, there could be inter-generational effects if immigrant parents are less able to invest in their children's education and health than natives. Because the size of the gap is not stable over workers' careers, there may be policies that could speed up this convergence or potentially eliminate the initial gap. But without understanding the source of this gap, we can only speculate what those policies are.

The goal of this paper is to understand the determinants of the wage path of immigrant workers, in order to understand why they initially earn less than native workers and why this difference shrinks over time. We focus on two potential explanations. First, labor market experience in the US may be more valuable for jobs than labor market experience in other countries. When immigrants begin working in the US, they "catch up" as they learn the skills specific to the United States that native workers take for granted. We refer to this throughout as "returns to experience." The second reason is that recent immigrants may not be able to immediately find their preferred job because of the lack of vacancies and the necessity of finding a job quickly to support themselves. As they spend more time in the US, they will be able to move up the job ladder relatively quickly because they began at lower-skill occupations. We will refer to this as the "job search" force for wage growth.

To study the effect of these two mechanisms, we develop and estimate a model with returns to experience and job growth, which we estimate using data on recent immigrants from the New Immigrant Survey (NIS). The data include multiple observations on an individual over time in the US and also information on their occupations and wages immediately before migration. The information on home country occupations, which is unavailable in datasets used in previous papers studying immigrant assimilation, is key to estimating our model. By having this information, we are able to compare workers who leave their home country in certain high-skilled occupations (e.g. doctor) and enter the US in a lower-skilled job (e.g. taxi driver) with those with similar occupational backgrounds who were able to get high-skilled jobs in the US. By tracking those two types of workers over their careers, we can see how much wage growth comes from just general returns to experience versus how much comes through the low-skilled job worker eventually finding his ideal high-skilled job. For those who initially found their optimal occupation and do not move,

[1] See Chiswick (1978), Borjas (1985), and LaLonde and Topel (1992).

we attribute their wage growth exclusively to returns to experience, whereas those who started in lower occupations and moved up have had wage growth both through job search and returns to experience. While there are details to deal with, the simplest way to interpret our identification is to estimate the returns to job search as the difference in wage growth patterns between these two workers. In comparison to previous literature, which has documented the wage gap, we are able to separate these two mechanisms by using this information on home country occupations.Eckstein and Weiss (2004) and Weiss et al. (2003) look at a similar question using a data set of highly-skilled Russian immigrants to Israel. These papers look at a one time shock of very specialized group of immigrants into a labor market very different than the United States.[2] In comparison, we are studying a case where there is a constant flow of immigrants who typically come from a lower skill distribution. Whereas some visas are allocated through employee sponsors, the majority of our sample is granted green cards through family reunification programs, which do not select immigrants based on skill characteristics.

In the first part of the paper, we analyze the observed career paths of immigrants in the US. In particular, we can test if the observed patterns of wage growth and occupation changes are consistent with job search and different returns to experience. In our second empirical component, we create a simple model of returns to experience and job search that can allow us to quantify the relative importance of the two forces. In the model, each period a worker gets an offer from an outside firm with some probability. If the offer is for a higher cognitive task (and consequently higher wage) job, he switches occupations. As workers spend more time in the labor market, they have a higher probability of being in a high occupation and wage job. At the same time, they exogenously accumulate general human capital. We can characterize worker wage and occupation growth in two parts. First, there is a stochastic job offer process that moves them up the occupational ladder; in addition, conditional on occupations and labor market experience, their wages are given by a Mincer wage equation. We allow both job offer rates and human capital accumulation to depend on a vector of worker characteristics, which allows us to quantify the differential effects of gender, home occupation, English skills, and other characteristics on wage growth and occupational transitions in the US. The results show that home occupation is a strong determinant of job offers, particularly for legal immigrants who move to the US after working in their home country for some period of time. Home occupation is less important for young immigrants, likely because for immigrants who move at a young age, their occupation in their home country is not a strong signal of their skill levels. We also see that similar workers with different initial occupation draws will converge towards the same point with time in the US labor market.

After estimating the parameters of this model, we use the results to decompose the immigrant-native wage gap. In the first exercise, we simulate the model to find each person's long run occu-

[2] de Matos (2011) looks at immigrant wage assimilation in Portugal using linked employer-employee data.

pation in the US. We then simulate their wages assuming they always work at this occupation, in order to understand the wage cost of having to work in different occupations. In this case the only wage growth is due to returns to work experience since occupation is held constant. We compare immigrant wages over time with data on wages of comparable native workers (using CPS data). This counterfactual decreases the immigrant-native wage gap by 7% relative to the baseline case.

We also use the model to understand the wage costs due to years of experience as an illegal immigrant. Our sample consists of individuals who were recently granted green cards, yet many of them moved to the US before this occurred. In our model, illegal immigrants draw from a different job offer distribution, which has fewer draws from high skill occupations. In a counterfactual, we simulate wage outcomes assuming that all immigrants are always in the US legally. Since our whole sample eventually becomes legal immigrants, we can calculate the wage loss due to these years as an illegal immigrant. We find that this leads to wage gains, showing a wage cost to years of labor market experience as an illegal immigrant.[3]

The existing literature has focused almost exclusively on identifying the extent of the wage gap between US natives and immigrants, conditioning on only education and experience. Chiswick (1978), Borjas (1985), and LaLonde and Topel (1992) study this using cross-sectional data from the US Census, and Duleep and Dowhan (2002) and Lubotsky (2007)[4]examine this issue using longitudinal data from Social Security Administration records. These studies find that the initial wage gap between immigrants and similar (in terms of education and experience) natives falls as immigrants spend more time in the US market. None of these studies have the crucial information on the immigrants home occupation which makes controlling for initial skills and identifying the mechanisms of interest extremely difficult.

2 Data: Immigrant Histories and Occupational Characteristics

Our identification strategy relies on our ability to see the home occupations of immigrants. Typical data sets used to study immigrant assimilation in the US, such as the Census or records from the Social Security Administration, lack any information about the pre-US careers of immigrants. We are able to solve this problem using the New Immigrant Survey (NIS), a representative survey of newly granted permanent residents of the United States. They sampled from a group of individuals

[3]In future work this can be used to calculate a willingness to pay to avoid a delay in being granted a visa. This is logical in this sample in that all of these individuals eventually receive green cards after a delay.

[4]Lubotsky finds that ignoring selective outward migration of immigrants can bias estimates of the wage gap. With the current release of the NIS data it is not possible to control for this. However, once the second round of the NIS is released we will be able to do so.

who had applied for permanent residency in the US and were granted Legal Permanent Resident (LPR), colloquially known as “Green Card”, status. The first wave of the survey was performed on a representative sample of around 8,500 visa holders who received LPR status between May and November in 2003. The data include information about individual’s labor market history in their home country and in the US, migration history (both legal and illegal), household demographics, language skills, and many other characteristics. Most importantly for our purposes, the labor market information includes occupation and wages in the home country, as well as for a person’s first and current job in the US.[5]

Our primary focus is on how pre-immigration characteristics affect career paths after people move to the US. This data enables us to research this question, unlike other sources used to study the wage path of immigrants. However, the dataset has some weaknesses. It does not contain information on those who chose not to immigrate or apply for LPR status. In addition, it does not have high-frequency data on job switches or administrative records on wages. These problems will restrict our analysis when it comes to selection issues with migrants vs. non-migrants as well as short-term occupational transitions. Instead, we focus on longer-term trends within worker careers of those who chose to become permanent US residents.

One of our main questions we study is how immigrants transition between occupations after moving to the US. The NIS data includes the 3-digit 2000 Census Occupational Codes for workers as well as their wages at those jobs. The occupation data will allow us to track whether immigrant wage growth was due to moving “up the ladder” across different occupations or whether it was due to additional experience within occupations. The traditional way to study occupational transitions in small samples (since there are 440 occupational codes, which leads to many empty cells) is to arbitrarily classify occupations into a small number of “similar” occupations. This grouping is necessarily ad hoc and loses significant precision in terms of grouping different occupations together.

We take a different approach here based on recent work on task-based human capital; for a summary of this topic see Sanders and Taber (2012). We characterize occupations continously according to the levels of cognitive and manual tasks performed, which generates a multi-dimensional score for each occupational code. Using these measures gives a natural way to characterize distance between occupations [6] and track how workers transition across time that is not dependent on ad-hoc groupings.

We follow the literature and use the O*NET database of occupational tasks to score each oc-

[5] A second round of surveys was completed in 2007 but has not yet been released. This will provide more information on how occupations and wages change for each immigrant with time spent in the US. We also will know which migrants chose to return to their home country, which is important if selective return migration upwardly biases the degree of wage assimilation.

