The Native-Immigrant Wage Gap in the United States

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Abstract

Immigrant workers in the US earn less than similar native workers. The economics literature has focused on documenting this gap, but usually not on finding the underlying causes. Without understanding the determinants of the wage path of immigrants, it is difficult to know what classes of policies would be the most effective to close the gap. This paper aims to quantitatively attribute the wage paths of immigrants into two underlying economics forces. First, labor market experience in the US may be more valuable for jobs in the US than labor market experience in other countries. Second, it can take time for new immigrants to be matched with their optimal occupation after moving to the US. Our empirical strategy consists of two parts. In the first, we identify patterns of wage growth and occupational change of immigrants from the New Immigrant Survey, particularly focused on difference between occupations in home countries and the United States. Usually data on home country jobs is not available so these comparisons are not possible. The descriptive statistics show that wage growth for immigrants is explained both by legal and illegal time in the US labor force as well as upwards occupational mobility. Then to quantitatively estimate the importance of the returns to experience versus job search, we develop a simple model of on-the-job human capital accumulation and job search that can replicate the observed patterns. We then use the estimated model to simulate counterfactuals to understand the importance of each factor.

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1 Motivation

Immigrants to 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 a matter of lower-skilled immigrants entering the US labor force or only discrimination: 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 in the US 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. 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 at the time of the survey.[2]

We develop and estimate a model where the wage path of immigrants depends on these two factors. We use panel data on immigrant careers that includes not just multiple observations on an individual over time in the US but also information on their occupations and wages both immediately before and immediately after migration, as well as information about visa status and other worker characteristics that are not typically used. The data comes from a recently-created panel study called the New Immigrant Survey (NIS). Using this information, 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. If we have

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

[2] Occupations 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.

enough observables so that the only residual factor for who finds the high and low type jobs in the US is luck, 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.

Our methodology has two primary components. First, we use the NIS data to document that returns to experience and job search both play a role in the falling wage gap over workers' careers. In the second part we develop and estimate an economic model that allows for transitions between occupations as individuals accumulate work experience in the US. We then use this model to directly quantify the effects of both mechanisms on wage growth. .

2 Literature Review

Previous literature documents the overall wage gap between immigrant and native workers. Chiswick (1978) uses Census data to compare the earnings of different immigrant cohorts at the same point in time, and finds that immigrants who have been in the U.S. for longer earn higher wages. Borjas (1985) argues that this is mostly due to changes in cohort quality. However, LaLonde and Topel (1992) finds evidence of assimilation within cohorts, calculating that the first 10 years of experience in the US labor market raises the earnings of new immigrants by 20%. Census data can only provide a limited explanation for wage assimilation, for it is done using a repeated cross section and does not track the same people over time. For these reasons, the assimilation estimates may be biased, and the data does not permit an examination of the mechanisms behind these trends.

Evidence from longitudinal data shows that the wage gap between natives and immigrants falls over the life cycle. Duleep and Dowhan (2002), using longitudinal data on earnings from the Social Security Administration, find that immigrant wages grow faster than natives. Also using Social Security data, Lubotsky (2007) studies the effect of selective emigration on the measured progress of immigrants to the US. He documents that about one-third of immigrants eventually return to their home country. He finds that the immigrant-native earnings gap closes by 10-15% during the first 20 years in the US, which is about half as fast as when estimated using repeated cross sections of census data. This is due to emigration by low wage immigrants. [3] Using Census-based panel data has many advantages over repeated cross-sections, however it still contains extremely limited information on how workers' careers in the US are related to their careers at home. Without this information it is hard to determine their counterfactual outcomes since controlling for quality becomes almost impossible.

There is little work that estimates the mechanisms behind immigrant wage growth, and none

[3] In the current version of this paper, we do not control for selective return migration. However, once the second round of the NIS is released, we will account for this.

that uses representative US data. A number of papers study the assimilation of highly skilled Russians who immigrated to Israel when the USSR collapsed. Eckstein and Weiss (2004) jointly estimate wage regressions for native Israelis and Russian immigrants, focusing on the rise of the return to imported human capital, accumulated experience in the host country, and mobility up the occupational ladder. They find that upon arrival immigrants receive no return to imported skills. Over time, the growth in wages is due to the rising price of skills, occupational transitions, work experience in Israel, and an economy-wide increase in wages. Weiss et al. (2003) develop and estimate an on-the-job search model, where workers vary in skills and jobs vary by skill level. They find that the lifetime earnings of immigrants are 57% less than those of comparable natives. Of this, 14% is due to frictions from unemployment and job distribution mismatch, and 43% is due to the gradual adoption of imported schooling and local experience. The composition of these immigrants is very different from those moving to the US. The immigrants to Israel were highly skilled, unlike immigrants to the US who have more variation in skill levels and are therefore more likely to start in low-skill occupations. Furthermore, the immigration to Israel was just a one time shock to Israel's economy, so therefore very different than the continuous flow of workers to the US. [4]

3 Data sources

The NIS is a nationally representative survey of new legalized immigrants in the United States. The sampling is based on administrative records from the Immigration and Naturalization Service on immigrants who were recently granted permanent residence. It is a panel survey, with both retrospective and current data, with two extant waves and more being performed now. The first round is from 2003 and the second round of surveys was completed in 2007.

