

Decomposing the Native-Immigrant Wage Gap in the United States

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Abstract

Immigrants in the US earn less than similar native workers. In order to understand the mechanisms of this wage gap, we quantitatively decompose it into two components. First, the value of labor market experience and the wage returns to education 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. We use panel data from the New Immigrant Survey which contains information on jobs in the US as well as in the immigrant's home country. Our identification of these forces depends crucially on knowing the home country occupation: we observe that immigrants who come from similar occupations have different career paths depending on their initial occupation in the US. Our empirical strategy consists of two parts. First, we summarize the effects of initial occupations in the US on immigrant career paths (both wage and occupational growth) conditional on home occupation and demographic characteristics. We interpret these results as providing evidence that both returns to experience and job search drive immigrant wage growth. Second, we create a simple model of on-the-job human capital accumulation and job search that can be used to look at counterfactual wage and occupation distributions to isolate each force.

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1 Introduction

Immigrants to the United States earn lower wages than natives, even 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. We focus on two potential explanations. First, labor market experience in the US may be more valuable for jobs there 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. Our data set (described below) supports this hypothesis of upward job mobility. Around 50% of the sample worked in high skill occupations at home, yet when they move to the US only 30% work in high skill occupations initially. Over time, people transition into higher skill occupations. At the time of the survey, 40% of the sample worked in a skilled job.²

We quantify these factors using the New Immigrant Survey (NIS), a data set with information on immigrant careers. 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 survey also asks for information on visa status, past legal and illegal work experience, and other worker demographics such as education and English skills.

In the first part of the paper, we analyze the observed career paths of immigrants to 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. Our primary innovation here is

¹See Chiswick (1978); Borjas (1985); LaLonde and Topel (1992).

²Occupations are reported using the US Census 2010 classifications. Skilled occupations are business, academic, scientific, educational, legal, health care, or protective service jobs. Unskilled jobs are services, sales, office workers, farmers, construction, repair, production, or food preparation jobs.

using the NIS's information on home country occupation and detailed demographic characteristics such as visa sponsor and language skills, which allows us to study the mechanisms behind this wage gap. 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. Data from both cross-sectional and longitudinal studies have documented this gap; see Chiswick (1978), Borjas (1985), and LaLonde and Topel (1992) for cross-sectional evidence from the US Census and Duleep and Dowhan (2002) and Lubotsky (2007)³ for longitudinal evidence from Social Security Administration records. These studies tend to 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 extremely difficult.

Using the NIS data on immigrant careers both at home and in the US, we use a simple identification strategy of comparing 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, 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 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 that allows him to possibly switch occupations. As workers spend more time in the labor market, they have a higher probability of moving up the occupation ladder and having their wages increase. At the same time, they exogenously accumulate general human capital. We can characterize worker wage and occupation growth in two parts: first, a stochastic job offer process that moves them up the occupational ladder, and then conditional on occupations their wages are given by a Mincer wage equation. We allow both 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

³Lubotsky 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.

wage growth and occupational transitions in the US.

Once we have estimated the parameters of this model, we decompose the immigrant-native wage gap. We first split the sample based on education and English proficiency to see the effects of implementing visa policies similar to other countries (such as Canada) that allocate visas according to skills. In the next decomposition, we simulate the model while not allowing any job growth after finding an initial job in the US. In this case the only wage growth is due to returns to work experience.

In a counterfactual, we simulate wage outcomes assuming that all immigrants are always in the US legally. In the data, illegal immigrants earn lower wages, and draw drops from a lower job offer distribution. 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 relatively small effects.

Our main contribution to the literature on immigrant wage growth is to provide the first estimates of the relative importance of the underlying mechanisms for the native-immigrant wage gap. There is little work that estimates the mechanisms behind immigrant wage growth, and none that uses representative US data. The closest work to ours are Eckstein and Weiss (2004) and Weiss et al. (2003) who look at a similar question using a data set of highly-skilled Russian immigrants to Israel. While there are differences in the details of our implementations as well, these papers look at a one time shock of very specialized group of immigrants into a labor market very different than the United States. There has also been some work done for other countries; for example de Matos (2011) looks at immigrant wage assimilation in Portugal using linked employer-employee data. In contrast to these studies, our estimates are generated from a representative sample of green card recipients to the US, so we have the ability to both look at differential effects by quality of immigrants and to generalize our results to the full US labor market.

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. When individuals who have applied for permanent residency in the US are granted Legal Permanent Resident (LPR), colloquially known as “Green Card”, status, the NIS surveyed recipients about their labor market history in their home

country, migration history, household demographics, language skills, and many other characteristics. 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 reports job information at home, as well as occupation and wage outcomes for the first and current job in the US.⁴

The benefits of this data are the pre-immigration labor market information and detailed demographic characteristics. Our primary focus will be on the effects of pre-immigration characteristics on the career paths of immigrants in the US. It does not contain data 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.

