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The Immigrant-Native Wage Gap in the United States

Rebecca Lessem* and Carl Sanders‡

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Abstract

Immigrants to the United States earn lower wages than native workers, and this gap decreases with time spent working in the US labor market. In this paper, we study the determinants of the wage path of immigrants in order to understand this wage gap between natives and immigrants. We focus on two particular explanations: differing returns to experience in the US and search frictions when finding optimal occupations. 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. Separating these factors is difficult due to potential self-selection of immigrants. To deal with this, we use data from the New Immigrant Survey which has detailed information on the occupations and wages of immigrants both before they enter the US as well as repeated observations after moving to the US. Reduced form evidence 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 importance of each factor. In the first simulation, we find that immigrant wages over a lifetime increase by 32% when returns to experience in the home country are the same as returns to experience in the US. In the second simulation, we match immigrants with their optimal occupation in their first US job, and find that this increases wages by 5%.

JEL Codes: J31, J15, J62

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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 intergenerational 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 causes of this wage gap between natives and immigrants and to determine why it falls over time. 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.

While there have been studies of the career paths of immigrants before, the available data has typically either been cross sectional studies or on limited panel data that may have good detail on immigrant careers in the US but very limited information on their jobs, wages, and characteristics before they migrated. Here 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. 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 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.

Using this intuition, we develop and estimate a model where the wage path of immigrants

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

depends on two factors that modern labor economics emphasizes for wage growth. 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.

An initial look at the data indicates that both returns to experience and job search can explain aspects of immigrants' careers. The data shows that the first few years of experience in the US are indeed the most valuable. In addition, immigrants switch occupations when they move to the US: only 20% of immigrants initially work in the same occupation in the US as in their home country.[2] Furthermore, they switch to lower skill requirement occupations after moving to the US. Analysis of the NIS data shows that only 3.5% of the sample worked in "food preparation and service related" occupations in their home country, but 10% worked in that sector in their initial job in the US. Similarly, 1.6% of the sample worked in "cleaning and building service" occupations in their home country, and that number jumped to 8.1% after moving to the US. Over time in the US, however, immigrants shift into higher skill occupations. In their first job in the US, around 28% of our sample worked in high skill jobs. At the time of the survey, around 42% were working in high skill jobs.

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. Then using counterfactual simulations we are able to decompose the effects of both forces on the falling wage gap. Preliminary results show that immigrant wages over a lifetime increase by 32% when returns to experience in the home country are equal to returns to experience in the US. In the second simulation, we match immigrants with their optimal occupation in their first US job, and find that this increases lifetime wages by 5%.

[2]Here we are defining occupations according to census definitions. There are 31 occupation categories.

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 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

[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.

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 NIS Data

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 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.

[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.

4 Descriptive Statistics

Table 1 shows summary statistics for the sample.[5] For educational attainment, 27% of the sample did not complete high school, and 35% have terminal high school degrees. The remainder has at least some college education. At the time of the survey, workers had lived in the US for an average of 6 years. Much previous immigration experience was illegal, as the average person had only lived in the US legally for about 4 years. Seventeen percent of the sample lived in the US illegally for some period of time. Therefore it will be important to distinguish between legal and illegal years of work experience. Over half of the sample has a sponsor for their visa, which can be a family member or an employer. Of those with sponsors, about 40% are from employers. This could potentially affect the degree of search frictions that people face in the US labor market.

4.1 Occupation Transitions

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. A broad look at the data bears this out. Table 2 shows the transitions between skilled and unskilled occupations for immigrant workers.[6] The first column shows that approximately one-third of the sample worked in skilled occupations in their home country. Going across each row, we see the percent of each group that works in a skilled occupation in the US (in their initial occupation and at the time of the survey). Around 50% the people who worked in a skilled occupation in their home country were initially working in a skilled occupation in the US. At the time of the survey, 70% were working in skilled occupations, showing significant movement over time. The second row shows the US occupations for people who worked in unskilled occupations in their home country. This group is much less likely to work in a skilled occupation in the US, although the percent in a skilled occupation increases with time in the US (from 18 to 30%).

Next we look at the determinants of a person's occupation in the US. Table 4 shows probit regressions on the likelihood of working in a skilled occupation in the US. In the first column, the dependent variable is a dummy variable that equals 1 if a person is working in a skilled occupation

[5] To create the sample we begin with individuals working in the US and drop those in school during the survey. The model will assume that people cannot move from skilled to unskilled occupations. To remain consistent with this assumption, we drop people who start in skilled occupations and transition to unskilled jobs. This causes us to lose 121 observations. Also, the model assumes people can only work in skilled occupation when living in the US legally, so we drop 190 observations who work in the skilled occupation when they have 0 years of legal work experience in the US.

[6] 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.

when they first move to the US. People who worked in a skilled occupation at home are much more likely to work in a skilled occupation in the US. We divide the sample into three groups based on education, where the excluded group is those who have less than a high school education. Education increases the probability that a person works in a skilled occupation. We also find that a person who attained part or all of their schooling in the US is more likely to work in the skilled occupation. Work experience at home has a negative effect on the likelihood of working in the skilled occupation. Since work experience at home is correlated with the age at which a person moves, we interpret this as being due to age effects in hiring. People who come to the US with work visas are more likely to work in the skilled occupation initially, which is logical since visas are costly for employers and are therefore more likely to be acquired for skilled workers.

In the second column of Table 3, we look at the transitions from low to high skill occupations with time in the US. [7] Legal years of work experience increase the probability that a person transitions to the high skill occupation, although illegal years of work experience do not seem to affect the transition rates.[8] Also, people with some college are more likely to get an offer from the high skill occupation.

