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Incomplete Compensation and Migration Behavior: Has Anything Changed Between 1990 and 2000?

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Incomplete Compensation and Migration Behavior: Has Anything Changed Between 1990 and 2000?

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Abstract. Spatial equilibrium models rely on migration to arbitrage away differences in utility across locations net of moving costs, where remaining differences in wages and rents reflect the compensating differentials related to site-specific amenities. Recent refinements to the spatial equilibrium model focus upon the prospect of disequilibrium in amenity markets. Amenity market disequilibrium implies over- or under-compensation (incomplete compensation) across some locations, which suggests a role for these factors in subsequent migration. This paper follows the theoretical and empirical approach of Clark, Herrin, Knapp, and White (2003). An intercity wage regression is estimated where fixed effects capture the impact of site characteristics on wages. We then regress the fixed effects on a comprehensive vector of site attributes, where the residuals capture incomplete compensation in wages. The derived measures of incomplete compensation are included in a binary logit model of migration. The results provide further evidence that incomplete compensation for site characteristics is a significant factor in migration decisions, and the findings are consistent with tendencies toward spatial equilibrium.

1. Introduction

Following the debates of the late 1970s and 1980s regarding the determinants of household migration, researchers now recognize the dual roles of disequilibrium factors in labor markets and equilibrium factors driven by changes in demand for site-specific attributes. Clark et al. (2003) developed a model that included factors that capture disequilibrium in amenity markets along with conventional equilibrium factors. Clark et al. estimated a three stage empirical model using the 1990 Public Use Microdata Sample (PUMS), where derived measures of city-specific incomplete compensation were included as determinants of migration. In the first stage, an intercity wage regression is regressed on demographic and human capital measures in addition to a control for the median house value and metropolitan area fixed effects [see Gabriel and Rosenthal (1999)]. The fixed effects capture the net impact of a location's site characteristics on wages. The fixed effects are regressed on a comprehensive vector of site attributes in the second stage. With adequate controls for the salient site characteristics, the residuals from the intercity wage regression can then be interpreted as measures of over- and under-compensation in wages. Finally, the measures of incomplete compensation are included in a discrete choice model of migration.

Clark et al. (2003) found that measures of over-compensation and under-compensation at both the origin and destination locations had the anticipated impacts on migration. Specifically, over-compensation at the origin, and under-compensation at the destination, *ceteris paribus*, decreased the likelihood of a move, while the opposite was found for under-compensation at the origin and over-compensation at the destination. A comparison of the marginal probabilities suggested that incomplete compensation measures were more important at the destination than the origin and that households were generally more responsive to under-compensation than over-compensation.

These findings provide the impetus for the present paper. Here we set out to determine whether results similar to Clark et al. (2003) can be obtained by applying the same empirical model to data from the recently released 2000 PUMS. Similar findings from the 2000 data would provide additional support for the hypothesis that incomplete amenity compensation is a significant factor in household migration decisions.[1] The paper is organized as follows. A description of the related literature is presented in Section 2. The third section describes the empirical model. Empirical findings are reported in Section 4 and the final section of the paper contains concluding remarks.

2. Relevant Literature

Equilibrium approaches to migration tend to emphasize locational attributes while disequilibrium models focus on economic opportunity variables. Research by some scholars (Greenwood, 1985; Greenwood and Hunt, 1989; Evans, 1990) found that disequilibrium factors were important determinants of migration, whereas other studies (Graves, 1979; Graves and Linneman, 1979; Knapp and Graves, 1982; Clark and Hunter, 1992; Mueser and Graves, 1995) demonstrate that site-characteristics play an important role. As Hunt (1993) suggests in his survey of migration models, disequilibrium in amenity markets had not yet been considered as a determinant of migration. Following Herzog and Schlottmann (1993), it became clear that amenity induced migration and amenity valuation were inextricably linked.

Since the work of Rosen (1979), which was refined by Roback (1982), and Blomquist, Berger and Hoehn (1988), it has been recognized that spatial variation in amenities are capitalized into local wages and land rents. While not the focus of these studies, migration is the mechanism by which amenity capitalization is revealed in local factor prices. Research explicitly aimed at examining the role of amenities as determinants of household migration followed (Berger and Blomquist (1992), Graves (1979), and Graves and Linneman (1979)). The studies following Rosen were grounded in the equilibrium approach to migration, where, in equilibrium, utility is spatially invariant and there is no incentive to migrate. However, Graves (1979) and Graves and Linneman (1979) found that shifts in amenity demands such as changes in income or life-cycle induced changes in preferences create incentives for migration. Therefore, two sources of amenity driven migration are evident from previous research. One is derived from the equilibrium approach, where changes in amenity demands influence migration. The second source of amenity driven migration results from disequilibrium in amenity markets, which includes the over-compensation or under-compensation for site attributes in local wages and land rents. Both sources of amenity driven migration are analyzed in Clark, et al. (2003) and in this paper.