The NIS data also 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 continuously 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 occupations⁵ 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 occupation. O*NET was created by the US Bureau of Labor Statistics and is a representative survey of the skills workers have and the tasks they perform at the occupation level. This is used to create an index of the manual and cognitive task requirements of each job using Principal Component

⁴A 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.

⁵See Poletaev and Robinson (2008) and Gathmann and Schonberg (2010).

Analysis similar to the procedure used in Poletaev and Robinson (2008).⁶ 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 returns 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 up to higher occupational tasks. On the other hand, 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 the larger task growth. We interpret this as consistent with our story of job search; home cognitive tasks reflects underlying skills, and conditional on those skills those who end up at lower occupations in the US have a higher probability of receiving a better job offer than one who began his career in a higher cognitive task occupation. In addition, of two workers in the same US occupation we expect 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.⁷ The average age in the sample 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. Many immigrants (17%) work as illegal immigrants

⁶Details for the procedure used here are available from the authors on request.

⁷To create the sample we include only individuals working in the US.

for some period of time, and the average person has over 2 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 we expect this group to face a significantly different labor market given these employer visas cannot be used at another employer without getting an entirely new visa granted. Most of the remainder of the sample moved on family reunification visas. Over 60% of the sample has education beyond high school.

3.1 Occupations

We expect that immigrants will move to lower skill jobs in the US than at home because skills are likely not perfectly transferable between countries. We use the task requirements of jobs to measure the skill requirements of each occupation. Table 2 shows the average cognitive and manual tasks of jobs at home and in the US.⁸ We see a substantial decrease in the cognitive tasks of their job after people move to the US, but we do not see a change for manual tasks. Table 3 looks at cognitive tasks, split by the country of origin (developed or developing country). Comparing the 2 samples, we see that, even though people in both groups have the same average job at home, people from developing countries have a larger occupational downgrade when they move to the US. This is consistent with multiple stories of immigrant wages; perhaps immigrants from developed countries have better social and job networks in the US and so take less of a hit on moving, or perhaps the underlying human capital requirements across occupations differ by the quality of the schooling in a country. What is important for us in the model below is that first, the ordering of occupations by cognitive tasks is the same across countries, and second, the size of the wage gap between any two occupations only depends on the per capita GDP of the home country. For example, the cognitive demands of “Doctor” must be greater than “Taxi Driver” in all countries, and in every country with GDP of \$10,000 US per capita the relative wages paid to “Doctors” vs “Taxi Drivers” are the same.

In Table 4, we estimate the determinants of manual and cognitive task requirements of the initial job in the US. 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 (manual) skills in their job at home are in jobs with higher cognitive (manual) task requirements in the US, implying that some skills are transferred from the home country to the US. The effect for cognitive

⁸The task measures are standardized to be between 0 and 1.

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. Those with employer sponsored work visas have jobs with higher cognitive task requirements and lower manual tasks.

Table 5 shows the determinants of manual and cognitive tasks of the job at the time of the survey. Most of the trends 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. 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. Legal work experience increases the task growth of cognitive tasks.

These results show some important empirical findings that we use to motivate the model in this paper. First of all, we see that the home country occupation is an important measure of a person's job opportunities in the US. Conditional on home occupation, people who are initially placed in lower skill jobs will have more task growth. Also, experience in the US leads to higher skill jobs. This suggests that search frictions play a role in the occupational matching of immigrants, as it takes time for people to find the correct job. Occupational transitions can play a large role in the native-immigrant wage gap if it takes time for immigrants to find jobs in their optimal occupations.

3.2 Wages

The previous section showed that immigrants move up the occupational ladder with time in the US. In this section we will 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 depend 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. 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 7 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. For this reason, in the model estimation we focus on cognitive 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.

Table 8 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 occupational growth 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.

4 Model

We use a full-information partial equilibrium labor search model. Each worker has an exogenous fixed characteristic $\theta_i \in \mathbb{R}$ called his or her “ability”. Immigrants have an exogenous time of labor force entry t_i^0 , and prior to that they worked in their home country from the completion of school until they left. Each period is a year and individuals maximize their expected lifetime income. Assume they work from age 20 to age 65 and then exogenously retire.

Let $j \in [0, \delta]$ be the unobserved productivity of a firm, where $\delta > 0$ is a parameter of the model. Since the previous section showed very small returns to manual tasks, we characterize each job according to the cognitive task level.