Categorizing occupations as simply "skilled" and "unskilled" 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.[9] The data in the O*NET database created by the Bureau of Labor Statistics gives a measure of the task requirements of each occupation. This is used to create an index of the manual, cognitive, and interpersonal task requirements of each job using Principal Component Analysis as described in Poletaev and Robinson (2008). 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." In Table 3, we show the manual and cognitive task requirements of jobs at home, in the US initially, and in the US at the time of the survey. When people move to the US, they switch to jobs with lower cognitive task requirements than at their home job. However, with time in the US, they transition to higher cognitive task jobs. We do not see a difference between the manual task requirements of jobs at home and initially in the US.

Next we look at the determinants of the task composition of jobs. This is shown in Table 5. In the first 2 columns, we show the determinants of the task composition of a person's first job in the US. The second two columns show this for each person's most recent job. Tasks at home affect the characteristics of jobs in the US. In addition, the last two columns show that the tasks of a person's first job in the US affects the tasks in their most recent job. Work experience at home affects the first job, but not the final job, in the US. Years of legal work experience affect the final cognitive

[7] Therefore, this regression only includes people who initially work in an unskilled occupation in the US.

[8] Because of this, in the model we will assume that only legal years of work experience affect the transitions to the high skill occupation.

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

tasks, whereas illegal years of experience affects the manual tasks of a job.

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 (which includes schooling, gender, and family background), the years of experience in the US labor market e, 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 whether or not a person works in a high skilled occupation at home, using this as a proxy for a person's productivity. The dummy variable sh_i indicates whether or not a person worked in a skilled occupation 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 increased productivity for those who worked in skilled occupations at home, 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 e_{it} on the conditional mean of j_{it} 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}:

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

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

under the assumption that given the distance, the effect of experience on the number of offers disappears. Then we can write this 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 $g(\cdot)$ is some unknown function of D_{it} but not e_{it}. Then the returns to experience are identified. With some additional assumptions of the effects of D_{it} on j_{it}, we can test whether $g(D_{it}) = 0\ \forall D_{it}$ (which would imply $\beta_j, \gamma_j = 0$) or not. Note that this doesn't imply that workers are actually paid differently based on their distance from the optimal occupation conditional on their skill level. Instead it is just a proxy (with a negative sign on it) for the number of offers we would expect them to have already received.

We use a measure of distance between two occupations that represents the difficulty in transferring across them. Shaw (1987) explains one potential method, which relies on estimating the probability that native workers transition between occupations. Here we take an approach from the task-specific human capital literature and create a distance index based on the difference on tasks performed across occupations, as in Poletaev and Robinson (2008) and Gathmann and Schonberg (2010). Assume for now we have created this index (to be detailed later) and denote the distance

between occupations j and k as D_{jk}. Our baseline empirical strategy is to estimate the equation

$$W_{it} = X_{it}\beta + e_{it}\beta_e - e_{it}^2\gamma_e + D_{j_{it}i^\star}\zeta + sh_i\gamma_{sh} + \varepsilon_{it}.$$

This is the same wage equation as above, but instead of the total number of outside offers j we use $D_{j_{it}i^\star}$, the distance between the worker's current occupation and their long-run "optimal" occupation, which, in the data, is their occupation in their home country. We interpret a negative coefficient on the distance measure $D_{ji^\star}$ as saying that job search forces are important for wage growth, conditioning on work experience. In the next section, we will use this intuition about the difference between the initial job and the ideal job to separate the effect of search from the returns to experience.

Table 6 shows the results of a regression on initial and current wages in the US (all in 2004 dollars). Different specifications use different measures of occupational distance. In the first and third columns, we use a binary measure of occupations, where each job is either skilled or unskilled. The distance term equals 1 if a person is in the same occupation as their home country and 0 otherwise. Using this binary specification, we see no effect of the distance term. People who move legally or have 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. High school and college education increase wages. People who have some schooling in the US earn lower wages, which could be because these people are still in school when working their first job. The third column of Table 6 shows this regression for the current job in the US. This allows us to look at returns to work experience in the US. Illegal years of work experience in the US do not affect wages, whereas legal years of experience increase wages.

In the second and fourth columns of Table 6, we classify occupations using the task measures explained previously. We classify each job using the cognitive and manual skill requirements. We assume wages can be written as

$$w_{it} = X_{it}\beta + E_{it}\beta_E - E_{it}^2\gamma_E + D^{cog}_{j_{it}i^*}\zeta_{cog} + D^{man}_{j_{it}i^*}\zeta_{man} + D^{int}_{j_{it}i^*}\zeta_{int} + cog_{hi}\gamma_{cog} + man_{hi}\gamma_{man} + int_{hi}\gamma_{int} + \varepsilon_{it}$$

In this equation, $D^z_{j_{it}i^*}$ is the distance between a person's current occupation and their optimal occupation in skill factor z, where z stands for manual, cognitive, and interpersonal skills.[10] $\zeta_z$is the importance of skill factor z 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 z_{hi} gives the task requirements for a persons home occupation, and $\gamma_z$is

[10]We define the optimal occupation as a person's job in the home country.

the return to skills for each task.

The results are shown in the second and fourth columns of Table 6. Most of the results are similar to before. However, we find returns to job search when using the continuous measure of cognitive tasks. 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. We however see the opposite effect for manual skills. This is likely because measuring the optimal occupation as the home country job when workers are younger will lead to it stating that workers would like to work at manually intensive jobs in the long run, whereas they would likely prefer to move to more cognitively-intensive jobs in the longer run. A better definition of the optimal long-term job would potentially change this result.

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. Essentially we are using the model to fill in what the offer rates would have to look like to generate the observed data in a simple model. We can use our results to back out the relative importance of the two factors for wage growth.

