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ABSTRACT

This study examines the relationship between an individual's occupation choice and destination choice. It portrays the relationship as an interaction between the supply of occupational skills by individuals and demand by different labor market regions. The analysis applies a two-equation simultaneous system: (1) a multinomial logit model of occupational choice and (2) a conditional logit model of state destination choice. The unusual merger of multinomial *logit* and conditional *logit* models in a simultaneous equation framework requires derivation of a unique variance-covariance matrix. The results indicate strong association between supply of (migration) and demand for (industry mix) an individual's occupational skills. [JEL Classification: R23, J61, J62]

1. INTRODUCTION

Population migration is the primary determinant of regional population change, dwarfing the small net natural change. Between 1995 and 2000, over 22 million individuals moved across states, representing over 8.5 percent of the U.S. population 5 years old and above. A change of this magnitude has a large impact. For example, migration affects regions' age composition, businesses' location decisions, wage rates, state and local tax revenues, public service allocations, and industrial clustering. Perhaps migration plays its most important role by increasing economic efficiency through allowing the sorting of workers and, indirectly, businesses, as they search for the best fit.

In sorting among labor markets, individuals' occupational skills are a major factor in determining which labor market region fits best. All else equal, utility maximizing individuals more likely choose a labor market region in which they can maximize the returns to their occupational skills. The relationship between choice of region and occupation is complex since individuals may change not only region, but also occupation. Individuals could change their occupation based on their choice of a region or *vice versa*, or make these choices simultaneously (e.g., Schaeffer, 1985).

We examine the relationship between individuals' occupation choice and destination choice. It portrays the relationship as an interaction between the supply of occupational skills by individuals and the demand by different labor market regions. A region's demand is affected by its industrial mix and employment growth by industrial sector. Unlike previous studies, this study recognizes a simultaneous relationship between an individual's occupational and destination choice, therefore, applies two-stage maximum likelihood estimation. The simultaneous system has two equations: (1) a multinomial logit model of occupational choice and (2) a conditional logit model of state destination choice. The unusual merger of multinomial *logit* and conditional *logit* models in a simultaneous equation framework requires derivation of a unique variance-covariance matrix; otherwise, statistical tests will be incorrect (Greene (2000)).

2. LITERATURE REVIEW

Aggregate Model and Individual Model of Migration

Sjaastad (1962) noted the difficulty in explaining the reasons rational people moved to supposedly wrong places, i.e., places economically worse than their origins. Most traditional aggregate models, which assume the same utility function for all individuals, cannot satisfactorily explain this. This failure may result primarily from aggregate models ignoring individual factors. Due to differences in individuals' characteristics, such as their education, marital status, proximity to home, and occupation, their preference for a destination place can differ even though their states of origin are the same. In other words, different individuals could place different relative value on each place attribute (Train, 1986).

In addition, an individual's current destination is not always his ultimate destination. Da Vanzo (1983) found that those who have moved before are more likely to move than those who have never migrated. She argued that first moves might fail, leading individuals to either move on or move back. Moving itself is likely a learning process, so that repeat moves become less costly or more effective. Zimmer (1973) found that repeat migrants were more likely in high-skilled occupations (professional and managerial occupations), than first-time movers or nonmigrants. Schaeffer (1985) added that repeat moves might simply be part of a career strategy. Individuals might choose an economically worse state because it provides the best chance for skills advancement. After mastering important skills, they explore other destinations in order to maximize the returns to their skills.

Most current migration studies tend to apply individual rather than aggregate migration models. Typically, researchers have applied the conditional logit model, including the early study by Mueller (1985) as well as later studies, such as by Davies, Greenwood, and Li (2001) (for a more complete review, see Cushing and Poot, 2004). Few, however, have incorporated individual factors. Our analysis uses Mueller's model as its starting point, but with the individual's occupational choice as one explanatory variable. Thus, the model examines which destination an individual chooses considering his or her occupational choice.

Migration and Occupational Change

Few studies have examined the relationship between occupation and migration. Some have focused on the relationship between occupational-mobility and migration, and mostly agreed that migration more likely leads to upward occupational mobility (Blau and Duncan, 1967; Chattopadhyay, 1998; to a certain extent Odland, 1996; Schaeffer, 1985). Other studies have looked at how the migration rate relates to the rate of occupational change. Most studies (Schroeder, 1976; Wilson, 1985) found no evidence of an inverse relationship suggested by Gleave and Palmer (1979), although Schlottmann and Herzog (1984) found that individuals making a career change have a higher likelihood of migrating.

A couple studies have examined whether individuals who simultaneously changed occupation and migrated achieved higher earnings. Krieg (1997) found little evidence of this. Bartel (1979) concluded that job-transfer-initiated moves led to higher earnings, while other kinds of job-change-initiated moves did not.

A few scholars have studied how an individual's occupation affects migration decisions. Most focused on the migration behavior of skilled individuals (Gani and Ward, 1995; Pashigian, 1979; Comay, 1972), although some looked at both skilled and unskilled workers (Ellis and Barff, 1993; Kleiner, 1976). Ellis and Barff (1993) and Kleiner (1976) concluded that individuals in high-skill occupations are more likely to move and more willing to move long distances than those in unskilled occupations (for a theoretical explanation see Schaeffer, 1985).

A major shortcoming of this last group of studies is that they disaggregated the sample by occupation category. This disaggregation raises two main problems. First, it assumes that individuals' occupations do not change. Unlike sex or race, however, individuals' occupations can change during the migration period. Secondly, individuals likely make decisions on occupational choice and destination choice simultaneously. Several studies (e.g., Bartel, 1979; Krieg, 1997; Schroeder, 1976) have found that a significant number of migrants indeed changed their occupation when they migrated.

Modeling Simultaneous Discrete Choice Models

Simultaneity means individuals do not separately face sets of occupational choices and destination choices, but a set of joint choices. Under this setting, occupational and destination choice variables become stochastic. Failure to account for this property could yield incorrect statistical tests (Greene, 2000).

Schmidt and Strauss (1975a) offered a method to estimate two simultaneous dependent qualitative variables. Their method operates by jointly solving the probability functions for individual's choice of both occupation and industrial sector. The symmetry of the two probability functions allows the method to generate a combined likelihood function that incorporates both functions, so that unbiased and consistent parameter estimates can be obtained simply by maximizing the likelihood function.

Although our model also deals with two probabilistic discrete choice functions, we cannot apply the Schmidt and Strauss (1975a) method. Their method was applicable because both models were multinomial *logit* models, while our analysis includes two different kinds of discrete choice models. We simultaneously use a multinomial *logit* model and conditional *logit* model for which the symmetry condition does not hold. The multinomial *logit* model estimates individuals' choice based on individual characteristics, whereas the conditional *logit* model estimates the choice based on the choice characteristics (place and occupational).

We apply a two-step maximum likelihood estimation, where the conditional *logit* model of destination choice is estimated using the predicted values of the occupational choice generated by the multinomial *logit* model of occupational choice. This method requires that the variance-covariance matrix of the parameter estimates be adjusted. The estimation applies the method developed by Murphy and Topel (1985) to compute the adjustments (see Greene, 2000, p. 134).

3. THE BASIC MODELS

We define a two-equation simultaneous system: one equation for occupational choice; the other for destination choice. The two equations take the following general forms:

(1) $$P_{ik} = f\,(X_{1i}, X_{2i}, P_{ij})$$

(2) $$P_{ij} = g\,(Z_i, X_{1i}, P_{ik})$$

Equation (1) represents the occupational-choice model. P_{ik} measures the probability of individual *i* choosing occupation *k*, which is a function of both the individual's characteristics (X_{1i} and X_{2i}) as well as the individual's destination choice, P_{ij}. Equation (2) represents the destination choice model, where P_{ij} measures the probability of individual *i* choosing state *j*, which is a function not only of the place attributes, Z_i, and the individual characteristics, X_{1i}, but also the individual's occupational choice, P_{ik}.

To solve the system, we first regress P_{ik} on all predetermined variables to obtain the predicted values of P_{ik}. Then, using these predicted values, $\hat{P}_{ik}$, in place of P_{ik}, we regress equation (2). Due to the simultaneity in this two-stage procedure, the estimated standard errors of the parameter estimates must be adjusted. The adjustment is described in Appendix 1.

Multinomial Logit Model of Occupational Choice

To estimate equation (1), we apply the typical multinomial-logit (MNL) model of occupational choice, as used by Schmidt and Straus (1975b). We extend the model by incorporating variables related to migration. Unlike typical MNL models, the individual's occupational choice is not a once-in-a-lifetime decision. Instead, it is a one-event decision, a decision made in the event of choosing a destination. In the initial period, we assume that individuals (except new entrants) have made their occupational choices. Now, facing a destination choice decision, they have to choose their occupation again, whether to stay or to move to another occupation. For that reason, the model includes previous occupation, representing previous choice of occupation, as an explanatory variable.

To represent different types of occupation skills, we use occupation categories defined by the U.S. Bureau of the Census 1980 Standard Occupational Code. We reclassify them into 5 categories:

1. Managerial and Professional Occupations
2. Sales Occupations

3. Operator Occupations
4. Laborer Occupations
5. Other occupations: Production-Precision, Clerical, and Service Worker Occupations.