When worker i and firm j are matched in time t , assume the log wage w_{ijt} the worker receives is

$$w_{ijt} = h_{it} + j + \varepsilon_{ijt}$$

where h_{it} is the human capital of worker i at time t .⁹ Human capital is given by

$$h_{it} = \theta_i + \beta_1 F_{it} + \beta_2 F_{it}^2 + \psi_1 US_{it} + \psi_2 US_{it}^2 + \mu_1 GDP_i + \mu_2 GDP_i \times US_{it} + \gamma X_i \text{ if } t \geq t_i^0$$

where F_{it} is the work experience in the native country at time of immigration to the US and US_{it} is the amount of work experience in the US. We would expect the returns to experience to differ across countries, so that work experience at home and in the US have different effects on wages in the US. We control for GDP of a person's home country and interact home country GDP with US work experience. The term X is fixed observable characteristics that could affect human capital, most importantly education. Individual ability θ_i is unobserved but we make no assumptions on it since it will end up being estimated as a fixed effect in wages.

Above we discussed the characteristics of any given match; however, there are frictions in matching. Every period, a worker receives an offer from an outside firm with probability $p(X_{it})$.¹⁰ If a person receives a new job offer, the index is drawn from a distribution with cdf $G(j'|X_{it})$, which is bounded on the interval $[a, b]$. We allow for the distribution to depend on fixed characteristics, most importantly a person's home occupation. This is important in that it allows for people with higher skill levels to draw from a higher distribution. If a worker receives an offer, he accepts it if it is a higher type than his previous job.¹¹ We assume workers accept whatever offer they receive in the first period, and we also assume that all workers receive jobs in the first period. There is also some probability that a person will lose their job. We assume each worker loses their job at the end of the first period with probability g . This is the only point that a person can lose their job. Without job loss the model could not explain workers who moved down in occupations; in reality this likely reflects matches between workers and firms, compensating differentials, or measurement error.

Wage growth in the model comes through 2 sources:

1. Individuals gain human capital by gaining US labor market experience.
2. Over time, they are more likely to receive an offer from higher type firms.

This setting leads to a large wage gap when immigrants enter the US. This is because they have no work experience in the US at this point. In addition, native workers have been in the US for more periods so they have received more job offers. This also leads the wage gap to narrow over time. First, since returns to experience are concave, immigrants will have faster wage growth than native workers who have been in the US for longer. In addition, as immigrants get closer to their

⁹One way to derive this wage offer function is a model where workers have all the bargaining power and the productivity of a match is given by

$$Y_{ijt} = \exp(h_i + j + \varepsilon_{ijt}).$$

¹⁰We assume that everyone receives a job in their first period in the US.

¹¹We assume that workers pick jobs before observing the ε draws in each period.

optimal occupation, their wage growth will slow as they have fewer opportunities to move up the occupational ladder.

5 Estimation

Estimation of the model is simplified by the fact that conditional on occupation choices, wages are just a standard Mincer regression of wages onto experience, demographics, and occupation. Changes to the returns to experience would not affect the stochastic process of job offers, leading to the same occupation choices and different wage levels. However, without estimating the parameters of the job offer distributions we cannot look at how the unconditional distribution of wages would change if there were changes to the job offer process, since their accepted job offers in this counterfactual would look different than in the observed data. For example, in the counterfactuals below we eliminate the differences between the legal and illegal immigrant labor market. Just changing the parameter on returns to experience would miss the fact that the offer rates differ between those markets and holding constant the observed occupations would not be correct.

Under the assumptions we made above, it is possible to derive closed form solutions for the likelihood of observing any offer after some length in the sample. We allow a separate offer distribution for the initial job offer in the US and job offers afterwards. This allows for factors such as visa status to affect the initial offer and subsequent offers differently, which is important because people with work visas will have their first job before moving to the US. The fact that we don't have yearly data makes the technical side more complicated; we know that we observe the maximum offer out of whatever offers were received, but we cannot observe any offer but the maximum and don't know how many offers were received over that timeframe. However, it is straightforward to integrate out over the possible number of offers, and for each possible number of offers to calculate the order statistic of the observed occupation. The explicit formulas are derived below, but the main economic intuition for our parameter estimates is that for each demographic subgroup we can see the average yearly rate of increase in their occupation types and the number of individuals who never moved; the second fact identifies the per-period offer rates and the first identifies the shape of the offer distribution.