3. Model

The theoretical foundation for the empirical model is derived from Henderson (1982) who showed an equilibrium tradeoff between the city wage and amenity bundle which he defines as a wage-opportunity locus (W_{OL}). As is seen in Figure 1, the W_{OL} is an equilibrium reduced-form model that is mapped by the tangencies of household wage-acceptance functions (W_{A1}-W_{A3}) and firm offer functions (F_{O1}-F_{03}). The wage-acceptance function is an iso-utility curve for consumers and the various curves W_{A1}-W_{A3} represent different individuals with different tastes. Likewise, the firm-offer curve is an iso-profit curve, and F_{O1}-F_{03} represent different competitive firms that are breaking even. In equilibrium, households and firms sort themselves along the W_{OL} such that no further re-allocations can generate utility or profit enhancing

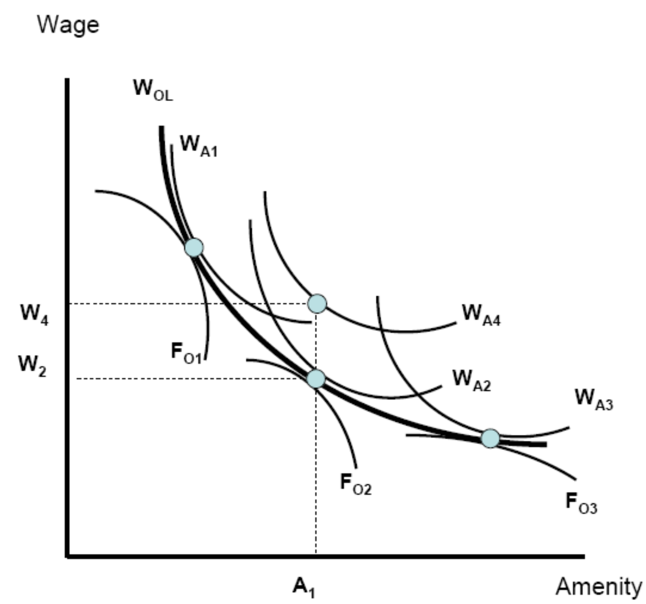

Figure 1. Wage-Amenity Tradeoff

[1] In contrast to migration studies using microdata, Clark (2006) found that net migration rates were not significantly influenced by the incomplete compensation measures derived in Clark et al. (2003).

moves[2]. However, if a particular city offers a wage-amenity bundle that is above or below the W_{OL} (e.g., W_{A4} at amenity level A_1), then that city is offering a wage that is higher than is necessary (i.e., $W_4>W_2$) to compensate for the city's amenity bundle. We define $W_4>W_2$ as over-compensation, which is assumed to generate in-migration. If the city is small relative to the national labor market, it is expected that in-migration would ultimately return the city to the equilibrium wage (W_2).

A sample of 142,138 households residing in 78 MSAs was drawn from the 2000 PUMS database[3]. The three stage process outlined in Clark et al. (2003) was applied to this sample. It is summarized as follows:

Stage 1: Deriving metropolitan fixed effects

Ordinary least squares was used to estimate the following hedonic wage equation of stage one. The equation to be estimated is:

$$\ln \text{(annual wage income)} = X_i\beta + a_j\delta_j + e_{ij} \qquad (1)$$

The vector X represents personal characteristics, and fixed effects dummy variables are expressed by δ_j, where the parameter a_j is a measure of the average effect on wage income, *ceteris paribus*, of residing in a given MSA. Equation (1) is estimated without an intercept term; therefore, the fixed effects represent unique intercepts for each of the 78 MSAs. Because there are no site characteristics in the model except the median price of housing, the coefficient on the fixed effects reflects the MSA-specific intercept term. The fixed effects vary as a result of the capitalization of site characteristics, as well as other unmeasured factors that lead to wage over- and under-compensation in the metropolitan area.

All variable definitions, data sources and descriptive statistics are included in Table 1. The vector of human capital and effort related variables include *education* and imputed *experience* (computed as age-education-6) in linear and quadratic form, *male,* the dichotomous variables A*sian*, *black*, *Hispanic*, and *other race*. Work effort is proxied by the *annual hours* of work, *married*, *children, and unemployed*. A dummy variable is used to measure whether the worker speaks *English* well. Housing costs are proxied by *median value*. The *occupational* and *industrial* classifications are included to account for compensating differentials related to the job and the industry. The occupational category also controls for human capital differences that are correlated with occupation.

Stage 2: Obtaining over-compensation and under-compensation measures

The purpose of this second stage is to explain the spatial variation in wages associated with the levels of site attributes. The estimated first stage fixed effects coefficients for each MSA are regressed on a comprehensive vector of site attributes. The residuals from stage two are interpreted as measures of incomplete compensation in wages.

The fiscal factors and natural amenities controls include measures of state and local taxation (*income tax*, *total tax*) and spending (*education spending, highway spending, hospital spending, police spending,* and *welfare spending*). The amenity list includes variables related to climate (*precipitation, heating, cooling, temperature difference, sunshine,* and *wind speed*), proximity to an ocean *coast*, *violent crime*, air quality (*pmna*), and average *commute time* to work for the metro area. In addition, unmeasured amenities and disamenities related to urban scale are proxied by population *density* in linear and quadratic form (*density squared*), and *total population.* We include the metropolitan area *unemployment rate* to account for local business cycles that can affect household perceptions of the MSA.

