The Review of Regional Studies, Vol. 33, No. 2, 2003, pp. 142 – 163

The Review of Regional Studies

Oklahoma State University

Occupation Choice, Information, and Migration*

Nancy E. White

Department of Economics, Bucknell University, 163 Coleman Hall
Lewisburg, PA 17837, e-mail: nwhite@bucknell.edu

Amy M. Wolaver

Department of Economics, Bucknell University, 161 Coleman Hall
Lewisburg, PA 17837, e-mail: awolaver@bucknell.edu

Abstract

We examine the relationship between occupational and geographical mobility using National Longitudinal Survey of Youth data. We develop a theoretical model that is a variation on the Jovanovic experience good model, which allows us to formalize the occupation choice decision. As individuals gain information on their own productivity, they may change occupations and locations. Occupation choice is introduced as an endogenous determinant of migration in recursive bivariate probit models for individuals who make good and bad matches in an occupation. We extend our analysis to feature an additional discussion of the migration-occupation choice relationship by race for both match types.

* The authors thank Bill Roark for his able research assistance. We are grateful to Dan Rickman and two anonymous referees for their comments and suggestions

1. INTRODUCTION

The role that information plays in migration decisions has been analyzed for decades and has been included in these models in many ways. Incomplete information is suggested as a determinant of return migration (DaVanzo and Morrison 1981; Allen 1979); exclusion from information (absence of social networks) has been linked to spatial mismatch, urban concentration of poverty, and inefficiencies in urban labor markets (O'Regan 1993; Stoll and Raphael 2000). In a study of U.S. internal migration, Gibbs (1994) found that information from origin labor markets, *ceteris paribus*, shortens destination search duration for most rural-to-urban migrants. Maier (1986) argues that information costs may cause education selectivity in migration decisions; that is, information costs should be lower for well-educated individuals who are likely to know better how to acquire and interpret information. Cooper (1994) studied the informational content of individuals' market wages relative to wages in alternative labor markets in the decision to migrate. In summary, migration specialists have carefully studied many aspects of information in location decisions; however, we know of no study that has formally linked information gathered by workers on their occupation-specific productivity to both the occupation change and migration decisions.

We study the relationship between occupation choice and migration by adapting the Jovanovic (1979) experience good model to the occupational decision, which we then link to the migration decision. Consistent with the original experience good model, workers have heterogeneous, initially unknown productivities at different occupation matches. As individuals work, they receive information, or signals, about their true productivity at that match. As signals are received, wages change to reflect the now-known match quality. If, for example, a worker receives a signal indicating a poor quality match, the worker exits that job and takes another until a better occupation match is found.[1] Therefore, as a worker gathers information about his or her productivity in an occupation, the relative trade-offs associated with job search in other occupations change, which may change the optimal location.

We use data from the National Longitudinal Survey of Youth (NLSY79) to analyze young adults who are in the labor force and who have experienced a change in employer between any pair of survey years from 1989/90 to 1994/96. We merged the Geocode files to the Work History files to create a panel data set for these individuals. The sample consists of individuals who have changed employers in order that we may focus our empirical analysis on the relationship between information gained on the job that leads to occupation change and migration. For each productivity (match quality) type of worker, occupation choice enters the migration decision in a bivariate probit model, where the dependent variables are migration and occupation change. The model is recursive in that occupation change is included as an independent variable in the migration equation.

---

[1] The original Jovanovic model is aspatial. The model provides an alternative explanation to on-the-job human capital accumulation for the rising wage-tenure profile observed in cross-sectional data. The longer a worker has been on the job, the more likely it is that the worker has received a signal about the match quality. Since workers with low match-specific productivity leave that job in search of better opportunities, only the high productivity workers remain; and as job tenure increases, the percentage of workers at that level of job tenure with high wages increases. The career patterns of workers proceed as follows: If the worker receives a poor match quality signal, the worker exits that match and takes another until a good match is found. Search costs are assumed to be lower than the expected gains to job mobility. For a full discussion of the model, see Jovanovic (1979).

The paper makes several contributions to the literature and follows in the tradition of linking individual characteristics such as ability with spatial search area (Sjaastad 1962). Firstly, the model demonstrates the importance of analyzing information from the individual's employment history (occupation choices) in the migration decision. We exploit the work history panel data to include information about workers' experience in previous occupations in the location decision. Because our theoretical model illustrates that the decisions of good and poor match quality workers within an occupation are likely to behave very differently in their migration and occupation choices, they are treated independently in the empirical analysis. Secondly, by adding a spatial dimension to a model that is well known in labor economics, we can jointly model the occupation and migration decisions in a utility maximization framework. Lastly, our analysis features a discussion of the relationship between occupation choice and migration by race and match quality.

The paper is arranged as follows. Section 2 is a brief review and a discussion of the general theoretical model. In Section 3, we discuss the empirical methods; and Section 4 is a discussion of the results of the estimations. Section 5 includes a conclusion and future considerations.

2. RELEVANT BACKGROUND LITERATURE AND THEORETICAL MODEL

Early studies typically held that employment opportunities were the primary determinants of migration; as early as 1938, Dorothy Swaine Thomas suggested further research into "the extent to which *change* of occupation is a concomitant of migration." Herzog and Schlottmann (1984) analyzed career change and spatial mobility and concluded that white male primary and repeat migrants experience greater career mobility than nonmigrants. Odland (1988) suggested that "occupation choices are influenced by the same conditions that affect migration: variations in labor market conditions over a set of regions, and the costs of migration between regions." Bartel's (1979) study of migration and job mobility focused on the impact of wages on the job change decision, where the relationship is conditional upon types of job separation. While Bartel finds that the probability of migrating is negatively related to wages for those who change jobs by quitting, she did not develop the theoretical framework for explaining this result, nor did she study the relationship for minorities. Following Bartel, the studies of Krieg (1997) and Krieg and Bohara (1999) modeled job change as endogenous to the migration decision, where wage earnings are found to influence both decisions.

The experience good model, first proposed by Jovanovic (1979), is the basis for our formal theoretical model of occupation switching and migration. As stated earlier, workers have different, initially unknown productivities at different occupation-job matches. Individuals must actually work for some period of time before the quality of the job match is known. Before the worker's quality in a match is known, workers receive a wage that is equal to the expected productivity of workers in the population at that job. As firms and individuals receive information on job match quality, wages adjust downward for a poor quality signal and upward for a good quality signal. In our model, information is received about a worker's match quality in a particular *occupation*. A worker who might be described as low productivity when compared to other occupations (e.g., a janitor) could have a good signal within that occupation, in which case the worker in our model is described as a high productivity worker. To minimize confusion in the exposition of this paper, high and low productivity workers within a particular occupation are described as being of good match quality and bad (poor) match quality, respectively.

We have made two crucial modifications to the original Jovanovic model. Firstly, we modify the experience good model to restrict the information workers gather on the job to occupation specific signals but to allow this information to transfer across firms within the same occupation. Secondly, we cast the decision to change occupation or location in a utility maximization framework, which allows us to specify more fully the spatial attributes of the model. For example, workers with a good match signal may leave an occupation in which they receive relatively high wages for a destination that offers more attractive geographical characteristics. Workers might also stay in a match after a bad signal if search costs are prohibitively high and the probability of finding a job in another occupation is low enough to mitigate any expected wage gains. We use the model described below to generate predictions about the relationship between occupation change and migration for high (good match) and low (bad match) productivity workers. While we do not explicitly include race in our theoretical model, we discuss some implications of the model based on known racial differences in search costs and housing and labor market segregation.