The NIS provides information on a a person's first and current job in the US, which allows us to study wage growth with work experience in the US. In particular, because we have information on jobs at different points in time for each immigrant, we can study wage growth and occupation transitions. The NIS also provides information on each person's labor market outcomes in their home country. This allows us to control for the skill level of immigrants. In addition, the data has detailed information on a person's immigration status, including how they got their visa and the years of experience in the US (both legal and illegal).

The current version of the paper uses just data from the first round of the NIS, which is sufficient for our purposes in that we have multiple job observations for each respondent in the US

[4] Recently there has been work on a similar question in other countries. de Matos (2011)looks at immigrant wage assimilation in Portugal using linked employer-employee data. She documents that job mobility and firm heterogeneity are important in the data, and builds a model that predicts these trends. In comparison to the US data, she does not find evidence that immigrants assimilate by switching occupations.

and information about their home occupations. The second round of the NIS (due to be released in spring 2013) 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.

In this paper, we study the movement of immigrants up the occupational ladder. To do this, we need a measure of the skill level of different jobs. One way to do this is to divide occupations into categories, say skilled and unskilled; however, this is a crude measure of the differences across occupations. A more sophisticated way to characterize them in the occupation literature is to use the task requirements of each job.[5] The O*NET database of occupational tasks, created by the US Bureau of Labor Statistics, 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, cognitive, and interpersonal task requirements of each job using Principal Component Analysis similar to the procedure used in Poletaev and Robinson (2008); see Sanders (2011) for details on the exact procedure used here. We use this data to obtain a continuous measure of the skill requirement of jobs, instead of just using a binary classification of "skilled" or "unskilled." This allows us to seperately analyze the effects of cognitive and manual task requirements of different occupations on wages and wage growth. As the descriptive statistics below show, this is a useful distinction.

4 Descriptive Statistics

Table 1 shows summary statistics on the sample.[6] 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 people in the sample worked in the US illegally for some period of time, in that the average person has over 2 years of work experience as an illegal immigrant. 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 the job search process to be different for this group in that they probably face fewer frictions. Over 60% of the sample has education beyond high school.

4.1 Occupations

We first discuss data on how immigrants move between different types of jobs. It might be expected that immigrants are unable to take the same or higher level job than they had in their home country, especially in their initial job in the US. We use the task requirements of jobs to measure the skill

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

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

level of jobs. Tables 2 and 3 show the average cognitive and manual tasks of jobs at home and in the US. The index records manual tasks between -1.56 and 1.34, and cognitive tasks between -1.55 and 1.30. We see that people work in jobs with higher cognitive tasks at home, but the task requirements increase with time in the US, indicating that people are moving up the occupational ladder. For manual tasks it is harder to see a clear trend.

In Table 4, we show the determinants of manual and cognitive task requirements of the initial job in the US. First we test the transmission of skills in jobs between home and the US, and find that people with higher cognitive (manual) skills in their job at home are in jobs with higher cognitive (manual) task requirements in the US. This implies that some skills are transferred. People with employer sponsored work visas have jobs with higher cognitive task requirements and lower manual tasks. This suggests, that at least for cognitive tasks, there are fewer search frictions for people with employer sponsored visas, which is intuitive. People with more years of work experience at home are in jobs with lower cognitive tasks and higher manual tasks. Education creases the cognitive task requirements of jobs and lowers the manual tasks. People who moved to the US illegally initially work in jobs with lower cognitive tasks and higher manual tasks.

Table 5 shows the determinants of manual and cognitive tasks 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 and illegal work experience increases the cognitive task requirements of a job, although the effects are stronger for legal work experience.

Table 6 shows the determinants of task growth between the first and current job in the US. We control for the initial distance (measured in task requirements) from the home country occupation. People who are further from their optimal occupation have more growth. Additionally, people who start with higher task requirements have smaller growth in cognitive tasks, though the opposite is true for manual tasks. Work experience increases the task growth of cognitive tasks and reduces that of manual tasks.

Overall, these results show some important empirical findings that we use to simplify the estimation of our model in this paper. First of all, we see that human capital leads to higher cognitive tasks. Therefore, when we think about people moving up the occupational ladder, these results highlight that we should be focusing on cognitive tasks. In the model we will use the cognitive task requirements as a measure of the skill level of jobs.[7]

[7] In future work we will allow for job offers to account for both cognitive and manual task requirements.

4.2 Wages

As a first step to understand the wage path of immigrants, we look for patterns in the data that can disentangle the effects of returns to experience versus job search on wages. We assume that workers are paid a wage depending on their observable demographic characteristics X_{it} (which includes schooling, gender, and family background), the years of experience in the US labor market e_{it}, and the number of outside job offers they have received j. We would expect outside job offers to lead to a higher wage because the worker can either switch to the higher-paying job or use that offer to negotiate for a raise in their current job. We also assume that wages depend on a person's occupation at home, using this as a proxy for a person's productivity. The variable sh_i indicates the skill level of a person's job at home. We write a reduced form wage equation as

$$W_{it} = X_{it}\beta + e_{it}\beta_e - e_{it}^2\gamma_e + j_{it}\beta_j - j_{it}^2\gamma_j + sh_i\gamma_{sh} + \varepsilon_{it},$$

where i indexes workers, t indexes their age, β is the vector of returns to demographic characteristics, β_e is the increase in wages with an additional year of work experience, γ_e is the amount which additional years of experience are less valuable than the first few, β_j is the average raise workers receive when they get an outside offer, γ_j is the decreasing additional value of each outside offer, γ_{sh} is the increase productivity for a unit of skill, and ε_{it} are other unobserved factors affecting wages.

