Dual Earner Migration Patterns: The Role of Locational Compatibility within Households

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October 26, 2018

Abstract

In this paper, I analyze how locational compatibility of married couples’ occupations affect their household migration decisions. I find that if spouses’ careers are concentrated in similar locations or if spouses have similar preferred locations, they are more likely to both earn more and move more. I then build a structural model in which households decide whether to move as a function of occupation-location match and individual location preference shocks. I estimate the model using full information maximum likelihood with data from the National Longitudinal Survey of Youth 1979, with separate estimation for households with married couples and for households with individuals. Using this model, I show that migration costs vary across occupation groups, with those in occupations that are more locationally disperse having lower migration costs. I then use the parameters estimates from model to show that differences in migration rates across household types is strongly associated with mismatch in locational preferences across couples by testing a counterfactual in which I match individuals to a spouse in their same occupation. Finally, I estimate the effects of a relocation incentive policy on migration rates and demonstrate that models which ignore family ties will overestimate the effects of such a policy.

Thanks to John Kennan, Chao Fu, Matt Wiswall, Chris Taber, Jeff Smith, Arpita Patnaik, Nicolas Badaracco, Hans Schwarz, Sandra Spirovska, Dennis McWeeney, and seminar participants at University of Wisconsin for helpful comments and suggestions on this paper. This research was partially supported by the Juli Plant Grainger Summer Research Fellowship generously provided by the University of Wisconsin-Madison.
1 Overview

How do couples decide where they should live when their careers are locationally incompatible? The choice of where one lives is tightly linked to where one works and the desirability of a given location will depend on the availability of quality jobs in one’s chosen career in that location. A couple has locationally incompatible careers if the places that are desirable for one spouse’s career are undesirable for the other’s. Past research on migration shows that married couples have lower rates of migration compared to single individuals, even controlling for differences in age, education, and experience. Despite much research on how married couples choose where to live, few papers have explored how occupational match between spouses may make it easier or harder for couples to migrate. In this paper, I estimate the different costs and benefits of relocation for couples with different occupational pairings and discuss how differences in migration rates by occupation may impact men and women differently.

I begin by performing two descriptive analyses of married couples’ migration patterns. I develop two measures of locational compatibility and estimate the impacts of each spouse’s location-occupation match on migration using a sample of married couples from the National Longitudinal Survey of Youth 1979 (NLSY79). I show that that the locational match of spouses’ occupation have asymmetric effects by gender, with husband’s occupation-location match quality playing a larger role in both migration decisions and earnings outcomes.

I then develop a static model of household migration decisions. Households choose their location to maximize joint utility, which is a function of their income offers in each location, leisure value by location, cost of living by location, distance from home location, and location-specific preference shocks. I estimate this model separately for a sample of married couples in the NLSY79 using full information maximum likelihood estimation (FIML).

Using this model, I test the hypothesis that individuals across all occupations have the same costs associated with leaving their home location. I reject this hypothesis and show that my model predicts the lowest migration costs for individuals in occupations that are more widely dispersed across locations (i.e., low scores on the index of occupational agglomeration) and for individuals who are not working.

I then perform two different thought experiments to better understand why we see lower migration rates for married couples than single couples. In the first, I predict migration rates for married couples if both spouses were in the same occupation and show that improving couple’s locational compatibility increases their migration rate from 1.94 percent in the original sample to 6.4 percent in the thought experiment. Next, I predict migration rates for the married couple if they had the same preferences as estimated in the original model, but one spouse is able to unilaterally make migration decisions based on on their own preferences. In this simulation, households where the husband decides based only on his own income and preferences move significantly more (10.9 percent movers) whereas households where the wife decides move less (1.7 percent movers). This is consistent with past research showing that women are more likely to be tied movers (i.e., move when their individual preferences do not predict migration).

Finally, I demonstrate that proper specification of a household’s decision-making process is important for
understanding the role that policy can play in influencing mobility rates within the United States. I estimate the effects of a counterfactual policy that mirrors relocation incentive programs in European countries, in which job-seekers who apply for and accept a job more than a certain distance from home receive $5000. I first show how this policy will affect migration rates in my primary model where households make joint location decisions and then demonstrate how a model which assumes individual control over location choice will overpredict the effect of a relocation incentive program. In particular, ignoring families ties heavily overstates how much a relocation incentive will encourage women to move. The relocation incentive program would increase migration rates for married couples by 1.8 percentage points if migration is considered a joint decision. Model estimates that ignore family ties over-predict migration rates for women, with the model predicting women would increase migration rates by 4.5 percentage points. This is consistent with research on a Germany relocation incentive program, which has previously shown that offering the relocation incentive has a strong effect on earnings for the general population, but is not a good predictor for married couples’ earnings post-migration partially due to lower take-up (Caliendo et al., 2017).

The paper is organized as follows. In section 2, I first position my question within the existing literature on household migration and then use two different measures of occupation-location match to establish a link between spousal match and migration rates. In section 3 and 4, I describe my data and my model, respectively. In section 5, I describe my estimation and identification strategy for the parameters of interest and in section 6, I report the results of my parameter estimates and model fit. Finally, I outline the results of my analysis in section 7, discuss my counterfactual exercises in section 9, and then conclude in section 8.

2 Motivation

2.1 Existing Literature

There is a large literature on household migration, starting with Mincer’s seminal model on the topic (1978). He shows that married couples tend to have lower mobility rates than single individuals because couples have to consider two sets of locational preferences rather than just choosing the location that maximizes one’s own utility or income. These considerations over another person’s location preferences result in what are referred to as ‘tied movers’ and ‘tied stayers.’ A tied mover would not choose to move as an individual agent, but they move because the gains of their spouse dominate their individual losses. A tied stayer is the opposite: a person who would accrue gains from moving as an individual, but chooses not to move due to spousal considerations. These family ties are mitigated if a couple’s preferences and earnings profiles are locationally compatible. Mincer posits two different ways that a married couple’s migration decision may approach that of a single mover: either one spouse’s average earnings is much higher than the other’s, in which case that spouse’s preferred location will win out, or the spouses’ earnings across locations are highly correlated.

Since there historically have been large disparities in the earnings of husbands and wives, many papers on family migration have focused on the impacts of the first case – the role of primary earners versus secondary earners. Past research has shown that household moves are typically initiated by job opportunities for the husband (Mincer, 1978; Boyle et al., 2001; Nivalainen, 2004; Gemici, 2016). This is due in part to
men historically being the primary breadwinner in most families as well as women tending to specialize in home production (Becker, 1973). If one spouse’s income makes up a small part of the family’s income, they are more likely to be the tied mover. As such, married women are more likely to end up non-optimally located than married men. Past studies find that migration is positively associated with wage growth for husbands and negatively associated with wage growth for women (LeClere and McLaughlin, 1997; Cooke, 2003; Gemici, 2016).

However, these papers are missing an important factor in a family’s migration decision: How does the locational compatibility of the spouses’ careers influence household migration? As more and more households are helmed by not one earner, but two, the second prediction of Mincer’s theory becomes more important: correlation between wages, rather than absolute level of wages of one earner, may be the larger driver of whether a household moves. Not only are more women working now than in the past, but the gender gap in earnings has declined, meaning that more households have a fairly even split of earnings between spouses. This makes the migration decision more dependent on both spouses being able to find work in a new location. For this reason, dual-earner couples and, in particular, couples who both have college degrees (termed ‘power couples’), tend to have a more difficult co-location problem and have increasingly chosen to live in urban areas where they are more likely to have job opportunities in both of their industries (Compton and Pollak, 2004; Costa and Kahn, 2000; Simon, 2017).

I hypothesize that couples whose job opportunities are locationally compatible will be more likely to migrate than those whose are dissimilar across locations. The role of occupation in the migration decision would be particularly important for a person in an occupation that is locationally concentrated. Such jobs make it harder for a couple to move because there are fewer job opportunities in other locations. For example, as of 2015, only 3% of individuals in the agricultural industry are located in the Mid-Atlantic Census Division, compared to 28% in the West North Central Division. On a level more granular than overall industries, there are many examples of career fields that have geographic hubs where many jobs are concentrated, such as the publishing industry in the New York metropolitan area, technology start ups in Silicon Valley, or historically the motor industry in Michigan.

A small body of literature has explored the role that the geographic-specificity of an occupation plays in couples’ migration decisions. Benson (2014; 2015) develops a model of marriage, migration, and occupational choice, in which individuals choose either geographically concentrated occupations or disperse occupations, marry, and then choose where to locate. He demonstrates that the equilibrium of such a model is for one gender to specialize into geographically specific occupations and the other to choose a geographically disperse occupation, due to the possibility that a couple will end up locationally mismatched if they both choose geographically concentrated occupations. Using an index of occupational clustering to measure the geographic specificity of different occupations, Benson finds that women are less likely to sort into geographically concentrated occupations and that women who do sort into geographically concentrated occupations are less likely to be married. Men, by contrast, have a higher likelihood of being in a geographically concentrated occupation and being in a geographically concentrated occupation is associated with higher probability of marriage. Additionally, while being in a geographically concentrated occupation is associated with higher earnings for married men, it is associated with lower earnings for married women, consistent with the hy-
pothesis that wives are more likely to end up geographically mismatched than husbands due to their role as a ‘tied mover.’