2.1 The Theoretical Model

Individuals are utility maximizers with a utility function of the form $U(C, L)$, where utility is a function of consumption goods (C) and location amenities (L). (We suppress subscripts on individuals for ease in exposition.) Workers are first randomly distributed in k finite locations where locations are sufficiently distant so as to represent spatially distinct features and separate labor markets. Utility maximization is subject to a budget constraint where lifetime consumption equals lifetime income.[2] There are j finite occupations in the economy: Workers have high or low productivity in each occupation, represented below by the $_H$ and $_L$ subscripts, respectively.[3] Occupations are experience goods; that is, workers initially have no information about their marginal productivity in each sector. Both firms and workers receive the match quality (productivity) signal after one period of work, and the information about the worker's occupation-specific productivity transfers across firms.[4] Before the worker's match quality is known, wages in each occupation equal expected productivity. This expectation is determined by the occupation- and location-specific distribution of worker types at time t, written as:

(1) $$\varpi_{j,k,t} = \beta_{j,k,t}\alpha_{Hj} + (1 - \beta_{j,k,t})\alpha_{Lj}$$

[2] Workers also risk neutral. We assume the following: all agents are workers, wages are not affected by hours worked, and are abstracting from the labor-leisure trade-off.

[3] The model could also be expanded to include industry- and firm-specific components of productivity. To simplify the analysis, we do not include these considerations. Workers could be low (or high) quality in all occupations. The assumption of a finite number of occupations in the aspatial model with nonbinding search costs would imply an eventual stopping point even after a low signal. Unlike the original Jovanovic (1979) model, the spatial model with possibly binding search costs allows search after a high signal or cessation of search after a low signal. Therefore, the additional assumption of a finite number of occupations does not affect our predictions.

where α_j = an individual's expected productivity (high or low) in occupation j such that $\alpha_{Hj} > \alpha_{Lj}$; $\beta_{j,\ k,\ t}$ = the fraction of the population that is a good match (high productivity) in occupation j, location k at time t; and $\varpi_{j,k,t}$ = the wage rate in occupation j, location k at time t.[5]

2.2 Occupation-Specific Information Process

Since the information on occupation-specific match quality transfers across firms, the wage for a worker who receives a high (good match) or low (poor match) productivity signal also transfers. For example, if a good match worker switches firms but remains in occupation j, irrespective of location, his/her wages will remain α_{Hj}. Workers can be high or low productivity in multiple sectors and in any given location, but if they have not worked in the occupation, their wages will equal the expected productivity in the occupation for the first period.[6] Thus, a signal changes the expected earnings in the current occupation relative to other occupations, and utility maximizers may change occupations and/or locations in response to this information.

2.3 Job Search

Job search may involve pecuniary costs associated with occupation search (e.g., costs associated with hiring an employment agency), costs associated with spatial search (e.g., travel costs), and psychic costs (e.g., leaving close friends or family members).[7] Search within a sector and across locations consumes some fraction, $(1 - \phi_{j,\ k,\ t})$, of the work period. Expected earnings are then $\phi_{j,k,t}\varpi_{j,k,t}$. This fraction, $\phi_{j,k,t}$, is determined by the job arrival rates in the sector, which in turn are dependent upon the distribution of sector-specific jobs across locations, the net growth rate of jobs in that sector in all destinations, information about the distribution of jobs, and worker characteristics.[8] We assume that search costs in alternative locations ($SC_{\sim k}$) and occupations ($SC_{\sim j}$), are higher than search costs in the same location and occupation.[9]

---

[4] The sector labor markets are competitive, and all firms in any given location know the total distribution of high and low productivity type workers in a sector so they can set initial wages accordingly. These two assumptions yield wages that equal the expected productivity of workers, given the information about the worker/occupation match.

[5] These assumptions are not central to the analysis and are made to simplify the decision rules for workers and firms in the presence of uncertainty about match productivity. An alternative specification is to model distributions of productivities across sectors. Since workers are risk neutral the location and occupation choice decisions would be based on the mean expected wages in either set-up. Risk aversion would make the variance of location- and occupation-specific wages model matter. The central findings, *ceteris paribus*, would remain unchanged, and so we make the simplifying assumption of risk neutrality.

[6] At the end of the first work period, all firms across all locations know a worker's productivity, high or low, in that occupation. The information gathering process is modeled more specifically in Jovanovic (1979); as tenure increases, the probability that the worker knows her true productivity increases and more low quality workers will leave that job. However, empirical results in Farber (1994) show that the hazard rates of job termination increase with tenure for the first three months of a job and thereafter decrease, suggesting that match quality information is gathered quickly after the beginning of the job. So we condense the information gathering process to one period.

[7] Workers cannot search while on the job and can search in only one sector and one location in time period t. See Herzog and Schlottmann (1981) for analysis of psychic costs of labor force migration in the U.S. Job search also involves time costs (loss of earnings while searching). Initially, when workers have no previous occupation experience, the search costs do not vary by occupation sector but differ by location.

[8] A job change is defined as any separation from a firm, regardless of whether the worker remains in the same occupation. Every job change entails location and occupation search costs.

[9] For analytical simplicity, we have normalized to zero the search costs and to one the job arrival rates in the same location and occupation.

2.4 General Model Solutions

To form predictions about the relationship between migration and occupation change, we must first detail the process of wage determination in our utility maximization model. Workers begin the second period with more information than they possessed in the first, namely, they now know their match quality in one occupation. High productivity workers' wages are α_{Hj} at any match in the same occupation, regardless of location or firm. In a purely labor market driven model, the high productivity worker remains in the same match because the highest possible wage in any sector is α_{Hj} and search is costly; that is, any job change would decrease utility. Labor market factors alone may suggest lower mobility for higher productivity workers; however, this outcome may be at odds with many studies of migration. There are three reasons that high productivity workers may be more mobile than low productivity workers. As Long (1973) and Ellis, Barff, and Renard (1993) have determined, lower levels of education or skills may spatially constrain mobility. Secondly, the studies of Graves (1979), Gyourko and Tracy (1989), and Graves and Linneman (1979) have established a causal relationship between household location decisions and natural amenity and public sector variables. If site-specific amenities are normal goods, as in Graves and Linneman (1979), it may be that high productivity workers, *ceteris paribus*, are more mobile than low productivity workers. Also, high productivity workers are likely to be better able to bear the higher search costs associated with migration. All of these factors suggest that high productivity individuals may be more geographically mobile than low productivity workers.

The second (and subsequent) period comparative statics derived from our theoretical model are presented in Tables 1 and 2.[10] The utility function allows for four possible occupation change/ migration outcomes: a worker may (1) switch occupations within the same location, (2) switch locations to remain in the same occupation, (3) switch both occupation and location, and (4) switch neither.

As our theory suggests, the expected utility associated with occupation and location changes differ between workers who have received good match and bad match signals. For example, utility maximizing good match workers may optimally switch occupations and locations if the job arrival rate in another occupation relative to the initial occupation is high enough to offset the wage reduction and search costs associated with the switch. In addition, if location attributes are normal goods, good match workers are more likely to migrate with or without an occupation change. Bad match workers experience wage losses if they remain in the same occupation. These wage losses are likely to inhibit their ability to overcome search costs, but they will have wage earnings incentives to search for a job in another occupation. The increase in search costs by adding a location search cost, $SC_{\sim k}$, to the occupation search costs, $SC_{\sim j}$, may be prohibitive to the bad match worker, which would indicate a negative relationship between occupation switching and migration. However, if job arrival rates in alternative occupations were better in other locations relative to the origin, we would expect a positive relationship between occupation change and migration. *A priori*, we do not have strong predictions about the sign of the

[10] Workers select their initial job sector given the expected wages in each occupation, amenities, and search costs. The expected utility from subsequent possible job and location changes after the worker's occupation-specific productivity becomes known. The reader may contact the authors for the theoretical model of initial sector choice.