Let the utility of choosing occupation k for individual i be:

$$U_{ik} = \boldsymbol{\beta_k}'\mathbf{X}_i + \varepsilon_{ik}$$

where $i = 1, 2, \ldots, N$, and $k = 1, 2, \ldots, 5$. The subscript k indexes the types of occupation in the choice set, ranging from 1 to 5, and variable $\mathbf{X}$ represents the individual characteristics. Assuming that the disturbances ε_{ik} are independent and identically distributed with extreme value distribution (McFadden, 1974; Greene, 2000), the probability of individual i choosing occupation k can be represented as:

$$P(Y=k) = P_{ik} = \frac{e^{\beta_k' X_i}}{\Sigma_k \, e^{\beta_k' X_i}}$$

for $k = 1, 2, \ldots, 5$. The model's log likelihood function is:

$$\text{Log } L_{MNL} = \sum_i \sum_k d_{ik} \text{Log } \mathbf{P}_{ik}$$

where $d_{ik} = 1$ if the occupation is chosen, and 0 otherwise. Applying maximum likelihood estimation yields parameter estimates, $\hat{\beta}_k$. Using the values of $\hat{\beta}_k$ and the fact that $\Sigma_k P_k = 1$, each of the five P_ks can be computed.

Conditional Logit Model of State Destination Choice

To estimate the second model, the state destination choice model, this study applies the conditional logit model, as used by Mueller (1985). The choice set consists of all possible state destinations. The analysis excludes Hawaii and Alaska, and combines the District of Columbia and Maryland. Thus, each individual chooses among 48 possible destinations, including his or her current state. Migration is defined as a change of residence between the beginning (1993) and ending period (1998).

Let the utility of choosing state j for individual i be

$$U_{ij} = \boldsymbol{\alpha}'\mathbf{Z}_{ij} + \varepsilon_{ij}$$

for $i = 1, 2, \ldots, N$, and $j = 1, 2 \ldots, 48$. The subscript j indexes the states in the choice set, and variable $\mathbf{Z}$ represents the place attributes and individual characteristics. Assuming the disturbances ε_{ij} are independent and identically distributed with extreme value distribution, the probability of individual i choosing state j is

$$P(Y=j) = P_{ij} = \frac{e^{\alpha' Z_{ij}}}{\Sigma_j \, e^{\alpha' Z_{ij}}}$$

for $i = 1, 2, \ldots, N$, and $j = 1, 2, \ldots, 48$.

In order to incorporate the individual characteristics, including $\hat{P}_k$, the model uses interaction terms between the individual characteristics and place attributes. In this case, the complete conditional *logit* model is

(3) $$P(Y=j) = P_{ij} = \frac{e^{\bar{\alpha}' \bar{Z}_{ij} + \tilde{\alpha}' \tilde{Z}_{ij} * X_i + \mathring{\alpha}' \mathring{Z}_{ij} * \hat{P}_k}}{\Sigma_j \, e^{\bar{\alpha}' \bar{Z}_{ij} + \tilde{\alpha}' \tilde{Z}_{ij} * X_i + \mathring{\alpha}' \mathring{Z}_{ij} * \hat{P}_k}}$$

where $i = 1, 2, \ldots, N$, and $j = 1, 2, \ldots, 48$.

Note that $\mathbf{Z}$ consists of $\bar{\mathbf{Z}}$, $\tilde{\mathbf{Z}}*\mathbf{X}$, and $\mathring{\mathbf{Z}}*\hat{\mathbf{P}}_k$. Of all the state-attribute variables in $\mathbf{Z}$, only $\bar{\mathbf{Z}}$ do not interact with any of the individual characteristics. Other place attributes, $\mathring{\mathbf{Z}}$, interact with the predicted probabilities of occupational choice, $\hat{\mathbf{P}}_k$, and $\tilde{\mathbf{Z}}$ interact with the other individual characteristic variables, $\mathbf{X}$. The model employs several individual characteristics, including education, age, race, marital status, family size, and a dummy for the presence of a working spouse, to explain individuals' choice between origin versus non-origin and between nearby versus distant states. In addition, the model uses two spatially related individual characteristics, house-tenure and the frequency of previous interstate moves, which capture the greater propensity for previous migrants to move again. In equation (3), this effect is shown as the interactions between $\tilde{\mathbf{Z}}$, which includes a distance variable and a non-origin dummy variable, and **X**, representing individuals' education, age, race, marital status, family size, etc. Including those individual characteristics should enable the model to explain aspects of migration choices, such as moving vs. staying or short distance vs. long distance, that are not explained by destination attributes.

The main focus of this essay is on the interactions between $\mathring{\mathbf{Z}}$ and $\hat{\mathbf{P}}_k$. We hypothesize that utility maximizing individuals will choose a destination where they can maximize the returns to their occupational skills. The labor market region with the strongest demand for their skills promises the highest returns to the skills. To indicate the strength of the state's demand for certain occupational skills, we use the state's industrial mix. Goetz (1999) and Schmidt and Strauss (1975b) showed that industrial sectors correlate strongly with types of occupation.

TABLES 1 through 4 illustrate the patterns of association between types of occupation and industrial sectors. They show that each state exhibits similar patterns of association. The patterns demonstrate that certain industrial sectors dominantly absorb certain types of occupations. They show that professional and managerial occupations are dominantly absorbed by the service sector, sales occupations by the retail sector, and operator occupations by the manufacturing sector. Some other occupations are dominated by two or more sectors. On the other hand, no sector dominantly absorbs laborer occupations, suggesting the demand for laborer employment is widely dispersed across industrial sectors.

Those patterns should represent the association between the supply of occupational skills from individuals and the demand from the state. According to these particular patterns, utility-maximizing individuals choosing professional or managerial skills will more likely choose a state with strong service sector demand. Similarly, individuals with operator occupation skills will more likely choose a state with strong manufacturing sector demand.

To measure the strength of demand by sector, the analysis could use either the size of employment in the sector or employment growth in that sector. The employment size of the sector, however, correlates strongly with the size of the state. In other words, big states tend to have greater total employment compared with small states. Thus, still controlling for the employment size, we use employment growth by sector in each state as a measure of the strength of the state's demand for certain occupations. This means that the variable, $\mathring{\mathbf{Z}}*\hat{\mathbf{P}}_{k}$, in equation (7), represents the interaction between employment growth (by sector) and predicted probability of choosing certain occupations.

The conditional logit of destination choice formulation applied in this study inherently assumes independence from irrelevant alternatives (IIA). IIA follows from the underlying assumption that the stochastic terms in the utility functions are independent. Intuitively, this assumption requires that the relative probabilities between choices must be independent of other alternatives, e.g., the relative probability of a Connecticut resident moving to New Jersey vs. Pennsylvania must be independent of the alternative of choosing New York. Undoubtedly, some individuals naturally make migration choices in a way that satisfies the IIA assumption. For example, some retirees might choose Florida as their retirement destination regardless of which other states are available. Also many "job-transfer" migrations may not consider alternatives. As a general proposition, however, IIA may be problematic.

A complete test of IIA in a model with 49 choices is impractical since it would require thousands of tests. Most likely, some of these tests would reject the hypothesis of IIA, while others would not. The sample size for this study is very large, however, which means that almost any difference between models would be statistically significant.

Ultimately, comparing empirical results from different modeling methods would better reveal the true importance (or cost) of maintaining the IIA assumption. Such a comparative study has not been carried out for a model of internal migration. In a study of local residential choice, Dahlberg and Eklöf (2003) found that as long as the model is not too parsimonious, the conditional logit model leads to exactly the same conclusions as models that relax the IIA assumption. This supports Train's (2003) suggestion that if the researcher specifies the observed variables sufficiently, then the remaining, unobserved, portion of utility is essentially "white noise." In this case, a conditional logit model would suffice. Alternative formulations that either partially relax (nested logit) or fully relax (mixed logit, heteroscedastic extreme value, or multinomial probit) the IIA assumption would be extremely difficult to solve for such a large model with so many choices. For this paper, we accept the arguments presented by Davies, Greenwood, and Li (2001) in support of the conditional logit formulation, as well as the conclusions of Dahlberg and Eklöf (2003). In keeping with Train's (2003) discussion, the analysis uses a model with a wide array of explanatory variables. We defer more thorough consideration of the statistical and practical importance of the IIA assumption for a separate paper.

4. DATA

The individual data come from the 1993 and 1998 panels of the National Longitudinal Survey of Youth (NLSY) 1979. The 1993 data represent initial characteristics, while the 1998 data represent end-of-period characteristics. Typically individual data would come from the Census PUMS (Public Use Microdata Sample) or CPS (Current Population Survey), which have larger samples. However, they do not have information on the individuals' previous occupation, which is crucial for this study. The NLSY data has 6,359 observations, after excluding individuals enrolled in school, out of the labor force, or with incomplete records. State-level employment data come from the Regional Economic Information System. Other state attributes such as distance, temperature, state adjacencies, and topography can be obtained from *U.S. Statistical Abstract* and other standard government sources.