However, these papers only focus on the individual’s own compatibility to a location, rather than joint compatibility. As such, I have completed two preliminary statistical exercises to demonstrate the role that spousal match in terms of geographic-specificity of occupation plays in migration as well as the relative earnings returns by occupation and location of men and women.

2.2 Statistical Exercises

To better understand how spousal occupation-location compatibility impacts a couple’s migration decision, I will be borrowing two measures from the regional and urban economics literature on industry and occupation agglomeration: Locational Ginis, which measure the relative spatial concentration of U.S. industries, and an index of pairwise coagglomeration, which measures the extent to which two pairs of industries are concentrated within the same region. While regional economics literature classically has used these measures for understanding what industries and firms benefit from co-locating in a region, I am adapting these measures to understand which skills or occupations are concentrated in a given region. The measures I use are adapted from Abel and Gabe’s work (2011; 2016) on how geographically concentrated occupations are more likely to require specific or unique skill sets and from Ellison and Glaesar’s work (1997) on how different industries benefit from co-locating in similar regions.

Following Benson (2014; 2015), I first look at the relationship between earnings, migration, and being in a geographically concentrated occupation. To measure occupational concentration, I compute a locational Gini for occupations, using 506 occupational categories (three-digit level) drawn from the 1990 US Census, retrieved from IPUMS.1 For these calculations, I restrict my sample to individuals who are of working age (25 to 65) and calculate the share of individuals employed in each occupation by state as well as each state’s total share of national employment. From this, I am able to calculate the locational Gini coefficient as follows:

\[
\theta_k = \left[ \frac{1}{n(n-1)} \right] \sum_{i=1}^{n} \sum_{j=1}^{n} |x_i - x_j| \\
4 \sum_{i=1}^{n} x_i
\]

where \(i, j\) = U.S. states, where \(i \neq j\) and \(n = 50\)

\[x_i = \frac{\text{state i’s share of employment in occupation k}}{\text{state i’s share of total employment}}\]

The locational Gini ranges from 0, when an occupation is dispersed across the country in a pattern similar to the distribution of all employment, to 0.5 when an occupation is geographically concentrated in a single state. Table 1 lists the ten occupations with the highest \(\theta\) values (panel A) and the lowest \(\theta\) values (panel B).

This measure describes how concentrated or disperse an individual’s occupation is. We would expect that individuals in more locationally disperse jobs would find it easier to move across states, due to the wider availability of jobs in their field in other locations. While the locational Gini provides a measure of how

1I use the 1990 US Census rather than more recent years to maintain consistency with the model estimation discussed later in the paper, which relies on data from the National Longitudinal Survey of Youth 1979 and captures the years 1982 to 1994.
Table 1: Locational Gini

Panel A. Occupational Categories with the Highest Agglomeration Levels

<table>
<thead>
<tr>
<th>SOC Code</th>
<th>Occupation Title</th>
<th>$\theta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>45-3000</td>
<td>Fishing and Hunting Workers</td>
<td>0.5</td>
</tr>
<tr>
<td>53-5000</td>
<td>Water Transportation Workers</td>
<td>0.3923</td>
</tr>
<tr>
<td>45-2000</td>
<td>Agricultural Workers</td>
<td>0.3914</td>
</tr>
<tr>
<td>47-5000</td>
<td>Extraction Workers</td>
<td>0.3753</td>
</tr>
<tr>
<td>53-2000</td>
<td>Air Transportation Workers</td>
<td>0.3714</td>
</tr>
<tr>
<td>53-4000</td>
<td>Rail Transportation Workers</td>
<td>0.3618</td>
</tr>
<tr>
<td>39-6000</td>
<td>Baggage Porters, Bell hops, and Concierges</td>
<td>0.3469</td>
</tr>
<tr>
<td>21-2000</td>
<td>Religious Workers</td>
<td>0.3464</td>
</tr>
<tr>
<td>45-4000</td>
<td>Forest, Construction and Logging Workers</td>
<td>0.3299</td>
</tr>
<tr>
<td>27-4000</td>
<td>Media and Communication Equipment Workers</td>
<td>0.3182</td>
</tr>
</tbody>
</table>

Panel B. Occupational Categories with the Lowest Agglomeration Levels

<table>
<thead>
<tr>
<th>SOC Code</th>
<th>Occupation Title</th>
<th>$\theta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>33-1000</td>
<td>Supervisor of Protective Service Workers</td>
<td>0.2394</td>
</tr>
<tr>
<td>25-4000</td>
<td>Librarian, Curators, and Archivists</td>
<td>0.2503</td>
</tr>
<tr>
<td>51-3000</td>
<td>Food Processing Workers</td>
<td>0.2509</td>
</tr>
<tr>
<td>49-3000</td>
<td>Vehical and Movile Equipment Mechanics and Installers</td>
<td>0.252</td>
</tr>
<tr>
<td>49-1000</td>
<td>Supervisors of Installation, Maintenance, and Repair Workers</td>
<td>0.2522</td>
</tr>
<tr>
<td>37-1000</td>
<td>Supervisors of Building and Ground Cleaning and Maintenance Workers</td>
<td>0.2529</td>
</tr>
<tr>
<td>11-9000</td>
<td>Other Management Occupations</td>
<td>0.2595</td>
</tr>
<tr>
<td>39-7000</td>
<td>Tour and Travel Guides</td>
<td>0.253</td>
</tr>
<tr>
<td>53-3000</td>
<td>Motor Vehicle Operators</td>
<td>0.2535</td>
</tr>
<tr>
<td>51-8000</td>
<td>Plant and System Operators</td>
<td>0.2537</td>
</tr>
</tbody>
</table>
locationally specific an occupation is, it does not help us understand the role of spouses’ occupational compatibility. For that, we need a measure of coagglomeration. If both spouse’s careers have high agglomeration levels but are concentrated in the same geographic region, we would not expect geographic mismatch for the trailing spouse in a move. In contrast, if spouses both have high agglomeration rates but are optimally located in different regions, we would expect the opposite. An index of coagglomeration tells us not just if two occupations are both geographically concentrated, but if they are concentrated in similar places or different places. Essentially, this measure tells us something about spousal match in terms of occupation.

The coagglomeration index for occupations is adapted from the work of Ellison and Glaesar (1997) and Abel and Gabe (2016) and is calculated as:

\[
\gamma_{k,l} = \sum_{i=1}^{n} (s_{i,k} - t_{i})(s_{i,l} - t_{i}) \left(1 - \sum_{i=1}^{n} t_{i}^2\right)
\]

\[i = \text{state, n= 50}\]
\[s_{i,k} = \text{state } i’s \text{ share of employment in occupation } k\]
\[t_{i} = \text{state } i’s \text{ share of total employment}\]

Using the 506 occupational categories previously used to calculate the locational Gini, I calculate a 506 X 506 matrix of values for each occupation-pair. Positive values of the index indicate that occupations are agglomerated in the similar places; values near zero indicate that the occupations have no tendency to co-agglomerate (i.e., one or both occupations are disperse); negative values indicate that the occupations are agglomerated in different places.

I next merge these measures onto panel data from the geocoded sample of the National Longitudinal Survey of Youth 1979 (NLSY79). For this exercise and the following exercise, I use the same sample of married couples that I later use to estimate my structural model of migration, which is described in more detail in section 3. In this sample, I consider one observation of a household to be each two-year block of time, where the location in year one corresponds to period one in the model (i.e., the home location) and the location in period two corresponds to the place the couple chooses to live. Thus, for one household, I see their earnings in the first period prior to moving or not moving; I see their migration decision; and I see their earnings in the second period after they have decided to move or not. If one spouse is unemployed (i.e., occupation = 0), they are dropped from the analysis.\(^2\)

I regress measures of household mobility rates and income measures on these measures of occupational agglomeration and coagglomeration, as well as a set of covariates:

\[Y_{i} = \beta_{1}\gamma_{h(i),w(i)} + \beta_{2}\theta_{h(i)} + \beta_{3}\theta_{w(i)} + \beta_{4}X_{i} + \epsilon_{i}\]

I have four different dependent variables \((Y_{i})\). First, the mobility rate, which is a categorical variable, equal to 1 if the household moved across states between period 1 and period 2 and 0 if not. Second, family income, defined as the log of the total earnings from wages and salary of both spouses. Third, the log of the husband’s

\(^2\)This is partially due to my decision to use log earnings as an outcome variable, which requires me to drop individuals with zero income. However, I have also run the analyses including couples with at least one spouse unemployed and the results were unchanged in substance.
yearly income from wages and salary, and fourth, the same measure for the wife. If either spouse had zero income, they were dropped from the analysis of individual income. I restricted the sample to working-age couples (i.e., both spouses between the age of 25 and 65). For all income measures, I report the results for the relationship between the indices and earnings in period 2; they are not substantively different in period 1.