We use a full-information labor search model. There is a mass of workers m indexed by $i \in [0,m]$ and a unit mass of firms indexed by $j \in [0,1]$. Workers have an exogenous fixed characteristic $\theta_i \in \mathbb{R}$ called their "ability" and firms have an exogenous fixed characteristic $\phi_j \in \{0,1\}$ called their "productivity." Immigrants have an exogenously given time of labor force entry $t_i^0 \geq 20$, and prior to that we assume they worked in their home country from age 20 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. All firms are identical except for their differing productivity. We order the firms so that if $j < p$ they have $\phi_j = 0$ (low productivity firms), and if $j \geq p$ they have $\phi_j = 1$ (high productivity firms.) The proportion of high-type firms in the economy (measured by p) is a parameter to be estimated. Productivity increases by δ at high productivity firms.[11] When worker i and firm j are matched in time t, assume the log wage w_{ijt}

[11] For now, we are just assuming firms are high or low productivity. In further work we will classify jobs using a continuous measure.

the worker receives is

$$w_{ijt} = h_i + \phi_j \delta + \varepsilon_{ijt}$$

where h_i is the endogenous "human capital" of worker i.[12] 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, $\beta_1 \neq \psi_1$, 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 one offer from an outside firm whose index is given by $j' \sim U[0,1]$. From the discussion above, the probability of an outside firm being the high (low) type is $1-p$ (p). The worker accepts the offer before seeing his wage shock realization and otherwise remains in the same firm. Assume workers accept whatever offer they receive in the first period.

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 a high type firm.

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 in time t of a native cohort in the median of the ability

[12] 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

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

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:

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

The expected value of firm productivity is the probability of being in a high-type firm, which after t years of receiving offers is $1-p^t$ (since workers accept the first offer from a high-type firm), so

$$E_0^N\left[w_{ijt}|\theta_i=\mu^N\right]=\mu^N+\psi_1 US_{it}^N+\psi_2\left[US_{it}^N\right]^2+\gamma X_i^N+\left(1-p^t\right)\delta$$

This shows clearly why average wages are increasing over time: first, E_{it} increases, and second, $1-p^t$ is increasing in t so workers are more likely to move to higher type jobs if they have been in labor market for a longer period of time.

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

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

which can be rewritten as

$$\mu^I+\gamma X_i^I+(\beta_1-\psi_1)F_{it^0}+\psi_1\left(F_{it^0}+US_{it}^I\right)+\beta_2 F_{it^0}^2+\psi_2\left[US_{it}^I\right]^2+\left(1-p^{t-t_i^0}\right)\delta.$$

Since the workers are assumed to be the same age and work every period, total experience is the same: $F_{it_i^0}+US_{it}$ for immigrants is the same as US_{it} 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:

$$E\left[\Delta w|\mu^I,\mu^N\right]=\left(\mu^N-\mu^I\right)+\gamma E\left(X_i^N-X_{it}^I\right)-(\beta_1-\psi_1)F_{it_i^0}+\psi_2(\left[US_{it}^N\right]^2-\left[US_{it}^I\right]^2)-\beta_2 F_{it^0}^2+p^t\left(p^{-t_i^0}-1\right)\delta$$

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 p^t is decreasing in t; 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 generate a native-immigrant wage gap that is falling over time.

The intuition for this if the first few years of experience in the US lead to the acquisition of the

most important skills, so immigrant workers will quickly catch up to their native counterparts who already learned those skills when they were younger. On the other hand, the initial experience gap will not change over time, so they can never completely catch up.

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 (p)

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 (p^t)

6 Estimation

To estimate a preliminary version of the model, we make a number of assumptions. First of all, we assume that there are only two types of jobs: skilled or unskilled.[13] We assume that people cannot work in high skill occupations unless they are in the US legally. This assumption is made because very few people in the data work in a high skilled occupation while living in the US illegally. We allow for returns to experience only for legal years in the US. We technically could allow for returns to illegal years of experience, but excluded this because the reduced form evidence showed no effect.

We also made some assumptions on the structure of the model. When a job offer is made, a person does not see the wage draw (the error term in our model). Therefore they will always take the job with the higher expected wage, which is the high skill occupation in this setting. We also assume that people cannot transition from high to low skill jobs (which, within the context of our model, means that people will not lose their jobs).

[13] We are working to extend the model to allow for a continuous measure of the skill level of each job using the task measures explained earlier. This will be included in future version of the paper.

For now we estimate a version of the model with no unobserved heterogeneity.[14] 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). Human capital includes education and occupation in one's home country.

The reduced form data analysis shows that people are the most likely to transition to high skill jobs in their first period in the US. In the context of our model, this means that the rate of job offers from high skill jobs is highest in the first period. We therefore allow for different job offer rates in the first period and in subsequent periods. For both job offer probabilities, we assume that

$p = \Phi(\alpha_0 + \alpha_1 X)$,

where X is a vector of characteristics including education and home occupation, $\Phi(\cdot)$ is the CDF of the standard normal distribution, and α is a set of parameters to be estimated.

6.1 Likelihood function

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. Write ϕ_j as a dummy variable that indicates whether or not occupation j is a high skilled occupation. Recall that wages are written as

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

where $h_{it}$is the endogenous human capital of worker i at time t. We can write

$$h_{it} = \psi_1 US_{it} + \psi_2 US_{it}^2 + \gamma X$$

where US_{it} is a person's labor market experience in the US, and demographics X include education and home country occupation. Then we know that

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

with σ_ε as the standard deviation of the ε distribution. Conditional on occupations, the likelihood for a given wage draw at time t is

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

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. Conditional on each person's characteristics, assume they have a probability p_{0i} of getting an offer from the high

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

skill sector in the first period, and a probability p_i of getting an offer from the high skill sector in subsequent periods. The following table shows the probability of each sequence of occupations in the data

After t periods	$\phi_2 = 0$	$\phi_2 = 1$
$\phi_1 = 0$	$(1-p_{0i}) \times (1-p_i)^t$	$(1-p_{0i}) \times (1-(1-p_i)^t)$
$\phi_1 = 1$	0	p_{0i}