We regress the estimated city-specific fixed effects from stage one on the site characteristic vector (Z_j) as shown in equation (2), where the residuals are denoted with u_j. To avoid confusion, we define the estimated city-specific fixed effects from stage one as a_j^*

[2] While Roback (1980) shows that interregional amenity differences are capitalized into both wages and land rents, Henderson (1982) notes that as long as the average land value is controlled in the equation, that this is akin to the individual who locates at the edge of the city, and hence all capitalization is reflected in wage differentials.

[3] The IPUMS interface was used to extract the 2000 PUMS 1% sample. A much smaller sample of metropolitan areas were identified in the 2000 PUMS sample than in the 1990 PUMS sample. This is because of a change in the manner in which spatial areas were defined. In the 1990 PUMS, the so-called PUMAs (Public Use Microdata Areas) were constructed by the Census to coincide with metropolitan boundaries. Hence, the 1990 PUMS identified all metropolitan areas with population of at least 100,000 persons (i.e. the minimum PUMA size). In contrast, the 2000 Census focused on Super-PUMAs with populations of at least 400,000. Thus, the minimum size for metropolitan areas that are identified in the 2000 PUMS was 400,000. Furthermore, states that defined their own Super-PUMAs were not required to have the boundaries of those areas coincide with the boundaries of metropolitan areas. Overall, this dramatically reduced the number of metropolitan areas that were reported by the Census. After adjusting the sample for missing data, we were left with 78 metropolitan areas as compared to 267 in 1990. While the spatial distribution of metropolitan areas across the four Census Regions was similar between 1990 and 2000, the size distribution was not. The average population of the metropolitan areas was 696,154 persons in the 1990 sample and 1,789,101 persons in 2000. As will be seen in the discussion of our findings, this limits some of our conclusions.

Table 1. Variable Names, Definitions, Expected Signs, Data Sources

Variable name	Definition [mean, standard deviation in brackets]	Expected Sign
log(annual wage income) [a]	Annual wage income earned in 1999: [10.38, 0.67]	dep. variable
Human Capital Variables		
education[a]	Years of education: [13.36, 2.95]	+
experience[a],	Years of experience, defined as age-education-6: [17.70, 10.77]	+
experience^2 [a]	experience*experience	-
male[a]	Dichotomous variable = 1 if individual is male, 0 otherwise [0.57, 0.50]	+
married[a]	Dichotomous variable = 1 if individual is married, 0 otherwise [0.52, 0.50]	?
children[a]	Number of children in the household, 0 otherwise: [0.46, 0.50]	?
black[a]	Dichotomous variable=1 if individual is black, 0 otherwise [0.14, 0.35]	?
Asian[a]	Dichotomous variable = 1 if individual is Asian or Pacific islander, 0 otherwise: [0.06, 0.23]	?
Hispanic[a]	Dichotomous variable = 1 if individual is of Hispanic ethnicity, 0 otherwise: [0.16, 0.37]	?
other race[a]	Dichotomous variable = 1 if individual is not white, black, or Asian; 0 otherwise: [0.09, 0.28]	?
annual hours[a]	Average total hours worked in 1989: [2250.56, 434.82]	+
unemployed[a]	Dichotomous variable = 1 if individual is currently (2000) unemployed, 0 otherwise; [0.02, 0.13]	-
English[a]	Dichotomous variable = 1 if individual speaks English well or very well, 0 otherwise: [0.95, 0.22]	+
Fiscal Variables		
income tax[b]	State income tax revenue/$1,000 taxable income: [103.86, 10.57]	+
total tax[b]	Per capita total tax liability for the metro area of residence (weighted county average for multi-county metro areas): [1025.42, 362.15]	+
education spending[b]	Per capita education spending for the metro area of residence (weighted county avg. for multi-county metro areas): [43.67, 8.10]	-
highway spending[b]	Per capita highway spending for the metro area of residence (weighted county avg. for multi-county metro areas): [4.14, 1.33]	-
hospital spending[b]	Per capita hospital spending for the metro area of residence (weighted county avg. for multi-county metro areas): [7.24, 5.51]	-
police spending[b]	Per capita highway spending for the metro area of residence (weighted county avg. for multi-county metro areas): [4.14, 1.33]	-
welfare spending[b]	Per capita public safety spending for the metro area of residence (weighted county avg. for multi-county metro areas): [5.66, 1.31]	-
highway spending[b]	Per capita welfare spending for the metro area of residence (weighted county avg. for multi-county metro areas): [3.91, 4.27]	-