If either spouse had zero income, they were dropped from the analysis of individual income. I restricted the sample to working-age couples (i.e., both spouses between the age of 25 and 65). For all income measures, I report the results for the relationship between the indices and earnings in period 2; they are not substantively different in period 1.

\[ \gamma_{h(i),w(i)} \] is the index of coagglomeration for household \( i \) with husband in occupation \( h(i) \) and wife in occupation \( w(i) \), normalized such that a one standard deviation increase is equivalent to \( \gamma \) increasing by one. \( \theta_j \) refers to the locational Gini evaluated at each spouse’s occupation \( j \), also standardized. Finally, \( X_i \) is a vector of covariates, including levels of education of each spouse, age, a dummy for whether each spouse is white, and state fixed effects. Table 2 shows the results of these regressions:

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HH Log Earnings</td>
<td>Husband Log Earnings</td>
<td>Wife Log Earnings</td>
<td>Move</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>0.0170**</td>
<td>0.00919</td>
<td>0.0476***</td>
<td>0.00245</td>
</tr>
<tr>
<td></td>
<td>(0.00685)</td>
<td>(0.00781)</td>
<td>(0.0114)</td>
<td>(0.00162)</td>
</tr>
<tr>
<td>( \theta_M )</td>
<td>-0.0136**</td>
<td>0.0104*</td>
<td>-0.0292***</td>
<td>-0.000853</td>
</tr>
<tr>
<td></td>
<td>(0.00626)</td>
<td>(0.00613)</td>
<td>(0.00914)</td>
<td>(0.00129)</td>
</tr>
<tr>
<td>( \theta_F )</td>
<td>-0.0580***</td>
<td>-0.0616***</td>
<td>-0.0475***</td>
<td>-0.00415</td>
</tr>
<tr>
<td></td>
<td>(0.00539)</td>
<td>(0.00596)</td>
<td>(0.00926)</td>
<td>(0.00351)</td>
</tr>
<tr>
<td>( N )</td>
<td>13,613</td>
<td>13,178</td>
<td>12,406</td>
<td>12,452</td>
</tr>
</tbody>
</table>

Covariates Included: Dummies for Education Level, age, Dummy for White, State FE

Standard errors in parentheses, calculated using bootstrap \( N = 500 \)

* \( p < 0.10 \), ** \( p < 0.05 \), *** \( p < 0.01 \)

These regressions indicate that a one standard deviation increase in spousal location compatibility, as measured by \( \gamma \), is associated with a non-significant 0.9 percent increase in husband’s income and a 4.8 percent increase in wife’s income. Note that the average husband’s income in this sample is $53,350 and the average wife’s income in this sample is $30,056, meaning that these percent increases translate to approximately $480 and $1464 respectively. A one standard deviation increase in spousal match is associated with a 0.25 percentage point increase in the likelihood that a household moved in the last five years, which is a large change for a sample in which which only 1.8 percent of couples move. It is non-significant, however, with \( p = 0.13 \). Nonetheless, this suggests that have occupations that are locationally compatible – that is, occupations which allow you to easily find jobs in similar locations – increases a couple’s ability to move.

The measures of agglomeration, \( \theta \), give us some information about which spouses’ occupational concen-
tration has a larger impact. One can think of this measure as a proxy for the degree to which a person’s occupation requires them to work in a specific location to find a job. In particular, while being in an agglomerated career has positive impacts on male earnings, own-occupation agglomeration is negatively associated with the wife’s earnings. Additionally, the level of concentration of one’s spouse’s occupation is significantly associated with a lower income regardless of gender. This suggests a gender asymmetry in the extent to which one’s occupation’s locational specificity impacts one’s earnings.

This confirms the findings of Benson, who found that geographic concentration was positively associated with male earnings and negatively associated with female earnings. He, however, did not control for spousal match. With the coagglomeration index included, we can see that the negative effect of agglomeration on earnings for women is almost fully mitigated if the place the woman’s occupation is concentrated is the same as her spouse. A one s.d. increase in own agglomeration reduces income by 4.7 percent, but a one s.d. increase in co-agglomeration increases income by 4.8 percent – suggesting that being in an agglomerated career is only a problem for women poorly matched to their spouse in terms of location preferences.

However, while these effects are significant in a statistical sense, they are small in a practical sense. Though the coagglomeration index measures spouses’ match to each other, it does not indicate whether a couple is well matched to their current location. A couple can score highly on agglomeration and coagglomeration measures, but still be locationally mismatched if they have not moved to the optimal location for their occupational pairing.

Thus, I next calculate a measure of how well matched individuals and couples are to their current location. Once again, I use the 1990 US Census data and restrict my sample to individuals between the age of 20 and 35 to mirror the age range of individuals in the NLSY data, but only use the 13 occupational categories used later in my model (see Appendix Table 1 for the full list). I regress earnings (measured as the annual income from wages and salary in thousand-dollar increments) on the interaction between dummies for occupation and state separately for each gender, with standard errors clustered at the state level. From this, I then predict each person’s predicted log income from occupation-location fixed effects. Table 3 shows the mean and variance of these fixed effects for each occupation, broken down by gender.
Table 3: Returns to occupation and location, US Census 1990

<table>
<thead>
<tr>
<th>Occupation</th>
<th>Mean, Men</th>
<th>Variance, Men</th>
<th>Mean, Women</th>
<th>Variance, Women</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Executive and Managerial</td>
<td>34.7</td>
<td>5.75</td>
<td>27.1</td>
<td>4.88</td>
</tr>
<tr>
<td>2 STEM, Social Sciences, and Legal</td>
<td>34.6</td>
<td>5.93</td>
<td>29.9</td>
<td>5.70</td>
</tr>
<tr>
<td>3 Education, Counseling and Social Work</td>
<td>21.6</td>
<td>3.32</td>
<td>19.4</td>
<td>3.14</td>
</tr>
<tr>
<td>4 Entertainment and Media</td>
<td>26.5</td>
<td>7.34</td>
<td>19.6</td>
<td>5.68</td>
</tr>
<tr>
<td>5 Health</td>
<td>30.4</td>
<td>10.8</td>
<td>30.0</td>
<td>6.05</td>
</tr>
<tr>
<td>6 Protective Services</td>
<td>30.8</td>
<td>8.10</td>
<td>20.6</td>
<td>7.70</td>
</tr>
<tr>
<td>7 General Service</td>
<td>19.3</td>
<td>4.17</td>
<td>10.2</td>
<td>2.43</td>
</tr>
<tr>
<td>8 Sales and Related</td>
<td>30.2</td>
<td>5.89</td>
<td>13.2</td>
<td>3.06</td>
</tr>
<tr>
<td>9 Office and Administrative</td>
<td>25.7</td>
<td>4.31</td>
<td>19.9</td>
<td>3.33</td>
</tr>
<tr>
<td>10 Farming, Fishing, and Forestry</td>
<td>19.5</td>
<td>7.14</td>
<td>8.2</td>
<td>4.27</td>
</tr>
<tr>
<td>11 Construction, Maintenance, and Repair</td>
<td>29.9</td>
<td>4.71</td>
<td>19.5</td>
<td>6.43</td>
</tr>
<tr>
<td>12 Manufacturing</td>
<td>31.5</td>
<td>4.56</td>
<td>15.0</td>
<td>2.91</td>
</tr>
<tr>
<td>13 Transportation</td>
<td>27.2</td>
<td>4.54</td>
<td>12.6</td>
<td>3.05</td>
</tr>
</tbody>
</table>

Column 2 and 4: Mean of occupation-state fixed effects across states, in terms of predicted income in $1000 increments

Column 3 and 5: Variance of occupation-state fixed effects across states

Sample: US Census 1990 (IPUMS), restricted to ages 20 to 35. N= 1,694,646

Based on these location-occupation fixed effects, I am able to characterize individuals in the sample as well or poorly matched. For each occupation, I rank the occupation-location fixed effects in terms of state and create a dummy variable for ‘poorly matched’ where a person is poorly matched if they are in a state that is in the bottom ten of the ranking of location fixed effects for their occupation.

Are these estimates of occupation-location fixed effects good measures of whether a given location is the a good place or a bad place to be working in for one’s occupation? One concern we might have is that high earnings for an occupation in a state is negatively associated with the number of jobs available in that state for that occupation. Part of a location choice decision is not just about what a person expects their earnings will be, but whether they expect to be able to find a job in their field. Thus, I check whether having a higher occupation-location fixed effect is positively associated with more individuals in that state working in that location and find that there is a significant and positive correlation between the occupation-location fixed effect for an occupation in a state and both the total number of individuals working in the occupation within that state and the percent of individuals in the state working in that occupation.

We also might be concerned that living in a location with a high average level of earnings does not necessarily translate to higher earnings for an individual. For example, a low quality worker in the ‘best’ state for their occupation may be poorly matched because they are in the bottom of the skill distribution for this labor market and may perform better in a market with less highly skilled competition. To address this concern, I check if my measure of being well-matched to a location is associated with higher earnings and find that for both men and women, being well-matched is positively associated with earnings, even after controlling for
location and individual characteristics, such as age, race, and education.

I next explore whether location-match is associated with couple’s migration decisions, by merging this measure of match onto the previously used sample of married couples from the NLSY-79. Figure 1 depicts the distribution of occupation-location for husbands and wives in my sample. Figure 2a depicts the distribution of occupation-location in their home location for husbands who do not move and husbands who do move; figure 2b depicts the same for wives. Men are on average in occupation-location pairs with higher payoffs, which is partially due to men having higher earnings on average in general, but may also reflect men’s selection into locations and occupations with higher payoffs. I have also estimated the fixed effects for men and women together rather than separately by gender and men were still, on average, more likely to have an occupation-location pair with a higher payoff, suggesting the importance of selection into either occupation or location. The distributions of period 1 occupation-location fixed effects are fairly similar for movers and non-movers of both genders, though there is slightly more mass at higher values for movers than non-movers in both cases.
We would predict that couples who are poorly-matched to their location in period 1 will have lower household incomes and be more likely to move than those who are well-matched and that these effects may be asymmetric by gender. To test this, I regress log household income in period 1 on the interaction between dummies for each spouse’s match to their location in the first period, a series of covariates (education, quadratic of age, and race of both spouses), and state fixed effects, with standard errors clustered at the state level. I then run a linear probability regression of a dummy for migration between period 1 and period 2 on the same variables. Table 5 depicts the results of these regressions.