[6] See Poletaev and Robinson (2008) and Gathmann and Schonberg (2010).

cupation. O*NET was created by the US Bureau of Labor Statistics and is a representative survey that asks workers about their skills and the tasks they perform in their occupation level. This is used to create an index of the manual and cognitive task requirements of each job using Principal Component Analysis, similar to the procedure used in Poletaev and Robinson (2008).[7] When workers make transitions between occupations, we look at the changes in these scores to see how the underlying tasks actually changed, not just the occupation name.

3 Descriptive Statistics

We focus on two facets of the data: how immigrants' wages grow during their careers and how they transit the occupational ladder.

When we simply regress wages and occupational task complexity on the other available controls, there are some expected patterns and some unexpected ones. In general, immigrant wages behave as we might expect. In particular, the return to labor market experience in the immigrant's home country are much lower than those measured in the US. In addition, those with higher education and who work in higher level of cognitive task occupations earn more, the returns to legal experience in the US are higher than illegal experience, those who were in higher occupations at home have higher wages even conditional on US occupation, and wages grow faster for those in high cognitive task jobs. There is no evidence in the data that the level of manual tasks workers perform in the US have any effect on their wages, and wages grow at very similar rates across education groups conditional on everything else.

The results for occupational transitions are more surprising: conditioning on demographics and home country occupation, those who work in higher cognitive task occupations in the US are less likely to move to higher occupational tasks. In addition, the partial effect of the cognitive tasks of home occupation on cognitive task growth in the US is positive and significant. In other words, comparing two immigrants who had the same home country occupation, the one who begins in the US in the lower cognitive task occupation has higher task growth. On the other hand, comparing two workers in the same occupation in the US, the one with the higher home country cognitive tasks will have larger task growth. We interpret this as consistent with our story of job search: home cognitive tasks reflect underlying skills, and conditional on those skills those who begin at lower occupations in the US have a higher probability of transitioning to a new job. In addition, comparing two workers in the same US occupation, the one with the higher skills (measured by home occupation) will receive better job offers.

Table 1 shows some general summary statistics on the sample.[8] The average age in the sample

[7] Details for the procedure used here are available from the authors on request.

[8] To create the sample we include only individuals working in the US.

is close to 40 and the sample is about 60% male. The average person has about 4 years of work experience in the US as a legal immigrant. Even though the survey is a sample of legalized immigrants, many (19%) had worked as illegal immigrants for some period of time; of this group, the average person has around 13 years of work experience as an illegal immigrant. Since the NIS data allows us to distinguish between legal and illegal work experience, we will allow for different search frictions and returns to experience depending on legal status. About one-quarter of the sample moved to the US on a visa sponsored by an employer. This is an important control in that people in this group likely had a job offer before moving to the US so they drew their initial job from a different distribution. In addition, they face different search frictions while in the US labor market given that their visa status is tied to their employer. Most of the remainder of the sample moved on family reunification visas. Over 60% of the sample has education beyond high school.

3.1 Wages

In this section we look at wages conditional on both occupation and other characteristics, in particular labor market experience at home and in the US. We assume that workers are paid a wage based on a standard Mincer wage equation that depends on the typical education and experience along with other demographic factors and individual labor market details.

In a first specification, we estimate wage regressions in levels and ignore individual fixed effects. We have two wage points for each person: for their initial and current job in the US. We control for education (dummy variable indicating whether or not a person has some college), years of work experience at home, gender, visa status (whether or not an employer sponsored a person's visa), and the manual and cognitive tasks of the home occupation (as a measure of skill). Home country occupation is split by the age that a person moves to the US. This allows for home country occupation to have a smaller effect for those who moved at younger ages, when their occupation is a weaker signal of their skills. We also interact home skills with home country GDP, to allow for differing effects based on home country. The productivity level of a job is given by the manual and cognitive task level of the job. For the current job in the US, we control for legal and illegal years of work experience.

Table 2 shows the results of a regression on initial and current wages in the US (all in 2004 dollars). People with employer-sponsored visas have higher wages, indicating that these individuals have fewer search frictions and get better job matches. People in occupations with higher cognitive tasks earn higher wages, but we see no effect for manual tasks. People who move from richer countries earn higher wages (in their current job). There are positive returns to work experience in the US. As expected, the returns to legal work experience are higher than illegal work experience. We interact experience in the US with home GDP, and find that people from wealthier countries have higher initial wages but a flatter wage profile in the US. [9]

Table 4 looks at the determinants of wage growth for each individual. This allows us to control for any individual fixed affects that could have been potentially biasing our results. In this setting, the returns to occupations are identified off of the change in wages for people who move to a higher skill occupation. Work experience leads to higher wages, as does an increase in the cognitive task requirements of jobs. Again we see no effect of the manual task level of jobs.

3.2 Occupations

In the previous section, we showed that the cognitive task levels of jobs had an important effect on wages, meaning that people should want to move to higher cognitive task occupations. In this section we explore how people move up the occupational ladder.[10] First we study the determinants of the cognitive task requirements of jobs in the US. Columns (1) and (2) of Table 5 show this for a person's original job in the US.[11] We first look at the effects of the jobs in the home country, splitting the sample by the age that a person moved to the US. A person who moves at an older age has more work experience at home, so his home occupation reveals a fair amount of information about their skill level. On the other hand, people who move at younger ages had less experience in their occupation at home and it is likely a weaker signal of their skills. We see that workers with higher cognitive skills in their job at home are in jobs with higher cognitive task requirements in the US, implying that some skills are transferred from the home country to the US. The effect for cognitive skills is stronger when people move at older ages. We also interact the home job tasks with GDP of a person's home country. This allows for the effects to differ based on the economic status of a person's home country, and we find that the effects of home country cognitive tasks are stronger for people from wealthier countries. This is consistent with multiple stories of immigrant job transitions. One explanation is that immigrants from developed countries have better social and job networks in the US and so take less of a hit on moving. Another possibility is that the underlying human capital requirements across occupations differ by the quality of the schooling in a country. For our model and estimation, we assume that the ordering of occupations by cognitive tasks is the same across countries. With sufficient data we could identify the productivity differences between tasks within each home country non-parametrically, but the data requirements are too high. Instead we make the assumption that the relative productivity of two occupations depends linearly on the GDP of the home country. For example, the cognitive demands of "Doc-

[9]Columns (1) and (3) include the English language skills variable, while it is excluded from columns (2) and (4). This is because this variable is only available for the household heads. We assume the husband and wife have the same English skills to include this control. The effects of other controls are similar in both specifications.

[10]The task measures are standardized to be between 0 and 1. Figures 1 and 2 show the distribution of cognitive tasks for the home job, initial job in US, and current job in the US.

[11]The only difference between the 2 columns is the inclusion of the "English skills" variable.

tor" must be greater than "Taxi Driver" in all countries, and the relative wages paid to "Doctors" vs "Taxi Drivers" will differ depending only on a country's GDP. Those with employer sponsored work visas have jobs with higher cognitive task requirements.

Most of the trends for current jobs (shown in the last two columns of Table 5) are similar to before. It is important to note that the effects of home skill occupation are smaller than for the initial job in the US. However, the tasks of the initial job in the US strongly affect the current job, meaning that the previous job could be absorbing some of the effect of the home job. Legal work experience increases the cognitive task requirements of a job. This shows that people move to higher task jobs with time in the US. However, illegal work experience does not affect the cognitive tasks of jobs, so this occupational mobility only seems to be occurring for legal immigrants.

Table 6 shows the determinants of task growth between the first and current job in the US. Legal work experience increases the task growth of cognitive tasks. This implies that people will move to higher skill jobs with time in the US. We control for the home country and initial occupation in the US. Conditional on initial occupation, people with higher cognitive skills at home (who moved after age 18) have higher task growth. This supports our argument that search frictions play a significant role in the job growth of immigrants. Furthermore, this effect goes away when we do not control for home country occupation, highlighting the importance of this variable to be able to study these issues.

4 Model

We use a full-information partial equilibrium labor search model. Workers are characterized by their fixed ability $\theta \in \mathbb{R}$. Occupations are characterized by their fixed productivity $\pi \in \mathbb{R}$. A worker with demographic characteristics given by the vector X and matched with a job of productivity π would receive a log wage given by a standard Mincer form

$$w = \beta X + \theta + \pi + \varepsilon$$

with β as the parameter governing returns to demographics and ε being a white noise wage shock independent of everything else.[12] We emphasize the demographic characteristics in the empirical work, so here we note that the X will contain measures of work experience both abroad and in the US and we explicitly allow for differing returns to work experience in the worker's home country.