5. EMPIRICAL RESULTS

Multinomial Logit Model of Occupational Choice

TABLE 5 presents the reduced form regression results for the multinomial *logit* model of occupational choice, which includes all predetermined variables in the system. Since place attributes do not structurally belong to the MNL model, the table shows only the parameter estimates of the relevant individual characteristics. Although this study focuses more on an individual's migration behavior, it is useful to see whether the occupational choice model yields reasonable results.

As expected, the results show that previous occupation strongly determines an individual's current occupational choice. Individuals are more likely to choose the same occupation as they had in the initial period. Education also significantly affects occupation choice. A more educated individual is more likely to choose professional & managerial occupations and less likely to choose operator and laborer occupations. Race significantly affects the choice of professional-managerial or sales occupations, with whites more likely to choose these occupations. Race does not significantly affect the likelihood of choosing an operator or laborer occupation. Males are more likely to choose an operator or laborer occupation, but sex does not significantly affect the choice of professional-managerial or sales occupations.

Conditional Logit Model of State Destination Choice

TABLE 6 presents the results for the conditional *logit* model of state destination choice. The results, in most cases, agree with those of previous migration studies. The first set of variables interact the dummy of non-origin with individual characteristics: Age, White, House Tenure, Male, Have a working spouse, Family size, and Frequency of previous interstate moves. These interaction terms represent the effect of those individual characteristics on the likelihood of choosing a non-origin state, i.e., the likelihood of moving. Age, House tenure, and Frequency of previous interstate moves significantly affect the likelihood of moving. Consistent with the migration literature, the older an individual and the longer an individual resides in a given house (stays in the origin) the less likely that person will move to another state. Similarly, the more frequently an individual has made interstate moves previously, the more likely that person will move again. Other individual characteristics do not significantly affect the likelihood of moving.

Another variable interacts educational attainment and moving distance. This term tests whether, as suggested, the higher the education, the more willing to move long distance. The parameter estimate is positive, as hypothesized, but of borderline statistical significance (with a t-value of 1.6).

All parameter estimates for place attribute variables are significant, except January temperature. Consistent with the migration literature, the results indicate that people are more likely to choose states with large employment size (Share), destinations that are closer (Distance), adjacent states (Adjacent), and warmer climates (July temperature). Surprisingly, however, the results show that individuals are more likely to choose states with higher humidity. This finding differs from the conventional wisdom that people are attracted to places with low humidity.

This study's focus is on the parameter estimates of the last interaction terms. The last three variables represent interactions between employment growth of certain sectors and the individual's predicted probability of choosing certain occupations. As already shown, some pairs of interaction (e.g., professional-managerial and services sector; sales and retail sector; operator and manufacturing sector; and laborer and overall sectors) show strong association between supply of and demand for occupational skills. The first of the three variables (*Emp-Growth*Pk_Strong Association*) represents the collection of these pairs that have a strong association. To check for robustness of results, the model also tests those pairs with other degree of associations. For that reason, the model also includes *Emp-Growth*Pk_Medium Association*, which represents the collection of the pairs with medium degree of association. This collection includes the pairings of professional-managerial and manufacturing sector; operator and services sector; laborer and retail sector; and laborer and manufacturing sector. Finally, the model includes a variable representing the collection of pairs with weak association ((*Emp-*

*Growth*Pk_Weak Association*). This collection includes other possible pairs that are not included in the first two variables.

TABLE 6 shows that the parameter estimate for the collection of pairs with strong association is positive and significant, of pairs with medium association is insignificant, and of pairs with weak association is negative and significant. This result confirms the study hypothesis, finding that individuals are indeed more likely to choose states where the demand for their occupational skill is strong. The results also suggest that individuals are less likely to choose states where the demand for their occupational skill is weak.

TABLE 6 also shows how the regression results are affected by the variance-covariance adjustment required due to the simultaneity problem. The adjusted standard errors are almost identical to the unadjusted standard errors, leaving the results of significance tests are unaffected. At least for our sample and model, the extra time and effort required to develop the variance-covariance adjustment does not seem to be necessary. A set of Monte Carlo tests would provide guidance regarding whether carrying out the adjustment might ever make a significant difference and, if so, under what conditions the adjustment is likely to have a noticeable effect on statistical conclusions.

7. CONCLUDING REMARKS

We have examined the relationship between individuals' occupation choice and destination choice. We portray the relationship as an interaction between the supply of occupational skills by individuals and the demand by different labor market regions. The relationship between choice of region and occupation is complex since individuals could change their occupation based on their choice of a region or *vice versa*, or make these choices simultaneously (e.g., Schaeffer, 1985). Unlike previous studies, we recognize this potentially simultaneous relationship between an individual's occupational and destination choice by applying a two-stage maximum likelihood estimation. The simultaneous system has two equations: (1) a multinomial logit model of occupational choice and (2) a conditional logit model of state destination choice. Our methodology should have broad applicability even beyond migration research, given that individuals frequently face simultaneous choices.

Our empirical results indicate a strong association between the supply of (migration) and the demand for (industry mix) an individual's occupational skills. We find that individuals more likely choose states where the demand for their occupational skill is the strongest, and *vice versa*. This agrees with the underlying principle of migration as a human capital investment, controlling for amenity variables.

The unusual merger of multinomial *logit* and conditional *logit* models in a simultaneous equation framework requires adjustment of the variance-covariance matrix. Otherwise, statistical tests may be incorrect. For our estimation, the variance-covariance adjustment had no perceptible effect on statistical results. Since the proliferation of microdata and advances in computer technology make this type of modeling more likely in the future, it would be worthwhile to conduct a series of Monte Carlo tests with different models and samples to better understand how often and under what conditions this adjustment is likely to qualitatively affect statistical results.

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APPENDIX 1: ADJUSTING THE VARIANCE

Let β, $\mathbf{D}_{MNL}$, and $\mathbf{V}_{MNL}$ be the parameter, the first derivative, and the variance of the log likelihood function of the occupational choice multinomial logit model and α, $\mathbf{D}_{CL}$, and $\mathbf{V}_{CL}$ be the parameter, first derivative, and variance of the destination choice conditional logit model. Then the correct asymptotic variance of the system, $\mathbf{V}_S$, can be computed as

$$\mathbf{V}_S = \mathbf{V}_{CL} + \mathbf{V}_{CL}(\mathbf{C}\mathbf{V}_{MNL}\mathbf{C}' - \mathbf{R}\mathbf{V}_{MNL}\mathbf{C}' - \mathbf{C}\mathbf{V}_{MNL}\mathbf{R}')\,\mathbf{V}_{CL}$$

where $\mathbf{R} = \mathbf{D}_{CL}\,\mathbf{D}_{MNL}'$ and $\mathbf{C} = \mathbf{D}_{CL}\,\mathbf{D}_{Cross}'$.

We have found that

$$\mathbf{D}_{MNL} = \frac{\partial \text{Ln L}_{MNL}}{\partial \beta_k} = \sum_i \mathbf{x}_i[\text{d}_{ik} - \mathbf{P}_{ik}]$$

and

$$\mathbf{D}_{CL} = \frac{\partial \text{Ln L}_{CL}}{\partial \alpha} = \sum_i \sum_j \text{d}_{ij}[\mathbf{z}_{ij} - \Sigma_j\, \mathbf{z}_{ij}\mathbf{P}_{ij}]$$

We still need to find

$$\mathbf{D}_{Cross} = \frac{\partial \text{Ln L}_{CL}}{\partial \beta_k}$$

where

$$\text{Ln L}_{CL} = \sum_i \sum_j \text{d}_{ij}\,\text{Ln P}_{ij}$$

P_{ij} is a function of β since $\mathbf{Z}$ in P_{ij} contains $\bar{\mathbf{Z}}$, $\tilde{\mathbf{Z}}*\mathbf{X}$, and $\mathring{\mathbf{Z}}*\hat{\mathbf{P}}_k$.

For each individual, *I*,

(i) $$\frac{\partial \text{Ln L}_{CL}}{\partial \beta_k} = \sum_j \text{d}_j \frac{1}{\text{P}_j}\frac{\partial \text{P}_j}{\partial \beta_k}$$

(ii) $$\frac{\partial P_j}{\partial \beta_k} = \frac{\partial \dfrac{e^{\alpha' z_j \hat{P}_k}}{\Sigma_j\, e^{\alpha' z_j \hat{P}_k}}}{\partial \beta_k} = \frac{[\Sigma]\dfrac{\partial e^{\alpha' z_j \hat{P}_k}}{\partial \beta_k} - e^{\alpha' z_j \hat{P}_k}\dfrac{\partial [\Sigma]}{\partial \beta_k}}{[\Sigma]^2}$$

where $[\Sigma] = \Sigma_j\, e^{\alpha' z_j \hat{P}_k}$.