Then we can calculate the probability of a person's sequence of occupation draws, which we denote as $Pr(\phi_1, \phi_2|X)$. Then we can wrote the log likelihood as

$$\mathscr{L}(\cdot) = \sum_{i=1}^{N} \log(L_w(w_{ij1}|h_{i1}, \phi_{i1})) + \log(L_w(w_{ij2}|h_{i2}, \phi_{i2}) + \log(Pr(\phi_{i1}, \phi_{i2}|X).$$

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 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 7 contains the parameter estimates and standard errors. We estimate two sets of job offer probabilities.[15] The first is for the initial job in the US. Working in a skilled occupation at home as well as education increase the probability that a worker gets an offer from a high skill job in the first period. We also estimate the probability that a person gets an offer from the high skill sector in each period after their first in the US. In this case, working in a skilled occupation at home has no effect. People with college education are more likely to get an offer from the high skill occupation.[16]

We also estimate the parameters of the wage distribution. People in skilled jobs earn higher wages. Returns to experience at home and in the US have the standard concave shape, although returns to work experience in the US are much higher. Education increases wages, as does having worked in the high skill occupation in one's home country.

[15] For these probabilities, the coefficients reported are probit parameters to keep the total probability between 0 and 1.

[16] The results do not show a parameter for having completed high school. This was estimated to be 0 and dropped from the estimation.

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 overpredicts 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 show the wage densities, split by home occupation, in Figures 3 and 4 for initial and current wages, respectively.

Next we split the sample by education level and years of work experience. In Figure 5, we plot the average wages (in the data and in the simulated model) for a person who did not complete high school with a given amount of work experience in the US. Figures 6 and 7 do this for people a high school education and some college, respectively. Overall, the model fits the data fairly well, except for people with more years of work experience, which is a relatively small fraction of the sample. In addition, we see from the data that wages drop off fairly rapidly with large amounts of work experience in the US. This is most likely due to the fact that people with more work experience are from older cohorts, and therefore may have different unobserved skill levels. In future work, we can hopefully explain this by adding cohort effects and unobserved heterogeneity to the model.

We also test the fit of the model in terms of predicting the correct occupations. Figures 8, 9, and 10 show the probability that a person works in a high skill occupation at the time of the survey, splitting the sample by years of experience in the US and education levels. As before, the model fits the data fairly well, except for at high levels of work experience.

7.2 Counterfactuals

We 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.[17]

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

7.2.1 Returns to experience

In the first counterfactual, we assume that immigrants have been living in the US for their entire life. This means that all of their work experience is in the US. For example, consider a college educated worker who moves to the US at age 30. In the baseline case, at age 30 he would have 0 years of work experience in the US and 8 in his home country. In the counterfactual, we assume that his 8 years of work experience at home get the same returns as work experience in the US. This counterfactual helps to tell us the effects of policies that help workers adapt to the US labor market, such as job training programs. Table 8 shows that this counterfactual raises lifetime income by 32% on average. This varies by education level, with the gains increasing with education.

7.2.2 Search frictions

In the next counterfactual, we assume that people are matched in their optimal occupation in their first job in the US.[18] 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. Comparing to the baseline case, Table 8 shows that eliminating search frictions increases lifetime earnings by 5%. The effects are largest (9%) for people with a high school degree since they are most likely to have worked at a skilled occupation at home and an unskilled one in the US.

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.

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. In the first simulation, we allow for returns to experience to be the same for labor market experience in the US and in a person's home country. This increases the lifetime earnings of immigrants by 32%. In the second simulation, we match immigrants with their optimal occupation in their first US job. This increases lifetime earnings by 5%.

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

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.

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9 Tables and Figures

Table 1: Summary Statistics

Variable	Mean
Age	37.7
Percent male	63.2%
Years living in the US	6.1
Years living legally in the US	3.9
Percent with no illegal years	83.0%
Fraction that have a sponsor	64.5%
Fraction of sponsors that are employers	38.5%
Less than high school	26.5%
High school	34.6%
College	38.9%
Sample Size	2422

Table 2: Occupation transitions

Occupation in home country	Percent of sample	Percent in skilled occupation in US	
		Initially	Time of survey
Skilled	30.06%	51.13%	70.29%
Unskilled	69.94%	18.28%	30.65%

Table 3: Task requirements of occupations

	Cognitive	Manual
Home	-0.003	-0.07
Initial job in US	-0.42	-0.07
Current job in US	-0.16	-0.16

Table 4: Working in skilled occupation

Variable	Initial	Transition
Skilled at home	0.68***	0.31*
	(0.08)	(0.19)
Illegal years in US		3.58
		(102.5)
Illegal years in US squared		-2.49
		(102.5)
Legal years in US		0.14**
		(0.06)
Legal years in US squared		-0.005*
		(0.003)
Work experience at home	-0.03**	0.03
	(0.01)	(0.04)
Work experience at home squared	0.0007*	-0.001
	(0.0004)	(0.001)
Male	-0.19***	-0.29*
	(0.07)	(0.16)
High school	0.87***	0.06
	(0.15)	(0.24)
College	1.55***	0.54**
	(0.15)	(0.26)
Any school in US?	0.30***	0.34*
	(0.10)	(0.20)
Work visa	1.40***	0.11
	(0.08)	(0.18)
Constant	-2.13***	-1.70***
	(0.17)	(0.43)
Pseudo R-squared	0.40	0.26
N	2115	492

Table 5: Skill transmission (tasks)