Table 4: Effects of Location Match on Household Income and Mobility, NLSY 1979

<table>
<thead>
<tr>
<th></th>
<th>(1) Probability Move</th>
<th>(2) Log Household Earnings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Omitted: $D_m = 0$ and $D_f = 0$</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>(.)</td>
<td>(.)</td>
</tr>
<tr>
<td>$D_m = 1$ and $D_f = 0$</td>
<td>0.0117 *</td>
<td>-0.105***</td>
</tr>
<tr>
<td></td>
<td>(0.00618)</td>
<td>(0.0248)</td>
</tr>
<tr>
<td>$D_m = 0$ and $D_f = 1$</td>
<td>0.0126**</td>
<td>-0.0441 *</td>
</tr>
<tr>
<td></td>
<td>(0.00633)</td>
<td>(0.0254)</td>
</tr>
<tr>
<td>$D_m = 1$ and $D_f = 1$</td>
<td>0.0181***</td>
<td>-0.199***</td>
</tr>
<tr>
<td></td>
<td>(0.00642)</td>
<td>(0.0258)</td>
</tr>
</tbody>
</table>

$N = 12965$  

$D_m = 1$ indicates that the husband is poorly matched, $D_f = 1$ indicates the wife is poorly matched

Standard errors in parentheses

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

We see a significant difference in migration probability between households where both spouses are well-matched (omitted category) and households where both spouses are poorly matched, with poorly matched households being 1.8 percentage points more likely to move. We also see a significant relationship for households where one spouse is mismatched and the other isn’t, though these effects are smaller. Notably, in this sample, there are gender asymmetries in the effects of match on household income: though being well-matched is positively associated with higher household income, these effects are only marginally significant if the wife is well-matched to the location. Having a well-matched husband and poorly matched wife is associated with 10.5 percent lower income than if both spouses are well-matched. Households with two spouses who are well-matched have earnings that are 20 percent higher than households with two spouses who are poorly matched.
I next explore whether those who move in this sample typically move to locations that are better in terms of location-match or worse. To do this, I create a measure of match improvement by subtracting each person’s occupation-location fixed effect in period 1 from their occupation-location fixed effect in period 2. A positive difference in ranking indicates that a person moved to a better state than they were previously in. For example, if a person is working in the 20th best state for their occupation in period 1 and moves to the 15th best state, their measure of change would equal 5. Figure 1 depicts the distribution of rank changes for men and women movers.

There is greater variance in the rank change for husbands than for wives, with husbands in particular being both more likely to move up over 20 positions or to move down over 20 positions. Rank changes for women are concentrated around zero and they have a slightly more negatively skewed distribution than the husband distribution. This is consistent with more women experiencing small drops in ranking than men, but fewer moving up in ranking.

These descriptive results provide suggestive evidence that decisions to move are influenced by not only how well-matched each member of the household is to their current location, but that the relationship between migration and husband’s match may play a particularly important role in the household’s migration decision. This, combined with the results from my two regression exercises, suggests that when spouses disagree about preferred location, the husband’s preferences take precedence, a fact consistent with past findings on migration patterns of couples. To explore this further, I expand on these findings by building a model of location and skill choice and estimating it using panel data from the National Longitudinal Survey of Youth 1979.

3 Data

In estimating my model, I use panel data from the geocoded sample of the National Longitudinal Survey of Youth 1979 (NLSY79). The full data set contains 12,866 men and women who were between the ages of 14 to 22 in 1979, the first year of the survey. The survey was collected annually until 1994 and biennially since then. To avoid changes in the timing of the survey, I focus my analysis on years prior to 1994. Since I want
to focus only on individuals already of working age, I also restrict my sample to individuals over the age of 25, meaning that I drop all observations prior to 1982.

To estimate my model, I must observe married couples in two consecutive periods. To increase sample coverage, I will consider one observation of a household as one two-year block of time, where the locations in year one corresponds to period one in the model (i.e., the home location) and the location in period two corresponds to the place the couple chooses to live.

I define home location as the location that the couple was living in the first year I observe them married and drop any couple-year observations for which the first period’s location is not the home location. Thus, I am only observing first-time moves for a couple or never-movers. I include this restriction because my model will assume that the ‘home location’ is exogenous. Since they were not yet married and making decisions as a household when they entered this location, it is a more plausible assumption that these couples were not selecting a location based on household unobservables for a household that did not exist yet.

Thus, for one household, I could conceivably include in my sample 11 observations of their household location choice if a household stays in their ‘home location’ for the entire sample period or only 1 observation if a household moves in the period following their marriage. In my sample, I have a total of 4,232 married couples and 17,483 two-period observations of households. The minimum number of observations per couple is 1, the median is 4.1, and the maximum is 11.

The data consists of information on each surveyed individual’s income from wages and salary in each year, occupation, education level, age, and gender. I also have this information for the spouse of the surveyed respondent, as well as information on the household’s current location in terms of US state and county and their past migration history.

In my sample, 1.94 percent of household observations, or 339 households, move between period 1 and 2. Table 5 shows descriptive statistics for the full sample, the sample of movers, and the sample of non-movers.
4 Model

My goal is to use this data to explore whether migration decisions by couples can be modeled as a function of the differing benefits and costs to migration by occupation. Are certain types of couples’ occupation pairings more likely to move than others? Based on the hypothesis that couples’ occupational match with both their location and each other affects migration decisions, I have developed a simple static model of locational choice, patterned after past models of individual location choice (e.g., Kennan and Walker, 2011; Dahl, 2002) and extended to fit a choice problem with two individuals in the household.

4.1 Generalized Multinomial Choice Problem

First, let us consider a generalized version of a static migration model, in which a person can choose between J locations and have potential earnings in each location given by

\[ w_{ij} = X'_{ij}\beta_j + \epsilon_{ij} \]

\[ j = 1, 2, ..., J \]

where \( w_{ij} \) is the earnings for each location \( j \), \( X_{ij} \) are observable traits that affect earnings and \( \epsilon_{ij} \) are the parts of earnings unobservable to the econometrician. While the individual knows their true \( w_{ij} \) for all \( j \in (1, 2, ..., J) \), the econometrician only observes earnings in the location the individual chooses.
Individuals have preferences for both earnings and non-pecuniary factors (e.g., distance from home location) that do not impact earnings. We can write an individual’s value of living in location $j$ as:

$$V_{ijh} = w_{ij} + u_{ijh}$$

$$V_{ijh} = \mathbb{E}[w_{ij}|x_i] + \mathbb{E}[u_{ijh}|z_i] + \epsilon_{ijh}$$

$$V_{ijh} = \nu_{jh} + \epsilon_{ijh}$$

The first equation splits the value function into utility from earnings ($w_{ij}$) and amenity values ($u_{ijh}$) which vary by individual $i$, location $j$, and the origin location of person $i$, $h$. In line 2, we then split these into the portions that do not vary at the individual level (i.e., the average earnings given individual observables and the average amenity values given individual observables $x_i$ and $z_i$) and the individual variation in both. This allows us to rewrite the utility function in terms of $\nu_{jh}$ which does not vary across individuals and $\epsilon_{ijh}$, which does. A person maximizes utility by choosing location such that:

$$D_{ijh} = \begin{cases} 
1, & \text{if } \nu_{jh} + \epsilon_{ijh} > \nu_{jmh} + \epsilon_{jmh}, \forall j \neq m \\
0, & \text{otherwise}
\end{cases}$$

where $D_{ijh}$ is an indicator for each location that only equals 1 for the location $j$ that the individual chooses. This $D_{ijh}$ also provides the selection rule: the econometrician only observes $w_{ij}$ if $D_{ijh} = 1$.

Since the individuals who select a given location are not a random sample of the population, we then have:

$$\mathbb{E}[\epsilon_{ij}|\text{earnings observed}] = \mathbb{E}[\epsilon_{ij}|D_{ijh} = 1, x_i, z_i]$$

$$= \mathbb{E}[\epsilon_{ij}|\nu_{jh} + \epsilon_{ijh} > \nu_{jmh} + \epsilon_{jmh}, \forall j \neq m]$$

$$\neq 0$$

Now, let us apply these ideas in a model of household migration. A household $i$ is made up of two people, whose identities are denoted with the superscripts for wife ($w$) and husband ($h$). Each individual in the household has earnings represented by the following functions if working:

$$w_{ij}^w = X_{w(i),j}^t \alpha_{ij}^w + \sigma^w \epsilon_{w(i),j}$$

$$w_{ij}^h = X_{h(i),j}^t \alpha_{ij}^h + \sigma^h \epsilon_{h(i),j}$$

where $j$ indicates the location a couple chooses from $j = \{1, 2, ..., J\}$ and the subscripts $w(i)$ and $h(i)$ indicate the covariates for each spouse in household $i$.

$X_i$ is a vector of individual covariates. The $\epsilon_{i,j}$ are the unobservable portions of earnings that vary by individual, which I will assume are independently distributed from a standard normal distribution, $F_j \sim N(0,1)$, meaning that $\sigma^w$ and $\sigma^h$ represent the variation in unobservables.