If we observed both work experience and number of outside job offers, we could directly estimate this model. However, the data does not include details on outside offers or within-job wage negotiations. This complicates the methodology, since the number of outside job offers will be correlated with the amount of time spent in the labor market. Consider the conditional mean of W_{it} if we only observe demographics and experience:

$$E\left[W_{it}|X_{it}, e_{it}\right] = X_{it}\beta + e_{it}\beta_e - e_{it}^2\gamma_e + \beta_j E\left[j_{it}|e_{it}\right] - \gamma_j E\left[j_{it}^2|e_{it}\right] + sh_i\gamma_{sh}$$

The number of outside offers will not have a constant conditional mean for all values of experience, so we will mis-estimate the true returns to experience by confounding experience and job offers. We need a proxy where if we condition on it as well, the effect of work experience on the conditional mean of the number of job offers disappears. That is, once we control for the proxy, experience will have no additional effect on the number of outside offers the worker received.

We use information on an immigrant's current job relative to their home occupation as this proxy for job offers. Consider two immigrants who are identical, except that through random luck one received an initial job in the US "further" from his optimal job choice. For example, both immigrants have the skills to be doctors if they could locate the job, but one works as a dental assistant and the other can only find a job as a taxi driver. If the key to the reduction in the wage gap is work experience, the wage gap of both workers should decrease at the same rate. On the other hand, if job search is the driving force, there is a higher probability that the taxi driver receives an offer that leads to an increase in wages. Effectively we want to compare immigrants with the same labor experience, who through random chance ended up differently on the career ladder, so that their rates of raises through outside offers will vary.

If workers have a large distance between their optimal and current occupations, then they will have received few offers, and if the difference is small they must have received many. If we also condition on the distance D_{it}:

$$\begin{aligned} E\left[W_{it}|X_{it},e_{it},D_{it}\right] &= X_{it}\beta + e_{it}\beta_e - e_{it}^2\gamma_e + \beta_j E\left[j_{it}|e_{it},D_{it}\right] - \gamma_j E\left[j_{it}^2|e_{it},D_{it}\right] + sh_i\gamma_{sh} \\ &= X_{it}\beta + e_{it}\beta_e - e_{it}^2\gamma_e + \beta_j E\left[j_{it}|D_{it}\right] - \gamma_j E\left[j_{it}^2|D_{it}\right] + sh_i\gamma_{sh} \end{aligned}$$

under the assumption that given the distance, the effect of experience on the number of offers disappears. Then we can write the expected wage as

$$E\left[W_{it}|X_{it},e_{it},D_{it}\right] = X_{it}\beta + e_{it}\beta_e - e_{it}^2\gamma_e + g\left(D_{it}\right) + sh_i\gamma_{sh}$$

where $g\left(D_{it}\right)$ is some unknown function of the distance from the optimal occupation, but is not a function of years of work experience. Note that this does not imply that workers are actually paid differently based on their distance from the optimal occupation. Instead it is just a proxy for the number of offers we would expect them to have already received.

We use the task measures of occupations described above to calculate a person's distance from their optimal occupation, which we define as their home country occupation. We take the difference between the cognitive task requirements of the current and home country job.We interpret a negative coefficient on the distance measure as saying that job search forces are important for wage growth. We assume log wages can be written as

$$w_{it} = X_{it}\beta + E_{it}\beta_E - E_{it}^2\gamma_E + D_{j_{it}i^*}^{cog}\zeta_{cog} + cog_{hi}\gamma_{cog} + \varepsilon_{it} \tag{1}$$

In equation (1), $D_{j_{it}i^*}^{z}$ is the distance between a person's current occupation and their optimal occupation in skill cognitive task requirements, $\zeta_{cog}$is the importance of skill factor of cognitive skills in job search. As before, we control for the home occupation, this time using the task requirements of the home occupation instead of just the skilled or unskilled classification. The factor cog_{hi} gives the task requirements for a persons home occupation, and $\gamma_{cog}$is the return to skills. Individual characteristics include education and years of home country work experience.

Table 7 shows the results of a regression on initial and current wages in the US (all in 2004 dollars). People with work visas have higher wages, indicating that these individuals have fewer search frictions and get better job matches. People who work in skilled occupations at home earn higher wages, showing that these people are more productive.

The second column of Table 7 shows this regression for the current job in the US. This allows us to look at returns to work experience in the US. Both legal and illegal work experience increases wages, although the effects are stronger for legal work experience.

These results show returns to job search. A person whose jobs requires less skills than his optimal job will have a negative distance measure. The positive coefficient on this distance measure implies that these people will have lower wages. This provides evidence that search is important for wage growth.

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. Work experience leads to higher wages, as does an increase in the cognitive task requirements of jobs. People with work visas do not have any increased wage growth.