TABLE 1

Second Period Expected Wage and Change in Utility for High Productivity Workers
for Each Possible Observed Migration/Occupation Change Decision
(Relative to No Migration, No Occupation Switch)
and Percent of Sample that Falls in each Cell

	Occupation Switch		No Occupation Switch	
	Expected Earnings	Observed Change in Utility	Expected Earnings	Observed Change in Utility
No Migration	$\phi_{\sim j,\mathrm{k}}\ \varpi_{\sim j,k} - SC_{\sim j}$	$\delta U(\cdot)/\delta C < 0$ $\delta U(\cdot)/\delta L = 0$	α_H	$\delta U(\cdot)/\delta C = 0$ $\delta U(\cdot)/\delta L = 0$
	Theoretically, no workers should fall in this cell			
% of workers	45.32		41.38	
Migration	$\phi_{\sim j,\sim k}\ \varpi_{\sim j,\sim k} - (SC_{\sim j} + SC_{\sim k})$	$\delta U(\cdot)/\delta C < 0$ $\delta U(\cdot)/\delta L > 0$	$\phi_{j,\sim k}\alpha_H - SC_{\sim k}$	$\delta U(\cdot)/\delta C < 0$ $\delta U(\cdot)/\delta L > 0$
% of workers	7.81		5.49	

Where *k* denotes the current location, ~*k* denotes an alternative location, *j* the current occupation, and ~*j* denotes the other occupation.

TABLE 2

Second Period Expected Wage After Low Productivity Signal For
Each Possible Observed Migration/Occupation Switching Decision
and Percent of Sample that Falls in each Cell

	Occupation Switch		No Occupation Switch	
	Expected Earnings	Observed Change in Utility	Expected Earnings	Observed Change in Utility
No Migration	$\phi_{\sim j,k}\ \varpi_{\sim j,k} - SC_{\sim j}$	$\delta U(\cdot)/\delta C > 0$ $\delta U(\cdot)/\delta L = 0$	α_L	$\delta U(\cdot)/\delta C = 0$ $\delta U(\cdot)/\delta L = 0$
% of workers	53.20		35.70	
Migration	$\phi_{\sim j,\sim k}\ \varpi_{\sim j,\sim k} - (SC_{\sim j} + SC_{\sim k})$	$\delta U(\cdot)/\delta C > 0$ or $\delta U(\cdot)/\delta L > 0$, or both;	$\phi_{j,\sim k}\alpha_L - SC_{\sim k}$	$\delta U(\cdot)/\delta C < 0$ $\delta U(\cdot)/\delta L > 0$
% of workers	6.13		4.97	

Source: Theoretical model and authors' calculations from NLSY 1990-96 white and African American job changers who reside in MSAs

endogenous variable occupation change in the empirical estimation for workers in either type of match.

Our theoretical model does not differentiate the occupation and migration decisions by race. However, there are a number of reasons that racial differences may foster different decision frameworks. Black workers may face different search costs because of occupational and housing segregation and different job arrival rates and wages because of labor market discrimination. Blacks may differ in observable characteristics such as higher propensities toward "linked" migration (Lee and Roseman 1997), stronger kinship ties (Johnson and Roseman 1990), and poorer quality of spatial job search attributed to racial residential segregation and social networks (Stoll and Raphael 2000). Evidence presented in Lee and Roseman (1999) indicates that blacks are more responsive to employment opportunities than whites in their location decisions, so it is useful to examine the decisions separately for both races.

3. EMPIRICAL METHODS AND DATA DESCRIPTION

3.1 Empirical Methods

Our theoretical model suggests that occupation and migration decisions are jointly made. Since the impetus for a change in jobs includes the new information about occupation match quality, occupation change may affect directly the migration decision. Therefore, the appropriate empirical method is a recursive bivariate probit specification. Theory suggests that low productivity workers in an occupation should be responsive to information about occupation match quality and seek a better match in an alternative occupation, which may involve migration. Conversely, high productivity workers are more likely to move to improve utility from the features of location. We expect that the endogenous occupation change information variable in the migration equation will be significant for low productivity workers, and the site characteristics will be important migration determinants for high productivity workers. Of additional interest is the covariance of the errors in the separate occupation and migration choice equations, rho (ρ), which is allowed to be non-zero. Rho measures the relationship between the unobservable factors in both decisions, after occupation choice is taken into account. A negative ρ, for example, implies that the unobservable factors that make one more likely to switch occupations make one less likely to migrate or vice versa.

From Greene (2000) and our theoretical model,

$$(2) \qquad y_1^* = \beta_1' x_1 + \varepsilon_1,\ y_1 = 1 \text{ if } y_1^* > 0, 0 \text{ otherwise}$$

$$(3) \qquad y_2^* = \beta_2' x_2 + \gamma_2 y_1 + \varepsilon_2,\ y_2 = 1 \text{ if } y_2^* > 0, 0 \text{ otherwise}$$

$$E[\varepsilon_1] = E[\varepsilon_2] = 0,\ \text{Var}[\varepsilon_1] = \text{Var}[\varepsilon_2] = 1,\ \text{Cov}[\varepsilon_1, \varepsilon_2] = \rho$$

where y_1 and y_2 are the occupation change and migration decisions; x_1 is a vector of personal, location, and labor market characteristics that affect occupation choice; and x_2 is a vector of personal, location, and labor market characteristics that affect migration. This specification is a multiple equation representation for two dichotomous variables with an endogenous variable in the migration equation, which is a recursive simultaneous equations model. According to Greene, the estimates are consistent under maximum likelihood estimation despite the endogeneity of the occupation choice variable.[11]

3.2 Data

The data on individuals are from the 1979 National Longitudinal Study of Youth (NLSY79). We merged the Geocode files to the main files and the Work History files to create a panel data

[11] See Greene (2000, pp. 852-854) for a full discussion of the differences between this model and ordinary least squares.

set for those workers who changed employers between any pair of survey years from 1989/1990 to 1994/1996. These years are chosen for several reasons. First, most of individuals have completed their education since they are aged 25 to 32 at the beginning of our sample period. Second, we are interested in the outcomes of workers who have some occupation match information. Third, much of the research on labor market outcomes using these data has been conducted on the first 11 years of the panel and focuses on white males. We examine whether the hypotheses from previous research hold for other groups of workers with weaker ties to the labor market. We only include job changers for several reasons. First, workers who do not change jobs but are transferred to a different location within the firm are likely to be constrained in their choice of potential locations. Our model is based on the assumption that individuals make choices constrained by job arrival rates and search costs. Second, the model does not allow us to consider promotions and demotions within a firm as a worker and/or firm responds to match information.[12] Therefore, the sample of workers that is consistent with our theoretical model includes only those individuals who have changed firms. We include only workers who lived in an MSA in both years of the employment change. This is for two reasons: (1) the location change variable is based on a change in labor markets and rural individuals are more difficult to place within a specific job market, and (2) location data are more consistently available across MSAs. Therefore, we chose to analyze workers who have left an employer in order to examine better the joint occupational mobility and inter-MSA migration decision.

We define employer change as the change in the CPS (current or most recent) employer in the survey. The NLSY data contain job characteristics for the CPS job and up to four additional jobs during a survey time period. The respondent must have worked at least 10 hours per week at these additional jobs for the interviewer to collect job characteristic information for at least nine weeks. This omission is likely to affect only the definition of the occupational tenure variable since no occupation or other data are known for those previous jobs. Because short-tenured jobs are likely to be poor occupation matches, the noise created by this omission is minimized.