If a spouse is not working, they instead receive utility from leisure rather than a wage. To keep the specification simple, I assume that the utility value of not working must be equal to the value of a part-time
minimum wage job. While it is not strictly true that all individuals can find a minimum job, this assumption approximates the idea that a person who is not working always has a low quality job as an outside option that they have rejected. Thus, for individuals not working their yearly utility is given as follows:

\[ w_{NW,j} = w_j \times 20 \times 50 \]

Households choose a location by maximizing the sum of their earnings, a function of migration costs, and a random household preference shock. Their utility in a given location \( j \) can represented as:

\[
U_{i,j} = w_{ij}^w + w_{ij}^h - \alpha_r r_j - C(i, j, \text{home}) + \eta_{ij}
\]

where

\[
C(i, j) = \beta_{d1}(\text{distance from home})_j + \beta_{d2}(\text{distance from home})^2_j + \sum_{k=1}^{K} C_k(1(k_w(i) = k) + 1(k_h(i) = k))\mathbb{1}(j \neq \text{home})
\]

\[
r_j = \text{cost of living in location } j
\]

Though the couple has full information about preferences/costs across locations, the econometrician only observes the earnings in the chosen location. I model migration costs as a function of distance from the starting location as well as constant costs that vary by different occupation types \( (k_w(i) \text{ and } k_h(i)) \). This means that a couple with two professionals will have a different moving cost than a couple with one professional worker and a services worker. For the migration costs, I collapse the 13 occupation categories used for the occupation-location fixed effects into 5 broader groups, due to concerns about small numbers of certain occupation groups migrating, as well as a category for non-employed individuals.\(^3\) I allow the cost of moving for non-employed individuals to vary by gender to capture the fact that women who are not working are more likely to be permanently out of the labor force than men in my sample, making this type systematically different by gender.

Similar to the individual problem, we can simplify our utility maximization to be a choice of location \( j \) given by the following set of equations:

\[
U_{i,j, \text{home}} = E[w_{ij}|X_{w(i),j}] + E[w_{ij}|X_{h(i),j}] - \alpha_r r_j - E[C(j, \text{ home})|Z_i] + \eta_{ij} + \sigma_w \epsilon(w(i), j) + \sigma_h \epsilon(h(i), j)
\]

where the first part contains the expected value of earnings for a couple given \( X_{w(i)} \) and \( X_{h(i)} \) and the expected amenity value for couple \( i \) given \( Z_i \), which contains individual observations that affect a location’s amenity value for household \( i \). Notice that we can again write this in the form we had in the single person choice problem, there are just more terms encompassed within both the observed variation across location \( (\nu_{ij, \text{ home}}) \) and the unobservable drivers of location choice \( (\epsilon_{ij}) \).

We can rewrite this choice problems in terms of a dummy \( D_{ij} \) where:

\[
D_{ij, \text{ home}} = \begin{cases} 
1, & \text{if } \nu_{ij, \text{ home}} + \epsilon_{ij} > \nu_{im, \text{ home}} + \epsilon_{im}, \forall j \neq m \\
0, & \text{otherwise}
\end{cases}
\]

\(^3\)In particular, there were few women in the construction and transportation occupations as well as few men in the education profession who moved across states.
As before, we have a selection problem, where the econometrician only observes the wife and husband’s income in the location they choose based on this decision rule.

### 4.2 Parameterizing the Model

When taking the model to data, I include as part of the earnings equation the following covariates: dummies for occupation, a dummy for whether an individual has a college degree, experience, experience squared, and a constant term. In the earnings equation, occupation is defined using the 13 occupational categories used in the descriptive exercises. When parameterizing the model, I will assume that only the effects of occupation vary by location, though this assumption can be relaxed. For individuals who are not employed, the utility value of leisure varies by the minimum wage in each state.\(^4\) I denote this occupation-location fixed effect for location \(j\) and occupation \(k\) as \(\alpha_{jk}\).

Experience is defined as follows:

\[
\text{Experience} = \begin{cases} 
\text{age} - 18, & \text{if highest education is HS degree} \\
\text{age} - 20, & \text{if highest education is some college} \\
\text{age} - 22, & \text{if highest education is college degree}
\end{cases}
\]

I also assume that these covariates’ effects on earnings vary across genders.

The earnings equations for those working are fully parameterized as:

\[
\begin{align*}
w_{ij}^w &= \alpha_0^W + \alpha_{jk}^W + \alpha_{ed}^W(\text{College}_{w(i)}) + \alpha_{exp}^W(\text{Exp}_{w(i)}) + \alpha_{exp\text{sq}}^W(\text{ExpSq}_{w(i)}) + \sigma^w \epsilon_{w(i),j} \\
w_{ij}^h &= \alpha_0^H + \alpha_{jk}^H + \alpha_{ed}^H(\text{College}_{h(i)}) + \alpha_{exp}^H(\text{Exp}_{h(i)}) + \alpha_{exp\text{sq}}^H(\text{ExpSq}_{h(i)}) + \sigma^h \epsilon_{h(i),j}
\end{align*}
\]

To estimate the model, I am making some assumptions about the structure of the unobserved error terms.

First, I will assume that the only observable portion of earnings that varies across location is the effect of occupation, meaning that we can write

\[
\nu_{j,\text{home}} = \alpha_{j,kw(i)} + \alpha_{j,kh(i)} - \alpha r_j - C(i,j)
\]

where \(C(i,j)\) is defined as above. For non-employed individuals, this \(\alpha\) term is equal to the leisure value based on a part-time minimum wage job.

As previously noted, the migration cost equations collapse the 13 occupation groups into 5 occupation categories, defined in Appendix Table 1, as well as separate migration costs for non-employed women and non-employed men. Distance is measured using the distance between state centroids, defined as the location that is the center of population of the state (U.S. Census Bureau, 2018A) and is measured in units of 1000.

\(^4\)Though there were changes to minimum wage law during my sample period, I abstract from these changes and use the minimum wage in 1988 for all years as reported by the US Department of Labor (2017).
miles (i.e., $d_{jh} = 0.35$ indicates a 350 mile distance). Housing costs are taken from US Census 1990 median gross housing costs by state (US Census Bureau, 2018B).

Second, I will assume that the random household preference shock ($e_{ij}$) is distributed as a Type I Extreme Value shock, which means that the choice equations imply a standard multinomial logit model (McFadden 1973), where we have:

$$P_{ij} = \text{Prob}(D_{ij, \text{home}} = 1) = \frac{\exp(\alpha_{j,k(i)} + \alpha_{j,h(i)} - \alpha_r r_j - C(i,j))}{\sum_s^J \exp(\alpha_{s,k(i)} + \alpha_{s,h(i)} - \alpha_r r_s - C(i,s))}$$

Since the absolute level of utility is not identified in this structural form, I normalize the non-idiosyncratic portion of utility, $\nu_{j,home}$, for one state, Alabama, to be 0.

Lastly, I will assume that the earnings unobservables are drawn from standard normal distributions and that households do not observe their individual variation in earnings across location prior to moving. This assumption allows me to impose that the migration decision is made independent of variation in earnings other than variation that is observable (i.e., the occupation-location match effect) and makes the log-likelihood function used in estimation more tractable. Though this may at first seem a strong assumption, most people do not know the exact earnings offer they would receive in all 51 locations (50 states plus DC), making it plausible to assume that each person’s earnings shock by location does not affect their migration decision.

5 Estimation and Identification

To estimate this model, we must estimate the $\alpha$ for each gender in the earnings equations: 1326 different occupation-location fixed effects, $\alpha_{jk}$ (51 states X 13 occupation groups X 2 genders) and 8 coefficients on covariates (college dummy, experience, experience squared, and a constant; all estimated separately by gender), the variance of the error terms for the earnings equations ($\sigma_w$ and $\sigma_h$), the coefficient on our measure of cost of living, the 2 coefficients on distance from home, and 7 different migration costs (5 occupation types + 2 non-employed types). Because the sample coverage is not large enough to identify occupation-location fixed effects for all occupations and all states (i.e., not all occupations are observed in every state), I estimate the occupation-location fixed effects using data for the US Census in 1990, using the same method previously described in the descriptive work and then merge them onto the NLSY79 data set.

I estimate all remaining parameters simultaneously using full information maximum likelihood, under the assumption that the probability you observe income $y_{ij}$ conditional on observables is independent of the probability you choose location $j$.

5.1 Identification

The migration cost parameters, which can alternatively be thought of as preferences for a home location, the distance parameters, the cost of living parameters, and the distribution of earnings in a location are
partially identified in my empirical results on the basis of my assumptions about the structure of the error terms. By assuming that the shocks to earnings and the shocks to location preferences are independently and identically distributed across individuals and that couples do not make their migration decision based on these earnings shocks, I am imposing that $E[\epsilon_{ij} | \text{location choice } = j] = 0$, which allows me to identify the earnings parameters without concerns about selection through a structural assumption that these error terms are normally distribution.

However, while these two assumptions makes my empirical results more tractable, identification of the model would also hold under weaker assumptions. In particular, I do not necessarily need to assume migration decision are independent of earnings draws. Previous work on nonparametric identification of extended Roy Models for location choice (e.g., Bayer, Khan, and Timmons, 2011; Dahl, 2002; Ransom, 2016) have demonstrated that a sufficient condition for identification of the relationship between earnings distributions and nonpecuniary benefits to a location (e.g., psychic costs of moving) is the use of different birth locations as an exclusionary restriction (i.e., a covariate which affects location choice, but not earnings).