5.1 Parameterization

Write a person's log wage as w_{ijt} , where i indexes individuals, j is a person's occupation at time t . Log wages depend on human capital, the job draw, and a white noise shock:

$$w_{ijt} = h_{it} + j + \varepsilon_{ijt} \tag{1}$$

Human capital h_{it} includes work experience (at home and in the US), education, and cognitive tasks of home job (as a measure of skill level), as well as a dummy for legal status to allow for human capital to have different values in the legal and illegal markets. We split legal and illegal work experience to allow for differing returns:

$$h_{it} = \beta X_i + \psi_1^{leg} US_{it}^{leg} + \psi_1^{leg} (US_{it}^{leg})^2 + \psi_1^{ill} US_{it}^{ill} + \psi_2^{ill} (US_{it}^{ill})^2 + \mu_1 GDP_i + \mu_2 GDP_i * US_{it}^{leg} + \gamma legal_{it}$$

For job offer probabilities, we assume that

$$p(X_{it}) = \begin{cases} p_{leg}(X_{it}) & \text{if } legal_{it} = 1 \\ p_{ill}(X_{it}) & \text{otherwise} \end{cases},$$

where, denoting $\Phi(\cdot)$ as the cdf of the normal distribution,

$$\begin{aligned} p_{leg}(X_{it}) &= \Phi(\alpha_0 + \alpha_1 college_i + \alpha_2 coghi + \alpha_3 sponsor_i + \alpha_4). \\ p_{ill}(X_{it}) &= \Phi(\alpha_0 + \alpha_1 college_i + \alpha_2 coghi) \end{aligned} \quad (2)$$

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. We also allow for an difference in the base job offer probability if a person is a legal immigrant at time t .

If a person gets a job offer,¹² it is characterized by a given occupation level, which we assume are drawn from the Kumarswamy distribution, a computationally simpler variant of the Beta Distribution, which has 2 parameters, a and b . We assume $a = 2$ and estimate $b^k(X_{it})$;, where $k = 1, 2$ for the initial job offer distribution and the distribution of all future offers, with

$$b^k(X_{it}) = \begin{cases} b_{leg}^k(X_{it}) & \text{if } legal_{it} = 1 \\ b_{ill}^k(X_{it}) & \text{if } legal_{it} = 0 \end{cases},$$

where

$$\begin{aligned} b_{leg}^k(X_{it}) &= \exp\left(\omega_{0,leg}^k + \omega_{1,leg}^k college + \omega_{2,leg}^k coghi + \omega_{3,leg}^k sponsor_{it}\right) \\ b_{ill}^k(X_{it}) &= \exp\left(\omega_{0,ill}^k + \omega_{1,ill}^k college + \omega_{2,ill}^k coghi\right). \end{aligned}$$

¹²For convenience we assume that the probability of a job offer is one in the first period of the worker's US career.

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 Likelihood function

Using equation (1), we know that

$$E [w_{ijt} | h_{it}, j]$$

can simply be estimated by OLS to recover consistent estimates of the wage parameters as long as we make the usual orthogonality assumptions on the error term. However, in the counterfactual we are concerned with changes in the unconditional (on occupations) distribution of w_{ijt} when the job offer process changes. To estimate this, it is necessary to estimate the parameters of the job offer model before we run our counterfactuals. The current form of the model can allow for the wage parameters and occupational transition parameters to be separately estimated, so it is these transition parameters we find below.

The first component is the initial job offer. Since each person gets a job offer in the first period, the likelihood is just the density of the offer pdf at the observed occupation:

$$L_1(occ_1) = G(occ_1 | X_{it})$$

To estimate the search part of the model, we need to calculate the likelihood that a person works in a given occupation at the time of the survey. Consider a person has been in the US for t_{leg} legal periods. In that time, they get a job offer with probability $p_{leg}(X_{it})$ in each period. They also have been in the US for t_{ill} illegal periods, and they get a job offer with probability $p_{ill}(X_{it})$ in each of those periods. To calculate the likelihood, we have to consider three cases: a person who switches to a higher occupation, a person who stays in the same occupation, and a person who moves to a lower occupation. First consider the case when a person moved to a higher occupation over time. We first need to calculate the probability that a person gets a given number of job offers. The probability that a person gets m legal offers and n illegal offers is given by the Bernoulli distribution:

$$q_{leg}(m | t_{leg}, X_{it}) \equiv \Pr(m \text{ legal offers} | t_{leg}, X_{it}) = \frac{t_{leg}!}{m!(t_{leg} - m)!} p_{leg}(X_{it})^m (1 - p_{leg}(X_{it}))^{t_{leg} - m}$$

$$q_{ill}(n | t_{ill}, X_{it}) \equiv \Pr(n \text{ illegal offers} | t_{ill}, X_{it}) = \frac{t_{ill}!}{n!(t_{ill} - n)!} p_{ill}(X_{it})^n (1 - p_{ill}(X_{it}))^{t_{ill} - n}.$$