Since the constraints on choices for workers who have received a high productivity signal in the occupation are different than the constraints for workers with poor match quality signals, it is important to disaggregate these two groups of workers. Good and bad occupation matches are identified by either a positive or negative occupation-specific wage premium. The occupation premium variable is defined as the percentage difference between the real wage earned by the individual and the occupation average wage, similar to the procedure used in Fallick (1993). The occupation average wage is adjusted for age, age squared, education, and gender by regressing real (in 1996 dollars, based on CPI-U) hourly wages on age, age squared, education, and gender separately by occupation and year using Current Population Annual Demographic Survey data from 1989 to 1996. Age, after controlling for education, is a proxy for experience since the CPS does not have actual experience. The sample average value in Table 3 for this variable is positive but is sensitive to the inclusion of outliers.[13] The occupation premium is not adjusted

[12] There may be transfers within companies as workers are promoted up the job ladder, but these types of occupational switches are not those described in the model. See Sicherman and Galor (1990) for an example of an occupational ladder model.

[13] When workers with occupation premiums of over 2,500 percent are excluded (five outliers), the mean becomes negative, -6.74 percent. The negative value is not surprising, given that the sample includes only those workers who

for race and location, which is the subject of future research.[14] The coefficients from these regressions (available from the authors upon request) are then used to predict the wage an individual should be earning based on personal and productivity characteristics, which is the adjusted occupation wage. We ran separate estimates for the full good and poor match quality workers (not shown) and for samples disaggregated by match quality and race.

A comprehensive selection of personal, productivity, and location variables is described in Table 3. We define migration (*migrate*) as a change of MSA. Individuals who changed counties within the MSA are not counted as migrants in order to capture the idea of separate labor and housing markets. Our sample consists of 237 separate origin locations and 245 separate destinations. A change in occupation (*ocmove*) is defined as a change at the two-digit level, which includes nine occupations.[15] Migration is defined as an annual change (or survey date to survey date) of location as defined above. For example, if a worker changed locations or changed jobs two or more times within a given year, we only count one of these changes. Some of the migration is repeat or return migration, but we do not exploit this additional information in our paper.

The occupation and location at each survey date are the values used to define occupation and location changes. We exclude the military sample from the analysis, regardless of the respondents' current industry. We exclude 1,519 individuals who had never changed employers. Workers with missing job information result in a reduction of 1,805 job changes. We exclude 1,604 employer changes from the construction and agriculture industries since these industries are characterized by temporary/seasonal work. We also drop 287 employer changes where the previous employer was the military since location changes made by military personnel are typically exogenous to the individual. Individuals who were never in an MSA (1,805) and Hispanics (1,115) are also omitted from the analysis. Hispanics are excluded from the sample because we chose to focus only on black and white racial differences in this paper. Finally, we eliminate 600 employer changes because of missing information about the location and 2,091 job changes that occurred or resulted in a move outside an MSA. Our final sample includes 4,468 employer changes, where some are multiple changes for the same individuals. Standard errors in the regressions are adjusted accordingly.

---

have changed employers. In the pure experience good model, voluntary job changes occur only after bad matches are discovered and wages have fallen to reflect this productivity information.

[14] Raphael and Riker (1999) offer a spatial argument for the differences in the occupation premium (discount) by race, which will likely be the subject of our subsequent work; that is, if blacks are relatively immobile and reside in locations with low employment growth, employers will infer this mobility difference and pay below average wages. We plan to decompose the occupation premium into parts based on observable characteristics, parts affected by occupation change and migration decisions, and parts based on labor market discrimination. If discrimination of this type affects wages, the decision not to adjust for race and location will result in the misclassification of workers as high or low productivity in the occupation; blacks will be more likely misclassified as low productivity workers and whites as high productivity workers. This misclassification will make it less likely that we will find any significant differences by race and productivity type in our results. Any differences we do find will be biased downwards in magnitude. The authors thank an anonymous reviewer for pointing out this difference.

[15] We define occupations at the two-digit level because previous studies have found considerable measurement error in occupations and industry codes in the Current Population Surveys at the three-digit level, but fewer errors exist at the two-digit and higher levels. See Mellow and Sider (1983) for a full discussion of this issue.

TABLE 3

Selected Variable Names and Definitions

Variable	Definitions [Sample means and standard deviations in brackets]
migrate	Respondent changes county and changes MSA =1, 0 otherwise [0.12, 0.32]
ocmove	Respondent changes occupation at the 2-digit level =1, [0.57, 0.49]
age	Respondent's age in years at time of job change [30.82, 2.82]
exper	Full time equivalent wks of experience (Total hrs/40 hrs) [460.24, 206.86]
educ	Years of education [13.33, 2.33]
faminc	Family income from all sources in survey year ($1000s) [33.39, 29.66]
female	= 1 if individual is female, 0 otherwise [0.52, 0.50]
married	= 1 if individual is married, 0 otherwise [0.43, 0.50]
numkid	The number of children in the household [0.98, 1.19]
femkid	An interaction term with presence of children and female [0.33, 0.47]
black	= 1 if individual is black, 0 otherwise [0.43, 0.50]
otenure	Weeks job tenure at initial employer [98.11, 125.27]
amtui	If received unemployment benefits, the money amount [149.85, 695.10]
homeown	= 1 if individual owns own home, 0 otherwise [0.31, 0.42]
dense	Difference in County population density 1990 [43.68, 3170.06]
crime	Difference in County crime rate in 1991 per 100,000 pop. [-9.71, 1363.56]
perc_black	Percentage of 1990 county population that is black [-.0015, 0.07]
uerate	Difference in Unemployment rate of county in 1990 [-.029, 8.99]
o_octn	Weeks of occupation tenure at initial occupation [169.36, 137.68]
emp_grow1	Difference in employment growth by occupation by MSA, 1990-1998: Avg. of other occupations - initial occ, origin location [-9.49, 83.97]
emp_grow2	Avg. other occs, other MSAs - initial occ, origin location [-24.51, 151.99]
emp_grow3	Avg. other occs, other MSAs - initial occ in destination [-24.76, 151.02]
emp_grow4	Avg. initial occ, other MSAs - initial occ, origin location [-33.22, 144.33]
loc_tenure	Years of location tenure (since 1979) in origin location [6.91, 4.55]
med_house	Difference in county median housing values [-942.44, 28596.52]
med_house2	Difference in change in county median housing value 1980-90 [-.61, 23.84]
pctax	Difference in Per capita county taxes in 1991 [-1.35, 237.21]
pwelf	Difference in Percent of county expenditures on welfare in 1991 [.0038,1.53]
ppolice	Difference in Percent of county expenditures on police in 1991 [-.021, 1.72]
peduc	Difference in Percent of county expend. on education in 1991 [-.032, 3.43]
tempvar	Difference in temperature (July maximum - January minimum) [.14, 5.15]
cdd	Difference in county Cooling degree days [4.96, 402.95]
hdd	Difference in county Heating degree days [2.89, 794.30]
precip	Difference in county Precipitation [.06, 4.99]
ocprem	% real wages above/below occupation average at initial job [6.63, 454.86]
oprof[a]	=1 if professional in initial occupation [.16, .37]
omngr	=1 if executive or related occupations at initial job [.11, .31]
osales	=1 if sales occupations at initial job [.06, .24]
oclrcl	=1 if clerical occupations at initial job [.20, .40]
ocraft	=1 if precision production occupations at initial job [.08, .27]
ooper	=1 if operative, except-transport occupations at initial job [.08, .27]
olabor	=1 if professional, technical & kindred occupation at initial job [.06, .23]
oserv	=1 if in service occupations at initial [.22, .42]
involex	= 1 if displaced from a previous job by plant closing or layoff [0.13,0.34]

Source: Authors' calculations from NLSY 1990-96 white and African American job changer sample, only those in MSAs. a. Omitted category = transportation occupation. Most site characteristics are *differences* between destination & origin location. $N = 4{,}468$

Data from the NLS Work History file are used to define the occupation tenure and work experience variables. For every week in the survey data, a job status variable is created that indicates either the worker's nonwork status (unemployed, out of labor force, etc.) or a job number. The job number is used to link information on usual hours worked and on occupation. We aggregate the data to the monthly level and define work experience (*exper*) as the usual hours worked multiplied by the number of weeks in the month divided by 40 hours per week, to identify full-time equivalent workweeks. Occupation tenure is similarly defined.