While I will not provide a formal proof of identification, I will now provide an informal discussion of how this identification strategy applies to my model. Following Bayer et al. (2011), I assume what they call ‘commonality’ of the earnings distributions across ‘home location’ – that is, I assume a common earnings distribution characterizes earnings offers for an individual regardless of the location they were married in. However, a person’s home location does affect the non-pecuniary benefits to living in a location: choosing a state other than one’s home state creates a negative psychic cost of moving and affects the distance associated with a move. Then, the fraction of those in each occupation who choose location $j$ when $j$ is not their home location and the fraction of those in each occupation who choose location $j$ when $j$ is their home location separately identifies preferences for location from earnings.\(^5\) Differences in distance moved by starting location also help identify the parameters on distance.

The main threat to the the validity of this identification strategy would be if there are particularly advantageous earnings draws in the location a couple is married in compared to other locations. Since I restrict my sample to those who are still fairly young when they marry (early to late twenties), where a couple is when they meet and marry is frequently the state where at least one spouse was born, which is more plausibly exogenous and unrelated to the earnings draws available to them.

### 5.2 Estimation

I estimate the earnings parameters and the utility parameters jointly using a likelihood estimator. Joint estimation of the earnings parameters and the preference parameters uses the full information available to me, meaning that I do not have to rely on the assumption that the ‘home location’ was assigned exogenously. Instead, my identification relies on the assumption that the earnings distribution in period 2 for each location is independent of the location you were married in, an exclusion restriction that, along with assumptions

\(^5\)This requires that I observe at least one person in each occupation group moving across states. This requirement is why I collapsed occupation groups into five broad categories out of concerns about identification off of very small samples of movers in some of the original 13 categories.
about functional form, correct for concerns about selection in the wage equation. I thus next use maximum
likelihood to jointly estimate the earnings parameters and the migration costs.

Because I have assumed that households make their migration decision before realizing their \( \epsilon \) earnings
shocks, the migration decision is independent of the probability we observe a given earnings level, meaning
that, for now the joint density of a choice of location \( j \) and earnings \( w_{ijk}^w \) and \( w_{ijk}^h \) will just be the product
of the three densities:

\[
\text{Prob}(D_{ij} = 1, w_W = w_{ijk}^w, w_H w_{ijk}^w) = \text{Prob}(D_{ij} = 1) \text{Prob}(w_W = w_{ijk}^w) \text{Prob}(w_H = w_{ijk}^h)
\]

\[
= \phi\left(\frac{w_{ijk}^w - \alpha_{j(i),k_H(i)} - X'_{w(i)} \alpha_{w}^1}{\sigma_w}\right) \phi\left(\frac{w_{ijk}^h - \alpha_{j(i),k_H(i)} - X'_{h(i)} \alpha_{h}^1}{\sigma_h}\right) \frac{\exp(\alpha_{j(kW(i))} + \alpha_{j,k_h(i)} - C(i,j))}{\sum_{s=1}^{J} \exp[\alpha_{s,k_w(i)} + \alpha_{s,k_h(i)} - C(i,s)]}
\]

\( \phi() \) is a standard Normal. The assumption that the probability we observe a given level of earnings is in-
dependent of the probability we observe a household in a given location is consistent with past models of
individual migration (e.g., Kennan and Walker, 2011).

I can therefore use full information maximum likelihood to estimate all of the parameters together, with
the log likelihood given by the following:

\[
\mathcal{L}C = \sum_{i=1}^{N} \sum_{j=1}^{J} D_{ij} \ln[\text{Prob}(D_{ij} = 1, w_W = w_{ijk}^w, w_H w_{ijk}^w)]
\]

\[
= \sum_{i=1}^{N} \sum_{j=1}^{J} D_{ij} \left[ -\frac{1}{2} \ln(2\pi) - \ln(\sigma_h) - \ln(\sigma_w) - \frac{(w_{ijk}^h - \alpha_{j(i),k_H(i)} - X'_h(i) \alpha_{h}^1)^2}{2\sigma_w^2} - \frac{(w_{ijk}^w - \alpha_{j(i),k_H(i)} - X'_w(i) \alpha_{w}^1)^2}{2\sigma_h^2} - \ln\left(\frac{\exp(\alpha_{j,k_w(i)} + \alpha_{j,k_h(i)} - C(i,j))}{\sum_{s=1}^{J} \exp[\alpha_{s,k_w(i)} + \alpha_{s,k_h(i)} - C(i,s)]}\right)\right]
\]

For estimation, I maximize this likelihood function using a quasi-Newton algorithm for maximization, which
approximates the Hessian using observed behavior of the function and the gradient. I have also attempted
to use the Nelder Mead method, but did not reach as close a fit to the data using a simplex search method.

6 Results

6.1 Parameter Estimates

Table 6 and table 7 report the parameter estimates for the earnings equation and the migration costs, respec-
tively. The standard errors are provided in parentheses. Superscripts on the earnings parameters indicate
whether the parameter is for earnings equation of the wife (W) or the husband (H). The superscript ‘ed’ is
on the coefficient on the dummy for college; ‘exp’ and ‘expsq’ are the coefficients for experience and experi-
ence squared respectively; ‘0’ indicates the coefficient on the constant term. Descriptions of the occupations
associated with each migration cost are listed within the table.
When interpreting the earnings coefficients, recall that the earnings equation includes as a fixed parameter from outside the model an occupation-location match term $\alpha_{jk}$, meaning that these estimates do not describe the direct relationship between the covariate and earnings. Rather, they represent the relationship between the covariate and the remainder of earnings after subtracting off the average earnings for a person of the same gender and occupation in that state. For example, $\alpha_{W_{Ed}}$ indicates that a woman’s earnings net of her occupation’s average in the state is higher by approximately $5600 than a woman without a college degree. This estimate is, of course, much lower than the typical estimate of a college wage premium since some of the college wage premium works through selection into occupation, meaning that it is already absorbed into the occupation-location fixed effect.

The earnings estimates suggest that being college educated is associated with higher earnings net of occupation-location fixed effects for both men and women, though the effect is slightly stronger for men. Men also have higher returns to experience and higher variance of the individual heterogeneity of earnings.

Table 6: Earnings Parameter Estimates

<table>
<thead>
<tr>
<th></th>
<th>$\alpha^W_{Exp}$</th>
<th>$\alpha^W_{ExpSq}$</th>
<th>$\alpha^W_{Ed}$</th>
<th>$\alpha^H_{Exp}$</th>
<th>$\alpha^H_{ExpSq}$</th>
<th>$\alpha^H_{Ed}$</th>
<th>$\alpha^H_0$</th>
<th>$\sigma^W$</th>
<th>$\sigma^H$</th>
</tr>
</thead>
<tbody>
<tr>
<td>FIML</td>
<td>0.5773</td>
<td>-0.0138</td>
<td>5.6491</td>
<td>0.3182</td>
<td>2.1485</td>
<td>-0.0833</td>
<td>6.1770</td>
<td>9.3295</td>
<td>18.195</td>
</tr>
<tr>
<td>SE</td>
<td>(0.1174)</td>
<td>(0.0059)</td>
<td>(0.2946)</td>
<td>(0.5874)</td>
<td>(0.2274)</td>
<td>(0.0115)</td>
<td>(0.5706)</td>
<td>(1.1395)</td>
<td>(0.00693)</td>
</tr>
</tbody>
</table>

All estimates are increments of 1000 dollars (in 1990 $) and represent the effect of the covariates on earnings net of occupation-location fixed effects.

Table 7 shows the different migration costs by occupation categories, the coefficients on distance, and the coefficient on cost of living. These estimates suggest that for each individual, the cost of moving ranges from around $15,000 to $22,000 dollars if working in the FIML estimation, meaning that the migration cost associated with being not in the home location for a couple would range from around $30,000 in a household with both spouses in occupation 2\(^6\) up to $44,000 for a household with both spouses in occupation 1.\(^7\)

Notably, migration costs are significantly lower if either spouse is not working. Men having a migration cost while not working of $15,500 and women having a migration cost while not working of $13,700, a statistically significant gender difference. This is consistent with women being more likely to be permanently out of the workforce than men and therefore having less location-specific human capital, such as job networks, to lose when re-locating. Because there are smaller location-specific differences in utility from leisure than from labor, we would expect that couples with one or both spouses out of the labor market have a greater incentive to pick up and move.

These estimates are also consistent with the findings from the earlier descriptive exercise, suggesting that concentration of an occupation does influence how easy it is for a household to change locations. Sales occupations and office and administration occupations – which make up occupation 2– have the two lowest scores

\(^6\)This occupation includes sales related occupations and office and administration occupations.

\(^7\)This occupation includes a variety of white collar high-pay occupations, including executives and managers, academic, legal, and health fields.
on the agglomeration index. STEM, Social Science, and Legal occupations – which make up the largest proportion of occupation 1 – in contrast, have much higher agglomeration levels, second only to occupations within occupation 5, which have the next highest migration costs in the FIML estimates.