For a person with m legal offers and n illegal offers, the probability that he ends in occupation occ_2 is given by the probability that occ_2 is the maximum job offer that he receives. Denoting $\hat{f}(\cdot)$ as the

distribution of the order statistic, then the likelihood that occ_2 is the maximum offer is given by

$$Z(occ_2|m, n) = (G_{leg}(occ_2|X_{it}))^m \hat{f}_{ill}(occ_2|X_{it}, n) + (G_{ill}(occ_2|X_{it}))^n \hat{f}_{leg}(occ_2|X_{it}, m).$$

The distribution of the order statistic $\hat{f}(\cdot)$ is given by

$$\begin{aligned} \hat{f}_{leg}(occ_2|m, X_{it}) &= mG_{leg}(occ_2|X_{it})^{m-1} g_{leg}(occ_2|X_{it}) \\ \hat{f}_{ill}(occ_2|n, X_{it}) &= nG_{ill}(occ_2|X_{it})^{n-1} g_{ill}(occ_2|X_{it}). \end{aligned}$$

We also need to consider the probability that a person loses their job (happens with probability g). However, in this case, the likelihood is exactly the same, since it is just the probability that his observed job is the maximum of all of his job offers. Then the likelihood for a person who moves to a higher occupation is given by

$$L_2^{m1}(occ_2|X_{it}, t_{leg}, t_{ill}) = \sum_{m=0}^{t_{leg}} \sum_{n=0}^{t_{ill}} q_{leg}(m|t_{leg}, X_{it}) q_{ill}(n|t_{ill}, X_{it}) Z(occ_2|m, n).$$

Now consider the case when a person stays in the same occupation over time. This means that each of his job offers were in an occupation lower than his initial occupation, in the case that he did not lose his job. If he lost his job in the first period, then the likelihood is the probability that the observed job is the maximum of all of his job offers. Then

$$\begin{aligned} L_2^s(occ_1|t_{leg}, t_{ill}) &= (1-g) \sum_{m=0}^{t_{leg}} \sum_{n=0}^{t_{ill}} q_{leg}(m|t_{leg}, X_{it}) q_{ill}(n|t_{ill}, X_{it}) G_{leg}(occ_1|X_{it})^m G_{ill}(occ_1|X_{it})^n \\ &\quad + g \sum_{m=0}^{t_{leg}} \sum_{n=0}^{t_{ill}} q_{leg}(m|t_{leg}, X_{it}) q_{ill}(n|t_{ill}, X_{it}) Z(occ_1|m, n) \end{aligned}$$

The last case is a person who moved to a lower occupation. In this case, he must have lost his job after the first period, and then his observed job is the maximum of job offers that he receives. Then

$$L_2^{m2}(occ_2|X_{it}, t_{leg}, t_{ill}) = g \sum_{m=0}^{t_{leg}} \sum_{n=0}^{t_{ill}} q_{leg}(m|t_{leg}, X_{it}) q_{ill}(n|t_{ill}, X_{it}) Z(occ_2|m, n)$$

Then we can calculate the probability of a person's sequence of occupation draws and wages. We write the log likelihood as

$$\begin{aligned}
\mathcal{L}(\cdot) &= \sum_{i=1}^N [\log(L_w(w_{ij1}|h_{i1}, occ_1, X_{i1})) + \log(L_w(w_{ij2}|h_{i2}, occ_2, X_{i2})) \\
&+ \log(L_1(occ_1|X_{it})) \\
&+ \log(L_{2i}^{m1}(occ_2|X_{it}, t_{leg}, t_{ill}))1(occ_2 > occ_1) + \log(L_{2i}^s(occ_2|t_{leg}, t_{ill}))1(occ_2 = occ_1) \\
&+ \log(L_{2i}^{m2}(occ_2|X_{it}, t_{leg}, t_{ill}))1(occ_2 < occ_1)] \tag{3}
\end{aligned}$$

where $1(\cdot)$ is the indicator function.

The structure of the likelihoods leads to least squares estimation of the wage parameters and maximization of a likelihood function for the occupation choices given the wage observations. When we add unobserved heterogeneity that affects both wages and transition probabilities we would no longer be able to do this two-step estimation. Numerical optimization is performed using standard techniques and the standard errors are created from the empirical estimates of the information matrix.

6 Results

6.1 Wages

The wage parameters are estimated using OLS and are in Tables 7 and 8, 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.

6.2 Occupations

The parameters of the job offer rate are shown in Table 9. 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 receiving a job offer indicate that workers are more likely to receive an offer if they are college educated, were in a higher cognitive task occupation in their home country, or have legal US immigrant status. Interestingly, those who have employer-sponsored visas are less likely to receive outside offers, which is consistent with the non-transferability of employer visas: given the workers came for one specific firm, they are less likely to leave. Also the higher the home country GDP, the less important the home occupation effect. 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.