The county-level climate, housing, and government finance data are from the 1994 City and County Data Book, with one notable exception: If the public sector variables were not available at the county level, we substituted city-level data from the 1992 Census of Governments. We constructed these variables from MSA-specific data weighted by population average in the sub-cities. If climate data for a county were not available, the state average was used.[16]

The occupation employment-level data by MSA are from two sources: Equal Employment Opportunity data (U.S. Department of Commerce, U.S. Census Bureau, 1990 Census of Population and Housing) and Occupation Employment Statistics (OES) (Bureau of Labor Statistics, description and data downloads available at: http://stats.bls.gov/oeshome.htm) data from 1998. A variable for local occupational employment growth was then constructed.[17] From these employment levels, annual occupational employment growth is computed and linked to the individual's initial occupation and origin location; the first occupation is used for occupation *j*, and an average of all other occupations is used for occupation *~j*. The variables *emp_grow1-4* represent the relevant differences in the job arrival rates between relevant cells in Tables 1 and 2 for the occupation change and migration decisions.

Information about occupation match quality is proxied in the model by two variables: occupation tenure in the occupation of the initial job (*o_octn*) and the occupation premium variable (*ocprem). A priori*, we expect these variables to be negatively related to an occupation change and, through the endogenous variable *ocmove,* indirect determinants of migration. In addition to information about match quality, the occupation tenure variable may also capture variation in search costs by sector; that is, with more experience in an occupation, there is likely better search strategy and improved networking information. Although workers are divided by

---

[16] All site data were linked to MSAs or to counties using a crosswalk from the Law Enforcement Agencies Identifiers Crosswalk 1996 (ICPSR study 2876, compiled by the United States Department of Justice, Bureau of Justice Statistics).

[17] We linked the two occupation codes (the OES and the Census) using a crosswalk from the National Crosswalk Service Center (available at: http://www.state.ia.us/ncdc/), aggregating up to the two-digit Census occupation level. The merge between the OES occupation codes and the Census codes was not perfect; for example, many OES occupations matched with several Census three-digit occupations. In these cases, weights to distribute the employment levels in the OES occupation to the multiple Census occupations were constructed by the frequency with which the Census occupation was linked to the OES occupation. (It is possible for the same Census occupation to appear more than once within the OES occupation because the link is made through the Standard Occupational Classification System. Both the Census and OES codes are based on the SOC structure, but several SOC occupations may be grouped together in one Census or OES occupation.) This method will undoubtedly introduce some error into the calculations, which is mitigated by the subsequent aggregation of the data to the two-digit Census level. An alternative method would be to use employment-level weights, constructed from the Current Population Survey or some other source, to distribute the MSA-occupation employment level among the Census occupations. However, some Census occupations were linked to multiple OES occupations, which would systematically over-weight these occupations, causing a biased error in the measurement of this variable; our method, instead, produces random errors in measurement.

match quality on the basis of the occupation premium variable, there may be a continuum of match qualities in the data; that is, some of the bad occupation-worker matches are likely to be worse than others, and some of the good occupation-worker matches are likely to be better than others. However, higher values for the occupation premium variable (*ocprem*) should be negatively associated with occupation changes.

Since the data include a recession year, we have also included indicator variables for these years and for involuntary job loss (*involex*) in the regressions as controls.

4. EMPIRICAL RESULTS

4.1 Sample Statistics

The descriptive statistics for the sample are presented in Table 3. Some of the sample properties merit brief mention. Recall that the sample consists of a panel data set of white and black workers who changed employers between any pair of survey years from 1989/1990 to 1994/1996. Occupation switchers are 57 percent of the sample; inter-MSA migrants comprise 12 percent of the sample. The average age is 31 years; 43 percent are married and 52 percent are female. The average number of children is approximately 1. Roughly 43 percent of the sample is black.[18] The average education attainment is 13 years.

4.2 Empirical Results for the Occupation Switching Equation

The empirical results from the recursive bivariate probit analysis are shown in Tables 4 through 7. The columns on the left demonstrate the coefficient estimates and standard errors from the occupation switching decision, and the columns on the right show the values for the migration equation. We only will discuss the determinants of occupation switching that are proxies for match quality, although other regressors are included in the model.

Information about match quality is proxied by occupation tenure in the initial job match (*o_octn*) and occupation premium (*ocprem).* For all the samples, occupation tenure performs as expected in the occupation switching equation; this variable is always statistically significant at the 5 percent level and the sign is negative. This measure of match quality, although indirect, is less subject to measurement error than the occupation premium variable as described below. The coefficient on the occupation premium variable is negative, as expected, in all of the bad match samples and the good match white sample, but is positive for the black good match sample, although it is not statistically significant for whites. The counterintuitive positive results may be due to several factors. First, as discussed in footnote 14, we did not adjust for race or location. If there is wage discrimination, the variable is a noisy measure of match productivity. Second, the theoretical model ignores the possibility of progression up an occupation ladder; it may be that the very best workers from the good match black sample are finding jobs in more desirable occupations. Finally, this variable may be capturing firm- and industry-specific match quality. In this case, workers with low or negative occupation premia may be in a poor firm or industry match but in a good occupation match and are more likely remain in the same occupation.

---

[18] Recall that the NLSY oversamples blacks and that we have dropped Hispanics from the sample.

TABLE 4

White, Good Match Sample Estimates, Occupational Mobility & Migration Results

Occupation Switch				Migration			
Variable	Coefficient	Std. Error		Variable	Coefficient	Std. Error	
				ocmove	-0.0463	0.2702	
age	-0.0036	0.0249		*age*	-0.0523	0.0334	***
married	0.0649	0.1254		*married*	0.0684	0.1692	
female	0.1566	0.1459		*female*	0.0829	0.1797	
marrfem	0.0381	0.2136		*marrfem*	-0.4922	0.2700	**
femkid	0.1814	0.1756		*femkid*	-0.4142	0.2643	***
numkid	-0.0745	0.0655		*numkid*	0.1205	0.0730	**
faminc	0.0007	0.0017		*faminc*	0.0014	0.0019	
educ	0.0243	0.0249		*educ*	0.0755	0.0277	*
exper	0.1230	0.0978		*exper*	-0.0439	0.1269	
exper2	-0.0004	0.0082		*exper2*	0.0101	0.0103	
otenure	0.0013	0.0004	*	*amtui*	-0.0004	0.0002	*
amtui	0.00003	0.0001		*med_house*	-0.0087	0.0048	**
involex	0.0097	0.1314		*med_house2*	0.0001	0.00004	*
o_octn	-0.0044	0.0004	*	*emp_grw1*	0.0000	0.0012	
emp_grow1	0.0002	0.0024		*emp_grw2*	0.0003	0.0015	
emp_grow2	-0.0006	0.0007		*emp_grw4*	-0.0003	0.0010	
emp_grow3	-0.0010	0.0026		*pctax*	-0.0019	0.0010	**
ocprem	-0.0002	0.0001		*pwelf*	0.3522	0.1860	**
oprof	-0.6953	0.2758	*	*ppolice*	-0.0410	0.0598	
omngr	-0.2175	0.2710		*peduc*	0.1159	0.0468	*
osales	-0.1781	0.2720		*tempvar*	0.0116	0.0321	
oclrcl	-0.1794	0.2695		*cdd*	-0.0006	0.0005	
ocraft	-0.4871	0.2978	***	*hdd*	-0.0004	0.0004	
ooper	0.2638	0.3264		*precip*	0.0073	0.0178	
olabor	1.0758	0.3881	*	*loc_tenure*	-0.0853	0.0154	*
oserv	-0.1746	0.2661		*otenure*	-0.0001	0.0004	
fulltime	-0.1265	0.1353		*dense*	-0.0181	0.0709	
constant	0.0200	0.8210		*dense2*	-0.0047	0.0025	**
				crime	0.0002	0.0001	**
				perc_black	-3.4591	2.0678	**
				perc_hisp	-2.7368	2.6245	
				uerate	0.0204	0.0076	*
ρ	-0.1529	0.1780		*homeown*	-0.6797	0.1548	*
χ^2 (1) = .715		*Pr* > χ^2 = .398		*constant*	-0.0005	1.0259	
N	894			Log likelihood	-705.12		

Source: Authors' calculations from 1990-1996 NLSY sample of white and African American job changers. Most site characteristics are in differences between destination and origin location. Statistically significant at the * 5%, **10%, and ***15% levels; standard errors adjusted for multiple observations per individual.
Indicator variables for year are included in regressions, but omitted from tables.