Table 7: Migration Cost Parameter Estimates

<table>
<thead>
<tr>
<th></th>
<th>$C_1$</th>
<th>$C_2$</th>
<th>$C_3$</th>
<th>$C_4$</th>
<th>$C_5$</th>
<th>$C_{6}^H$</th>
<th>$C_{6}^W$</th>
<th>$\alpha_r$</th>
<th>$\beta_{dist}$</th>
<th>$\beta_{distsq}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>SE</td>
<td>0.2874</td>
<td>0.3468</td>
<td>0.5526</td>
<td>0.4749</td>
<td>0.2664</td>
<td>0.9972</td>
<td>0.3906</td>
<td>0.0962</td>
<td>0.5119</td>
<td>1.3210</td>
</tr>
</tbody>
</table>

All estimates are increments of 1000 dollars (in 1990 $); Distance is specified in 1000 mile increments (i.e., dist = miles/1000
SE were derived numerically for FIML using the inverse of the Hessian

Occ. 1 = White Collar: Professionals, Managers, Academic, Health; Occ. 2 = White Collar: Sales and Administrative
Occ. 3 = White Collar: Education, Counseling and Communication; Occ. 4 = Blue Collar: Services
Occ. 5 = Blue Collar: Manufacturing, Transportation, Construction, etc.; Occ. 6 = Not Working, W= wife; H= husband

6.2 Model Fit

Table 8 shows the model fit for a set of data moments.

I am able to fit both the overall migration rate (1.9 percent) as well as match the general pattern that college graduates move significantly more than non-college graduates in my sample. The model slightly underestimates the migration rate for college graduates (by 0.2 percentage points) and overestimates the migration rate for non-college graduates by the same amount.

For earnings, I do not perfectly capture the average earnings in the sample. However, the discrepancies between the true data and the model prediction are small in level – for example, the estimate of the wife’s means earnings in period corresponds to a difference of $146 for FIML. Moreover, I do match the pattern of changes in earnings across the two periods, with wives doing similarly across periods and husbands doing better in period 2.

Figure 4 shows how well the model fits the migration rate for each occupational group by gender.

Fig. 4: Model Fit on Migration Rate by Occupation, for Men (left) and Women (right)
Table 8: Model Fit

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>FIML</th>
</tr>
</thead>
<tbody>
<tr>
<td>Migration Rate – All</td>
<td>0.019</td>
<td>0.019</td>
</tr>
<tr>
<td>Migration Rate – College</td>
<td>0.024</td>
<td>0.022</td>
</tr>
<tr>
<td>Migration Rate – No College</td>
<td>0.014</td>
<td>0.016</td>
</tr>
<tr>
<td>Mean Earnings, Wife Period 1</td>
<td>23.6147</td>
<td>24.4395</td>
</tr>
<tr>
<td>Mean Earnings, Husband Period 1</td>
<td>50.997</td>
<td>53.6073</td>
</tr>
<tr>
<td>Mean Earnings, Wife Period 2</td>
<td>23.8325</td>
<td>23.9781</td>
</tr>
<tr>
<td>Mean Earnings, Husband Period 2</td>
<td>52.4584</td>
<td>54.1301</td>
</tr>
<tr>
<td>Variance Earnings, Wife Period 1</td>
<td>454.0</td>
<td>426.4</td>
</tr>
<tr>
<td>Variance Earnings, Husband Period 1</td>
<td>1156.3</td>
<td>1208.6</td>
</tr>
<tr>
<td>Variance Earnings, Wife Period 2</td>
<td>470.3</td>
<td>417.5</td>
</tr>
<tr>
<td>Variance Earnings, Husband Period 2</td>
<td>1245.0</td>
<td>1212.5</td>
</tr>
</tbody>
</table>

All earnings values are in $1000 real 1990 dollars.

College refers to households with a college-educated husband.

Though I am able to match migration rate well in some occupation categories, namely Occupation 3 (Education, Counseling and Communication), Occupation 5 (Blue Collar Manufacturing, Transportation, Construction, etc.), and Occupation 6 (Non-employed), there is middling fit for the white collar positions. In particular, I am unable to match the rate of migration for men in Occupation 2 (Sales and Office Administration). This discrepancy is likely due to gender differences in the payoffs associated with occupation 2. As previously noted in table 3, the average occupation-location returns for men in a sales position is $30,000, whereas the average for women in that occupation is $13,000. This suggests that the more granular occupations men have within this occupation group are on average higher paying and also have a higher variance in earnings across states. Since the moving cost associated with an occupation was not estimated separately by gender, the ultimate estimate of $C_2$ would be too high to capture men’s true willingness to move across locations.

7 Extensions of the Model

7.1 Evaluating the Importance of Occupation in Household Migration Decisions

I next test the relevance of occupation in my model by suppressing variation in migration costs by occupation. To test the null hypothesis that migration costs are the same across occupational groups, I estimate a constrained maximum likelihood where

\[ C_1 = C_2 = C_3 = C_4 = C_5 = C_6^F = C_6^M \]

I then can calculate the ratio of the likelihoods, \( R = \frac{L(\hat{\beta}^{null})}{L(\hat{\beta})} \), from which I can calculate a standard test statistic, \(-2 \log (R)\), which is distributed under a chi-squared distribution with 7 degrees of freedom (determined by the null hypotheses’ number of restrictions). Therefore, the test statistic for whether we can
reject the hypothesis that all occupations have the same migration cost is:

\[-2[LL(\hat{\beta}^{null}) - LL(\hat{\beta})]\]

Table 9 lists the parameter estimates from the original model in column 1 and the parameter estimates under the parameter constraint. The \(\chi^2\) test statistic is 890, meaning that we can reject the null and conclude that the migration costs are significantly different across occupations.

Table 9: Alternative Migration Cost Specification

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Original Model</th>
<th>Constrained Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a_W^{Exp})</td>
<td>0.5773</td>
<td>0.5774</td>
</tr>
<tr>
<td>(a_W^{ExpSq})</td>
<td>-0.0138</td>
<td>-0.0138</td>
</tr>
<tr>
<td>(a_W^{Ed})</td>
<td>5.6491</td>
<td>5.6492</td>
</tr>
<tr>
<td>(a_0^W)</td>
<td>0.3182</td>
<td>0.3178</td>
</tr>
<tr>
<td>(H^\prime)</td>
<td>2.1485</td>
<td>2.1459</td>
</tr>
<tr>
<td>(a_H^{ExpSq})</td>
<td>-0.0833</td>
<td>-0.832</td>
</tr>
<tr>
<td>(a_H^{Ed})</td>
<td>6.1779</td>
<td>6.1741</td>
</tr>
<tr>
<td>(a_0^H)</td>
<td>9.3295</td>
<td>9.3438</td>
</tr>
<tr>
<td>(\sigma_W)</td>
<td>18.195</td>
<td>18.1950</td>
</tr>
<tr>
<td>(\sigma_H)</td>
<td>33.3606</td>
<td>33.3605</td>
</tr>
<tr>
<td>(C_1)</td>
<td>-22.3312</td>
<td>-17.7060</td>
</tr>
<tr>
<td>(C_2)</td>
<td>-14.9265</td>
<td>-17.7060</td>
</tr>
<tr>
<td>(C_3)</td>
<td>-17.3219</td>
<td>-17.7060</td>
</tr>
<tr>
<td>(C_4)</td>
<td>-17.0858</td>
<td>-17.7060</td>
</tr>
<tr>
<td>(C_5)</td>
<td>-16.1025</td>
<td>-17.7060</td>
</tr>
<tr>
<td>(C_6^W)</td>
<td>-13.6925</td>
<td>-17.7060</td>
</tr>
<tr>
<td>(C_6^H)</td>
<td>-15.4025</td>
<td>-17.7060</td>
</tr>
<tr>
<td>(\alpha_r)</td>
<td>-4.4097</td>
<td>-5.0237</td>
</tr>
<tr>
<td>(\beta_{dist})</td>
<td>-16.2149</td>
<td>-16.1645</td>
</tr>
<tr>
<td>(\beta_{distsq})</td>
<td>43.3663</td>
<td>46.9974</td>
</tr>
<tr>
<td>Log-Likelihood</td>
<td>-146060</td>
<td>-146510</td>
</tr>
<tr>
<td>(\chi^2) Test Statistic</td>
<td>890.26***</td>
<td></td>
</tr>
</tbody>
</table>

7.2 Decomposing the Importance of Marriage in the Migration Decision

One of the reasons to consider a model of household migration rather than a model of individual migration is to understand why we see much lower migration rates for two-earner households. In a sample of similarly aged, unmarried individuals in the NLSY79, 5.3 percent of singles move across state lines, which is a migration rate almost three times higher than that of the married sample. The reason we see lower migration rates for married couples than single individuals could be due to the ‘tied mover’ problem where spouses’ preferences are in conflict or it could simply be driven by higher costs for for married versus single individuals. To explore whether locational compatibility of occupations are enough to drive lower rates of
migration for married households, I next use my model to run two thought experiments.

In the first, I use the parameter estimates from the model to estimate how many couples would move if each person was married to themselves – meaning that their preferences across locations are now perfectly in line with their “spouse”. This thought experiment looks at how improving locational compatibility increases the mobility rate. We would expect that if there is mismatch in preferences over locations, one type of spouse should be less likely to move when matched to themself, meaning that they are tied movers, and the other spouse should be more likely to move, meaning that they are tied stayers.