	First job in US		Current job in US	
	Manual skills	Cognitive Skills	Manual Skills	Cognitive skills
Manual skills of home job	0.26***		0.10***	
	(0.02)		(0.03)	
Manual skills in initial US job			0.58***	
			(0.03)	
Cognitive skills of home job		0.36***		0.09***
		(0.02)		(0.03)
Cognitive skills in initial US job				0.62***
				(0.03)
Male	0.13***	0.04	0.07*	0.001
	(0.03)	(0.03)	(0.04)	(0.04)
Work visa	-0.33***	0.59***	-0.04	0.05
	(0.03)	(0.03)	(0.04)	(0.04)
Home experience	0.01**	-0.009*	-0.002	-0.006
	(0.005)	(0.005)	(0.007)	(0.007)
Home experience squared	-0.0003**	0.0001	0.0001	-6.99e-6
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
High school	-0.09*	0.13***	-0.16***	0.04
	(0.04)	(0.04)	(0.06)	(0.05)
College	-0.39***	0.35***	-0.29***	0.26***
	(0.04)	(0.04)	(0.06)	(0.06)
School US	-0.18***	0.06	-0.01	0.11***
	(0.04)	(0.04)	(0.04)	(0.04)
Legal years of work experience			0.006	0.04***
			(0.01)	(0.01)
Legal years squared			0.0002	-0.001**
			(0.0006)	(0.0006)
Illegal years of work experience			0.04***	-0.008
			(0.01)	(0.01)
Illegal years squared			-0.0013**	0.0001
			(0.0007)	(0.0006)
Constant	0.11**	-0.73***	-0.03	-0.17*
	(0.04)	(0.05)	(0.09)	(0.09)
R-squared	0.28	0.44	0.62	0.72
N	2113	2113	813	813

Table 6: Wage regressions

	Initial wage	Initial wage	Current wage	Current wage
Male	0.60**	0.45**	3.78***	2.87***
	(0.24)	(0.22)	(0.54)	(0.48)
Illegal years work experience			0.38	0.32
			(0.27)	(0.23)
Illegal years squared			-0.01	-0.009
			(0.01)	(0.008)
Legal years work experience			0.41**	0.32*
			(0.20)	(0.17)
Legal years squared			-0.02*	-.01
			(0.008)	(0.01)
Moved legally	2.27***	1.38***	4.35**	1.74
	(0.40)	(0.35)	(2.10)	(1.78)
Work experience at home	0.04	0.09**	-0.17*	-0.14*
	(0.04)	(0.04)	(0.09)	(0.08)
Home work experience squared	-0.002	-0.002**	-0.001	-0.0002
	(0.001)	(0.001)	(0.003)	(0.002)
Skilled at home	1.83***		3.63***	
	(0.29)		(0.61)	
Home Cognitive		4.57***		7.97***
		(0.19)		(0.43)
Home Manual		-0.39**		-1.30***
		(0.19)		(0.41)
High School	1.03***	0.25	1.77**	0.21
	(0.33)	(0.29)	(0.76)	(0.66)
College	3.19***	0.86**	8.58***	2.44***
	(0.36)	(0.34)	(0.88)	(0.82)
Any school in US	-1.17***	-1.48***	0.25	-0.22
	(0.36)	(0.31)	(0.66)	(0.57)
Match	0.45		0.44	
	(0.29)		(0.60)	
Cognitive skill difference		3.93***		5.26***
		(0.17)		(0.37)
Manual skill difference		-0.40**		-1.37***
		(0.16)		(0.35)
Work visa	5.81***	3.00***	6.93***	4.25***
	(0.28)	(0.27)	(0.60)	(0.54)
Constant	3.67***	8.70***	4.33**	12.87***
	(0.54)	(0.44)	(2.13)	(1.83)
R-squared	0.34	0.51	0.51	0.64
N	2014	2012	1066	1066

Table 7: Parameter Estimates and Standard Errors

	Parameter	SE
Occupation parameters		
Init. Occ: Constant	-2.18	(0.12)
Init. Occ: Skilled at Home	0.686	(0.07)
Init. Occ: High School	1.03	(0.13)
Init. Occ: College	1.93	(0.13)
US Trans: Constant	-2.09	(0.07)
US Trans.: Skilled at Home	0.0642	(0.10)
US Trans.: College	0.469	(0.09)
Wage parameters		
US Skilled Firm Premium	0.671	(0.01)
Variance of Wage Distribution	0.389	(0.00)
Wage Const.	1.94	(0.02)
Home Returns to Exp.	0.00191	(0.00)
Home Return to Exp Sq.	-0.000129	(0.00)
US Return to Exp.	0.1	(0.00)
US Return to Exp. Sq.	-0.00437	(0.00)
US Wage Return to HS	0.0493	(0.02)
US Wage Return to College	0.18	(0.02)
US Wage Return to Home Skills	0.0844	(0.01)

For occupation terms, the coeffiencts are probit parameters. Wages are in logs.

Table 8: Proportional Welfare Effects of Counterfactuals

	Overall	No High School	High School	College
Baseline	1	1	1	1
No Occupation Frictions	1.05	1.05	1.09	1.03
Equal Returns to Experience	1.32	1.22	1.3	1.38