Table 1 (continued). Variable Names, Definitions, Expected Signs, Data Sources

Variable name	Definition [mean, standard deviation in brackets]	Expected Sign
Amenity Variables		
precipitation[c]	Annual inches of precipitation[36.01, 14.23]	+
heating[c]	Number of heating degree days per year (1 heating degree day = heating the residence 1 degree to 65° F for 1 day: [461.37, 2130.71]	+
cooling[c]	Number of cooling degree days per year (1 cooling degree day = cooling the residence 1 degree to 65° F for 1 day: [1509.90, 1072.96]	+
temperature difference[c]	Difference between average max. July temp. and average max. January temp.:[37.54, 10.60]	+
sunshine[c]	Percentage of available sunshine: [60.22, 9.47]	-
wind speed[c]	Average annual wind speed: [8.93, 1.34]	+
coast	Dichotomous variable = 1 if the MSA of residence has an ocean coastline, 0 otherwise: [0.52, 0.50]	-
violent crime[d]	Violent crime rate = number of violent crimes divided by total population – 2000: [0.02, 0.013]	+
commute time[e]	Average commuting time to work in minutes for the metro area.: [25.12, 3.42]	+
density[e]	Population density = divided by metropolitan land area:	?
density squared	[666.76, 958.46]	?
total population[e]	Total 2000 metropolitan population: [1789101, 1851801]	?
median value[e]	Median value of housing for the metro area of residence: [76443.46, 38416.10]	?
pmna[f]	Dichotomous variable = 1 if the metro area of residence was declared a nonattainment region for concentrations of particulate matter of 10 microns or less in 1990, 0 otherwise: [0.12, 0.32]	+
unemployment rate[g]	MSA unemployment rate – 1999: [4.75, 3.06]	+

a – 2000 Public Use Microdata Sample drawn from IPUMS database; b – County and City Extra for 2002; c – National Oceanic and Atmospheric Administration Climatology of the United States; d – FBI Uniform Crime Reports; e- 2000 Census of Population and Housing; f – EPA Criteria Pollutant; g – U.S. Bureau of Labor Statistics.

and we denote the predicted values from the estimation of equation (2) as $\hat{a}_j$.

$$a_j^* = Z_j \gamma_j + u_j \qquad (2)$$

In general, a positive error $u_j > 0$ implies $a_j^* > \hat{a}_j$; that is, equation (2) under-*predicts* the hedonic wage compensation. If equation (2) under-predicts the hedonic wage, this implies that the actual wage is higher than the predicted wage and there is over-compensation. Likewise, a negative error $u_j < 0$ implies $a_j^* < \hat{a}_j$, in which case the model *over-predicts* the fixed effects and there is under-compensation in wages given the site characteristics.

Stage 3: The Migration Equation

Lastly, the PUMS data are used to determine whether wage under or over-compensation influences the probability of migrating to another city. Migration is defined as a household's change in metropolitan area over the period 1995-2000. Nonmovers are defined as those who have changed houses without changing metropolitan areas. Following Clark et al. (2003), we select only those households who changed residence over the period so as to focus on the location decisions of marginal households (i.e., those households that drive hedonic compensation). Hence, among this relatively mobile subset of the general population, we investigate the importance of incomplete compensation at the origin and/or the destination in determining the optimal location.

The binary logit model is shown in the following equation:

$$\text{Prob(Migr)}_i = X_i\beta_i + Z_{oj}\beta_{oj} + Z_{dj}\beta_{dj} + g_o N_{oj*}\text{abs}(u_{oj}) + h_o P_{oj} u_{oj} + g_d N_{dj}\text{abs}(u_{dj}) + h_d P_{dj} u_{dj} + e_i \quad (3)$$

The X_i vector of personal characteristics is defined above and e_i represents the usual error term. The site characteristics vector Z_j is subscripted to denote the levels of these characteristics at the origin (o) and destination (d). The four remaining terms are comprised of the residuals (u_j) drawn from equation (2) as well as indicator variables to differentiate positive (P) from negative (N) residuals for both the origin and destination. Because we are utilizing micro-data, it is reasonable to assume that public sector characteristics are exogenous to migration. This construction of the migration equation permits under- and over-compensation to have different effects at the origin as compared to the destination. We let $P_j = 1$ if a given $u_j > 0$; $P_j = 0$ otherwise, and $N_j = 1$ if $u_j < 0$; $N_j = 0$ otherwise. For ease of interpretation, we then take the absolute value of the negative residuals multiplied by the N_o and N_d dummy variables. The coefficients g_o, g_d, h_o, and h_d capture the influence on migration of hedonic over or under-compensation for origin and destination. We assume that potential migrants respond to utility differences that include incomplete compensation of site characteristics in wages. Whether a location has a positive or negative fixed effect is largely irrelevant to this analysis. If, for example, an individual is over-compensated at any location, that individual is better off than if he/she resided, *ceteris paribus*, at an alternative location. We expect, *a priori*, that over-compensation at the origin deters migration ($h_o<0$) , while over-compensation at the destination encourages it ($h_d>0$). The opposite should be true for under-compensation at the origin and destination respectively (i.e., $g_o>0$, $g_d<0$).

The vector of ***Personal Characteristics*** includes the *age* and *education* of the householder, marital status (*married*), the presence of *children* in the household, race and ethnicity (*Asian, black, Hispanic,* and *other race*) and the employment status of the householder (*unemployed*). The origin and destination ***Locational Characteristics*** that are used in the specification of the fixed effects equation (stage two) are also included in the migration model.