5 Model

The data on wages and occupational transitions suggests that work experience and job search both play a role in reducing the immigrant-native wage gap, but since we don't have data on external job offers we can't directly quantify the relative importance of each factor. In this next section, we aim to do this by estimating an economic model where workers can transition between occupations. After doing this, we can calculate how different types of policies will affect immigrant wage growth.

We use a full-information partial equilibrium labor search model. There is a mass of workers m indexed by $i \in [0,m]$, where workers have an exogenous fixed characteristic $\theta_i \in \mathbb{R}$ called their "ability". Immigrants have an exogenous given time of labor force entry t_i^0, and prior to that we assume they worked in their home country from the completion of school until they left. Let the unit of time in the model be one year, and individuals maximize their expected lifetime income. Assume they work from age 20 to age 65 and then exogenously retire.

There is a unit mass of firms indexed by $j \in [a,b]$, where j indexes the productivity of a firm. The productivity of firm type j is given by $j \times \delta$, $\delta > 0$ a parameter.

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

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

where h_{it} is the endogenous "human capital" of worker i at time t.[8] Human capital is given by

$$h_{it} = \theta_i + \beta_1 F_{it^0} + \beta_2 F_{it^0}^2 + \psi_1 US_{it} + \psi_2 US_{it}^2 + \gamma X \; if \, t \geq t_i^0$$

where F_{it^0} 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. The term X is fixed observable characteristics that could affect human capital, most importantly education. We also assume that $\theta_i \sim N\left(\mu^I, \sigma^2\right)$ and estimate the distribution of individual ability.

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_i.[9] If a person receives a new job offer, the index is given by $j' \sim U[a,b]$. The worker accepts the offer if it is a higher type than his previous job.[10] We assume workers accept whatever offer they receive in the first period.[11]

Wage growth in the model comes through 2 sources:

1. Individuals gain human capital by working.
2. Over time, they are more likely to receive an offer from higher type firms.

5.1 The Wage Gap

In the model, if a researcher ran a regression of wages on worker characteristics (demographics, experience, education) there would be a wage gap between natives and immigrants. In particular, if education levels only reflected the worker's location in the distribution of ability for their country, looking at workers with the same overall experience (grouping native and US) and education there would be a role for country of origin to play. In our model, this comes from two channels. The first is that returns to experience are higher in the US, and native workers are in the US for their entire career. The second is search frictions, in that native workers have more years in the US, and are therefore more likely to get an offer from the high type firm.

To see this, look at the average wages at time t of a native cohort in the median of the ability

[8] One 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 simply

$$Y_{ijt} = \exp\left(h_i + \phi_j \delta + \varepsilon_{ijt}\right)$$

[9] We assume that everyone receives a job in their first period in the US.

[10] We assume that workers pick jobs before observing the ε draws in each period.

[11] This comes from the assumption of 0 costs which leads to a reservation wage of 0.

distribution, looking forward from time 0. We write the mean of the ability distribution for natives as μ^N, and their total labor market experience as US_{it}^N:

$$E_0^N \left[w_{ijt}|\theta_i = \mu^N\right] = \mu^N + \psi_1 US_{it}^N + \psi_2 \left[US_{it}^N\right]^2 + \gamma X_i^N + E_{i0}\left[j|US_{it}^N\right]\delta \tag{2}$$

The expected value of firm productivity is the expectation of the highest job offer in US_{it} years. This has 2 components: the expected number of job offers and the expected productivity. Denote the probability that a person with US_{it} years of labor market experience gets k job offers as $q_{ik}(US_{it})$. This function is given by

$$q_{ik}(US_{it}^N) = \frac{US_{it}^N!}{k!(US_{it}-k)!} p_i^k (1-p_i)^{US_{it}^N - k} \tag{3}$$

Conditional on receiving k job offers, the expected productivity of the observed job is the expectation of the maximum offer. The distribution of the maximum value is given by the distribution of the kth order statistic. Denote j^* as the maximum offer and $f_{max}(j^*|k)$ the distribution of the order statistic, conditional on receiving k offers:

$$f_{max}(j^*|k) = \frac{k!}{(k-1)!}\left[\frac{j^*-a}{b-a}\right]^{k-1}\frac{1}{b-a} = k\left[\frac{j^*-a}{b-a}\right]^{k-1}\frac{1}{b-a} \tag{4}$$

Then the expected maximum value with k job offers is given by

$$j_k = \int_a^b j^* f_{max}(j^*|k)\,dj^*.$$

Now we can solve for the expected productivity for a person who has been in the US for a given number of years, to substitute into equation (2). This is given by

$$E_{i0}[j|US_{it}^N] = \sum_{k=1}^{t_i} q_{ik}(US_{it}^N)\, j_k$$

On the other hand, expected wages for immigrants of the same age and in the median of the ability distribution is

$$E_0^I \left[w_{ijt}|\theta_i = \mu^I\right] = \mu^I + \beta_1 F_{it^0} + \beta_2 F_{it^0}^2 + \psi_1 US_{it}^I + \psi_2 \left[US_{it}^I\right]^2 + \gamma X_i^I + E_{i0}\left[j|US_{it}^I\right]\delta,$$

which can be rewritten as

$$E_0^I \left[w_{ijt}|\theta_i = \mu^I\right] = \mu^I + \gamma X_i^I + (\beta_1 - \psi_1) F_{it^0} + \psi_1\left(F_{it^0} + US_{it}^I\right) + \beta_2 F_{it^0}^2 + \psi_2\left[US_{it}^I\right]^2 + E_{i0}\left[j|US_{it}^I\right]\delta.$$