(iii) $$\frac{\partial e^{\alpha' z_j \hat{P}_k}}{\partial \beta_k} = \alpha' z_j \frac{\partial \hat{P}_k}{\partial \beta_k}\; e^{\alpha' z_j \hat{P}_k}$$

For example, letting $j = 1, 2, 3$,

(iv) $$\frac{\partial [\Sigma]}{\partial \beta_k} = \frac{\partial e^{\alpha' z_1 \hat{P}_k}}{\partial \beta_k} + \frac{\partial e^{\alpha' z_2 \hat{P}_k}}{\partial \beta_k} + \frac{\partial e^{\alpha' z_3 \hat{P}_k}}{\partial \beta_k}$$

$$= \alpha' z_1 \frac{\partial \hat{P}_k}{\partial \beta_k}\; e^{\alpha' z_1 \hat{P}_k} + \alpha' z_2 \frac{\partial \hat{P}_k}{\partial \beta_k}\; e^{\alpha' z_2 \hat{P}_k} + \alpha' z_3 \frac{\partial \hat{P}_k}{\partial \beta_k}\; e^{\alpha' z_3 \hat{P}_k}$$

$$= \Sigma_j\, \alpha' z_j \frac{\partial \hat{P}_k}{\partial \beta_k} e^{\alpha' z_j \hat{P}_k}$$

To solve $\dfrac{\partial \hat{P}_k}{\partial \beta_k}$, let's suppose two possible different occupations, to be labeled *k* and *l*.

For *k* equal *l*

$$\frac{\partial \hat{P}_l}{\partial \beta_k} = \frac{\partial \dfrac{e^{\beta_l' X}}{[\Sigma_k]}}{\partial \beta_k} = \frac{([\Sigma_k] x\, e^{\beta_l' X} - e^{\beta_l' X} x\, e^{\beta_k' X})}{[\Sigma_k]^2} = x(\hat{P}_l - \hat{P}_l \hat{P}_k)$$

where $[\Sigma_k] = \Sigma_k\, e^{\beta_k' X}$. For *k* not equal to *l*

$$\frac{\partial \hat{P}_l}{\partial \beta_k} = \frac{-e^{\beta_l' X} x\, e^{\beta_k' X}}{[\Sigma_k]^2} = x(0 - \hat{P}_l \hat{P}_k)$$

In general,

(v) $$\frac{\partial \hat{P}_l}{\partial \beta_k} = x(d_k \hat{P}_l - \hat{P}_l \hat{P}_k)$$

where $d_k = 1$ if *l* equals *k*, and 0 otherwise.

Substituting (v) into (iv) yields

(iv*) $$\frac{\partial[\Sigma]}{\partial\beta_k} = \Sigma_j\ \alpha'z_j\ (x(d_k\hat{P}_k - \hat{P}_k\hat{P}_k))e^{\alpha'z_j\hat{P}_k}$$

Substituting (v) into (iii) yields

(iii*) $$\frac{\partial e^{\alpha'z_j\hat{P}_k}}{\partial\beta_k} = \alpha'z_j\ (x(d_k\hat{P}_k - \hat{P}_k\hat{P}_k))e^{\alpha'z_j\hat{P}_k}$$

Substituting (iii*) and (iv*) into (ii) yields

(ii*) $$\frac{\partial P_j}{\partial\beta_k} = \frac{[\Sigma]\alpha'z_j\ (x(d_k\hat{P}_k - \hat{P}_k\hat{P}_k))e^{\alpha z_j\hat{P}_k} - e^{\alpha'z_j\hat{P}_k}\ \Sigma_j\ \alpha'z_j\ (x(d_k\hat{P}_k - \hat{P}_k\hat{P}_k))e^{\alpha'z_j\hat{P}_k}}{[\Sigma]^2}$$

$$= \frac{\alpha'z_j\ (x(d_k\hat{P}_k - \hat{P}_k\hat{P}_k))e^{\alpha'zj\hat{P}k}}{[\Sigma]} - \frac{P_j\ \Sigma_j\ \alpha'z_j\ (x(d_k\hat{P}_k - \hat{P}_k\hat{P}_k))e^{\alpha'zj\hat{P}k}}{[\Sigma]}$$

$$= \alpha'z_j\,((x(d_k\hat{P}_k - \hat{P}_k\hat{P}_k))P_j - P_j\ \Sigma_j\ \alpha'z_j\ ((x(d_k\hat{P}_k - \hat{P}_k\hat{P}_k))\ P_j$$

$$= P_j\ (\alpha'z_j - \Sigma_j\ \alpha'z_jP_j)\ (x(d_k\hat{P}_k - \hat{P}_k\hat{P}_k)$$

Substituting (ii*) into (i) yields

(i*) $$\frac{\partial \log L_{CL}}{\partial\beta_k} = \sum_j d_j \frac{1}{P_j} \{\ P_j\ (\alpha'z_j - \Sigma_j\ \alpha'z_jP_j)\ (x(d_k\hat{P}_k - \hat{P}_k\hat{P}_k))\ \}$$

$$= \sum_j d_j(\alpha'z_j - \Sigma_j\alpha'z_jP_j)(x(d_k\hat{P}_k - \hat{P}_k\hat{P}_k))$$

Thus, the solution for all individuals is

$$\frac{\partial \log L_{CL}}{\partial\beta_k} = \sum_i \sum_j d_j(\alpha'z_j - \Sigma_j\alpha'z_jP_j)(x(d_k\hat{P}_k - \hat{P}_k\hat{P}_k))$$

The solution above applies to the general form of the conditional *logit* model equation.

APPENDIX 2 describes the solution applied to the form of the conditional *logit* model equation applied in this study.

APPENDIX 2: ADJUSTING THE VARIANCE: THE FORM OF THE CONDITIONAL *LOGIT* MODEL EQUATION FOR THIS STUDY

For simplicity, let's leave out the subscript *i* denoting the individual. In this particular study, the real P_j takes the following form

$$P_j = e^{\alpha_A' \mathbf{z}_{Aj} + \alpha_H(z_{1j}*\hat{P}_{1j} + z_{2j}*\hat{P}_2 + z_{3j}*\hat{P}_3 + z_{4j}*\hat{P}_4) + \alpha_M(z_{1j}*\hat{P}_3 + z_{2j}*\hat{P}_4 + z_{3j}*\hat{P}_1 + z_{3j}*\hat{P}_4)}$$

$$^{+ \alpha_W(z_{1j}*\hat{P}_2 + z_{1j}*\hat{P}_4 + z_{2j}*\hat{P}_1 + z_{2j}*\hat{P}_3 + z_{3j}*\hat{P}_2 + z_{4j}*\hat{P}_1 + z_{4j}*\hat{P}_2 + z_{4j}*\hat{P}_3)} / \Sigma_j \, e^{\alpha'(\mathbf{z}_j \hat{P}_k)}$$

where α consists of α_A, α_H, α_M, and α_W. α_A is the coefficient for variable $\mathbf{Z}_A$, α_H is the coefficient for the variable representing the collective interactions of pairs with strong association; α_M is for those with medium degree of association; and α_W is for those with weak association. **Z** consists of $\mathbf{Z}_A$, representing place attributes that do not interact with $\hat{P}_k$, as well as Z_1, Z_2, Z_3, and Z_4, representing the employment growth for each sector. Each of Z_1, Z_2, Z_3, and Z_4, interacts with $\hat{P}_k$. [Note that the number of k (occupation categories) in $\hat{P}_k$ is four, with the 5th category as the reference. The model also includes four sectors: services, manufacturing, retail-trade, and all other.]

Let's simplify the above form into

$$P_j = \frac{e^{[ZP]}}{[\Sigma]}$$

Given $\text{Ln } L_{CL} = \sum_i \sum_j d_{ij} \text{ Ln } P_{ij}$, then for each individual *I*,

$$\frac{\partial \text{Ln } L_{CL}}{\partial \beta_k} = \sum_j d_j \frac{1}{P_j} \frac{\partial P_j}{\partial \beta_k}$$

For $k = 1$,

$$\frac{\partial P_j}{\partial \beta_1} = \frac{[\Sigma]\,\frac{\partial e^{[Z\hat{P}_k]}}{\partial \beta_1} - e^{[Z\hat{P}_k]}\,\frac{\partial[\Sigma]}{\partial \beta_1}}{[\Sigma]^2} = \frac{[\Sigma][\alpha'z\,[\frac{\partial \hat{P}_k}{\partial \beta_1}]\,]e^{[Z\hat{P}_k]} - e^{[Z\hat{P}_k]}\,\Sigma_j\,[\alpha'z\,[\frac{\partial \hat{P}_k}{\partial \beta_1}]]e^{[Z'P]}}{[\Sigma]^2}$$

$$= [\alpha'z\,[\frac{\partial \hat{P}_k}{\partial \beta_1}]]P_j - P_j\,\Sigma_j\,[\alpha'z\,[\frac{\partial \hat{P}_k}{\partial \beta_1}]]P_j$$