4. Empirical Results

Results of the wage income regression from equation (1) are summarized in Table 2. After controlling for workers' occupational and industrial classifications, all of the coefficients for personal characteristics are signed as expected with p-values less than 0.001. The magnitudes of the coefficients are also reasonable. For example, males earn 20.7% more than females, and English fluency raises income by 10.8%. Also, different racial and ethnic groups earn between 5.8% and 16.7% less than whites. Additionally, virtually all of the estimated coefficients for the occupational and industrial dummy variables are significant at the 5% level. Finally, an F-test is used to determine if the set of fixed effect MSA dummy variables significantly increases the explanatory power of the regression. The computed F-Statistic is 30.16, which suggest with virtual certainty that inclusion of the fixed effect variables improves the explanatory power, and that location features contribute to spatial variation in wage income.[4]

The second stage results are shown in Table 3. White's test of the residuals from this regression shows no evidence of heteroskedasticity. Nine of the 21 estimated coefficients are significant at the 5% level or better, while three others are significant at 10%. The significant coefficients are *precipitation, cooling, tempdiff, sunshine, commute time, density, density squared, population, total tax, police spending, welfare spending,* and *unemployment rate*.[5] The positive coefficient for *unemployment rate* indicates that higher metropolitan area unemployment is perceived as a disamenity requiring higher compensating wage income. This result is consistent with many other estimates (see Topel, 1986, for a summary of these studies). The positive coefficients on *police spending* and *welfare spending* suggest these site attributes are disamenities. Perhaps these variables are capturing the impacts of omitted socioeconomic disamenities that necessitate higher per capita spending on police and welfare.

The adjusted R^2 of 0.81 and F = 16.32 suggests with near certainty ($p < 0.0001$) that site-specific amenity and fiscal characteristics explain much of the MSA-

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[4] The equation is estimated without an intercept in order to avoid losing any of the 78 different MSA fixed effect coefficient estimates. The fixed effect coefficients therefore capture both the intercept influence as well as the average city-specific effect. However, they are not expressed relative to an omitted city as would be the case had the intercept been included.

[5] The sign of the coefficient on *commute time* appears anomalous.

Table 2. Wage-Opportunity Locus[a]

Variable	Coefficient	t-score
Human Capital and Median Value:		
education	0.069096	112.77
experience	0.028834	70.38
experience²	-0.000426	-47.48
male	0.207844	65.67
children	0.078844	28.06
black	-0.166761	-39.79
asian	-0.145828	-23.41
other race	-0.057768	-9.10
hispanic	-0.127669	-23.51
english	0.108007	15.48
annual hours	0.000260	79.81
median value	0.000020	2.29
Occupational Dummy Variables:		
administration	0.093347	2.87
architect/engineer	0.343005	10.19
business operations	0.333780	9.98
computers/math	0.445348	13.39
construction	0.145935	4.38
education/librarian	0.137974	4.12
entertainment	0.231328	6.82
extractive	0.119316	1.58
finance	0.343612	10.26
food	-0.033536	-1.00
health	0.312665	9.43
legal	0.438559	12.65
maintenance	-0.065591	-1.97
materials mover	0.015925	0.49

Variable	Coefficient	t-score
Occupational Dummy Variables – continued:		
management	0.436586	13.38
production	0.060330	1.84
protective services	0.142203	4.21
repair	0.179293	5.44
sales	0.240795	7.37
science	0.194800	5.48
service	-0.036870	-1.08
social science	0.064792	1.88
Industrial Dummy Variables:		
agriculture/forestry/fishery	-0.095078	-3.25
military industrial	-0.200211	-7.42
arts/entertainment	-0.196271	-21.77
construction	-0.014094	-1.50
education/social	-0.100109	-12.87
financial/insurance/real est.	0.040330	5.40
information/communication	0.067535	7.49
Manufacturing	0.032751	4.62
mining	0.152175	4.73
professional/scientific	-0.017216	-2.36
public administration	0.054925	5.96
Retail	-0.165634	-22.96
Transportation	0.022457	2.59
Other	-0.160095	-17.57

a. intercept suppressed, number of observations = 142,138, unreported MSA dummy variables = 78

specific wage variation. Therefore, the residuals from this regression can be reasonably interpreted as a measure of wage compensation net of amenity and public sector influences. Specifically, positive residuals represent MSA wage and salary income greater than that which the second stage regression predicts. Similarly, negative residuals measure MSA wage and salary income below what the regression predicts. We next use these residuals as measures of wage and salary over- and under-compensation to explain household migration between MSAs for a sample of 99,955 households that changed residence during the 1995-2000 period. Specifically, we estimated equation (3) to predict the probability that a household migrates, where migration is defined as a change of MSA. The results are shown in Table 4. The marginal impact of a regressor on the probability of migrating (i.e., changing MSA) is computed as $\beta*p*(1-p)$, where β is a regressor's estimated coefficient and p is the estimated probability of migrating computed at the mean values of all the regressors.[6] For example, aging one year lowers the probability of migrating by 0.2% while being male raises it by 1.2%.

Computing the odds ratio for each regressor, shown in the last column of Table 4, is perhaps a more revealing way to interpret the logit findings. This ratio represents the change in the odds of migration resulting from a one standard deviation increase in a regressor. With a logit specification, the odds of migration are specified in equation (4).

[6] $\beta*p*(1-p)$ for a dummy variable is computed as the discrete change in p as the variable changes from 0 to 1.