4.3 Migration Results

Our theoretical model suggests the factors that may influence the occupation decision; these variables indirectly affect the propensity to migrate through the occupation decision. The worker's occupation decision yields the best information about what the worker knows about her match quality. From the aspatial experience good model, if the worker remains in the same

TABLE 5

White, Bad Match Sample Estimates, Occupational Mobility and Migration Results

Occupation Switch				Migration			
Variable	Coefficient	Std. Error		Variable	Coefficient	Std. Error	
				ocmove	-1.1747	0.5478	*
age	-0.0089	0.0177		*age*	0.0095	0.0277	
Married	0.0242	0.0872		*married*	0.0519	0.1204	
female	-0.1324	0.1189		*female*	-0.0264	0.1828	
Marrfem	0.1154	0.1546		*marrfem*	-0.1070	0.2207	
Femkid	0.1362	0.1454		*femkid*	-0.0566	0.1951	
Numkid	0.0440	0.0490		*numkid*	0.0734	0.0602	
faminc	-0.0002	0.0016		*faminc*	-0.0010	0.0022	
educ	-0.0166	0.0181		*educ*	0.0294	0.0271	
exper	0.1231	0.0701	**	*exper*	-0.0505	0.0937	
exper2	-0.0046	0.0061		*exper2*	0.0024	0.0089	
otenure	0.0015	0.0004	*	*amtui*	0.0001	0.0001	
amtui	-0.00001	0.0001		*med_house*	-0.0059	0.0064	
involex	0.2289	0.1238	**	*med_house2*	0.0010	0.0003	*
o_octn	-0.0036	0.0004	*	*emp_grw1*	0.0002	0.0007	
emp_grow1	0.0013	0.0009		*emp_grw2*	0.0001	0.0004	
emp_grow2	0.0003	0.0004		*emp_grw4*	-0.0004	0.0003	
emp_grow3	-0.0016	0.0007	*	*pctax*	-0.0029	0.0020	***
Ocprem	-0.0026	0.0021		*pwelf*	0.2524	0.1934	
oprof	-0.6735	0.1920	*	*ppolice*	0.1280	0.0819	***
omngr	-0.2131	0.2016		*peduc*	0.0041	0.0319	
osales	-0.1071	0.1946		*tempvar*	-0.0179	0.0155	
oclrcl	-0.4229	0.1982	*	*cdd*	0.0006	0.0003	*
ocraft	-0.3549	0.2151	**	*hdd*	0.0005	0.0002	*
ooper	-0.0632	0.2265		*precip*	-0.0006	0.0143	
olabor	0.0323	0.2532		*loc_tenure*	-0.0508	0.0146	*
oserv	-0.4306	0.1925	*	*otenure*	0.0005	0.0004	
fulltime	-0.0620	0.0920	*	*dense*	-0.0341	0.0888	
constant	1.0661	0.5555	**	*dense2*	0.0123	0.0067	**
				crime	-0.000001	0.0001	
				perc_black	0.3110	1.8437	
				perc_hisp	-1.8984	1.8447	
				uerate	0.0123	0.0096	
ρ	0.6758	0.3078	***	*homeown*	-0.5768	0.1734	*
χ^2 (1) = 2.10	$Pr > \chi^2 = .147$			*constant*	-0.7465	1.2169	
N	1478			Log likelihood	-1130.97		

Source: Authors' calculations from 1990-1996 NLSY sample of job changers. Statistically significant at the * 5%, **10%, and ***15% levels; standard errors adjusted for multiple observations per individual. Most site characteristics are in differences between destination and origin location. Year indicators are included in regressions, but omitted from table.

occupation, it is a good match; if the worker switches, it is a poor match. This information translates into the different earnings expectations and liquidity constraints faced by job changers. The occupation change variable is therefore an important predictor of the migration choice and our best proxy for the occupation signals that workers have received. Our spatial interpretation of the theory predicts that low productivity workers should be responsive to information about occupation match quality and seek a better match in an alternative occupation, which may involve migration. On the other hand, good match workers are likely to move to improve utility

TABLE 6

Black, Good Match Sample Estimates, Occupational Mobility & Migration Results

Occupation Switch				Migration			
Variable	Coefficient	Std. Error		Variable	Coefficient	Std. Error	
				ocmove	-0.7522	0.6398	
age	-0.0125	0.0378		*age*	-0.0567	0.0613	
married	0.1939	0.1888		*married*	0.7768	0.2606	*
female	0.2099	0.2556		*female*	-0.3815	0.4064	
marrfem	-0.1440	0.2217		*marrfem*	0.0207	0.4109	
femkid	-0.0771	0.2577		*femkid*	0.3533	0.3798	
numkid	-0.0515	0.0853		*numkid*	-0.0768	0.1173	
faminc	0.0029	0.0032		*faminc*	0.0146	0.0037	*
educ	0.0015	0.0403		*educ*	0.1352	0.0717	**
exper	0.1356	0.1154		*exper*	0.2374	0.1859	
exper2	0.0024	0.0101		*exper2*	-0.0387	0.0185	*
otenure	0.0027	0.0006	*	*amtui*	0.0001	0.0002	
amtui	0.0002	0.0002		*med_house*	-0.0153	0.0123	
involex	0.0490	0.1968		*med_house2*	0.00003	0.00002	
o_octn	-0.0050	0.0007	*	*emp_grw1*	0.0019	0.0020	
emp_grow1	-0.0028	0.0046		*emp_grw2*	0.0005	0.0010	
emp_grow2	0.0018	0.0012		*emp_grw4*	0.0004	0.0007	
emp_grow3	0.0020	0.0044		*pctax*	-0.0119	0.0054	*
ocprem	0.0029	0.0014	*	*pwelf*	1.4538	0.5977	*
oprof	-0.2261	0.3573		*ppolice*	-0.1783	0.1195	***
omngr	-0.2235	0.3816		*peduc*	0.0460	0.0583	
osales	0.8066	0.3364	*	*tempvar*	0.1507	0.0845	**
oclrcl	0.2543	0.3279		*cdd*	0.0025	0.0013	*
ocraft	0.9056	0.4098	*	*hdd*	0.0001	0.0006	
ooper	0.6462	0.3332	**	*precip*	0.0625	0.0458	
olabor	0.6886	0.4291	***	*loc_tenure*	-0.0838	0.0220	*
oserv	0.4338	0.2825	***	*otenure*	0.0018	0.0009	*
fulltime	-0.5906	0.2075	*	*dense*	0.1144	0.0904	
constant	0.4166	1.2113		*dense2*	0.0029	0.0009	*
				crime	0.0005	0.0002	*
				perc_black	-5.9462	2.7412	*
				perc_hisp	-21.8172	8.1111	*
				uerate	-0.0562	0.0330	**
ρ	0.1046	0.4704		*homeown*	-2.4198	0.7406	*
χ^2 (1) = .049		$Pr > \chi^2 = .825$		*constant*	-2.2834	2.0583	
N	456			Log likelihood	-293.58		

Source: Authors' calculations from 1990-1996 NLSY sample of white and African American job changers. Most site characteristics are in differences between destination and origin location. Statistically significant at the * 5%, **10%, and ***15% levels; standard errors adjusted for multiple observations per individual.
Year indicators are included in regressions, but omitted from tables.

from the features of location if the utility gains from moving exceed search costs. Therefore, we expect that site features are more important determinants of migration for high productivity workers.