Note that in this case $\alpha'z$ refers to the multiplication between α_H, α_M, α_W and Z_1, Z_2, Z_3, and Z_4 only. This is because the derivative of the term $\alpha_A'Z_A$ with respect to β_k is zero. Thus,

$$\frac{\partial \log L_{CL}}{\partial \beta_1} = d_j \left\{ [\alpha'z\,[\frac{\partial \hat{P}_k}{\partial \beta_1}]] - \Sigma_j\,[\alpha'z\,[\frac{\partial \hat{P}_k}{\partial \beta_1}]]P_j \right\}$$

where in this case

$$[\alpha'z\,[\frac{\partial \hat{P}_k}{\partial \beta_1}]] = \alpha_H (Z_1 \frac{\partial \hat{P}_1}{\partial \beta_1} + Z_2 \frac{\partial \hat{P}_2}{\partial \beta_1} + Z_3 \frac{\partial \hat{P}_3}{\partial \beta_1} + Z_4 \frac{\partial \hat{P}_4}{\partial \beta_1}) + \alpha_M (Z_1 \frac{\partial \hat{P}_3}{\partial \beta_1} + Z_2 \frac{\partial \hat{P}_4}{\partial \beta_1} + Z_3 \frac{\partial \hat{P}_1}{\partial \beta_1} + Z_3 \frac{\partial \hat{P}_4}{\partial \beta_1})$$

$$+ \alpha_L (Z_1 \frac{\partial \hat{P}_2}{\partial \beta_1} + Z_1 \frac{\partial \hat{P}_4}{\partial \beta_1} + Z_2 \frac{\partial \hat{P}_1}{\partial \beta_1} + Z_2 \frac{\partial \hat{P}_3}{\partial \beta_1} + Z_3 \frac{\partial \hat{P}_2}{\partial \beta_1} + Z_4 \frac{\partial \hat{P}_1}{\partial \beta_1} + Z_4 \frac{\partial \hat{P}_2}{\partial \beta_1} + Z_4 \frac{\partial \hat{P}_3}{\partial \beta_1})$$

$$= \alpha_H \,x \{(z_1(\hat{P}_1 - \hat{P}_1\hat{P}_1) + z_2(0 - \hat{P}_2\hat{P}_1) + z_3(0 - \hat{P}_3\hat{P}_1) + z_4(0 - \hat{P}_4\hat{P}_1)\}$$

$$+ \alpha_M \,x \{(z_1(0 - \hat{P}_3\hat{P}_1) + z_2(0 - \hat{P}_4\hat{P}_1) + z_3(\hat{P}_1 - \hat{P}_1\hat{P}_1) + z_3(0 - \hat{P}_4\hat{P}_1)\}$$

$$+ \alpha_L \,x \{(z_1(0 - \hat{P}_2\hat{P}_1) + z_1(0 - \hat{P}_4\hat{P}_1) + z_2(\hat{P}_1 - \hat{P}_1\hat{P}_1) + z_2(0 - \hat{P}_3\hat{P}_1)$$

$$+ (z_3(0 - \hat{P}_2\hat{P}_1) + z_4(\hat{P}_1 - \hat{P}_1\hat{P}_1) + z_4(0 - \hat{P}_2\hat{P}_1) + z_4(0 - \hat{P}_3\hat{P}_1)\}$$

Similarly, for k = 2,

$$\frac{\partial \text{Log } L_{CL}}{\partial \beta_2} = d_j \left\{ [\alpha'z\,[\frac{\partial \hat{P}_k}{\partial \beta_2}]] - \Sigma_j\,[\alpha'z\,[\frac{\partial \hat{P}_k}{\partial \beta_2}]] \quad P_j \right\}$$

where

$$[\alpha'z\,[\frac{\partial \hat{P}_k}{\partial \beta_2}]] = \alpha_H \,x \{(z_1(0 - \hat{P}_1\hat{P}_2) + z_2(\hat{P}_2 - \hat{P}_2\hat{P}_2) + z_3(0 - \hat{P}_3\hat{P}_2) + z_4(0 - \hat{P}_4\hat{P}_2)\}$$

$$+ \alpha_M \,x\{(z_1(0 - \hat{P}_3\hat{P}_2) + z_2(0 - \hat{P}_4\hat{P}_2) + z_3(\hat{P}_1 - \hat{P}_1\hat{P}_2) + z_3(0 - \hat{P}_4\hat{P}_2)\}$$

$$+ \alpha_L \,x\{(z_1(\hat{P}_2 - \hat{P}_2\hat{P}_2) + z_1(0 - \hat{P}_4\hat{P}_2) + z_2(0 - \hat{P}_1\hat{P}_2)$$

$$+ z_2(0 - \hat{P}_3\hat{P}_2) + (z_3(\hat{P}_2 - \hat{P}_2\hat{P}_2) + z_4(0 - \hat{P}_1\hat{P}_2) + z_4(\hat{P}_2 - \hat{P}_2\hat{P}_2) + z_4(0 - \hat{P}_3\hat{P}_2)\}$$

For k=3,

$$\frac{\partial \mathrm{Log}\ L_{CL}}{\partial \beta_3} = d_j \left\{ [\alpha' z\, [\frac{\partial \hat{P}_k}{\partial \beta_3}]] - \Sigma_j\, [\alpha' z\, [\frac{\partial \hat{P}_k}{\partial \beta_3}]] P_j \right\}$$

where

$$[\alpha' z\, [\frac{\partial \hat{P}_k}{\partial \beta_3}]] = \alpha_H \,x\{(z_1(0 - \hat{P}_1\hat{P}_3) + z_2(0 - \hat{P}_2\hat{P}_3) + z_3(\hat{P}_3 - \hat{P}_3\hat{P}_3) + z_4(0 - \hat{P}_4\hat{P}_3)\}$$

$$+ \alpha_M \,x\{(z_1(\hat{P}_3 - \hat{P}_3\hat{P}_3) + z_2(0 - \hat{P}_4\hat{P}_3) + z_3(0 - \hat{P}_1\hat{P}_3) + z_3(0 - \hat{P}_4\hat{P}_3)\}$$

$$+ \alpha_L \,x\{(z_1(0 - \hat{P}_2\hat{P}_3) + z_1(0 - \hat{P}_4\hat{P}_3) + z_2(0 - \hat{P}_1\hat{P}_3) + z_2(\hat{P}_3 - \hat{P}_3\hat{P}_3)$$

$$+ (z_3(0 - \hat{P}_2\hat{P}_3) + z_4(0 - \hat{P}_1\hat{P}_3) + z_4(0 - \hat{P}_2\hat{P}_3) + z_4(\hat{P}_3 - \hat{P}_3\hat{P}_3)\}$$

Finally, for k=4,

$$\frac{\partial \mathrm{Log}\ L_{CL}}{\partial \beta_4} = d_j \left\{ [\alpha' z\, [\frac{\partial \hat{P}_k}{\partial \beta_4}]] - \Sigma_j\, [\alpha' z\, [\frac{\partial \hat{P}_k}{\partial \beta_4}]] P_j \right\}$$

where

$$[\alpha' z\, [\frac{\partial \hat{P}_k}{\partial \beta_4}]] = \alpha_H \,x\{(z_1(0 - \hat{P}_1\hat{P}_4) + z_2(0 - \hat{P}_2\hat{P}_4) + z_3(0 - \hat{P}_3\hat{P}_4) + z_4(\hat{P}_4 - \hat{P}_4\hat{P}_4)\}$$

$$+ \alpha_M \,x\{(z_1(0 - \hat{P}_3\hat{P}_4) + z_2(\hat{P}_4 - \hat{P}_4\hat{P}_4) + z_3(0 - \hat{P}_1\hat{P}_4) + z_3(\hat{P}_4 - \hat{P}_4\hat{P}_4)\}$$

$$+ \alpha_L \,x\{(z_1(0 - \hat{P}_2\hat{P}_4) + z_1(\hat{P}_4 - \hat{P}_4\hat{P}_4) + z_2(0 - \hat{P}_1\hat{P}_4) + z_2(0 - \hat{P}_3\hat{P}_4)$$

$$+ (z_3(0 - \hat{P}_2\hat{P}_4) + z_4(0 - \hat{P}_1\hat{P}_4) + z_4(0 - \hat{P}_2\hat{P}_4) + z_4(0 - \hat{P}_3\hat{P}_4)\}$$

TABLE 1: Distribution of Managerial and Professional Occupations across Industrial Sectors by State, 1990