Table 3. Fixed Effect Regression (dependent variable = a_j*: location specific fixed effects)[a]

Variable	Coefficient	Standard error	t-ratio	pr.>|t|
intercept	7.013	1.460	4.80	<0.001
precipitation	0.013	0.005	2.38	0.021
heating	2.42×10^{-5}	1.10×10^{-4}	0.22	0.828
cooling	3.88×10^{-4}	1.14×10^{-4}	3.40	0.001
temperature difference	0.034	0.013	2.60	0.012
sunshine	-0.031	0.011	-2.71	0.009
wind speed	-0.020	0.047	-0.43	0.671
violent crime	0.857	3.31	0.26	0.797
coast	0.016	0.029	0.55	0.586
commute time	-0.065	0.027	-2.38	0.021
pmna	0.037	0.158	0.24	0.814
density	-8.61×10^{-4}	2.51×10^{-4}	-3.42	0.001
density squared	4.86×10^{-8}	2.61×10^{-8}	1.87	0.067
total population	1.68×10^{-7}	4.83×10^{-8}	3.48	0.001
income tax	-0.001	0.006	-0.18	0.855
total tax	-3.43×10^{-4}	2.04×10^{-4}	-1.68	0.099
education spending	0.008	0.010	0.81	0.422
highway spending	-0.029	0.045	-0.64	0.525
hospital spending	0.013	0.011	1.21	0.231
police spending	0.127	0.045	2.80	0.007
welfare spending	0.036	0.019	1.89	0.065
unemployment rate	0.042	0.016	2.64	0.011

a. number of observations: 78, R_{ADJ}^2: 0.807, F-statistic: 16.32

$$\Omega(Z, z_1) = \frac{p}{1-p} = e^{\sum_j \beta_j Z_j}. \tag{4}$$

The odds ratio for a one standard deviation (σ) increase in z_1 can then be expressed as

$$\frac{\Omega(Z, z_1 + \sigma)}{\Omega(Z, z_1)} = \frac{e^{\beta_1(Z_1+\sigma) + \sum_{j-1} \beta_j Z_j}}{e^{\beta_1 Z_1 + \sum_{j-1} \beta_j Z_j}} = \frac{e^{\beta_1 Z_1} e^{\beta_1 \sigma} e^{\sum_{j-1} \beta_j Z_j}}{e^{\beta_1 Z_1} e^{\sum_{j-1} \beta_j Z_j}} = e^{\beta_1 \sigma}. \tag{5}$$

That is, the odds ratio for a regressor is simply the product of the exponential of its corresponding coefficient estimate times the standard deviation of the variable.

The site-specific characteristics are measured at both the MSA of origin and destination. Forty-one of the 46 estimated coefficients in this category are significant at the 0.001 level. With few exceptions (e.g., *air quality*, *pmna*), all of the significant estimated coefficients have the anticipated signs. The odds ratios reported in Table 4 can be used to illustrate the strength of the findings. For example, a one standard deviation increase in an amenity such as per capita education spending at the destination MSA increases the odds of migrating by 19.2% while the same increase at the origin MSA lowers the odds of migrating by about 16.6%. For a disamenity such as travel time to work, a standard deviation increase in the average commuting time at the destination MSA lowers the odds of migrating by approximately 27.8%, while the same increase travel time at the origin MSA increases the odds of migrating by 110.6%.[7]

The four estimated coefficients for the measures of incomplete compensation are of the correct sign and they are significant at less than the 0.001 level. The

[7] A one standard deviation increase in *commute time* raises the average commute 17%.

odds ratios suggest that a standard deviation increase in *over-compensation* at the destination MSA makes the odds of migration 72.1% higher, while the same increase in *over*-compensation at the origin MSA lowers the odds of migration by 39.5%. Similarly, a standard deviation increase in *under*-compensation at the destination MSA lowers the odds of migration by 45.5%, while the same increase in *under-compensation* at the origin MSA increases the odds of migrating by 85.3%. Another method of evaluating the impact of incomplete compensation on the propensity to migrate is to consider the migration response that would have been expected in the absence of incomplete compensation. Column 4 of Table 4 shows the marginal probabilities used for these calculations. Recall that under-compensation at the origin and over-compensation at the destination are the measures that increase the probability of migrating. In the absence of under-compensation at the origin, the probability of migrating would fall by 3.8%. The probability of migrating would fall 4.7% without over-compensation at the destination. Overall, these results suggest that the probability of migrating would have been 8.5% lower without the combined average effects of under-compensation at the origin and over-compensation at the destination.

Table 4. Migration Equation (dependent variable: change MSA = 1, 0 otherwise)