Figure 1: Initial Wages

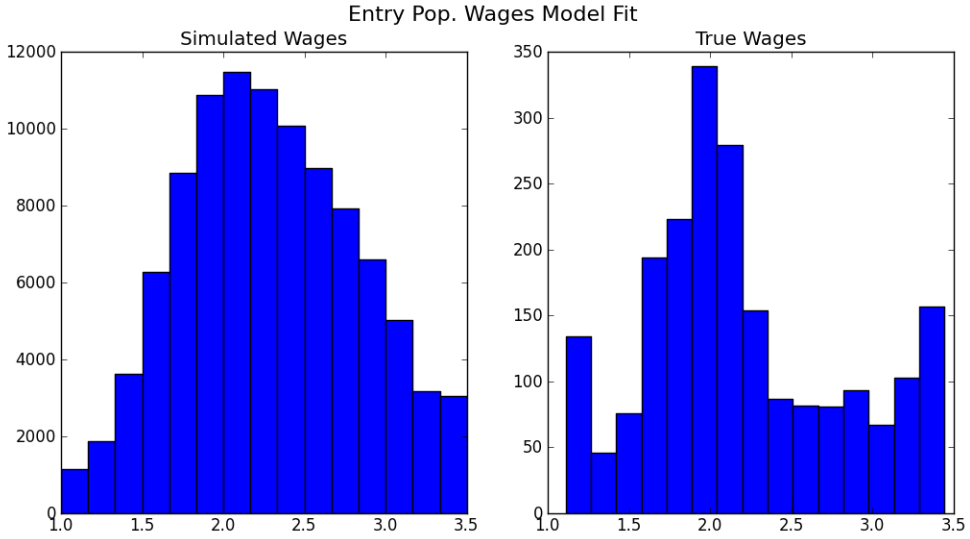

Figure 2: Model Fit- Current Wages

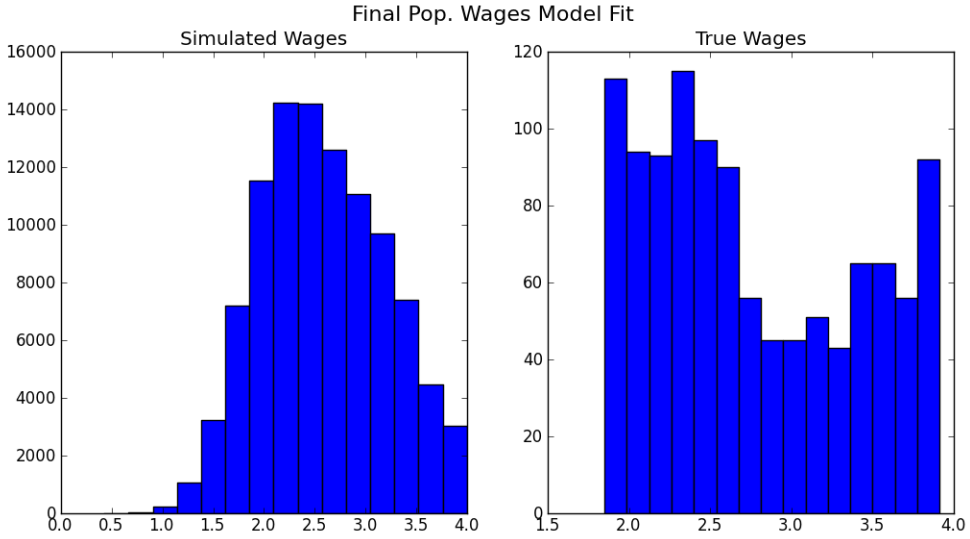

Figure 3: Model Fit- Current Wages by Home Occupation

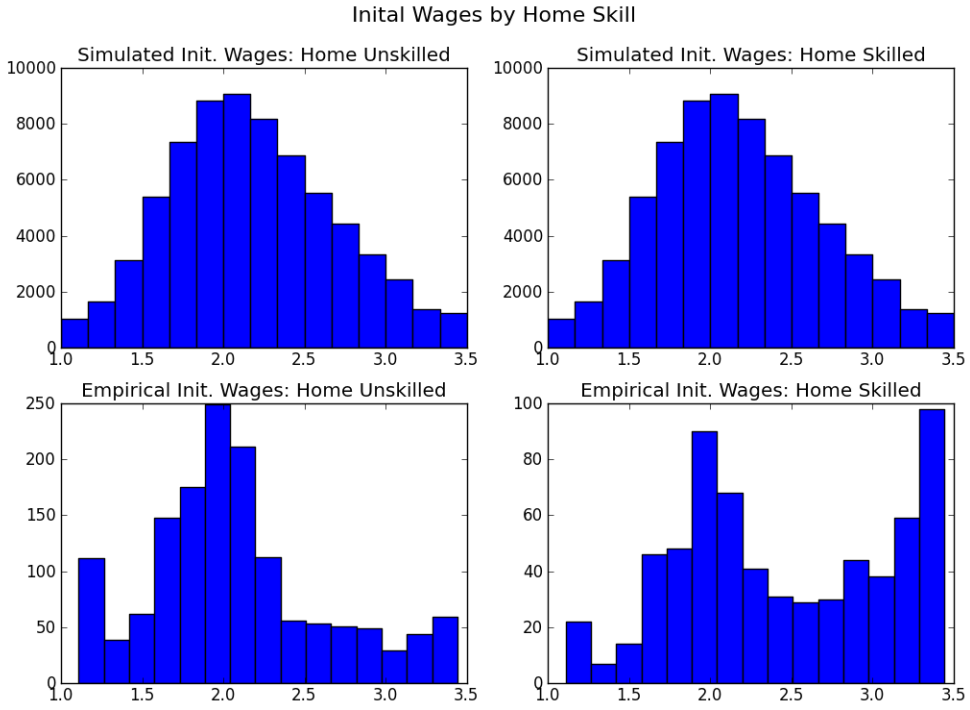

Figure 4: Model fit- Current wages by Occupation

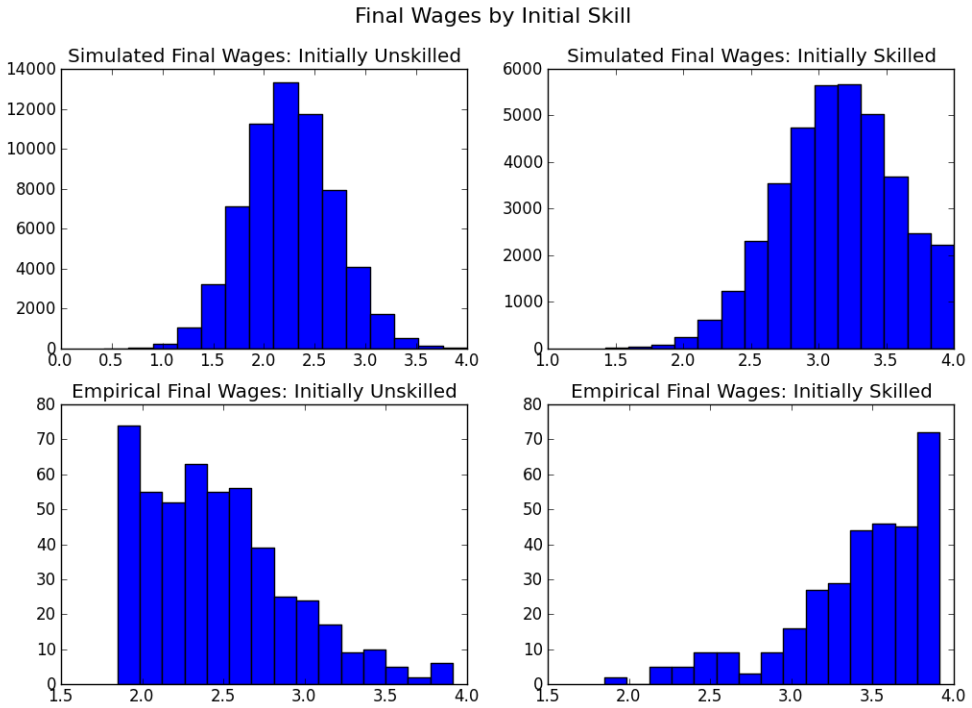