Since the workers are assumed to be the same age and work every period, total experience is the same: $F_{it_i^0} + US_{it}^I$ for immigrants is the same as US_{it}^N for natives. So looking at the wage gap between the median ability native worker and median ability immigrant worker over time, those terms cancel and we are left with:

$$\begin{aligned} E\left[\Delta w|\mu^I,\mu^N\right] &= \left(\mu^N-\mu^I\right)+\gamma E\left(X_i^N-X_{it}^I\right)-\left(\beta_1-\psi_1\right)F_{it_i^0}+\psi_2(\left[US_{it}^N\right]^2-\left[US_{it}^I\right]^2)-\beta_2 F_{it^0}^2 \\ &+ \left(E_{i0}[j|US_{it}^N]-E_{i0}\left[j|US_{it}^I\right]\right)\delta \end{aligned}$$

The first term represents the difference in average skills across countries, the second is the average different values of demographics, the third is the differing returns of work experience across countries, the squared terms reflect the concavity of experience, and the last term reflects the fewer opportunities for more recent labor force entrants to find high-productivity firms. The gap is falling over time because once native workers have moved up the ladder they have no further up to go, but immigrants can catch up by locating high-productivity jobs themselves.Decreasing marginal returns to experience also generate a native-immigrant wage gap that is falling over time.

In conclusion, our model can explain both the initial wage gap and the fall in that gap over time.

The initial wage gap is explained by

1. Unobservable differences in ability (e.g. differences in schooling across countries) coming from the $\mu^N - \mu^I$.
2. Potentially different education and demographic levels at the same ability levels $X_i^N - X_i^I$
3. A lower return to foreign work experience in the US market $(\psi_1 - \beta_1)$
4. Inability to find a high-productivity firm right away in the US

The fall in the wage gap over time within a cohort is explained by

1. Decreasing marginal returns to work experience in the US (ψ_2)
2. Increasing chances to find a high-productivity firm over time for immigrants, while natives have already transitioned

6 Estimation

For now we estimate a version of the model for the wage path of immigrants with no unobserved heterogeneity.[12] We match the wage offers and occupations of the individuals in the sample (using data on people's initial and current jobs in the US).

6.1 Parameterization

Write a person's log wage as w_{ijt}, where i indexes individuals, j is a person's occupation, and we are at time t. Recall that log wages are written as

$$w_{ijt} = h_{it} + j\delta + \varepsilon_{ijt} \tag{5}$$

Human capital h_{it} includes education, occupation in one's home country, and work experience:

$$h_{it} = \beta_1 F_{it^0} + \beta_2 F_{it^0}^2 + \psi_1 US_{it} + \psi_2 US_{it}^2 + \gamma_1 College + \gamma_2 sk_{home}$$

For job offer probabilities, we assume that

$$p = \Phi(\alpha_0 + \alpha_1 college + \alpha_2 sk_{home}). \tag{6}$$

In equation (6), α is a set of parameters to be estimated, and sk_{occ1} is a person's task level at their first occupation, an d$\Phi(\cdot)$ is the CDF of the standard normal distribution. This specification allows for higher job offer rates if a person is more skilled in their home country. If a person gets a job offer, we assume it is drawn from the $U(a,b)$ distribution, where a and b are determined by using the observed values in the data.

6.2 Likelihood function

Using equation (5), we know that

$$w_{ijt}|h_{it}, j \sim N(h_{it} + j\delta, \sigma_\varepsilon^2)$$

where σ_ε is the standard deviation of the ε distribution. Conditional on occupation j, the likelihood for a given wage draw at time t is

$$L_w(w_{ijt}|h_{it}, \phi_j) = \frac{1}{\sigma_\varepsilon\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{w_{ijt} - h_{it} - \phi_j\delta}{\sigma_\varepsilon}\right)^2\right)$$

[12]Unobserved heterogeneity in job offers and wages will be included in future work

The above likelihood is conditional on a person's occupation in each period. We also need to calculate the probability that a person works in a given sequence of occupations. We assume that each person gets a job offer in the initial period. Therefore the likelihood for the initial occupation draw for each individual is the same: $L_1 = \frac{1}{b-a}$, where a and b are the lower and upper bounds of occupations as explained above.

Now consider the second occupation observed in the data. A person has been in the US for $t_i$periods, and they get a job offer with probability p_i in each period. To calculate the likelihood, we have to consider two cases: a person who switches occupations and a person who stays in the same occupation.[13] First consider the case when a person moved to a higher occupation over time. The likelihood is given by

$$L_{2i}^{m}(occ_2|t_i) = \sum_{k=0}^{t_i} q_{ik}(t_i) f_{max}(occ_2|k),$$

where $q_{ik}(\cdot)$ is the probability that he gets k job offers as defined in equation 3 and $f_{max}(occ_2|k)$ is the probability that $occ_2$is his highest occupation when he gets k job offers as defined in equation (4).