The occupation change variable (*ocmove*) is significant at the 5 percent level only for those in a bad match in the initial occupation; however, the sign is negative. For the full sample of workers in poor occupation matches, the information gained by a job changer that she is of low

TABLE 7

Black, Bad Match Sample Estimates, Occupational Mobility & Migration Results

Occupation Switch				Migration			
Variable	Coefficient	Std. Error		Variable	Coefficient	Std. Error	
				ocmove	-0.2235	0.5696	
age	0.0016	0.0198		*age*	-0.0301	0.0293	
married	0.0018	0.1039		*married*	0.2500	0.1379	**
female	-0.1959	0.1413		*female*	0.3418	0.2375	***
marrfem	-0.1769	0.1138	***	*marrfem*	-0.2489	0.1991	
femkid	0.0916	0.1472		*femkid*	-0.1546	0.2262	
numkid	0.0305	0.0416		*numkid*	0.0006	0.0605	
faminc	-0.0039	0.0019	*	*faminc*	-0.0035	0.0030	
educ	-0.0140	0.0222		*educ*	-0.0302	0.0331	
exper	0.1804	0.0748	*	*exper*	0.0992	0.1173	
exper2	-0.0090	0.0082		*exper2*	-0.0022	0.0115	
otenure	0.0012	0.0004	*	*amtui*	-0.000005	0.0001	
amtui	-0.0001	0.00005	*	*med_house*	-0.0173	0.0054	*
involex	-0.1772	0.1175	***	*med_house2*	0.0002	0.0000	*
o_octn	-0.0049	0.0004	*	*emp_grw1*	0.0027	0.0011	*
emp_grow1	0.0023	0.0027		*emp_grw2*	-0.0018	0.0008	*
emp_grow2	0.0000	0.0007		*emp_grw4*	0.0003	0.0004	
emp_grow3	-0.0024	0.0025		*pctax*	-0.0011	0.0008	
ocprem	-0.0044	0.0022	*	*pwelf*	0.3077	0.1872	**
oprof	-0.0366	0.2008		*ppolice*	-0.0960	0.0539	**
omngr	0.5091	0.2093	*	*peduc*	-0.0082	0.0242	
osales	0.1406	0.1865		*tempvar*	0.0139	0.0257	
oclrcl	0.1799	0.1822		*cdd*	-0.0009	0.0004	*
ocraft	0.4822	0.2524	**	*hdd*	-0.0004	0.0003	
ooper	0.1614	0.1979		*precip*	-0.0401	0.0183	*
olabor	0.0409	0.1965		*loc_tenure*	-0.1053	0.0131	*
oserv	-0.0876	0.1692		*otenure*	0.0004	0.0006	
fulltime	-0.0836	0.0963		*dense*	-0.0524	0.0603	
constant	0.4548	0.5985		*dense2*	-0.0025	0.0018	
				crime	0.0001	0.0001	***
				perc_black	-0.4392	1.6724	
				perc_hisp	0.4976	2.7128	
				uerate	-0.0202	0.0093	*
ρ	0.1263	0.3764		*homeown*	-0.4795	0.1818	*
χ^2 (1) = .110		$Pr > \chi^2 = .740$		*constant*	0.1405	1.0857	
N	1388			Log likelihood	-1058.13		

Source: Authors' calculations from 1990-1996 NLSY sample of white and African American job changers. Statistically significant at the * 5%, **10%, and ***15% levels; standard errors adjusted for multiple observations per individual. Most site characteristics are in differences between destination and origin location. Year indicators are included in regressions, but omitted from table.

quality in an initial occupation reduces the likelihood of migrating. This result suggests that poorly matched workers use the information on occupation match quality in the initial job to search locally rather than across MSAs for a better match in a subsequent occupation. This is likely because a signal changes the expected earnings in the initial occupation relative to other occupations; for example, a low quality signal implies that wages fall below the expected population productivity in the occupation. Therefore, known low quality workers in the initial occupation attempt to increase earnings by searching for a better match in an alternative occupation. The result on the occupation information variable (*ocmove*) suggests that geographical search costs in a new occupation are greater than the expected wage gains from occupation mobility or that the alternative economic opportunities in the origin location are such that search costs are lower and/or job arrival rates are higher than in alternative destinations. Thus, utility maximization implies that these workers search locally rather than nationally.

High quality workers, on the other hand, are unresponsive to the information contained in the variable (*ocmove*) in the migration decision. Referring to the outcomes for occupation switch and migration demonstrated in Table 1, high quality workers may improve utility by leaving an occupation in which they receive relatively high wages for a destination with more attractive location attributes. These workers may be better able to overcome the geographical search costs associated with migration. Therefore, we expect good match individuals to be more responsive to the features of a location in the migration decision. Our empirical results are consistent with our theoretical predictions in that high quality workers are more responsive than low quality workers, *ceteris paribus*, to public sector and climate measures. One reason for the unresponsiveness of migration to occupation change is that good match workers may be a relatively heterogeneous group; some may stay in the same occupation as predicted by the experience good model, while others may be moving up an occupation ladder into a better position. The set of site characteristics within racial groups are more important determinants for good occupation match workers as compared with bad match workers. The differences are more pronounced between the black subsamples, which suggests that white bad match workers have relatively fewer locational constraints than blacks.

For whites, the coefficient on the unemployment rate is positive; it is statistically significant in the good match sample. If labor market discrimination is a factor, whites may be more likely to be hired and less sensitive to the inhibiting aspects of the unemployment rate. Higher unemployment rates may be the result of migration of workers to a desirable location, raising the unemployment rate by increasing labor supply. Since employment growth rates are already included, for whites this variable may be capturing unmeasured amenities in the location. Because of labor market discrimination, it may be capturing a disamenity for blacks.

Bad match whites are the only group, when disaggregated, for which the decision to migrate is influenced by the information contained in the variable *ocmove*: For this subgroup, occupation change is negatively related to the probability of migrating. It is this group for which earnings increases are associated with a new occupation and for which geographical search costs are likely to be prohibitively costly relative to earnings gains from moving. Job search for bad occupation match whites is likely to be local rather than national so as to minimize search costs. Within the white population, it appears that migration is selective of occupation match quality.

4.4 The Unmeasured Factors in the Relationship Between Occupation Choice and Migration

The values of ρ, the correlation coefficient between the two equations, are presented in Tables 4-7. In the full (not shown) and the white samples of poor quality occupation match workers, ρ is statistically significant at the 5 percent and 15 percent levels, respectively, and is positive. Therefore, the unobservable measures that make one more likely to migrate make one more likely to switch occupations. Conversely, the unobservable measures that make one less likely to migrate may cause one to be less likely to change occupations. For both match quality types of black and the good match white workers, the two decisions are statistically unrelated.

In light of the existing literature on black migration, one could argue that the unmeasured factors in the migration equation, especially those relating to social networks, may be as important as those that we have measured. Some of the critical unmeasured factors in the occupation decision may include beliefs about social access to jobs and experience with statistical discrimination related to racial immobility. Given this existing literature, *a priori*, one would expect ρ to be statistically significant. Surprisingly, the estimates are statistically significant only for the full sample of bad match workers and for white bad match workers.