Figure 5: Model Fit- Wages by Experience (No High School)

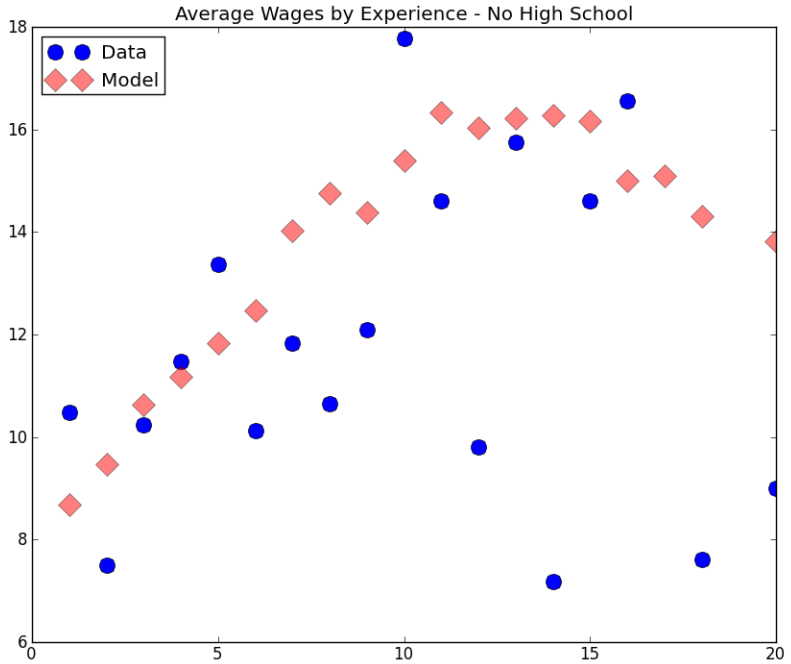

Figure 6: Model Fit- Wages by Experience (High School)

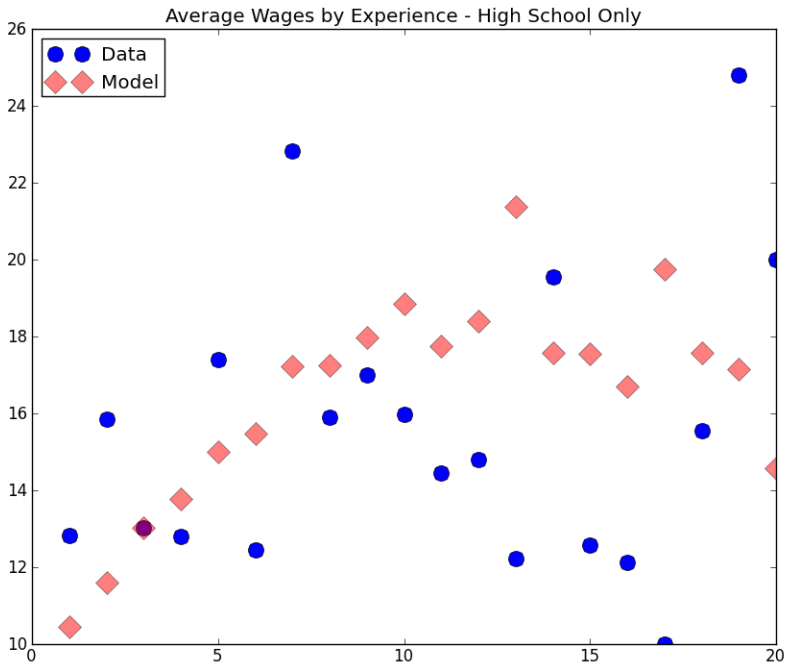

Figure 7: Model FIt- Wages by Experience (College)

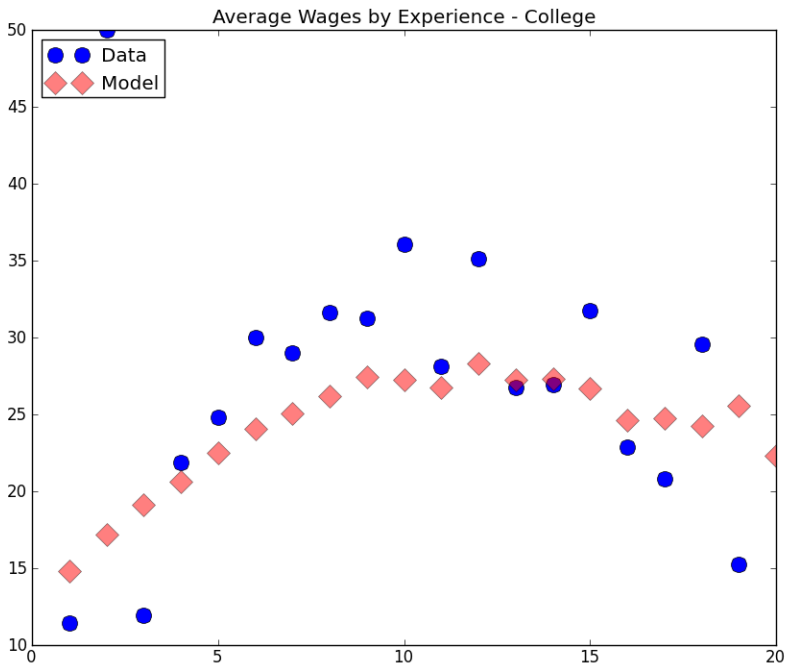

Figure 8: Model Fit- Current Occupations (No high school)