Workers are mobile across occupations due to frictions in matching. When immigrant workers

[12] This functional form for wages is consistent with a model where workers have all the bargaining power and the productivity of a match is given by

$$Y = \exp(\beta X + \theta + \pi + \varepsilon).$$

arrive in the US at normalized time 0, they receive a job offer from an occupation with a productivity level π_0 with a CDF conditional on their characteristics denoted by $F_{\pi_0}(\cdot|X_{i0})$. Every following period, they can potentially move occupations. The timing within a period is as follows: a worker begins the period either unemployed or matched with the chosen firm from the previous period. First, with probability q an employed worker loses their prior job. Next, with probability $p(X_{it})$ they receive an offer from an occupation of productivity π drawn from a conditional CDF $F_{\pi}(\cdot|X_{it})$. This distribution could differ from that of the initial period but it is constant over time. Offers cannot be recalled and neither the offer probability or offer distribution depends on the worker's employment status. After deciding whether to move, the worker receives wages from the chosen occupation and moves to the next period. If the worker is unemployed at time of the possible offer but does not receive one he receives wages of 0 and moves to the next period in the unemployed state.

A worker's optimal choices are easy to characterize because of a lack of intertemporal tradeoffs to higher productivity occupations. Choosing the higher productivity out of the current and offered occupations leads to a current higher wage and starting the next period in a more productive firm than otherwise. As long as the worker's indirect utility is increasing in wages, he or she will always choose the higher productivity of the two possible occupations when deciding on an offer. A particularly important assumption for this result is that the job offer rates do not depend on employment status or the current firm or else unemployed workers might refuse bad jobs in order to have a better chance of finding a good job in the future.

Given this decision rule, observed wages will grow within worker careers for two reasons. First, a quadratic function of worker experience is included in the demographic characteristics X_{it}, so as long as the marginal return to another year of experience is positive average wages would increase. This is the model equivalent to the "returns to experience" motive discussed in our motivation. Second, as workers receive more job offers they will move on average to higher productivity jobs. Within their careers they will occasionally lose their job and have to restart the search process, but the average effect will be higher wages with more time in the labor market. This is the model equivalent of the "search" factor of wage growth from above. Estimating the model will allow us to separate the importance of each of these forces on the total wage growth we observe.

5 Estimation

We estimate the model in two steps. The wage parameters can be estimated with a standard fixed-effects Mincer regression of wages onto demographics and occupational productivity. In the second step we derive the likelihood function for the observed occupation choices. The likelihood is complicated by the fact that we do not observe entire worker histories, but just their first and last jobs in the US and their durations, but are missing occupations between them. Simulated Maximum Likelihood allows us to deal with this issue in a computationally simple way. In the first section here we discuss the parametrization of the wage equation and the occupational transition process, then we derive the likelihood and describe the missing data problem and the details of our estimator.

5.1 Parametrization

Log wages for individual i at occupation j in time t depend on demographics X_{it}, the occupation's productivity π_j, and a white noise shock:

$$w_{it} = \beta X_{it} + \theta_i + \pi_j + \varepsilon_{it} \tag{1}$$

Demographics include both fixed and time-varying characteristics. The fixed characteristics we consider are gender, cognitive and manual skills of home job, years of home work experience, education, English skills, and whether not a person has an employer sponsored work visa. The time-varying characteristics are the years of work experience in the US (both legal and illegal).

Our experience terms are of particular note. We allow for the returns to experience to be different between the home country and the US. Additionally the returns to experience in the US can depend on whether the individual was in the US legally or not, and the returns to legal years of experience can differ depending on the GDP of the home country. Our goal with this specification is to allow for individuals with different demographics to have different returns to experience in the US, exploiting the fact that we have detailed data on individual characteristics.

We split legal and illegal work experience to allow for differing returns:

$$h_{it} \quad = \quad \beta X_i + \psi_1^{leg} US_{it}^{leg} + \psi_1^{leg} (US_{it}^{leg})^2 + \psi_1^{ill} US_{it}^{ill} + \psi_2^{ill} (US_{it}^{ill})^2 + \mu_1 GDP_i + \gamma legal_{it}$$

For the occupation choice process, we show below that the conditional job offer rate, job loss rate, and job offer distribution are non-parametrically identified. However, our sample is too small to support non-parametric estimators of these objects, so we make parametric assumptions for estimation.

Job offer probabilities are assumed to differ by residency status. Denoting $\Phi(\cdot)$ as the cdf of the normal distribution,

$$p\left(X_{it}\right) = \begin{cases} \Phi(\alpha_0 + \alpha_1 \cdot college_i + \alpha_2 \cdot cog_{hi} + \alpha_3 \cdot cog_{hi} \cdot GDP_{hi} + \alpha_4 \cdot sponsor_i + \alpha_5 \cdot english_i + \alpha_6) & \text{if } legal_{it} = \\ \Phi(\alpha_0 + \alpha_1 \cdot college_i + \alpha_2 \cdot cog_{hi} + \alpha_3 \cdot cog_{hi} \cdot GDP_{hi} + \alpha_4 \cdot sponsor_i + \alpha_5 \cdot english_i) & \text{otherwise} \end{cases}$$

The probability that a person gets a job offer depends on education, the tasks of the home country job, and whether or not a person has an employer sponsored visa. The job offer rates for illegal differs both by a constant and the fact that they do not have sponsors.

If a person gets a job offer, it is characterized by a given occupational productivity π, which we assume is drawn from the Kumarswamy distribution, a computationally simpler variant of the Beta Distribution. It has 2 parameters, a and b, with a pdf given by

$$f\left(\pi\right) = a \cdot b\pi^{a-1}\left(1-\pi^{a}\right)^{b-1}.$$

We assume $a = 2$ but allow the b parameter to differ according to observables. In particular, we estimate $b_0\left(X_{it}\right)$ and $b(X_{it})$, where b_0 is the parameter for the initial job offer distribution and b is used in the distribution of all future offers. We all the parameters to differ according to legal status with functional forms

$$b_0(X_i) = \begin{cases} \exp\left(\kappa_0 + \kappa_1 \cdot college + \kappa_2 \cdot cog_{hi} \cdot young + \kappa_3 \cdot cog_{hi} \cdot (1 - young_i) + \kappa_4 \cdot cog_{hi} \cdot GDP_{hi} + \kappa_5 \cdot english_i + \right. \\ \exp\left(\lambda_0 + \lambda_1 \cdot college + \lambda_2 \cdot cog_{hi} \cdot young_i + \lambda_3 \cdot cog_{hi} \cdot (1 - young_i) + \lambda_4 \cdot cog_{hi} \cdot GDP_h + \lambda_5 \cdot english_i + \right. \end{cases}$$

$$b(X_i) = \begin{cases} \exp\left(\mu_0 + \mu_1 \cdot college + \mu_2 \cdot cog_{hi} \cdot young_i + \mu_3 \cdot cog_{hi} \cdot (1 - young_i) + \mu_4 \cdot cog_{hi} \cdot GDP_{hi} + \mu_5 \cdot english_i + \right. \\ \exp\left(\nu_0 + \nu_1 \cdot college + \nu_2 \cdot cog_{hi} \cdot young_i + \nu_3 \cdot cog_{hi} \cdot (1 - young_i) + \nu_4 \cdot cog_{hi} \cdot GDP_{hi} + \nu_5 \cdot english_i + \right. \end{cases}$$

We allow the parameters to vary based on whether or not a person is a legal immigrant at time t. The distribution of job offers also depends on education, tasks of home job, and whether or not a person has an employer sponsored visa (when a legal immigrant).

5.2 The Occupation Transition Process: SMLE Estimation

To derive the likelihood, it is easiest to begin by writing the likelihood of the occupational history assuming we observed all jobs. We then deal with the missing data by integrating out the data we don't observe using Simulated Maximum Likelihood. Assume for one individual (suppressing i notation) we see their occupation in each period. Denoting the whole path of occupation for a worker from time 1 (labor market entry in the US) to T (time of the survey), we have one observation per year of the occupation:

$$L(\pi_0, \pi_1, ..., \pi_T) = l_0(\pi_0)\, l_1(\pi_1|\pi_0)\, l_2(\pi_2|\pi_1, \pi_0) \ldots l_T(\pi_T|\pi_{T-1}, \pi_{T-2}, \ldots \pi_0)$$

where l_t is the conditional density of observing a worker in occupation π_t as a function of this history. The model implies that the only thing about the past a worker considers when choosing is the job they chose in the previous period, so we can decompose the likelihood into a Markov chain. The model also implies that the conditional likelihoods are the same over time since there are no time-varying parameters in the offer distribution or job offer and loss rates. These two facts mean we can write the likelihood as

$$L(\pi_0, \pi_1, ..., \pi_T) = l_0(\pi_0)\, l(\pi_1|\pi_0)\, l(\pi_2|\pi_1) \ldots l(\pi_T|\pi_{T-1})$$

for some l_0 and l.

We treat unemployment as its own "job" with some arbitrary value of g not in the interior of the job offer distribution. For purposes of this section, normalize the support of the job offer distribution to $[0,1]$ and assume $g_t = -1$ if the worker is unemployed. This simply allows us to unify the notation of employed and unemployed states.