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

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

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 legal and illegal job offers. People with more education get higher occupational draws, but only when they are in the US legally. The same is true for English skills. People with higher skill home occupations draw higher skill occupations in the US, but the effect is only significant when in the US legally for people who moved after age 18. One interesting result is that having an employer-sponsored visa shifts the distribution to the right even though it was estimated to reduce the probability of getting an outside offer in the offer rate results. The interpretation is that employer-sponsored individuals are less likely to move occupations, but conditional on moving make larger distance moves in terms of cognitive task changes. This is consistent with a story of employer-sponsored visas having higher switching costs.

6.3 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 1 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 are estimated by OLS those tables summarize the model fit there. More detailed analyses of model fit are work in progress.

6.4 Decomposition

We can use the estimated model to understand the contribution of returns to experience and occupational transitions to the wage growth of immigrants. We compare this to the baseline case, where 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

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

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 and education level.

Consider an immigrant who enters the US, is matched with their initial occupation, and then is forced to stay there the remainder of their career. The wage losses between this and the situation where they are free to move to the highest outside offer they receive can be considered the contribution of job search to their wage growth. Since the only other mechanism in the model for wage growth is returns to experience, comparing the true wages vs. the no-occupation-change simulation can decompose this wage growth into orthogonal components.

The results are shown in Table 10. Of course the difference in wages is 0 at entry by the definition of the counterfactual. If the counterfactual worker had moved up the occupational ladder, his wages would be 10% higher after 3 years, 15% after 5 and 20% after 8. This demonstrates the importance of considering the life cycle of earnings in looking at wage gaps: those with flatter returns to experience profiles would have higher returns to job search, so the effects of search get more pronounced over time. In particular, those from the richest countries have the lowest returns to experience but highest average returns to job search, so a simple decomposition of the wage gap at entry would entirely miss this effect.

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.

Table 11 reports the results of two possible changes in admissions policies. The column “More than High School” gives the average wages across if the US excluded immigrants who did not have any schooling above high school in their home country. The column “English competent” would exclude non-competent English speakers. The effects for having more than a high school education are large; the education composition of immigrants is of primary importance for these wage gaps, which is to be expected. The exact size of the change differs across time, being largest late in careers since the highly educated have higher job finding rates. However, a policy that would “increase” (via selection) immigrant wages even more is English competency testing. The intuition is simple: those with more than high school are almost all English competent, and those with only high school who are English competent tend to either be from developed countries or are just high types from their home country. A more detailed look at the effects of converting to a specific point system is work in progress.

6.5 Counterfactuals

The model we wrote down is not strictly required for the decomposition above since it takes all the wage and occupational paths from the data as fixed. However, a number of potential policies affecting immigrants would affect both their returns to experience and occupational transitions. The most obvious of such policies would be skills training and job search assistance; while our model could simulate the effects of these if we knew the exact benefits, without data on costs the problem of program evaluation is beyond the scope of this paper. On the other hand, there are a number of partial equilibrium counterfactuals the model is well-suited to evaluate. \

For an example, let all US experience be treated by the model as experience in the legal labor market. This counterfactual is conceptually similar to an amnesty where regardless of the method of entrance to the US workers are treated equally. Table 12 reports the results. The effects on wages are effectively 0. There are multiple reasons for this result. In terms of the model, the estimates for the job offer distributions barely differ. The selected nature of the data must also contribute: since the sample is new Green Card recipients, immigrants who enter illegally and would never apply for a Green Card are excluded and possibly suffer worse from being excluded from the legal labor market.

7 Conclusion

In this paper, we study the determinants of the wage path of immigrants, focusing on 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.

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8 Tables and Figures

Table 1: Summary Statistics

Variable	Mean
Age	37.63
Percent male	63.04%
Years living legally in the US	3.82
Years living illegally in the US	2.30
Fraction that have an employer sponsor	24.72%
More than high school	61.62%
High English skills	35.38%
From developed country	7.22%
Sample Size	2,965

Table 2: Task requirements of jobs

	Cognitive	Manual
Home	0.52 (0.16)	0.39 (0.17)
Initial US job	0.44 (0.17)	0.38 (0.18)
Current US job	0.45 (0.17)	0.37 (0.18)

Notes: mean values reported, standard deviations in parentheses.

Table 3: Cognitive task requirements of jobs by country of origin

	From developed country	From developing country
Home	0.53 (0.18)	0.52 (0.16)
Initial US job	0.49 (0.18)	0.43 (0.16)
Current US job	0.51 (0.20)	0.44 (0.17)

Notes: mean values reported, standard deviations in parentheses.