In the second, I explore whether the lower migration rate stems from the higher costs associated with two people in the household having a distaste for migration rather than just one – that is, married couple household’s total disutility from moving is twice as high as single household’s total disutility because two people are displaced rather than one. To do this, I look at how many household would move if the migration decision was based only on one spouse’s earnings and migration cost. In this specification, a household’s utility is rewritten as:

\[
U_{i,j} = w_{ij} - 0.5 \cdot \alpha r_j - C(i, j, \text{home}) + \eta_{ij}
\]

where

\[
C(i, j) = 0.5(\beta d_1(\text{distance from home})_j + \beta d_2(\text{distance from home})_j^2) + \sum_{k=1}^{K}[C_k(1(k_i = k)]1(j \neq \text{home})
\]

where \(w_{ij}\) are the earnings of whichever spouse is deciding on the migration decision, defined in the same way as in the previous model (see page 17), \(\eta_{ij}\) are the preference shocks for each location, and the migration costs is a function of distance from home as well as \(k(i)\), which is the occupation of whichever spouse is deciding on the migration decision. I discount the utility values of housing costs and distance costs by half to address the fact these costs are spread across two people in the household model and the differing housing cost of an individual versus a family.

We would expect that both types of spouses should move more when making the decision to move, because they now only have one cost of migration to incorporate into their decision. However, the magnitude of the change in migration relative to the thought experiment in which individuals are matched to themself gives us a sense of the relative importance of differing location preferences versus just having more costs when two people are being uprooted.

It should be noted that these are not true “counterfactuals.” These thought experiments implicitly assume that single individuals and married individuals do not differ on any traits other than the ones I manipulate in the experiment. In reality, there are many other decisions endogenous to marriage that may also impact migration decisions, which I am not considering (e.g., the number of children one has). Nonetheless, they provide some insight into which mechanisms cause lower migration rates for married couples.

Table 10 shows the population’s migration rate broken down by gender for the sample of married individuals in the data and the model, the two thought experiments, as well as the migration rate in the NLSY79 for single individuals of the same demographic group as our married sample (i.e., 25 to 35, no longer in school).
Table 10: Thought Experiment Results

<table>
<thead>
<tr>
<th></th>
<th>Migration Rate</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Married Data</td>
<td>0.0194</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Married Model</td>
<td>0.0193</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single Data</td>
<td>0.053</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Migration Rate</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Thought Experiment 1</td>
<td>0.0169</td>
<td>0.111</td>
<td>0.0641</td>
<td></td>
</tr>
<tr>
<td>Thought Experiment 2</td>
<td>0.0174</td>
<td>0.1095</td>
<td>0.0635</td>
<td></td>
</tr>
</tbody>
</table>

The results of these thought experiments suggest that improving occupational match changes migration rates as much, if not more than removing a spouse from the household. Specifically, if husbands are making location decisions independently, slightly less than 11 percent of households would move. In contrast, if the wife could decide unilaterally, fewer households would move (1.74 percent). Removing occupational mismatch increases migration rates for men to 11.1 percent for men and decreases migration rates to 1.69 percent for women. This gender asymmetry is consistent with past research that suggests that women are more likely to be tied movers (i.e., move when they themselves would prefer not to) and men are more likely to be tied stayers (i.e., not move when they themselves would prefer not to).

8 Counterfactuals

Though the previous thought experiments help us understand the role that familial ties play in migration patterns, they are unrealistic when thought of in the context of policy intended to increase mobility or encourage migration out of economically distressed areas. After all, policy makers cannot force couples to pick different spouses or select out of marriage. The following counterfactual will therefore evaluate the effects of a scenario with more realistic policy implications under two different models: a model where we assume households make joint relocation decisions and a model where we assume individuals make relocation decisions.

What would be the effect of a relocation incentive that offered an individual $5000 if they take a job more than 250 miles from their current location? Though the United States does not currently offer nation-wide relocation incentives, some cities and states, including Vermont, Alaska, Baltimore, and others, offer either cash or housing cost assistance to people who move to them. Multiple European countries have relocation incentive for jobseekers who accept jobs in regions different from their current region. Evaluations of the effects of these programs on inter-region mobility in Germany (Caliendo et al., 2017) and France (Glover and Roulet, 2018) suggest that take-up of the relocation assistance is typically associated with long term gains in earnings. Glover and Roulet (2018) look at gender heterogeneity in take up and show that inducement to take up the relocation assistance differentially affects women, who are more likely in the absence of the assistance to search over a smaller geographic area.
Neither of these evaluations incorporate family ties into their analysis of the effects of relocation assistance on migration rates. One might expect that relocation assistance will be more effective for unmarried individuals than married individuals, meaning that models of individual migration may overstate the effects of relocation assistance.

Thus, I test the effects of two different models for evaluating of a $5000 relocation incentive. First, I test a policy in which every individual receives the incentive if they relocate more than 250 miles from their starting location in the model where households make joint decisions. Next, I test this same policy in the individual migration model described in thought experiment 2 above. If men and women were making the migration decision based only on their own utility and receive the relocation incentive, does it induce more or less changes in migration rates than in the joint household decision-making model?

Table 11 shows the original migration rates predicted by the model in column 1, the migration rates predicted with the relocation incentive program in column 2, and the percentage point change in migration in response to the policy in column 3. An analysis that assumes men and women are making relocation decisions as individuals vastly overestimates how sensitive their migration decision will be to a 5000 dollar relocation incentive, particularly for women. This means that program evaluations of relocation incentive policies are missing important heterogeneity when they estimate an average treatment effect that includes both single and married households in the treatment group. When designing evaluations of these policies, it is important to consider the household make-up of the treated population to properly estimate the benefits of these programs.

Table 11: Counterfactual: Effects of a Relocation Incentive on Migration Rates

<table>
<thead>
<tr>
<th>Model Migration Rate</th>
<th>Counterfactual Migration Rate</th>
<th>Percentage Point Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Joint Household Decision</td>
<td>0.0193</td>
<td>0.0369</td>
</tr>
<tr>
<td>Individual Decision</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Women</td>
<td>0.0174</td>
<td>0.0623</td>
</tr>
<tr>
<td>Men</td>
<td>0.1095</td>
<td>0.1262</td>
</tr>
<tr>
<td>Total Sample</td>
<td>0.0635</td>
<td>0.0942</td>
</tr>
</tbody>
</table>

9 Conclusion

In this paper, I develop and estimate a static model of married couples’ migration choices and the role that occupation-location match plays in these decisions. I show that this simple model of household migration provides a reasonable fit to the data, in particular matching migration rates for the overall population as well as for most occupational groups. I then discuss the implications of how household location choices are modeled in the context of relocation incentive programs, demonstrating that ignoring marital ties will result in mis-estimating the magnitude of policy effects.
The main contribution of this paper is to demonstrate that the occupation a person is in plays an important role in a person’s likelihood of moving for dual earner households. Specifically, couples for whom their occupations are locationally compatible (i.e., concentrated in similar locations) are more likely to move across state lines. I also demonstrate that occupation-location match plays an important role in these decisions. Using the model, I am able to conclude that there are significantly different costs to migration across occupation pairs, with white collar professionals having the highest migration costs and those in sales and administrative occupations having the lowest migration costs. The novel contribution of breaking down migration decisions by occupation of husbands and wives clarifies the types of careers that are particularly likely to be tied movers or stayers – or vice versa.

There is still more work to do on this topic to better understand the role that spouses’ locational compatibility in terms of occupation plays in migration decisions. Future work could better quantify the role that skill investment or sorting into different occupations plays in the differential effects of occupation by gender on household migration. For example, are women more or less likely to sort into occupations that are geographically concentrated? In the same way that one might select into a field that will allow one to have a more flexible schedule if planning to have children (Goldin and Katz, 2012; Bronson 2015; Wiswall and Zafar, 2015; Bursztyn, Fujiwara, and Pallais 2017), one might select into an occupation that is locationally flexible in anticipation of the fact that marriage will reduce a person’s ability to choose where they locate.

When considering place-based policies meant to encourage people to settle in a location, one must consider the difficulty in overcoming the frictions associated with moving two careers rather than just one. Relocation incentives will only be effective if they are large enough to overcome the career trade-offs one or both of the spouses will face when the household moves. Having a better understanding of how and why households with two-earners decide to move is a necessary part of understanding what policy levers will be most effective in encouraging welfare-improving relocations.
References


## 10 Appendix

### 10.1 Occupation Definitions

Appendix Table 1. Occupational Categories Crosswalk

<table>
<thead>
<tr>
<th>Occupation for Migration Costs</th>
<th>Occupation for Earnings Equations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Occupation 1</td>
<td>1 Executive and Managerial</td>
</tr>
<tr>
<td></td>
<td>2 STEM, Social Sciences, and Legal</td>
</tr>
<tr>
<td></td>
<td>5 Health</td>
</tr>
<tr>
<td>Occupation 2</td>
<td>8 Sales and Related</td>
</tr>
<tr>
<td></td>
<td>9 Office and Administrative</td>
</tr>
<tr>
<td>Occupation 3</td>
<td>3 Education, Counseling and Social Work</td>
</tr>
<tr>
<td></td>
<td>4 Entertainment and Media</td>
</tr>
<tr>
<td>Occupation 4</td>
<td>6 Protective Services</td>
</tr>
<tr>
<td></td>
<td>7 General Service</td>
</tr>
<tr>
<td>Occupation 5</td>
<td>10 Farming, Fishing, and Forestry</td>
</tr>
<tr>
<td></td>
<td>11 Construction, Maintenance, and Repair</td>
</tr>
<tr>
<td></td>
<td>12 Manufacturing</td>
</tr>
<tr>
<td></td>
<td>13 Transportation</td>
</tr>
</tbody>
</table>