The first component of the likelihood is the initial job offer. We assume each worker gets a job offer in the first period, the likelihood is just the density of the time 0 offer pdf at the observed occupation:

$$l_0(\pi_0) = f_{\pi_0}(\pi_0|X_{i0}).$$

The later conditional likelihoods come from the model. For example, consider a worker who is working in occupation π_t after being unemployed at the end of period $t-1$. The only way for this to happen in the model is for the worker to get a job offer and the offer to be at π_t. This likelihood is then

$$l\left(\pi_t|\text{Unemployed}_{t-1}, X_{it}\right) = p(X_{it})\, f_\pi(\pi_t|X_{it}).$$

The model breaks down $f(\pi_t|\pi_{t-1})$ into five different cases.

The first two deal with transitions into unemployment:

1. Unemployed at time t when employed the previous period. In this case, the worker must have gotten fired with probability q and not gotten an offer with probability $(1-p(X_{it}))$, so the likelihood is
$$l(\pi_t = -1|\pi_{t-1} \neq -1, X_{it}) = q \cdot (1 - p(X_{it})).$$

2. Unemployed both at the end of last period and the end of this one. The worker must have not received an offer in period t, so the likelihood is

$$l\left(\pi_t = -1 | \pi_{t-1} = -1, X_{it}\right) = 1 - p\left(X_{it}\right).$$

The other three deal with the mobility of employed workers:

3. Moves to a higher productivity firm, or moves to a firm from unemployment. The worker must have got an offer at the productivity level π_t, so the likelihood is

$$l\left(\pi_t > \pi_{t-1} | \pi_{t-1}, X_{it}\right) = p\left(X_{it}\right) \cdot f_\pi\left(\pi_t | X_{it}\right).$$

4. Moves to a lower productivity firm but not unemployment. The worker must have gotten fired and also receieved an offer at the productivity level π_t, so the likelihood is

$$l\left(\pi_t < \pi_{t-1} | \pi_{t-1}, X_{it}\right) = q \cdot p\left(X_{it}\right) \cdot f_\pi\left(\pi_t | X_{it}\right).$$

5. Remains at the same job as before. The worker must have not gotten fired and then either didn't get an offer or received an offer below π_{t-1}. The likelihood is

$$l\left(\pi_t = \pi_{t-1} | \pi_{t-1} \neq -1, X_{it}\right) = (1-q) \cdot \left(\left[1 - p\left(X_{it}\right)\right] + p\left(X_{it}\right) \cdot F_\pi\left(\pi_{t-1} | X_{it}\right)\right).$$

For each conditional likelihood we can use Maximum Likelihood Estimation to recover the model parameters.

Unfortunately, the data does not contain a full record of occupations each year. Instead, we have π_0, π_T, and the durations (in years) of both jobs, d_0 and d_T respectively. Denote the first period of the final job by $K = T - d_T$. The likelihood of the observed data can be written as

$$\begin{aligned} L\left(\pi_0, \pi_T, d_0, d_T\right) &= f_{\pi_0}\left(\pi_0\right) \cdot f_\pi\left(\pi_t = \pi_0 | \pi_{t-1} = \pi_0\right)^{d_0 - 1} \times \\ &\quad \Pr\left(\pi_{d_0} \neq \pi_{d_0 + 1}\right) \times f_\pi\left(\pi_K | \pi_0, d_0\right) \cdot f_\pi\left(\pi_t = \pi_T | \pi_{t-1} = \pi_T\right)^{d_T - 1}. \end{aligned}$$

This reads as: in the first period the worker received the offer π_0 and kept it for $d_0 - 1$ periods. In the period after that, we know they moved jobs. The individual then receives their offer in period K for their final job and stays there for $d_T - 1$ periods without leaving.

Without the term $f_\pi\left(\pi_K | \pi_0, d_0\right)$, the first period of the final job, this would be straightforward to calculate using the conditional likelihoods from above. However, $f_\pi\left(\pi_K | \pi_0, d_0\right)$ requires calculating the conditional distribution of observing some job π in period K as a function of the initial job π_0 while missing data on job transitions from periods d_0 to K. Direct calculation of this requires evaluating a $K - d_0$ dimensional integral for each individual for each likelihood evaluation. Instead of direct computation we use a simulation-based estimation method.

The Simulated Maximum Likelihood (SMLE) estimator begins by writing down the likelihood as if we observed the entire occupational history and then integrating out the missing data directly. We can transform the full likelihood into the observed likelihood by integrating out over all the missing middle jobs.

$$L\left(\pi_0, \pi_1, ...\pi_{d_0}, \pi_K, \pi_{K+1}, ..., \pi_T\right) = \underset{\pi_{d_0+1},...,\pi_{K-1}}{\int\cdots\int} L\left(\pi_0, \pi_1, ..., \pi_T\right) d\pi_{d_0+1}...d\pi_K =$$

$$l_0\left(\pi_0\right) l\left(\pi_1|\pi_0\right)...l\left(\pi_{d_0}|\pi_{d_0-1}\right) \times$$

$$\underset{\pi_{d_0+1},...,\pi_{K-1}}{\int\cdots\int} l\left(\pi_K|\pi_{K-1}\right) l\left(\pi_{K-1}|\pi_{K-2}\right)...l\left(\pi_{d_0+1}|\pi_{d_0}\right) d\pi_{K-1}...d\pi_{d_0+1} \times$$

$$l\left(\pi_{K+1}|\pi_K\right)...l\left(\pi_T|\pi_{T-1}\right).$$

The SMLE method notes that this integral can be written as $E_{\pi_{K-1},...,\pi_{d_0+1}|\pi_{d_0}}\left[l\left(\pi_K|\pi_{K-1}\right)\right]$, the expected value of the conditional likelihood for period K with the expectation taken over the possible paths that led to π_K. Since our model is cheap to simulate, it is easy to start the model at d_0 with current job π_0 and simulate the job path forward until period K. Doing this S times for each individual's data, we can then calculate the value $l\left(\pi_K|\pi_{K-1}^S\right)$ for each data point π_K combined with simulated job in period $K-1$ π_{K-1}^S. We know that as long as π_{K-1}^S is drawn from the correct conditional distribution, as $S \to \infty$

$$\frac{1}{S}\sum_{i=1}^{S} l\left(\pi_K|\pi_{K-1}^S\right) \to_p E_{\pi_{K-1},...,\pi_{d_0+1}|\pi_{d_0}}\left[l\left(\pi_K|\pi_{K-1}\right)\right].$$

Using this, the SMLE estimator maximizes the calculated likelihood for the data points combined with the simulations used to eliminate the missing data problem.

6 Identification

The primary reason we make our model assumptions is that we can establish non-parametric identification of three parameters of interest: the probability of receiving a job offer, the probability of job loss, and the full job offer distribution. In other words, all of our information about the occupational transition process comes from the data and is not functional-form specific. Of course in estimation we will need to assume some flexible functional forms since the sample is not large enough to make non-parametric estimation feasible. In this section we explain how we recover the job offer process from the data.

The simplest method to understand this is by first showing that the job loss and offer rates are identified. For this section we suppress the observable demographics X_i since these are exogenous and we can repeat the same argument once per value of X. Consider a worker who is at job π_0 in the initial period. We will observe them at the same job next period only if they did not lose their job and if they recieved an offer it was lower than π_0. The probability of this event is

$$\Pr(\pi_1 = \pi_0) = (1-q)(p + (1-p) F_\pi(\pi_0)).$$

Now consider workers who have $\pi_0 = 1$, that is, the workers at the top of the distribution. The probability of them getting an offer lower than 1 is 1, so $F_\pi(1) = 1$ and this reduces to

$$\Pr(\pi_1 = \pi_0 | \pi_0 = 1) = 1 - q.$$

This directly identifies q, the probability of job loss. Intutitively, we have data about how long it takes a worker to switch jobs, as well as a ranking of jobs. If we look at individuals only in the highest type of jobs, the only model mechanism for leaving this job is job loss since they will rarely get a better offer to make a job-to-job move.

Once we have identified the probability of job loss q, we can use a similar argument to recover the probability of a job offer p. Consider workers who have $\pi_0 = 0$, that is, the workers at the bottom of the job distribution. Since we know the probability of an offer above 0 is 1, $F_\pi(0) = 0$ and the probability of job staying becomes

$$\Pr(\pi_1 = \pi_0 | \pi_0 = 0) = (1-q) \cdot p.$$

Since we already know q, this probability gives us p. As above, if we look at individuals only in the worst type of jobs who did not lose their jobs, the only model mechanism for moving up is receiving an outside offer so we know all upwards moves come with an offer and every time they stay in their job there was not an offer.