Table 4: Tasks of initial US job

	(1)	(2)
	Cognitive	Manual
Cognitive skills at home (moved before age 18)	0.0890** (0.0362)	-0.0499 (0.0413)
Cognitive skills at home (moved after age 18)	0.164*** (0.0219)	-0.0290 (0.0252)
Manual skills at home (moved before age 18)	0.137*** (0.0424)	0.305*** (0.0480)
Manual skills at home (moved after age 18)	0.118*** (0.0218)	0.322*** (0.0241)
Home cognitive skills * home GDP	0.00410*** (0.00113)	0.00327** (0.00129)
Home manual skills * home GDP	-0.00420*** (0.00155)	-0.00940*** (0.00176)
Cognitive tasks of initial US job		-0.392*** (0.0212)
Manual tasks of initial US job	-0.302*** (0.0163)	
Male	-0.00325 (0.00548)	0.00266 (0.00624)
Employer sponsored visa	0.0763*** (0.00647)	0.000463 (0.00757)
More than 12 years education	0.0393*** (0.00672)	-0.0163** (0.00771)
Moved to US illegally	0.00155 (0.00752)	0.0112 (0.00856)
English skills	0.0425*** (0.00628)	-0.0321*** (0.00719)
Years experience at home	-0.000973 (0.000788)	0.000781 (0.000898)
Home experience squared	0.0000321* (0.0000193)	-0.0000241 (0.0000220)
Constant	0.367*** (0.0151)	0.477*** (0.0166)
Observations	2566	2566
Adjusted R^2	0.347	0.273

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

Table 5: Tasks of current US job

	(1)	(2)
	Cognitive	Manual
Cognitive skills at home (moved before age 18)	0.0451 (0.0323)	0.0710** (0.0356)
Cognitive skills at home (moved after age 18)	0.0567*** (0.0195)	0.0412* (0.0215)
Manual skills at home (moved before age 18)	0.0649* (0.0379)	0.0777* (0.0418)
Manual skills at home (moved after age 18)	0.0349* (0.0196)	0.101*** (0.0215)
Home cognitive skills * home GDP	-0.000577 (0.00100)	-0.00110 (0.00111)
Home manual skills * home GDP	0.00161 (0.00137)	0.000790 (0.00151)
Cognitive tasks of initial US job	0.579*** (0.0178)	0.203*** (0.0233)
Manual tasks of initial US job	0.160*** (0.0185)	0.542*** (0.0173)
Cognitive skills at current US job		-0.388*** (0.0215)
Manual skills at current US job	-0.319*** (0.0177)	
Years of illegal work experience	0.000368 (0.00144)	-0.00562*** (0.00159)
Illegal years squared	-0.00000263 (0.0000713)	0.000220*** (0.0000784)
Years of legal work experience	0.00279* (0.00144)	-0.00955*** (0.00158)
Legal years US squared	-0.0000774 (0.0000760)	0.000374*** (0.0000834)
Employer sponsored visa	0.0289*** (0.00588)	0.0165** (0.00651)
Years experience at home	-0.000739 (0.000730)	-0.000622 (0.000804)
Observations	2323	2323
Adjusted R^2	0.580	0.520

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Also includes controls for gender, English skills, work experience at home, education, and a constant term.

Table 6: Task growth

	(1)	(2)
	Cognitive	Manual
Cognitive skills at home (moved before age 18)	0.0262 (0.0345)	0.0607 (0.0380)
Cognitive skills at home (moved after age 18)	0.0461** (0.0208)	0.0237 (0.0229)
Manual skills at home (moved before age 18)	0.0425 (0.0405)	0.0616 (0.0446)
Manual skills at home (moved after age 18)	0.00531 (0.0208)	0.0988*** (0.0229)
Home cognitive skills * home GDP	-0.000182 (0.00107)	-0.00104 (0.00118)
Home manual skills * home GDP	0.00146 (0.00146)	0.000233 (0.00161)
Cognitive tasks of initial US job	-0.413*** (0.0190)	-0.0245 (0.0209)
Manual tasks of initial US job	-0.0151 (0.0168)	-0.452*** (0.0185)
Years of illegal work experience	0.00253 (0.00154)	-0.00660*** (0.00169)
Illegal years squared	-0.0000881 (0.0000760)	0.000254*** (0.0000837)
Years of legal work experience	0.00660*** (0.00153)	-0.0121*** (0.00168)
Legal years US squared	-0.000224*** (0.0000807)	0.000461*** (0.0000889)
Employer sponsored visa	0.0266*** (0.00629)	0.00619 (0.00692)
Observations	2323	2323
Adjusted R^2	0.197	0.226

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Also includes controls for English skills, work experience at home, education, and a constant term.