State	Agri.	Construct.	Finance	Manufact.	Mining	Retail-Tr.	Service	Transport.	Wholesale	Total
					Industry					
Maine	3.0	2.7	5.6	12.4	0.1	5.4	64.9	3.8	2.1	100.0
New Hampshire	1.8	2.6	6.8	25.1	0.0	5.5	52.7	3.7	1.8	100.0
Vermont	8.4	2.6	4.4	10.4	0.6	5.7	60.8	3.8	3.3	100.0
Massachusetts	1.0	2.9	7.7	17.3	0.1	6.0	58.7	3.7	2.6	100.0
Rhode Island	1.1	2.5	7.3	16.3	0.1	8.0	58.7	3.4	2.6	100.0
Connecticut	1.1	2.7	10.9	19.5	0.2	5.6	52.0	4.9	3.1	100.0
New York	1.4	2.4	9.5	12.8	0.1	5.9	60.6	4.8	2.6	100.0
New Jersey	1.1	3.3	9.8	14.7	0.2	6.6	54.4	6.5	3.5	100.0
Pennsylvania	2.8	3.5	6.3	14.9	0.4	6.7	58.9	4.3	2.2	100.0
Ohio	3.5	2.8	5.7	16.6	0.4	8.0	56.2	4.1	2.8	100.0
Indiana	5.8	3.0	5.7	17.1	0.2	7.5	54.4	4.2	2.1	100.0
Illinois	4.2	2.7	7.9	14.8	0.2	7.0	55.1	4.9	3.1	100.0
Michigan	3.1	2.8	5.2	19.1	0.1	7.7	55.9	3.5	2.4	100.0
Wisconsin	10.4	2.6	5.7	15.8	0.1	6.1	53.5	3.7	2.0	100.0
Minnesota	9.6	2.7	6.2	15.7	0.1	6.2	52.1	4.2	3.3	100.0
Iowa	20.9	1.8	5.8	10.9	0.0	5.9	49.5	3.3	1.9	100.0
Missouri	7.5	2.7	5.5	14.1	0.1	7.3	54.7	5.4	2.6	100.0
North Dakota	29.3	4.0	4.2	3.9	1.0	5.5	47.1	4.0	1.0	100.0
South Dakota	32.1	2.7	5.1	6.1	0.3	5.1	43.4	4.3	1.0	100.0
Nebraska	20.3	2.8	5.6	6.8	0.2	6.4	50.1	5.6	2.1	100.0
Kansas	12.4	2.7	5.7	11.6	0.8	6.1	52.7	5.6	2.5	100.0
Delaware	9.4	5.5	4.5	10.2	0.0	7.1	57.7	5.5	0.1	100.0
Maryland & DC	1.8	4.5	8.2	8.6	0.1	6.1	64.0	4.4	2.3	100.0
Virginia	2.9	5.0	7.0	10.4	0.2	7.1	59.9	5.3	2.2	100.0
West Virginia	4.6	3.3	3.4	8.0	1.9	6.3	65.4	6.2	0.9	100.0
North Carolina	5.1	3.4	5.1	15.6	0.1	7.4	56.1	4.6	2.5	100.0
South Carolina	3.2	5.1	5.5	15.0	0.1	7.3	56.5	5.2	2.1	100.0
Georgia	3.6	3.7	6.5	11.8	0.2	8.1	54.9	7.6	3.6	100.0
Florida	2.7	4.2	8.2	10.7	0.2	8.2	56.9	5.9	3.1	100.0
Kentucky	10.6	2.8	5.8	11.1	0.8	8.2	54.7	4.3	1.7	100.0
Tennessee	4.5	3.2	5.9	14.1	0.2	7.0	56.0	6.6	2.4	100.0
Alabama	4.2	4.1	5.3	11.5	0.2	7.7	59.2	5.9	1.9	100.0
Mississippi	7.8	3.2	4.3	11.4	0.9	6.6	59.9	4.0	1.8	100.0
Arkansas	12.0	2.6	5.3	10.1	0.3	7.7	54.8	5.1	1.9	100.0
Louisiana	3.9	3.8	6.0	7.7	2.3	7.0	61.5	5.1	2.7	100.0
Oklahoma	7.7	2.9	6.1	9.6	3.7	6.2	56.2	5.6	2.1	100.0
Texas	4.2	3.9	6.8	12.3	3.0	7.9	53.5	5.5	3.0	100.0
Montana	18.8	3.4	3.8	4.2	0.6	5.9	56.1	5.7	1.5	100.0
Idaho	15.0	2.8	4.8	10.3	0.6	6.1	53.9	3.7	2.8	100.0
Wyoming	13.2	4.0	3.8	4.7	5.3	5.1	57.9	5.9	0.1	100.0
Colorado	4.6	3.7	6.6	13.2	1.9	6.3	54.7	6.6	2.4	100.0
New Mexico	3.3	4.3	5.0	7.9	1.9	6.7	65.7	3.9	1.4	100.0
Arizona	2.3	3.9	7.3	14.2	0.5	7.0	57.0	5.7	2.0	100.0
Utah	3.8	3.0	5.4	13.9	0.7	7.1	59.4	4.8	1.8	100.0
Nevada	2.6	6.0	7.9	5.4	1.5	8.1	61.3	5.3	2.0	100.0
Washington	4.4	3.7	6.5	15.7	0.1	6.9	55.3	5.1	2.5	100.0
Oregon	6.5	3.3	7.3	12.5	0.2	7.7	55.5	4.5	2.7	100.0
California	2.4	3.8	8.0	17.1	0.3	6.3	54.8	4.5	2.8	100.0
Average	**7.2**	**3.4**	**6.2**	**12.4**	**0.7**	**6.7**	**56.4**	**4.9**	**2.2**	**100.0**

Source: 1990 5% PUMS, U.S. Census Bureau.

TABLE 2: Distribution of Sales Occupations across Industrial Sectors by State, 1990

State	Agri.	Construct.	Finance	Manufact.	Mining	Retail-Tr.	Service	Transport.	Wholesale	Total
					Industry					
Maine	0.4	0.8	13.5	4.0	0.0	67.6	3.7	1.3	8.7	100.0
New Hampshire	0.5	0.6	14.0	7.0	0.0	59.2	6.7	1.7	10.3	100.0
Vermont	1.1	0.0	12.4	4.0	0.0	63.2	6.6	0.8	11.9	100.0
Massachusetts	0.4	0.5	13.9	6.4	0.0	58.6	8.1	2.0	10.1	100.0
Rhode Island	0.7	0.3	12.2	5.9	0.0	64.6	4.2	1.3	10.8	100.0
Connecticut	0.4	0.6	17.5	6.3	0.0	56.6	7.7	1.1	9.8	100.0
New York	0.2	0.5	14.9	6.3	0.0	58.5	7.1	1.9	10.5	100.0
New Jersey	0.2	0.6	16.2	7.0	0.0	53.9	7.2	2.0	12.8	100.0
Pennsylvania	0.3	0.7	11.1	6.1	0.0	63.1	6.9	1.5	10.2	100.0
Ohio	0.4	0.8	10.9	7.1	0.0	62.3	6.8	1.5	10.1	100.0
Indiana	0.3	0.7	10.4	6.3	0.1	63.3	6.8	1.7	10.5	100.0
Illinois	0.3	0.7	13.8	7.0	0.0	57.2	7.7	2.1	11.3	100.0
Michigan	0.4	0.6	10.9	6.3	0.0	64.3	6.6	1.3	9.5	100.0
Wisconsin	0.4	1.0	12.6	7.4	0.0	61.7	6.4	1.0	9.6	100.0
Minnesota	0.5	0.6	13.5	7.9	0.0	56.0	7.4	1.5	12.6	100.0
Iowa	1.0	0.7	11.5	6.0	0.2	61.0	5.7	2.3	11.7	100.0
Missouri	0.4	0.8	11.4	6.3	0.0	60.4	7.4	2.6	10.6	100.0
North Dakota	0.7	0.2	11.3	2.8	0.6	68.5	5.7	0.8	9.6	100.0
South Dakota	0.5	0.9	9.3	6.4	0.0	62.9	4.5	1.8	13.7	100.0
Nebraska	0.7	0.5	13.4	5.6	0.0	58.1	7.7	1.3	12.7	100.0
Kansas	0.5	0.4	12.2	4.8	0.0	62.2	5.7	2.3	11.8	100.0
Delaware	0.0	0.0	11.7	1.7	0.0	69.9	8.6	2.4	5.8	100.0
Maryland & DC	0.3	0.8	14.4	4.5	0.0	60.0	7.2	2.2	10.5	100.0
Virginia	0.2	0.5	12.3	4.3	0.0	65.4	7.6	1.5	8.2	100.0
West Virginia	0.1	0.1	9.9	4.5	0.3	72.1	5.1	0.5	7.5	100.0
North Carolina	0.1	0.5	10.6	5.8	0.1	65.2	6.0	1.3	10.4	100.0
South Carolina	0.2	0.9	9.9	4.2	0.0	66.7	6.6	1.2	10.2	100.0
Georgia	0.3	0.6	11.7	5.7	0.0	60.5	7.3	2.2	11.7	100.0
Florida	0.3	0.8	14.7	4.5	0.0	58.9	7.7	2.0	11.0	100.0
Kentucky	0.2	0.7	10.3	4.5	0.3	67.4	6.6	1.9	8.1	100.0
Tennessee	0.2	0.5	11.1	5.0	0.1	63.5	6.7	1.7	11.2	100.0
Alabama	0.2	0.6	9.0	4.8	0.0	67.9	6.4	1.3	9.6	100.0
Mississippi	0.3	0.4	8.2	3.7	0.0	70.6	5.9	1.4	9.4	100.0
Arkansas	0.3	0.8	10.0	5.5	0.2	64.3	6.5	2.3	10.3	100.0
Louisiana	0.2	0.6	9.7	3.7	0.7	67.0	7.1	1.8	9.2	100.0
Oklahoma	0.3	0.5	10.6	4.6	0.4	64.2	7.8	1.7	10.0	100.0
Texas	0.3	0.6	11.5	4.7	0.4	62.0	7.3	1.9	11.3	100.0
Montana	0.7	0.4	9.4	3.7	0.1	72.4	3.2	1.5	8.5	100.0
Idaho	0.8	1.2	11.3	3.2	0.0	62.1	6.7	2.3	12.4	100.0
Wyoming	0.0	1.0	11.4	3.4	0.6	65.6	6.7	3.3	8.1	100.0
Colorado	0.1	0.5	15.6	4.7	0.2	59.0	7.5	1.7	10.8	100.0
New Mexico	0.1	0.3	9.5	4.6	0.1	66.8	7.8	1.6	9.1	100.0
Arizona	0.2	0.3	14.7	5.7	0.0	58.6	8.7	1.5	10.3	100.0
Utah	0.2	0.4	10.8	5.3	0.1	61.0	9.7	2.6	9.9	100.0
Nevada	0.0	0.3	11.4	2.5	0.1	54.6	22.2	1.5	7.5	100.0
Washington	0.6	0.5	13.3	5.4	0.0	58.2	7.7	2.0	12.3	100.0
Oregon	0.4	0.4	11.1	6.2	0.0	61.9	6.9	1.3	11.8	100.0
California	0.3	0.6	15.5	6.0	0.0	57.3	7.6	1.7	11.0	100.0
Average	**0.4**	**0.6**	**12.0**	**5.2**	**0.1**	**62.6**	**7.1**	**1.7**	**10.3**	**100.0**