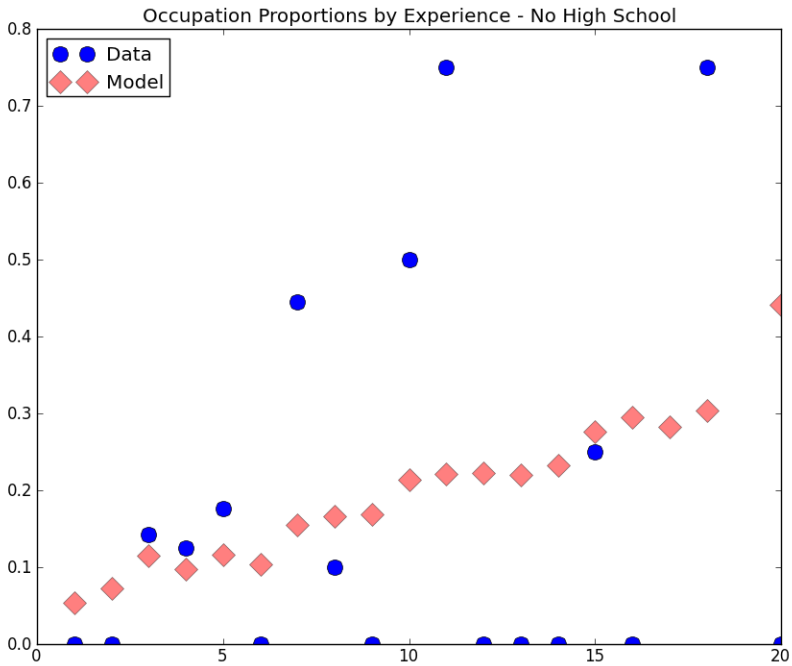

Figure 9: Model Fit- Occupations (High school)

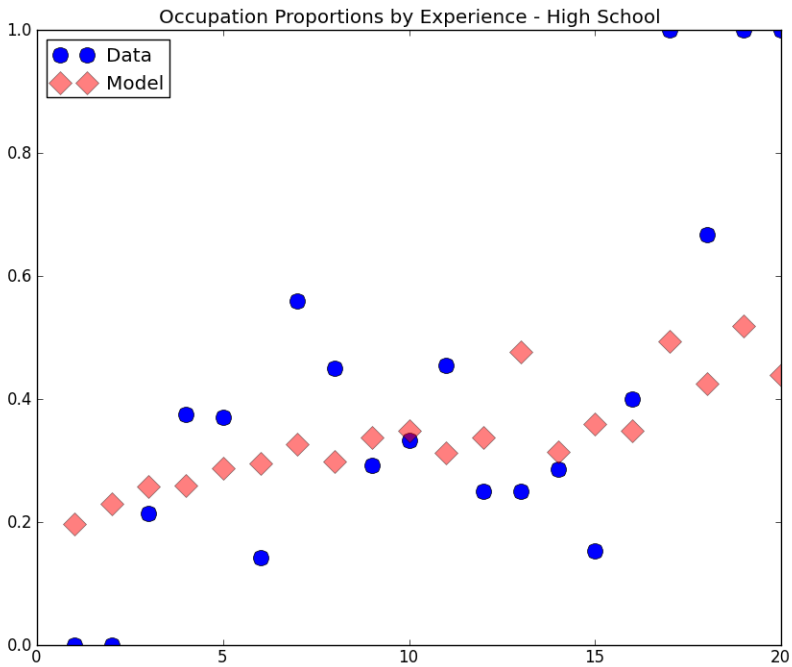
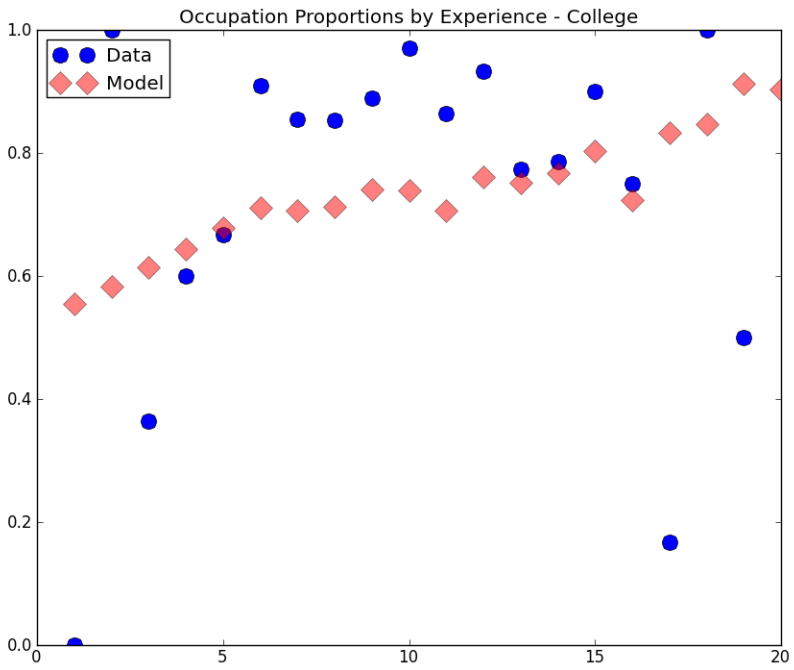
Figure 10: Model Fit-Occupations (College)