Variable	**Coefficient**	**Z**	**pr.>|Z|**	**βp(1-p)**	**odds ratio**
age	-0.017	-18.39	<0.001	-0.002	0.837
education	0.166	43.09	<0.001	0.019	1.622
male	0.109	4.87	<0.001	0.012	1.052
married	0.044	1.93	0.054	0.005	1.022
children	-0.366	-17.33	<0.001	-0.042	0.833
black	-0.143	-4.60	<0.001	-0.016	0.953
Asian	0.170	4.36	<0.001	0.020	1.039
Hispanic	0.007	0.17	0.863	0.0008	1.002
other race	-0.011	-0.22	0.827	-0.0013	0.997
unemployed	0.029	0.39	0.693	0.003	1.004
median value$_d$	6.0^{-5}	14.81	<0.001	7.33×10^{-6}	25.07
median value$_o$	-7.0×10^{-5}	-16.17	<0.001	-7.59×10^{-6}	0.034
income tax$_d$	-0.0095	-3.54	<0.001	-0.001	0.878
income tax$_o$	0.0054	2.01	0.044	6.1×10^{-4}	1.076
total tax$_d$	-0.0019	-13.07	<0.001	-2.1×10^{-4}	0.418
total tax$_o$	0.0019	13.88	<0.001	2.2×10^{-4}	2.506
education spending$_d$	0.024	3.70	<0.001	0.0027	1.192
education spending$_o$	-0.025	-3.80	<0.001	-0.0028	0.834
highway spending$_d$	-0.033	-1.23	0.217	-0.0037	0.960
highway spending$_o$	-0.038	-1.39	0.164	-0.0044	0.954
hospital spending$_d$	0.078	11.35	<0.001	0.0089	1.373
hospital spending$_o$	-0.076	-10.69	<0.001	-0.0087	0.738
police spending$_d$	0.394	9.67	<0.001	0.045	1.681
police spending$_o$	-0.398	-10.17	<0.001	-0.045	0.587
welfare spending$_d$	0.106	7.12	<0.001	0.012	1.701
welfare spending$_o$	-0.105	-7.28	<0.001	-0.012	0.589
precipitation$_d$	0.047	10.56	<0.001	0.0053	1.900
precipitation$_o$	-0.051	-11.75	<0.001	-0.0057	0.503
heating$_d$	-1.0×10^{-5}	-0.21	0.838	-1.24×10^{-6}	0.977
heating$_o$	8.0×10^{-5}	1.41	0.158	8.97×10^{-6}	1.181
cooling$_d$	0.0014	13.08	<0.001	1.61×10^{-4}	3.988
cooling$_o$	-0.0015	-13.77	<0.001	-1.66×10^{-4}	0.247

Table 4 (continued). Migration Equation (dependent variable: change MSA = 1, 0 otherwise)[a]

Variable	Coefficient	Z	pr.>|Z|	βp(1-p)	odds ratio
temperature diff.	0.079	8.38	<0.001	0.009	2.690
temperature diff.	-0.108	-11.62	<0.001	-0.012	0.258
sunshine$_d$	-0.106	-10.80	<0.001	-0.012	0.372
sunshine$_o$	0.117	12.40	<0.001	0.013	2.925
wind speed$_d$	0.095	4.03	<0.001	0.011	1.135
wind speed$_o$	-0.029	-1.25	0.212	-0.003	0.961
violent crime$_d$	-11.461	-5.83	<0.001	-1.301[b]	0.888
violent crime$_o$	9.366	4.79	<0.001	1.064[b]	1.101
coast$_d$	0.102	7.74	<0.001	0.012	1.331
coast$_o$	-0.078	-5.85	<0.001	-0.009	0.802
commute time$_d$	-0.067	-3.34	0.001	-0.008	0.722
commute time$_o$	0.151	7.58	<0.001	0.017	2.106
pmna$_d$	1.668	18.40	<0.001	0.241	2.158
pmna$_o$	-1.382	-15.12	<0.001	-0.133	0.526
density$_d$	-0.0045	-18.58	<0.001	-5.1×10^{-4}	0.0001
density$_o$	0.0042	17.83	<0.001	4.7×10^{-4}	1.12×10^{4}
density squared$_d$	3.14×10^{-7}	16.89	<0.001	3.56×10^{-8}	380.474
density squared$_o$	-2.88×10^{-7}	-15.75	<0.001	-3.28×10^{-8}	0.0036
total population$_d$	3.13×10^{-7}	7.60	<0.001	3.56×10^{-8}	2.679
total population$_o$	-4.86×10^{-7}	-12.07	<0.001	-5.51×10^{-8}	0.212
overcomp.$_d$	4.163	14.73	<0.001	0.473	1.721
overcomp.$_o$	-3.919	-14.22	<0.001	-0.445	0.605
undercomp.$_d$	-3.296	-12.58	<0.001	-0.374	0.545
undercomp.$_o$	3.346	13.48	<0.001	0.380	1.853

a. number of obs: 99,955; CHMSA=1: 15,724; CHMSA=0: 84,231; log likelihood: -38812 (0.497). Descriptive statistics for personal variables [mean, std. dev.]: *age [37.73,10.18]; education [13.78,2.92]; male [0.68,0.47]; married [0.51,0.50]; children [0.50,0.50]; black [0.13,0.34]; asian [0.05,0.23]; hispanic [0.14,0.35]; other race [0.07,0.26]; unemployed [0.02,0.13].*

b. The absolute values of marginal probabilities cannot be greater than 1. Note that the 95% confidence intervals for these marginal probabilities contain -1 and 1 respectively.