Lastly, once we know q and p,

$$F_\pi(\pi_0) = \frac{\Pr(\pi_1 = \pi_0)}{(1-q)(1-p)} - \frac{p}{1-p},$$

and we can look at individuals with different π_0 to trace out the whole distribution of F_π since the right hand side is data and known parameters. Effectively once we know the probabilities of losing a job and getting a job offer, there is a one-to-one mapping between your old job and the probability of getting an offer below your old job.

For this identification argument we only required a limited part of the data: the type of the first job and one observation in period 1 of whether the individual remained in that job or not. The duration of the first job, the type of the final job, and the duration of the final job are all not strictly required for identification but increase the power of our estimators.

7 Results

7.1 Wages

The wage parameters are estimated using OLS and are in Tables 2 and 4, for wage levels and growth, respectively. Since the model delivers the OLS regressions discussed above in the Descriptive Statistics section as the true wage process conditional on occupations, the discussion there suffices. The occupation offer process is where the primary contribution of the model comes in.

7.2 Occupations

The parameters of the job offer rate are shown in Table 8. There are three sets of parameters: the probability of getting an offer in each period and the distribution that the offer is drawn from for the initial job offer and for all subsequent offers.

The results for the probability of recieving a job offer indicate that workers are more likely to recieve an offer if they are college educated, were in a higher cognitive task occupation in their home country, or have strong english skills. As home country GDP increases, the effect of home occupation becomes smaller. It's not clear why this is; one potential story is that those who come from more developed countries are more likely to be attached to a particular firm or occupation even conditioning on visa status. This would make them less likely to search for new jobs and therefore would be less likely to get a job offer each period. We also estimate a per-period job loss rate and find that each person loses their job with 7% probability each period. This can explain the fact that some people move to lower skill jobs with time in the US. This reflects them losing their job and then having to search for a new one

We estimate one of the parameters of the Kumaraswamy distribution for job offers. For reference, the median of this distribution as a function of the estimated individual index b_{it} is given by

$$\text{Med}\left(\text{offer}|b_{it}\right) = \sqrt{1-\left(\frac{1}{2}\right)^{\frac{1}{b_{it}}}},$$

so an increase in the index b_{it} will lead to a lower median offer. In this context, a higher parameter value means a lower likelihood of drawing a high task job.

We estimate a separate set of parameters for the initial and then all future jobs in the US. The reason for this is that for some people, the initial job search could be done while in their home country, while searches for all future jobs will be done while in the US. This allows for factors such as an employer sponsored to have differential effects, expecting it to be strongest for the first job. We estimate a separate set of parameters for legal and illegal job offers, expecting that legal status strongly effects the job offers that people draw. For example, the effects of education should be weaker for illegal immigrants since higher skill jobs will not be likely to hire people without work visas. The results show that people with more education get higher occupational draws, except for the case of illegal immigrants in their initial job in the US, where the parameter is not statistically significant. The same is true for English skills. Legal immigrants with higher skill home occupations draw higher skill occupations in the US. We split this parameter by the age that a person moves to the the US, expecting home occupation to play a smaller role for people who move at younger ages. For example, a person who moves at age 18 likely only worked in a part time job at home, whereas a person who moves at age 30 had settled in a career at home at the time of the move. For legal immigrants, home occupation increases jobs for people who move at all ages. For illegal immigrants, the effect is only statistically significant for migrants who move at older ages in their current job. We also interact home country occupation with home country GDP, and find that the effects of home country are stronger for people from richer countries. This suggests stronger skill transmission for people moving from developed countries, which could reflect more similar occupations between countries or a stronger signal when a person moves from a developed countries. Having an employer-sponsored visa shifts the distribution to the right. We control for the share of immigrants in the location that a migrant lives in. This actually decreases the job levels for legal immigrants in their current US occupation.

7.3 Model Fit

We test the fit of the model in terms of predicting the life cycle average level of cognitive occupational tasks from simulations of the model versus the data. Figure 3 shows the average task level of each person's occupation, splitting the sample by years of experience in the US. This shows that the model is fitting the occupations fairly well. Since the wage section of the model is estimated by OLS, those tables summarize the model fit there. More detailed analyses of model fit are work in progress.

7.4 Effects of different characteristics

To better understand the magnitude of these parameters, we fix each individual's characteristics and simulate their jobs with time in the US. To do this, we first simulate the average job path for a person with a low level of education, no employee sponsored visa, with low English skills, moves at an older age, and has all work experience in the US as a legal immigrant. For home country GDP, home country occupation, and immigrant share at US location, we assume this person is at the 25th percentile values. We vary these factors one at a time, and show the results in Figure 4. In panel (a), we assume the person has high education and an employer-sponsored US visa. Both increase the initial offer, but the employer sponsored has a larger efffect. Education increases the growth rate of jobs with time in the US. In panel (b), we assume that home country GDP and immigrant share in the US destination jump to the 75th percentile. Both of these increase the initial job by about the same amount, and they seem to have similar growth rates to the baseline case. In panel (c), we assume home country occupation is at the 75th percentile, and that this person has strong English skills. These both increase the initial offer, and English skills also seems to increase the growth rate. In panel (d), we assume that the person works as an illegal immigrant for his time in the US, and that he moves when young.

We also can use the model to study the effects of a person's initial job draw in the US. In Figure 5, we again simulate the job path for an individual with this fixed set of characteristics. Instead of allowing the initial job draw to be endogenous, we set the first job at the 25th and 75th percentile of initial jobs observed in the data. We then simulate job draws over a period of time. We see that the jobs converge towards a similar point. The person with a low initial draw steadily moves up the occupational ladder. The job outcomes for the person with the high initial draw actually decrease over time. This is due to the fact that he can lose his job, and when that happens, he draws a new job, which on average is lower than the initial draw.

7.5 Costs of search

We can use the estimated model to understand the contribution of returns to experience and occupational transitions to the wage growth of immigrants. In the baseline case, we simulate the wage and occupation path of immigrants over their lifetime. We assume that the age of entry of the US is exogenous (given by the date they move to the US) and that people retire at age 65. We also do not allow for return migration.[13] We compare to native wages to understand how different factors contribute to the wage gap. For data on native wages, we use the CPS and compute the average wages of native workers, conditional on age, years of work experience, and education. We then can impute the "native" wage for each immigrant with a given number of years of work experience

[13] We will be able to account for return migration in future work once the second round of the NIS is released.

and education level. Table 10 shows the wage regression results we use to impute these wages.

In a first exercise, we simulate each person's occupation with time in the US as the baseline case. In the counterfactual, we assume that they are at their "long-run" US occupation, which we define as their average job after 10 periods in the US. Panel (a) of Figure 6 shows the occupation outcomes in each of these cases, averaged over the whole sample. Panel (b) shows average wage outcomes in each case. Wages increase in both scenarios due to returns to experience. In the counterfactual, initial wages are higher due to the higher due to the higher initial occupation draw. Over time, the increase in wages in the baseline is due to job growth and returns to experience, whereas the increase in wages in the counterfactual is due only to returns to experience. We see that for the whole sample, the slopes are quite similar, meaning that most job growth is coming from returns to experience.

We next use this counterfactual to compare these wage outcomes to comparable natives, using the imputed wages (assuming immigrants had been in the US for their whole career) from the CPS data. Table 11 compares immigrant and native wages in the baseline and counterfactual. As the figure showed, the counterfactual has a larger increase in wages in earlier years, as with time individuals move closer to the long run occupation. In the year of entry into the US labor market, the wage gap between immigrants and comparable natives shrinks from \$7.86 to \$7.31 in the counterfactual, a 7% reduction. This shows that at least in early years after entry, search frictions are playing a role in the native-immigrant wage gap.

7.6 Skill specific visa policies

Another possible decomposition is to look at the effects of demographic composition on the wage gap at both entry and over time. In many countries visa applicants are admitted according to a points system based on "desirable" demographic characteristics. While the US does not have this system, by simply looking at average wages across demographic groups we could evaluate the effects of policies like these on the US wage gap.

We split the sample based on education and english skills, to detemine what would happen to the wage gap if the US visa system selected based on skills. First we look at the wage gap if the US excluded immigrants who did not have any schooling above high school in their home country. We also look at a policy that only includes competent English speakers.The first panel of Figure 7shows the occupational outcomes for these 2 populations, compared to the whole sample. Unsurprisingly, they are in higher occupations due to these higher skills. The group with English skills has higher occupational skills than the college educated group, but this is likely because most of this group also has a college education. The second panel of this figure shows the corresponding trends for wages.

Tables 12 and 13 report the results of these two possible changes in admissions policies. In each case, we show the immigrant wages and the wages of comparable natives a given number of years after entry into the US labor market. Since we are comparating to observationally similar natives, the average wages for natives also go up compared to the baseline simulations, given that these are more skilled groups. However, we see that the native-immigrant wage gap is smaller for these groups. This suggests that allowing a higher skilled immigrant population not only leads to higher immigrant wages, but also a smaller gap between immigrants and natives.