Now consider the case when a person stays in the same occupation over time. Then

$$L_{2i}^{s}(occ_1|t_i) = \sum_{k=0}^{t_i} q_{ik}(t_i) Z_k(occ_1),$$

where $Z_k(occ1)$ is the probability that all k offers are less than $occ1$:

$$Z_k(occ_1) = \left(\frac{occ_1 - a}{b-a}\right)^k$$

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

$$\begin{aligned} \mathscr{L}(\cdot) &= \sum_{i=1}^{N} \log(L_w(w_{ij1}|h_{i1}, j_1)) + \log(L_w(w_{ij2}|h_{i2}, j_2) + \log(L_1) \\ &+ \log(L_{2i}^{m}(occ_2|t_1, occ_1))1(occ_2 > occ_1) + \log(L_{2i}^{s}(occ_2|t_1, occ_1))1(occ2 = occ_1) \end{aligned}$$

The structure of the likelihoods leads to least squares estimation of those parameters and a non-standard discrete choice likelihood for the occupation choices. One note is that while this model

[13] We do not allow for job loss in the model, so we cannot explain moves to lower occupations. We drop these observations but will include them in future work.

can be estimated in 2 steps by first estimating the wage parameters conditioning on occupation choice, and then estimating the occupational choice parameters, data generated by this model would have the wrong wage distributions if the occupational choice parameters are wrong. When we add unobserved heterogeneity that affects both wages and transition probabilities we would no longer be able to do this two-step estimation.

7 Results

Table 9 contains the parameter estimates and standard errors. The wage parameters show that people working in jobs with higher cognitive tasks earn more. There are positive returns to legal and illegal work experience. In addition, work experience at home, as well as education, increase wages.

We also estimate the parameters of the job offer rate. People with more education are more likely to get job offers, as are legal immigrants and people who worked in a higher skill occupation at home.

The signs of the results seem fairly intuitive, but the interesting information comes from their relative sizes and importance in wage growth that we discuss below.

7.1 Model Fit

We show how well the model fit wage draws and occupations. Figure 1 shows the density of wages in the model and data for the initial wage in the US. We see that the model over-predicts the number of people with very low wages, and cannot match the magnitude of the spike in the density in the middle of the wage distribution. Figure 2 shows the distribution of wages in the model and data for the current job. The data does not show the usual log-normality pattern that wage distributions often have, so the model has a difficult time matching the shape of the distribution although it does well to match the level and variance.

We also test the fit of the model in terms of predicting the correct occupations. Figure 3 shows average task level of each person's occupation, splitting the sample by years of experience in the US.

7.2 Counterfactuals

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.[14]

7.2.1 Search frictions

For now, we assume that people are matched in their optimal (home) occupation in their first job as a legal immigrant in the US.[15] This assumes that there are no search frictions. This can be used to estimate the effects of programs that help immigrants to find new jobs once they move to the US. Figure 4 shows the results of this counterfactual. It increases lifetime wages by 4%.

8 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. The results can help design policies to decrease economic inequality between recent immigrants and natives. If the most important factor for the falling wage gap is the fact that immigrants lack skills specific to the US labor market, education and job training programs are a natural way to alleviate the differences quickly. On the other hand, if starting low on the job ladder due to lack of access to better jobs is the cause, increased access to information and easier job-to-job mobility would be the best policy focus.

Data from the NIS 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. Using the estimated model, we simulate counterfactuals to understand the returns to each factor.

Future work will estimate the model using the task classifications of occupations. This will allow for a continuous measure of job levels, allowing for a finer gradient for occupation transitions. In particular, the reduced form evidence shows that this is important. Also, the second round of the NIS is due to be released this spring. 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.

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

[15] Here we are defining optimal occupations as a person's occupation in their home country.

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9 Tables and Figures

Table 1: Summary Statistics

Variable	Mean
Age	37.4
Percent male	62.1%
Years living legally in the US	4.0
Years living illegally in the US	2.4
Fraction that have an employer sponsor	24.2%
More than high school	60.8%
Sample Size	2678

Table 2: Cognitive task requirements of jobs

	Mean	Standard deviation	Minimum	Maximum
Home	-0.002	0.760	-1.551	1.296
Initial US job	-0.415	0.815	-1.551	1.296
Current US job	-0.320	0.829	-1.551	1.296

Table 3: Manual task requirements of jobs

	Mean	Standard deviation	Minimum	Maximum
Home	-0.088	0.807	-1.560	1.354
Initial US job	-0.086	0.758	-1.560	1.354
Current US job	-0.105	0.770	-1.560	1.354

Table 4: Tasks of initial US job

	(1) Cognitive	(2) Manual
Cognitive tasks of home job	0.378***	-0.0136
	(0.0188)	(0.0205)
Cognitive tasks of initial US job		-0.162***
		(0.0193)
Manual tasks of home job	0.0453***	0.230***
	(0.0176)	(0.0173)
Manual tasks of initial US job	-0.157***	
	(0.0188)	
Male	0.0593**	0.109***
	(0.0260)	(0.0263)
Employer sponsored visa	0.420***	-0.197***
	(0.0305)	(0.0318)
Years experience at home	-0.0110***	0.0191***
	(0.00372)	(0.00376)
Home experience squared	0.000147	-0.000443***
	(0.000109)	(0.000111)
More than 12 years education	0.229***	-0.208***
	(0.0315)	(0.0320)
Moved to US illegally	-0.143***	0.158***
	(0.0350)	(0.0355)
Constant	-0.585***	-0.171***
	(0.0402)	(0.0422)
Observations	2691	2691
Adjusted R^2	0.394	0.277