Source: 1990 5% PUMS, U.S. Census Bureau.

TABLE 3: Distribution of Operator Occupations across Industrial Sectors by State, 1990

	Industry									
State	**Agri.**	**Construct.**	**Finance**	**Manufact.**	**Mining**	**Retail-Tr.**	**Service**	**Transport.**	**Wholesale**	**Total**
Maine	2.3	7.3	0.6	56.4	0.1	7.7	7.8	12.2	5.6	100.0
New Hampshire	0.4	7.3	0.3	63.1	0.0	5.1	7.5	11.3	5.0	100.0
Vermont	0.3	6.8	0.2	61.4	1.0	7.1	9.8	7.2	6.1	100.0
Massachusetts	0.7	4.3	0.4	55.2	0.1	7.2	10.1	16.0	5.9	100.0
Rhode ISland	0.2	3.7	0.7	64.8	0.0	7.4	9.2	9.5	4.6	100.0
Connecticut	0.5	5.0	0.7	59.0	0.2	6.7	10.7	11.2	5.8	100.0
New York	0.3	4.6	0.7	50.3	0.2	5.9	11.9	20.0	6.0	100.0
New Jersey	0.4	4.1	0.6	52.1	0.2	6.8	11.3	17.8	6.8	100.0
Pennsylvania	0.5	4.9	0.3	58.7	1.1	6.4	8.8	13.9	5.5	100.0
Ohio	0.5	3.2	0.4	62.5	0.9	5.2	9.9	12.9	4.6	100.0
Indiana	0.6	3.6	0.2	64.2	0.8	5.2	8.5	12.8	4.1	100.0
Illinois	0.8	3.4	0.4	56.0	0.8	5.8	10.0	17.1	5.8	100.0
Michigan	0.5	3.6	0.3	65.5	0.4	5.4	9.7	10.3	4.2	100.0
Wisconsin	0.7	4.4	0.3	63.3	0.3	5.1	7.8	13.5	4.5	100.0
Minnesota	1.1	5.1	0.5	53.5	0.4	7.3	11.8	15.8	4.5	100.0
Iowa	1.5	6.5	0.8	53.2	0.6	6.2	12.4	13.8	5.2	100.0
Missouri	1.3	4.2	0.1	54.7	0.5	6.2	9.4	18.2	5.3	100.0
North Dakota	9.3	10.8	0.6	20.1	4.9	10.6	10.4	26.6	6.6	100.0
South Dakota	3.3	6.4	0.4	45.9	1.0	7.5	10.8	18.3	6.4	100.0
Nebraska	2.4	6.0	0.4	44.8	0.8	7.8	10.9	19.7	7.0	100.0
Kansas	2.1	7.0	0.6	46.5	2.6	7.2	12.0	17.2	4.9	100.0
Delaware	1.5	5.5	0.2	50.4	0.0	11.4	6.8	15.4	8.8	100.0
Maryland & DC	0.6	8.0	0.7	40.9	0.8	8.3	15.1	19.9	5.7	100.0
Virginia	0.7	6.1	0.4	54.6	1.8	6.2	11.4	13.8	4.9	100.0
West Virginia	0.2	8.8	0.1	41.3	11.7	5.1	11.9	15.6	5.3	100.0
North Carolina	1.0	3.9	0.2	70.4	0.3	4.5	6.8	9.6	3.3	100.0
South Carolina	1.0	4.5	0.2	70.0	0.2	4.8	7.0	8.2	4.1	100.0
Georgia	1.0	4.9	0.2	60.0	0.4	6.4	8.4	13.9	4.9	100.0
Florida	1.5	7.2	0.6	40.3	0.5	10.0	15.0	18.2	6.7	100.0
Kentucky	0.4	4.9	0.2	56.8	4.7	5.5	9.4	14.1	4.0	100.0
Tennessee	0.5	4.4	0.1	66.4	0.5	4.3	7.2	13.0	3.7	100.0
Alabama	0.9	4.7	0.2	65.5	1.2	4.3	7.6	11.7	3.9	100.0
Mississippi	1.6	4.7	0.3	65.1	1.3	3.4	6.3	13.6	3.7	100.0
Arkansas	1.0	5.9	0.3	62.1	0.7	5.1	6.4	13.4	5.0	100.0
Louisiana	1.1	9.5	0.4	37.9	4.7	6.7	12.1	21.5	6.1	100.0
Oklahoma	1.1	7.4	0.4	45.2	4.4	6.7	12.4	17.5	4.8	100.0
Texas	1.1	7.4	0.3	43.8	2.9	7.8	12.6	17.6	6.4	100.0
Montana	3.4	12.8	0.1	24.5	6.1	9.7	12.2	26.8	4.4	100.0
Idaho	5.9	9.5	0.7	42.4	1.9	5.9	11.4	16.4	5.9	100.0
Wyoming	1.1	12.3	0.0	20.4	18.0	10.3	12.2	24.0	1.7	100.0
Colorado	1.2	7.6	0.3	43.4	2.0	8.3	14.3	16.6	6.2	100.0
New Mexico	2.2	11.1	0.2	33.2	4.3	10.6	13.7	17.5	7.2	100.0
Arizona	0.9	8.5	0.3	38.9	3.1	9.0	15.2	18.4	5.6	100.0
Utah	0.5	5.8	0.3	50.1	2.3	7.2	11.0	16.4	6.3	100.0
Nevada	0.1	8.0	0.3	23.6	6.9	11.1	22.0	22.2	5.9	100.0
Washington	1.7	6.3	0.3	48.8	0.3	7.5	10.8	18.1	6.2	100.0
Oregon	2.0	5.5	0.2	52.9	0.5	5.2	9.9	17.5	6.3	100.0
California	1.7	4.9	0.4	51.3	0.7	7.3	12.9	14.3	6.7	100.0
Average	**1.4**	**6.3**	**0.4**	**51.1**	**2.1**	**6.9**	**10.7**	**15.8**	**5.4**	**100.0**

Source: 1990 5% PUMS, U.S. Census Bureau.

TABLE 4: Distribution of Laborer Occupations across Industrial Sectors by State, 1990