7.7 Cost of labor market experience as an illegal immigrant

The NIS sample consists of individuals who were recently granted green card status. However, much of the sample lives and works in the US as an illegal immigrant prior to receiving a visa. Anecdotal evidence suggests that many of these people move expecting to be granted a visa (typically due to family reunification policies) in the near future. We calculate the wage loss for these individuals due to these years as an illegal immigrant. To do this, in a counterfactual we assume that all US experience is in the legal labor market. Figure **??** shows the occupation and wage outcomes in this case compared to the baseline (which in this case only consists of people who initially had some experience as an illegal immigrant). Table **??** reports the average wages for a different numbers of years after US entry. The costs of illegal labor market experience diminish with time, which is partially due to the fact that part of the sample is granted legal status within the time frame. In future work this counterfactual can be used to calculate the willingness to pay for a quicker visa for this population.

8 Conclusion

In this paper, we study the determinants of the wage path of immigrants, focusing on the returns to experience in the US and search frictions when finding optimal occupations, in order to understand how these factors affect the wage gap between natives and immigrants. Labor market experience in the US may be more valuable for jobs in the US than labor market experience in other countries. In addition, it can take time for new immigrants to be matched with their optimal occupation after moving to the US. Data from the New Immigrant Survey shows that both search frictions and work experience affect immigrant wages. We develop and estimate a simple model of on-the-job human capital accumulation and job search that can allow us to decompose these effects, as well as look at the effects of demographic composition. We then use the model to simulate counterfactuals where the job offer process can change.

The second round of the NIS has been completed and the data is currently being prepared. This additional data will give us more job observations for each respondent. It will also inform us to which people returned to their home countries. We can match this to their wage observations in the US to control for selective return migration.

References

Borjas, G. J. (1985). Assimilation, changes in cohort quality, and the earnings of immigrants. *Journal of Labor Economics*, 3 (4):463–489.

Chiswick, B. (1978). The effect of americanization on the earnings of foreign-born men. *Journal of Political Economy*, 86:897–921.

de Matos, A. D. (2011). The careers of immigrants. *Working Paper*.

Duleep, H. O. and Dowhan, D. J. (2002). Insights from longitudinal data on the earnings growth of u.s. foreign-born men. *Demography*, 39(3):485–506.

Eckstein, Z. and Weiss, Y. (2004). On the wage growth of immigrants: Israel, 1990-2000. *Journal of the European Economic Association*, 2(4):665–695.

Gathmann, C. and Schonberg, U. (2010). How general is human capital? a task-based approach. *Journal of Labor Economics*, 28(1).

LaLonde, R. J. and Topel, R. H. (1992). Assimilation of immigrants in the u.s. labor market. In Borjas, G. J. and Freeman, R. B., editors, *Immigration and the Work Force*. The University of Chicago Press.

Lubotsky, D. (2007). Chutes or ladders? a longitudinal analysis of immigrant earnings. *Journal of Political Economy*, 115(5):820–867.

Poletaev, M. and Robinson, C. (2008). Human capital specificity: Evidence from the dictionary of occupational titles and displaced worker surveys, 1984-2000. *Journal of Labor Economics*, 26(3):387–420.

Sanders, C. and Taber, C. (2012). Life-cycle wage growth and heterogeneous human capital. *Annual Review of Economics*, 4:399–425.

Weiss, Y., Sauer, R. M., and Gotlibovski, M. (2003). Immigration, search, and the loss of skill. *Journal of Labor Economics*, 21(3):557–591.

9 Tables and Figures

Table 1: Summary Statistics

Variable	Mean
Age	38.1
Percent male	55.3%
Years living legally in the US	4.5
Years living illegally in the US	2.2
Percent with non-zero illegal experience	19.1%
Fraction that have an employer sponsor	27.8%
More than high school	60.1%
High English skills	32.3%
Sample Size	3,575

Table 2: Wages in the US

	(1) Initial Wages	(2) Current Wages
Cognitive skills at home (moved before age 18)	0.150	0.263*
	(0.168)	(0.135)
Cognitive skills at home (moved after age 18)	0.156	0.227**
	(0.113)	(0.0969)
Manual skills at home (moved before age 18)	-0.486**	-0.298**
	(0.196)	(0.145)
Manual skills at home (moved after age 18)	-0.273***	-0.171**
	(0.102)	(0.0864)
Home cognitive skills * home GDP	0.00372	-0.00297
	(0.00830)	(0.00720)
Home manual skills * home GDP	0.0147*	0.0162**
	(0.00802)	(0.00682)
Cognitive skills of job	1.163***	1.067***
	(0.0787)	(0.0648)
Manual skills of job	-0.141**	-0.162***
	(0.0687)	(0.0579)
Years of legal work experience		0.121***
		(0.0134)
Years of illegal work experience		0.0456***
		(0.0166)
Home GDP	-0.00430	-0.00196
	(0.00583)	(0.00509)
Legal US experience * home GDP		-0.00134*
		(0.000719)
Employer sponsored visa	0.345***	0.407***
	(0.0257)	(0.0217)
Legal immigrant	0.344***	-0.127***
	(0.0348)	(0.0301)
Share of immigrations at location	-0.381***	-0.123
	(0.135)	(0.114)
Observations	2895	2870
Adjusted R^2	0.376	0.501

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Education, English skills, gender, home country work experience (and its square), and square terms for legal and illegal US work experience are included in the regression but not reported.

Table 3: Wages (droppping manual tasks)

	(1) Initial Wages	(2) Current Wages
Cognitive skills at home (moved before age 18)	0.122	0.230**
	(0.137)	(0.112)
Cognitive skills at home (moved after age 18)	0.236**	0.266***
	(0.112)	(0.0955)
Home cognitive skills * home GDP	0.000592	-0.00497
	(0.00824)	(0.00714)
Cognitive skills of job	1.214***	1.136***
	(0.0734)	(0.0595)
Years of legal work experience		0.125***
		(0.0134)
Years of illegal work experience		0.0456***
		(0.0166)
Home GDP	0.00281	0.00539
	(0.00461)	(0.00404)
Legal US experience * home GDP		-0.00146**
		(0.000720)
Employer sponsored visa	0.347***	0.406***
	(0.0256)	(0.0217)
Legal immigrant	0.350***	-0.121***
	(0.0349)	(0.0299)
Share of immigrations at location	-0.392***	-0.122
	(0.136)	(0.114)
Observations	2895	2870
Adjusted R^2	0.373	0.499

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Education, English skills, gender, home country work experience (and its square), and square terms for legal and illegal US work experience are included in the regression but not reported.

Table 4: Wage growth

	(1)	(2)
Cognitive task growth	0.339***	0.373***
	(0.101)	(0.0933)
Manual task growth	-0.0766	
	(0.0862)	
Cognitive skills at home (moved before age 18)	0.0186	0.0670
	(0.168)	(0.138)
Cognitive skills at home (moved after age 18)	-0.0253	-0.0626
	(0.116)	(0.113)
Manual skills at home (moved before age 18)	0.259	
	(0.197)	
Manual skills at home (moved after age 18)	0.104	
	(0.103)	
Home cognitive skills * home GDP	-0.00519	-0.00545
	(0.00849)	(0.00843)
Home manual skills * home GDP	0.00642	
	(0.00798)	
Cognitive tasks of initial US job	0.0726	0.114
	(0.0901)	(0.0829)
Manual tasks of initial US job	-0.0929	
	(0.0793)	
Years of illegal work experience	0.253***	0.253***
	(0.0171)	(0.0171)
Years of legal work experience	0.171***	0.171***
	(0.0165)	(0.0164)
Legal US experience * home GDP	-0.00195**	-0.00193**
	(0.000829)	(0.000828)
Becomes legal	0.187	0.172
	(0.223)	(0.223)
Increase in immigrant share at location	-5.013***	-5.037***
	(1.561)	(1.561)
Observations	2197	2197

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls for home experience, employer sponsored visa, English skills, education, and square terms for illegal and legal work experience included but not reported.