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Tasks of current US job

	(1) Cognitive	(2) Manual
Cognitive tasks of home job	0.0733***	
	(0.0165)	
Cognitive tasks of initial US job	0.673***	
	(0.0158)	
Manual tasks of home job	0.0261*	.
	(0.0144)	.
Manual tasks of initial US job	-0.0210	0.654***
	(0.0156)	(0.0151)
Male	-0.0251	0.0451**
	(0.0213)	(0.0210)
Employer sponsored visa	0.0985***	-0.0514**
	(0.0257)	(0.0242)
Years experience at home	-0.00525	0.00347
	(0.00320)	(0.00311)
Home experience squared	0.0000129	-0.0000655
	(0.0000974)	(0.0000942)
More than 12 years education	0.140***	-0.106***
	(0.0260)	(0.0243)
Years of illegal work experience	0.0233***	0.00377
	(0.00625)	(0.00623)
Illegal years squared	-0.000887***	-0.0000479
	(0.000310)	(0.000310)
Years of legal work experience	0.0476***	-0.0267***
	(0.00615)	(0.00594)
Legal years US squared	-0.00141***	0.00103***
	(0.000332)	(0.000317)
Constant	-0.243***	0.0494
	(0.0388)	(0.0355)
Observations	2228	2444
Adjusted R^2	0.680	0.605

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Task growth

	(1) Cognitive	(2) Manual
dist1C	0.0688***	
	(0.0162)	
Cognitive tasks of initial US job	-0.255***	
	(0.0178)	
More than 12 years education	0.137***	-0.104***
	(0.0255)	(0.0243)
Years of legal work experience	0.0479***	-0.0261***
	(0.00611)	(0.00593)
Years of illegal work experience	0.0236***	0.00351
	(0.00625)	(0.00623)
Employer sponsored visa	0.1000***	-0.0487**
	(0.0256)	(0.0242)
Legal years US squared	-0.00143***	0.00101***
	(0.000331)	(0.000317)
Illegal years squared	-0.000908***	-0.0000261
	(0.000310)	(0.000310)
Years experience at home	-0.00548*	0.00321
	(0.00318)	(0.00311)
Home experience squared	0.0000218	-0.0000588
	(0.0000970)	(0.0000943)
dist1M		0.100***
		(0.0137)
Manual tasks of initial US job		-0.243***
		(0.0171)
Constant	-0.256***	0.0774**
	(0.0361)	(0.0330)
Observations	2228	2444

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Wages in US

	(1) First job	(2) Current job
Male	0.0769***	0.150***
	(0.0229)	(0.0194)
Cognitive tasks of home job	0.445***	0.464***
	(0.0197)	(0.0171)
Cognitive distance	-0.386***	-0.370***
	(0.0171)	(0.0146)
More than 12 years education	0.108***	0.102***
	(0.0284)	(0.0239)
Years experience at home	0.0150***	-0.00103
	(0.00334)	(0.00297)
Home experience squared	-0.000505***	-0.0000793
	(0.0000969)	(0.0000903)
Moved to US illegally	-0.0221	
	(0.0333)	
Employer sponsored visa	0.280***	0.265***
	(0.0281)	(0.0238)
Years of illegal work experience		0.0438***
		(0.00582)
Illegal years squared		-0.00130***
		(0.000289)
Years of legal work experience		0.0705***
		(0.00577)
Legal years US squared		-0.00234***
		(0.000308)
Constant	2.273***	2.211***
	(0.0379)	(0.0361)
Observations	2254	2217
Adjusted R^2	0.419	0.582

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Wage growth

	(1)
Cognitive task growth	0.208***
	(0.0229)
Years of legal work experience	0.0602***
	(0.00711)
Years of illegal work experience	0.0502***
	(0.00911)
Legal years US squared	-0.00255***
	(0.000401)
Illegal years squared	-0.00162***
	(0.000500)
Employer sponsored visa	0.000827
	(0.0276)
Constant	-0.0416*
	(0.0224)
Observations	1780

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Parameter estimates

Wage parameters		Transition parameters	
Return to cognitive task of occupation	0.38	Baseline term	-1.37
	(0.010)		(0.058)
Standard deviation of wage distribution	0.49	Some college	0.22
	(0.0029)		(0.060)
Wage constant	2.32	Home occupation	0.11
	(0.018)		(0.037)
Return to home experience	0.011	Legal immigrant	0.26
	(0.00099)		(0.067)
Home experience squared	-0.00060		
	(0.0000082)		
Return to illegal work experience	0.081		
	(0.0047)		
Illegal work experience squared	-0.0053		
	(0.00031)		
Return to legal work experience	0.055		
	(0.0043)		
Legal work experience squared	-0.0015		
	(0.00032)		
Return to some college education	0.11		
	(0.016)		
Return to occupation in home country	0.078		
	(0.010)		
Return to employer sponsored work visa	0.28		
	(0.014)		