4.5 Specification Tests

We have performed additional specifications tests. A number of estimations were performed that excluded possible endogenous variables from the migration equation (e.g., home ownership) and substituted the National Amenities Index for the climate measures. We also estimated the models with real wages instead of family income in the regressions. None of these changes resulted in significant differences from the estimates presented in this paper. These results are available from the authors by request. We also tested the fit of the model by using the predicted probabilities from the regressions to assign workers to one cell. The conditional probability of the model correctly placing individuals in each category was calculated. The model predicts best the categories where there is no occupation switch. The model performs least well at predicting workers who do not migrate but switch occupations, particularly for bad match workers of both races. It is likely that many unobservable factors such as additional labor and residential market constraints, place ties, and nonpecuniary characteristics of occupations are very important components in worker decisions, particularly for the workers in poor occupation matches.

5. CONCLUSION

Our theoretical work is a spatial extension on a well-known experience good model. Workers gather information about their productivity in an occupation, which changes the relative trade-offs associated with job search in other occupations and which may change the optimal location.

We utilize work history panel data from the NLSY to examine the relationship between the occupation and location decisions. While there is much agreement that these are linked, we know of no other study that has attempted to determine whether migration influenced by information on the quality of an occupation match. In contrast to prior expectations, our recursive bivariate probit empirical analysis shows that the decisions are linked only for workers in a bad occupation match, which is largely driven by the results from poorly matched whites. The coefficient estimates for occupation premium and involuntary job loss in the occupation change decision are closer to the model's predictions for workers in a bad match than for good match workers. Occupation change is a significant determinant of migration for poorly matched whites.

Our research suggests that poorly matched workers use information on occupation match quality in the initial job to search locally rather than across MSAs and attempt to increase earnings by searching for a better match in an alternative occupation. Migration is selective by worker quality because geographical search costs in addition to occupation search costs are greater than the expected earnings gains either from higher job arrival rates or from the increase in expected wages from a concurrent migration and occupation change.

Good match workers experience increased wages within the occupation and are consequently more mobile than poorly matched workers. They are unresponsive to the match quality signals that we have endogenized in the migration decision but are highly responsive to site measures. This is consistent with an increased ability to overcome liquidity constraints of a geographical search and because location features are normal goods. Migration may not be as responsive to occupation change for this group of workers for another reason: this group may be more heterogeneous than the poorly matched workers. Some may retain their good occupation match and others may be moving up a career ladder. This would muddy the information contained in the occupation change variable and cause the results to be statistically insignificant.

It is clear from the estimates on the demographic and spatial variables in the disaggregated samples that blacks and whites engage in different migration processes. One of the most interesting results from our migration equations demonstrates that bad occupation match blacks who migrate appear to locate to destinations with poorer growth in economic opportunity, irrespective of occupation choice. The location decision may be related to characteristics of locations' housing market, including racial ties to place, and the effects of social networks in wages. This finding merits further investigation and is beyond the scope of this paper.

If the relative geographical immobility and occupational segregation of blacks is caused by access to information and a reliance on informal social networks, a national jobs bank may be a mitigating factor, easing both location and occupational segregation. Policies aimed at occupational segregation could include stricter enforcement of equal employment opportunity laws.

REFERENCES

Allen, J., 1979. "Information and Subsequent Migration: Further Analysis and Additional Evidence," *Southern Economic Journal* 45, 1274-84.

Bartel, A.P., 1979. "The Migration Decision: What Role Does Job Mobility Play?" *American Economic Review* 69, 775-86.

Cooper, J.M.R., 1994. "Migration and Market Wage Risk," *Journal of Regional Science* 34, 563-82.

DaVanzo, J. and P.A. Morrison, 1981. "Return and Other Sequences of Migration in the United States," *Demography* 18(1), 85-101.

Ellis, M., R. Barff, and B. Renard, 1993. "Migration Regions and Interstate Labor Flows by Occupation in the United States," *Growth and Change* 24, 166-90.

Fallick, B.C., 1993. "The Industrial Mobility of Displaced Workers," *Journal of Labor Economics* 11, 302-23.

Farber, H.S., 1994. "The Analysis of Interfirm Worker Mobility," *Journal of Labor Economics* 12(4), 554-93.

Gibbs, R.M., 1994. "The Information Effects of Origin on Migrants' Job Search Behavior," *Journal of Regional Science* 34 (2), 163-78.

Graves, P.E., 1979. "A Life-Cycle Empirical Analysis of Migration and Climate, by Race," *Journal of Urban Economics* 6, 135-47.

Graves, P.E. and P. Linneman, 1979. "Household Migration: Theoretical and Empirical Results," *Journal of Urban Economics* 6, 383-404.

Greene, W., 2000. *Econometric Analysis.* Fourth Edition. Prentice-Hall, Inc.: Upper Saddle River, NJ.

Gyourko, J. and J. Tracy, 1989. "The Importance of Local Fiscal Conditions in Analyzing Local Labor Markets," *Journal of Political Economy* 97, 1208-31.

Herzog, H.W., Jr. and A.M. Schlottmann, 1981. "Labor Force Migration and Allocative Efficiency in the United States: The Roles of Information and Psychic Costs," *Economic Inquiry* 19, 439-75.

Herzog, H.W., Jr. and A.M. Schlottmann, 1984. "Career and Geographic Mobility Interactions: Implications for the Age Selectivity of Migration," *Journal of Human Resources* 19, 72-86.

Johnson, J.H., Jr. and C.C. Roseman, 1990. " Increasing Black Outmigration from Los Angeles: The Role of Household Dynamics and Kinship Systems," *Annals of the Association of American Geographers* 80, 205-22.

Jovanovic, B., 1979. "Job Matching and the Theory of Turnover," *Journal of Political Economy* 98, 827-52.

Krieg, R.G., 1997. "Occupational Change, Employer Change, Internal Migration, and Earnings," *Regional Science and Urban Economics* 27(1), 1-16.

Krieg, R.G. and A.K. Bohara, 1999. "A Simultaneous Probit Model of Earnings, Migration, Job Change with Wage Heterogeneity," *Annals of Regional Science* 33, 453-67.

Lee, S. and C.C. Roseman, 1997. "Independent and Linked Migrants: Determinants of African American Interstate Migration," *Growth and Change* 28, 309-34.

Lee, S. and C.C. Roseman, 1999. "Migration Determinants and Employment Consequences of White and Black Families," *Economic Geography* 75(2), 109-36.

Long, L.H., 1973. "Migration Differentials by Education and Occupation: Trends and Variations," *Demography* 10, 243-58.

Maier, G., 1986. "Cumulative Causation and Selectivity in Labour Market Oriented Migration Caused by Imperfect Information," *Regional Studies* 19, 231-41.

Mellow, W. and H. Sider, 1983. "Accuracy of Response in Labor Market Surveys: Evidence and Implications," *Journal of Labor Economics* 1(4), 331-44.

Odland, J., 1988. "Migration and Occupational Choice Among Young Labor Force Entrants: A Human Capital Model," *Geographical Analysis* 20, 281-96.

O'Regan, K.M., 1993. "The Effect of Social Networks and Concentrated Poverty on Black and Hispanic Youth Unemployment," *Annals of Regional Science* 27, 327-42.

Raphael, S. and D. Riker, 1999. "Geographic Mobility, Race, and Wage Differentials," *Journal of Urban Economics* 45, 17-46.

Sicherman N. and O. Galor, 1990. "A Theory of Career Mobility," *Journal of Political Economy* 98, 169-92.

Sjaastad, L., 1962. "The Costs and Returns of Human Migration," *Journal of Political Economy* 70, 80-93.

Stoll, M.A. and S. Raphael, 2000. "Racial Differences in Spatial Job Search Patterns: Exploring the Causes and Consequences," *Economic Geography* 76(3), 201-30.

Thomas, D.S., 1938. *Research Memorandum on Migration Differentials*. Social Science Research Council, No. 43: New York.