Table 5: Determinants of Tasks of Jobs in the US

	(1)	(2)	(3)
	Initial job	Current job	
Cognitive skills at home (moved before age 18)	0.146***	0.136***	0.0307
	(0.0356)	(0.0275)	(0.0250)
Cognitive skills at home (moved after age 18)	0.128***	0.155***	0.0217
	(0.0249)	(0.0197)	(0.0177)
Home cognitive skills * home GDP	0.00291***	0.00224***	0.000714
	(0.000741)	(0.000652)	(0.000558)
Cognitive tasks of initial US job			0.645***
			(0.0173)
Years of legal work experience		0.0112***	0.00903***
		(0.00348)	(0.00284)
Years of illegal work experience		0.00924*	0.00694
		(0.00523)	(0.00476)
Legal immigrant	-0.0180	0.00903	0.000584
	(0.0112)	(0.00941)	(0.0100)
Share of immigrations at location	-0.00344	0.00266	-0.0175
	(0.0424)	(0.0360)	(0.0317)
Employer sponsored visa	0.108***	0.0897***	0.0311***
	(0.00774)	(0.00660)	(0.00590)
Education requirements of home job	0.00541***		
	(0.00136)		
Observations	1799	2870	2306
Adjusted R^2	0.308	0.263	0.544

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls for education, English skills, home experience, and the square term for illegal and legal work experience are included but not reported.

Table 6: Task growth

	(1) Cognitive task growth
Cognitive skills at home (moved before age 18)	0.0212
	(0.0255)
Cognitive skills at home (moved after age 18)	0.0147
	(0.0177)
Home cognitive skills * home GDP	0.000683
	(0.000560)
Cognitive tasks of initial US job	-0.345***
	(0.0175)
Years of legal work experience	0.00944***
	(0.00305)
Years of illegal work experience	0.00634
	(0.00392)
Becomes legal	0.0514
	(0.0509)
Observations	2197
Adjusted R^2	0.163

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls for education, English skills, employer sponsored visa, home work experience, and square terms for US work experience included but not reported.

Table 7: Job loss

	(1)
Cognitive tasks of initial US job	1.525***
	(0.186)
Cognitive tasks of home job	0.0449
	(0.181)
Years of legal work experience	0.283***
	(0.0280)
Legal years US squared	-0.0183***
	(0.00288)
Years of illegal work experience	0.177***
	(0.0303)
Illegal years squared	-0.00909***
	(0.00230)
Employer sponsored visa	-0.376***
	(0.0658)
Male	-0.0464
	(0.0519)
Years experience at home	0.0143*
	(0.00790)
Home experience squared	-0.000197
	(0.000226)
More than 12 years education	-0.203***
	(0.0646)
English skills	-0.155**
	(0.0626)
Constant	-1.422***
	(0.119)
Observations	3011
Adjusted R^2	

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Transition parameter estimates

Job offer probabilities		Job offer distribution		
			Initial job	Current job
Constant term	-0.55	Constant term	2.32	2.27
	(0.03)		(0.35)	(0.06)
College	0.39	Legal immigrants	0.23	0.08
	(0.03)		(0.26)	(0.07)
Home occupation	0.20	Education (illegal)	-0.25	-0.21
	(0.04)		(0.21)	(0.09)
Home occupation * gdp	-0.017	Education (legal)	-0.28	-0.27
	(0.003)		(0.06)	(0.03)
Sponsor	0.036	Home occupation (illegal, young)	-0.22	0.31
	(0.038)		(0.72)	(0.18)
Legal	-0.018	Home occupation(illegal)	0.40	-0.34
	(0.028)		(0.51)	(0.15)
English	0.25	Home occupation (legal,young)	-1.00	-0.25
	(0.03)		(0.27)	(0.06)
Probability of job loss	0.07	Home occupation (legal)	-1.15	-0.29
	(0.003)		(0.15)	(0.03)
		Home occupation*gdp (illegal)	-0.03	-0.046
			(0.02)	(0.010)
		Home occupation*gdp(legal)	-0.01	-0.030
			(0.005)	(0.002)
		Sponsor (legal)	-0.46	-0.24
			(0.06)	(0.02)
		English (illegal)	0.03	-0.22
			(0.21)	(0.09)
		English (legal)	-0.20	-0.20
			(0.05)	(0.03)
		Immigrant share (illegal)	-0.76	0.18
			(1.01)	(0.19)
		Immigrant share (legal)	-0.54	0.81
			(0.31)	(0.05)

Table 9: Wage parameter estimates

	(1)
Cognitive tasks of job	0.994***
	(0.0565)
Educational requirements of job	0.0681***
	(0.00434)
English requirements of job	-0.0816***
	(0.0188)
Foreign language requirements of job	0.0555**
	(0.0222)
Cognitive tasks of home job	0.335***
	(0.0903)
Home cognitive skills * home GDP	-0.0119*
	(0.00683)
Years of illegal work experience	0.0546***
	(0.00862)
Illegal years squared	-0.00130***
	(0.000473)
Years of legal work experience	0.0616***
	(0.00835)
Legal years US squared	-0.00277***
	(0.000516)
Employer sponsored visa	0.354***
	(0.0198)
Legal US experience * home GDP	-0.000228
	(0.000473)
Home GDP	0.00803**
	(0.00388)
Legal immigrant	0.0618***
	(0.0180)
Observations	3821

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls for home experience, education, and english skills included but not reported

Table 10: CPS Wage Regressions

Dependent variable = wage	
Education	7.14
	(0.08)
Years experience	0.70
	(0.01)
Experience squared	-0.012
	(0.0003)
Constant	6.13
	(0.12)
Number of observations	70,572
R-squared	0.14

Table 11: Counterfactual: originally placed in long run occupation

Years	Average wages	Counterfactual wages	Percent increase	Native wages
0	10.86	11.41	5.1%	18.72
3	14.32	14.65	2.3%	19.66
5	15.62	15.81	1.2%	20.19
8	17.86	17.91	0.28%	20.83

Table 12: Counterfactual: Admit those with college education

Years after entry	Immigrant wages	Native wages	Wage gap	Wage gap for full sample
0	12.41	20.80	67.61%	72.38%
3	17.18	21.89	27.42%	37.29%
5	18.84	22.52	19.53%	29.26%
8	21.62	23.30	7.77%	16.63%

Table 13: Counterfactual: Admit based on English skills

Years after entry	Immigrant wages	Native wages	Wage gap	Wage gap for full sample
0	13.84	19.75	42.70%	72.38%
3	19.98	20.86	4.40%	37.29%
5	21.95	21.51	-2.00%	29.26%
8	25.30	22.32	-11.78%	16.63%

Figure 1: Home Country Occupations

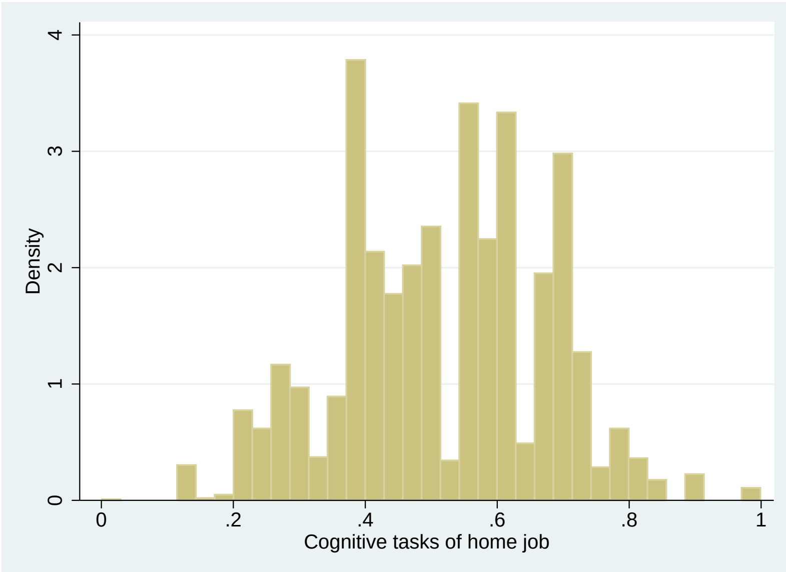
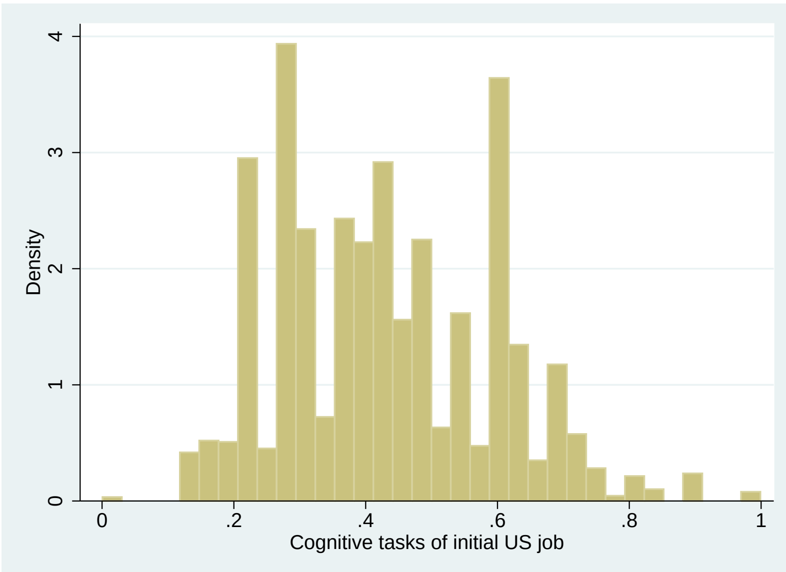