Figure 1: Model fit -wages in initial US job

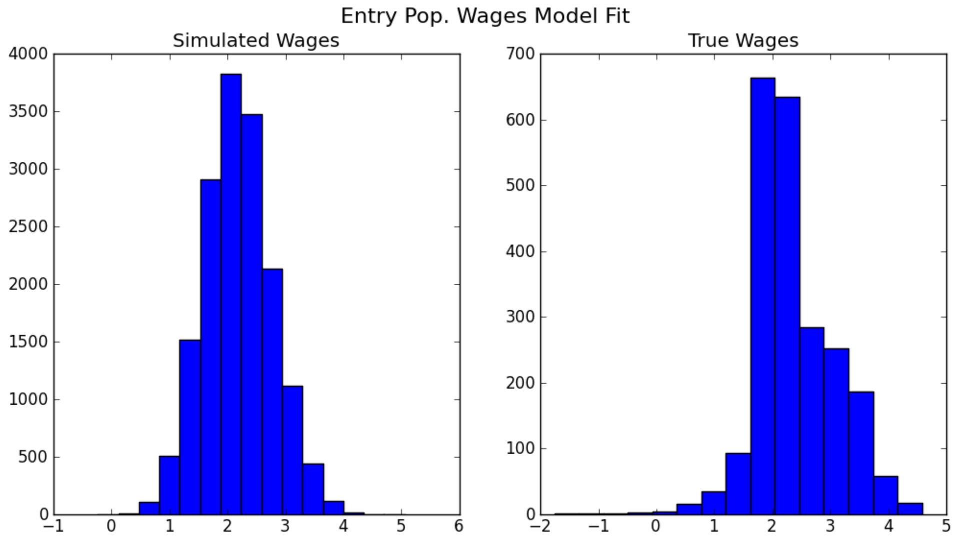

Figure 2: Model fit- wages at current US job

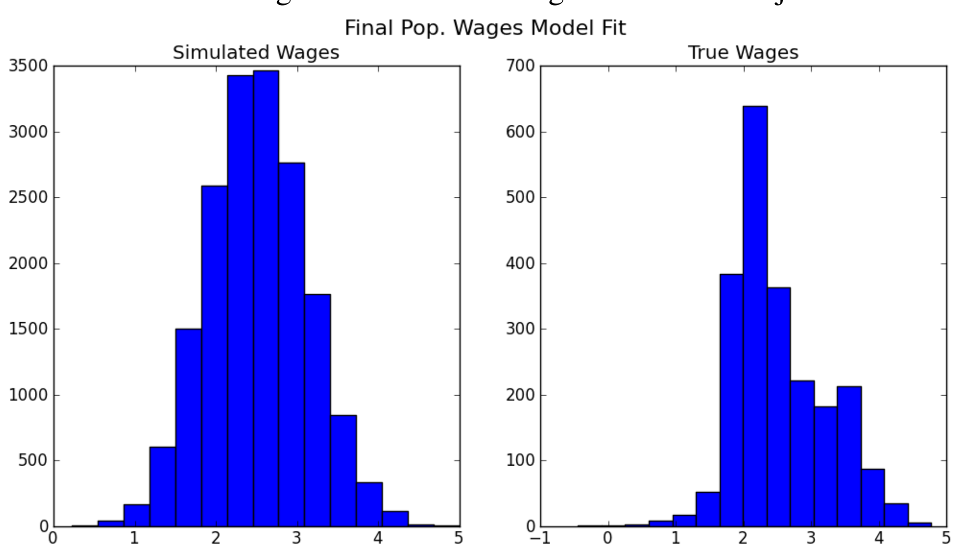

Figure 3: Model fit- current occupations in US

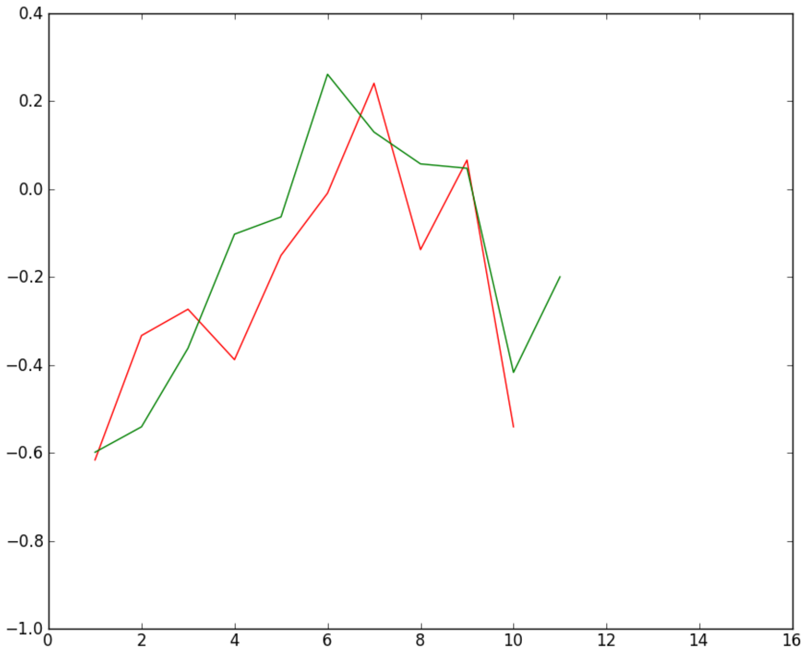

Figure 4: Counterfactual - no search frictions