	Industry									
State	**Agri.**	**Construct.**	**Finance**	**Manufact.**	**Mining**	**Retail-Tr.**	**Service**	**Transport.**	**Wholesale**	**Total**
Maine	26.3	13.0	0.4	25.8	0.1	19.7	6.3	3.8	4.6	100.0
New Hampshire	14.0	19.5	2.1	18.1	0.0	28.7	7.2	6.9	3.5	100.0
Vermont	29.9	15.6	5.1	13.7	0.0	19.4	9.9	3.3	3.1	100.0
Massachusetts	14.6	16.6	1.1	16.7	0.1	29.5	7.9	7.2	6.3	100.0
Rhode Island	21.3	12.6	1.6	20.4	0.4	22.6	10.6	4.1	6.3	100.0
Connecticut	18.9	16.8	1.3	12.0	0.4	30.6	9.5	5.1	5.4	100.0
New York	13.4	19.4	1.6	15.8	0.1	23.4	11.1	10.0	5.3	100.0
New Jersey	13.6	16.6	1.4	18.3	0.1	24.5	8.1	10.0	7.4	100.0
Pennsylvania	12.8	15.1	0.9	26.2	0.6	23.6	7.9	7.1	5.8	100.0
Ohio	13.9	13.3	1.2	24.4	0.3	25.5	9.8	5.5	6.1	100.0
Indiana	17.1	16.1	0.9	24.5	0.4	20.7	9.1	5.6	5.6	100.0
Illinois	16.2	13.5	1.3	20.8	0.6	22.8	9.8	8.6	6.6	100.0
Michigan	16.3	12.9	1.1	21.5	0.3	27.5	10.1	4.6	5.7	100.0
Wisconsin	23.3	10.8	1.0	27.1	0.0	19.8	8.3	4.5	5.1	100.0
Minnesota	24.7	10.6	1.0	19.3	0.2	22.5	9.0	5.9	6.8	100.0
Iowa	32.6	11.9	0.4	19.4	0.2	19.3	5.3	3.1	7.8	100.0
Missouri	21.6	15.7	0.9	18.6	0.3	21.8	9.4	6.7	5.1	100.0
North Dakota	45.9	12.3	0.2	7.9	2.3	15.9	5.6	6.5	3.4	100.0
South Dakota	42.2	9.5	0.5	8.8	1.1	20.0	7.2	5.1	5.7	100.0
Nebraska	34.4	12.1	1.5	14.9	0.4	16.5	6.5	7.5	6.1	100.0
Kansas	24.5	14.4	1.0	16.7	1.0	22.3	7.9	5.9	6.3	100.0
Delaware	18.7	13.1	0.3	34.0	0.0	15.6	9.2	2.7	6.5	100.0
Maryland & DC	17.8	22.7	1.1	9.4	0.0	23.2	10.1	9.0	6.7	100.0
Virginia	20.9	21.7	1.2	17.2	0.3	21.0	8.0	5.2	4.7	100.0
West Virginia	10.9	20.8	2.1	19.5	7.4	22.7	6.4	7.0	3.1	100.0
North Carolina	24.4	14.2	1.0	26.3	0.1	17.7	7.1	5.5	3.7	100.0
South Carolina	21.2	16.3	0.5	24.5	0.2	19.1	8.8	4.4	4.9	100.0
Georgia	21.0	17.8	0.8	21.0	0.2	18.0	8.0	7.1	6.2	100.0
Florida	31.8	16.7	1.0	8.0	0.1	20.9	10.7	6.0	4.7	100.0
Kentucky	24.9	15.7	1.0	21.0	1.6	19.0	6.5	6.0	4.2	100.0
Tennessee	17.7	15.5	1.0	25.0	0.5	19.9	7.7	8.0	4.9	100.0
Alabama	20.0	16.5	0.5	25.4	0.5	18.7	7.1	5.6	5.8	100.0
Mississippi	23.8	14.6	0.7	28.1	1.1	17.3	5.8	4.5	4.3	100.0
Arkansas	28.3	12.3	0.5	28.8	0.2	16.3	4.5	5.1	4.2	100.0
Louisiana	21.8	18.2	0.7	15.8	2.0	20.0	7.2	7.4	7.0	100.0
Oklahoma	26.9	15.3	1.0	14.6	0.9	23.9	8.0	5.2	4.3	100.0
Texas	27.8	17.4	1.1	11.8	0.8	20.3	8.7	6.3	5.9	100.0
Montana	38.2	12.4	1.1	18.5	0.7	11.1	6.2	6.7	5.1	100.0
Idaho	44.9	9.6	1.1	16.3	0.4	10.5	6.7	4.3	6.3	100.0
Wyoming	31.9	18.2	1.5	7.9	5.3	17.9	9.7	5.6	2.0	100.0
Colorado	25.1	15.6	1.3	10.2	0.5	22.2	12.1	7.1	6.0	100.0
New Mexico	26.1	19.8	0.6	9.0	1.3	19.9	10.8	7.0	5.5	100.0
Arizona	27.3	16.7	1.5	7.4	0.4	23.0	13.7	5.6	4.3	100.0
Utah	19.3	17.6	0.8	12.5	0.8	26.0	13.2	5.5	4.2	100.0
Nevada	18.2	21.9	3.4	6.3	1.4	21.7	17.3	5.8	4.0	100.0
Washington	33.2	13.0	1.0	15.3	0.1	18.9	6.9	5.2	6.3	100.0
Oregon	33.0	8.5	0.5	23.1	0.1	18.5	6.9	4.0	5.4	100.0
California	34.3	18.3	0.7	10.9	0.2	16.3	8.5	5.2	5.5	100.0
Average	**24.3**	**15.4**	**1.1**	**17.9**	**0.7**	**20.8**	**8.6**	**5.9**	**5.3**	**100.0**

Source: 1990 5% PUMS , U.S. Census Bureau.

TABLE 5: Multinomial Logit Model of Occupational Choice, Selected Variables (N=6359)

Choice of Occupation in 1998	Expanatory Variables (Characterisrics in 1993)	Parameter Estimates	Standard Error	t-Value
Professional_ Managerial	Prof_Mgr	1.905	0.088	21.7 ***
	Sales	1.261	0.127	9.9 ***
	Laborer	-0.296	0.189	-1.6
	Operator	-0.187	0.156	-1.2
	Educational Attainment	0.323	0.018	18 ***
	Age	-0.017	0.014	-1.2
	White	0.314	0.073	4.3 ***
	Male	0.106	0.071	1.5
	Move	-0.093	0.213	-0.4
	House Tenure	-0.011	0.007	-1.5
	Having a working spouse	0.311	0.080	3.9 ***
Sales	Prof_Mgr	0.604	0.217	2.8 ***
	Sales	2.619	0.171	15.3 ***
	Laborer	0.569	0.313	1.8 *
	Operator	-0.254	0.378	-0.7
	Educational Attainment	0.194	0.035	5.6 ***
	Age	-0.037	0.028	-1.3
	White	0.406	0.144	2.8 ***
	Male	-0.098	0.141	-0.7
	Move	-0.924	0.607	-1.5
	House Tenure	-0.004	0.014	-0.3
	Having a working spouse	0.255	0.159	1.6 *
Operator Occupations	Prof_Mgr	0.533	0.171	3.1 ***
	Sales	0.256	0.239	1.1
	Laborer	1.042	0.152	6.9 ***
	Operator	2.111	0.112	18.8 ***
	Educational Attainment	-0.205	0.025	-8.4 ***
	Age	-0.017	0.018	-1.0
	White	-0.160	0.100	-1.6
	Male	0.756	0.096	7.8 ***
	Move	0.157	0.302	0.5
	House Tenure	-0.003	0.009	-0.3
	Having a working spouse	-0.188	0.099	-1.9 *
Laborer Occupations	Prof_Mgr	-0.025	0.264	-0.1
	Sales	0.185	0.309	0.6
	Laborer	1.562	0.158	9.9 ***
	Operator	0.546	0.190	2.9 ***
	Educational Attainment	-0.193	0.032	-6.1 ***
	Age	0.017	0.024	0.7
	White	-0.042	0.136	-0.3
	Male	1.627	0.155	10.5 ***
	Move	-0.323	0.409	-0.8
	House Tenure	-0.001	0.012	-0.1
	Having a working spouse	-0.507	0.132	-3.8 ***

Log Likelihood value = -6264

Note: *** indicates significance at the one-percent level; ** indicates significance at the five-percent level; and * indicates significance at the ten percent level.

TABLE 6: Conditional Logit Model of State Destination Choice (N=6359)

Explanatory Variables	**Parameter Estimates**	**Non-Adjusted**		**Adjusted**	
		Standard Error	**t-Value**	**Standard Error**	**t-Value**
Age*Non_Origin	-0.061	0.021	-2.88 ***	0.021	-2.88 ***
White*Non_Origin	-0.047	0.096	-0.49	0.097	-0.48
House_Tenure*Non_Origin	-0.089	0.011	-8.21 ***	0.011	-8.25 ***
Male*Non_Origin	0.129	0.095	1.36	0.094	1.37
Spouse_Working*Non_Origin	-0.079	0.107	-0.74	0.107	-0.74
Family_Size*Non_Origin	-0.041	0.035	-1.17	0.035	-1.17
Freq_of_Previous Interstate Moves*Non_Origin	0.324	0.032	10.21 ***	0.032	10.22 ***
Education*Distance	1.726	1.072	1.61	1.071	1.61
Distance	-66.869	18.430	-3.63 ***	18.308	-3.65 ***
Dummy of Non_Origin	-3.112	0.759	-4.10 ***	0.759	-4.10 ***
Dummy of Adjacent	1.195	0.128	9.34 ***	0.128	9.35 ***
State's Employment Share	0.086	0.017	5.00 ***	0.017	5.00 ***
January Temperature	0.008	0.006	1.34	0.006	1.34
July Temperature	0.025	0.012	2.05 **	0.012	2.05 **
Humidity	0.022	0.005	4.30 ***	0.005	4.29 ***
Emp-Growth*Pk_Strong Association	0.456	0.089	5.14 ***	0.091	5.01 ***
Emp-Growth*Pk_Medium Association	0.029	0.060	0.49	0.060	0.49
Emp-Growth*Pk_Weak Association	-0.112	0.067	-1.66 *	0.067	-1.67 *

Note: *** indicates significance at the one-percent level; ** indicates significance at the five-percent level; and * indicates significance at the ten percent level.