Figure 2: Occupations in the US

(a) Initial job



(b) Current job

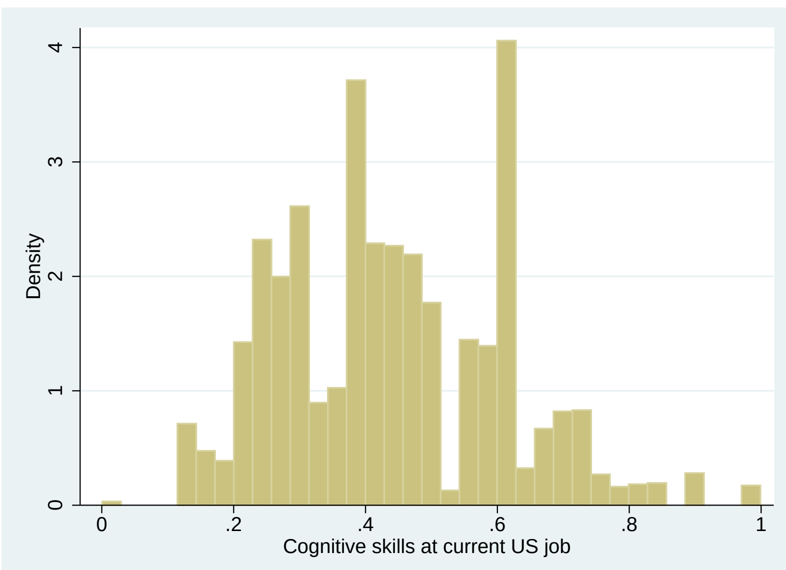


Figure 3: Model fit: occupations

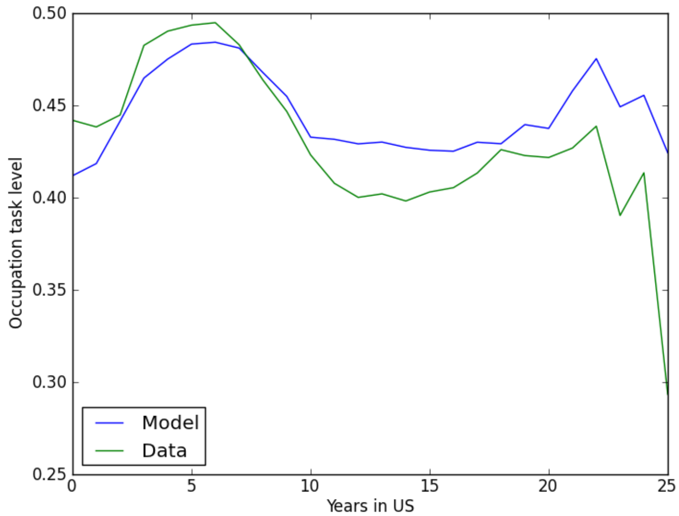
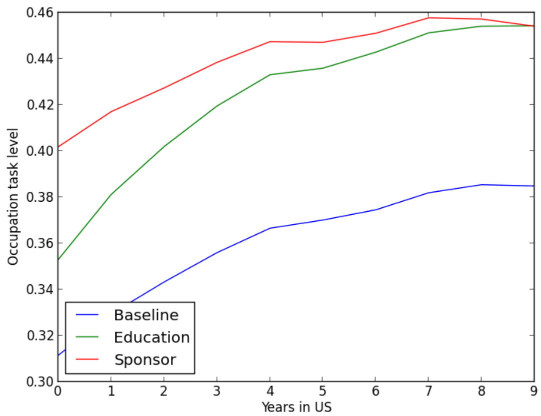
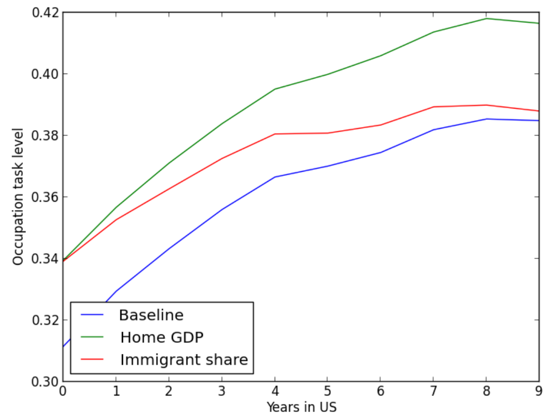


Figure 4: Effects of characteristics on jobs

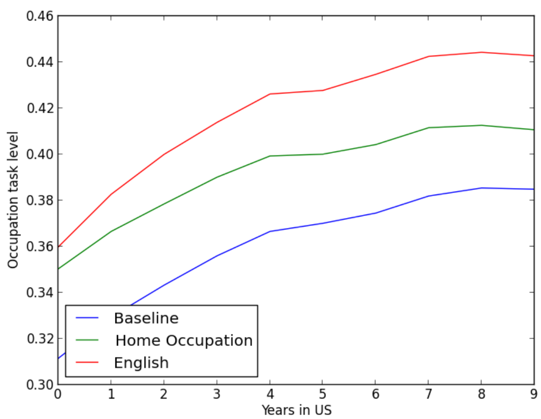
(a) Education and employer sponsored visa



(b) Home country GDP and immigrant share in US location



(c) Home country occupation and English skills



(d) Illegal immigrant in US and age of move

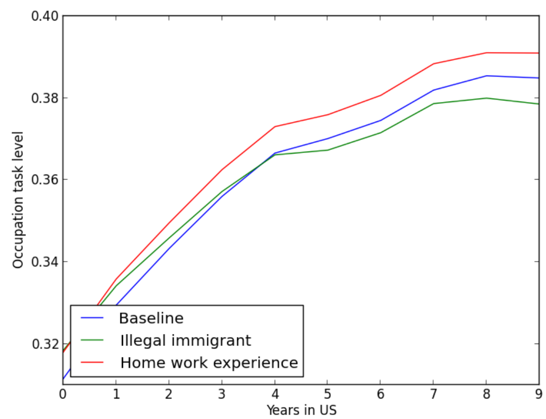


Figure 5: Effect of initial job

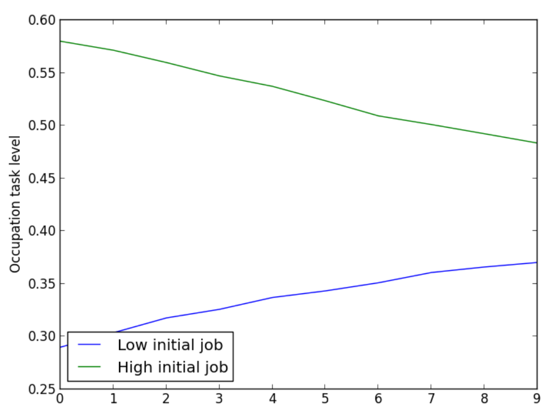


Figure 6: Costs of search

(a) Occupations

(b) Wages

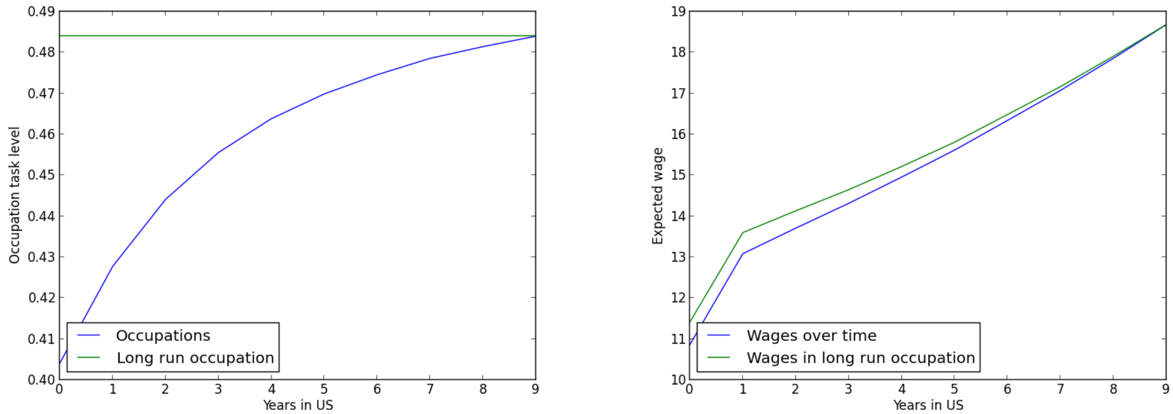


Figure 7: Decomposition based on skills

(a) Occupations

(b) Wages