Table 7: Wages in US

	(1)	(2)
	Initial job	Current job
Cognitive skills at home (moved before age 18)	-0.0826 (0.195)	-0.0720 (0.165)
Cognitive skills at home (moved after age 18)	0.113 (0.130)	0.380*** (0.112)
Manual skills at home (moved before age 18)	-0.273 (0.215)	0.257 (0.181)
Manual skills at home (moved after age 18)	-0.250** (0.117)	-0.0281 (0.103)
Home cognitive skills * home GDP	0.00452 (0.00919)	-0.0122 (0.00806)
Home manual skills * home GDP	0.00618 (0.00968)	0.00842 (0.00850)
Cognitive skills of job	1.299*** (0.0946)	1.079*** (0.0795)
Manual skills of job	-0.193** (0.0812)	-0.0660 (0.0726)
Years of illegal work experience		0.0323*** (0.00641)
Illegal years squared		-0.00102*** (0.000312)
Years of legal work experience		0.0774*** (0.00751)
Legal years US squared		-0.00234*** (0.000387)
Legal US experience * home GDP		-0.00123*** (0.000321)
Home GDP	-0.000421 (0.00679)	0.0114* (0.00609)
Moved to US illegally	-0.0521 (0.0370)	
Employer sponsored visa	0.303*** (0.0313)	0.329*** (0.0272)
Observations	1927	1908
Adjusted R^2	0.385	0.517

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Also includes controls for gender, English skills, work experience at home, education, and a constant term.

Table 8: Wage growth

	(1)
Cognitive task growth	0.339*** (0.125)
Manual growth	0.0358 (0.108)
Cognitive skills at home (moved before age 18)	-0.252 (0.206)
Cognitive skills at home (moved after age 18)	0.0851 (0.136)
Manual skills at home (moved before age 18)	0.891*** (0.231)
Manual skills at home (moved after age 18)	0.210* (0.124)
Home cognitive skills * home GDP	-0.0145 (0.00966)
Home manual skills * home GDP	-0.00271 (0.0101)
Cognitive tasks of initial US job	-0.0351 (0.112)
Manual tasks of initial US job	0.00574 (0.1000)
Years of illegal work experience	0.0371*** (0.0100)
Illegal years squared	-0.00133** (0.000533)
Years of legal work experience	0.0521*** (0.00917)
Legal years US squared	-0.00169*** (0.000471)
Legal US experience * home GDP	-0.00109*** (0.000390)
Home GDP	0.0136* (0.00732)
Employer sponsored visa	0.0245 (0.0331)
Observations	1491

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Also includes controls for English skills, work experience at home, education, and a constant term.

Table 9: Transition parameter estimates

Job offer probabilities		Job offer distribution		
			Initial job	Current job
Constant term	-0.65 (0.11)	Constant term	2.10 (0.18)	2.40 (0.095)
College	0.15 (0.076)	Legal immigrants	0.43 (0.20)	0.15 (0.11)
Home occupation	0.47 (0.21)	Education (illegal)	-0.16 (0.16)	-0.14 (0.086)
Home occupation * gdp	-0.025 (0.0066)	Education (legal)	-0.38 (0.067)	-0.22 (0.051)
Sponsor	-0.35 (0.076)	Home occupation (illegal, young)	-0.20 (0.50)	0.068 (0.20)
Legal	0.21 (0.089)	Home occupation(illegal)	-0.49 (0.34)	0.18 (0.22)
English	-0.11 (0.071)	Home occupation (legal,young)	-1.01 (0.19)	-0.091 (0.19)
Probability of job loss	0.33 (0.014)	Home occupation (legal)	-1.25 (0.12)	-0.31 (0.13)
		Home occupation*gdp (illegal)	-0.029 (0.016)	-0.018 (0.011)
		Home occupation*gdp(legal)	-0.021 (0.0035)	-0.039 (0.0027)
		Sponsor (legal)	-0.32 (0.054)	-0.38 (0.039)
		English (illegal)	0.0026 (0.18)	-0.18 (0.096)
		English (legal)	-0.33 (0.044)	-0.41 (0.032)

Table 10: Decomposition: No job growth in US

Years	Average wages	Counterfactual wages	Percent increase	Native wages
3	13.93	12.65	-9.19%	19.54
5	16.58	14.18	-14.47%	20.09
8	20.30	16.45	-19.01%	20.78

Table 11: Split by characteristics

Years	More than high school		English competent	
	Immigrants wages	Native wages	Immigrants wages	Native wages
3	16.54	21.74	18.76	20.75
5	19.98	22.39	22.68	21.41
8	24.78	23.21	27.98	22.24

Table 12: Counterfactual: all experience as legal immigrant

Years	Average wages	Counterfactual wages	Percent increase	Native wages
3	13.81	13.87	0.46%	19.54
5	16.63	16.83	1.24%	20.09
8	20.52	20.85	1.60%	20.78

Figure 1: Model fit- current occupations in US