Next, we examine temporal changes in the migration propensity with respect to our measures of incomplete compensation. Table 5 shows the odds ratios for the two time periods. Two results are apparent from this comparison: First, the overall ordinal pattern of the effects of incomplete compensation is the same for 2000 as for 1990. Over-compensation at the destination and under-compensation at the origin are stronger than over-compensation at the origin and under-compensation at the destination. That is, for mobile households, the pull of over-compensation at the destination and the push of under-compensation at the origin exceed the holding power of over-compensation at the origin and the repulsion of under-compensation at the destination. Second, households appeared to be more responsive to incomplete compensation during the 1990s than during the 1980s. A standard deviation increase in over-compensation at the destination MSA made migration 40.9% more likely in 1990 but 72.1% more likely in 2000. This finding suggests that the pull of over-compensation has strengthened for these cities. Similarly, a standard deviation increase in over-compensation at the origin MSA lowered the odds of migration by 21.6% in 1990 but by 39.5% in 2000, which implies stronger holding power of the origin MSAs. Similar comparisons show greater responsiveness in 2000 to under-compensation at both the origin and destination MSAs. These results provide preliminary evidence that, for a one standard deviation change in the incomplete compensation measures, the tendencies toward equilibrium found in 1990 appear to have strengthened in 2000[8].

Table 5. Comparison of Odds Ratios for Incomplete Compensation Variables (1990 v. 2000)

Incomplete Compensation Variable	Odds Ratios (1990)	Odds Ratios (2000)
$overcomp_d$	1.409	1.721
$overcomp_o$	0.784	0.605
$undercomp_d$	0.576	0.545
$undercomp_o$	1.470	1.853

Finally, in Table 6, we turn to a temporal and spatial comparison of the incomplete compensation measures. Recall that 78 metropolitan areas were used to derive the second stage residuals that are the measures of incomplete compensation. For this sample of cities, there is a slight tendency of patterns from 1990 to persist in 2000. Specifically, 34.6% of those MSAs that over-compensated in wages in 1990 also over-compensated in 2000, and 21.8% of those that under-compensated in 1990 were also under-compensating in 2000. However, these results imply that the remaining 43.6% showed signs in 2000 that were opposite those of 1990. Across the four regions, there are two noteworthy spatial differences in incomplete compensation. In 2000, Northeastern MSAs comprised 19.2% of the sample, but made up only 2.8% of the under-compensating MSAs. And, Midwestern MSAs were 17.9% of the sample in 1990, but were 28% of the sample that overcompensated in that year.

While measures of incomplete compensation from 1990 and 2000 are centered on zero since they represent residuals from the Stage 2 regression[9], the variance differs by more than a factor of 10. That is, the standard deviation from 1990 sub-sample is 3.17, and is only 0.27 for the 2000 sample. Not surprisingly, a measure of equivalence of variance reveals that these are significantly different at the 99% degree of confidence[10]. There are several possible explanations for these differences. First, it is possible that the earlier residuals were higher since they were derived from a more complete sample of cities (i.e., 267 vs. 78). In fact, the in-sample fit for the Stage 2 regression is stronger in 2000 (R^2_{adj}=0.81) when compared to 1990 (R^2_{adj}=0.72). When the second stage regression for the 1990 sample was estimated on the 78 cities available from the 2000 PUMS sample, the R^2_{adj} increased to 0.75. In addition, it is possible that the better fit also reflects the increasing importance of site-specific amenities and fiscal characteristics on the locational choice, which has subsequently led to smaller residuals in the Stage 2 regression.

5. Conclusion

Our results from the 2000 PUMS yield further evidence that measures of incomplete compensation for site characteristics are significant determinants of migration. Each stage of the three stage empirical model generates results that are remarkably consistent with Clark et al. (2003), which used 1990 data from the PUMS. However, there are a few differences. In the second stage, the site characteristics explain slightly more variation in the wage in 2000 as compared with 1990. In the third stage, a comparison of the odds ratios reveals a stronger migration response to incomplete compensation in the latter period, even as the mean level of incomplete compensation appears to have fallen.

These findings have important implications for our understanding of migration behavior. First, we continue to find that measures which capture disequilibrium in amenity markets, that is, our incomplete compensation variables, are significant determinants of migration. The results presented here add to the evidence that migrants are cognizant of the "utility deal" offered by cities that over- or under-compensate for their local amenity and fiscal mix. Secondly, equilibrium drivers such as amenities are important factors in the migration decision. In fact, these factors appear to explain more of the differences in real wages over time. With the advent of the Internet, information about any given community is readily available and at

[8] However, these comparisons must be qualified given that the size distribution of metropolitan areas differs between the two periods. Because the average size of the metropolitan areas is substantially larger in 2000 relative to 1990, the higher responsiveness may indicate that the pull of new locations and the holding power of existing locations are stronger in larger metropolitan areas.

[9] Note that the mean of 1990 sample will not be equal to zero. The residuals are derived from a subset of 78 MSAs drawn from the larger set of 267 MSAs that were available in 1990, and hence included in the second stage regression. The mean value of the 78 residuals from the 1990 regression was –0.0214.

[10] The Bartlett test, which is a χ^2 with one degree of freedom is 274.08. This tests the null hypothesis that the subgroup variances of each year are equal, and assumes normally distributed variables.

Table 6. Under-compensation and Over-compensation in 1990 and 2000

	Over-compensation 2000	**Under-compensation 2000**
Over-compensation 1990	*27 MSA's (34.6%)* *NE: 6; MW: 6; South: 9; West: 6* Akron, OH - Midwest Albuquerque, NM - West Atlanta, GA - South Baltimore, MD - South Buffalo, NY - Northeast Cleveland, OH - Northeast Dallas, TX - South Ft. Wayne, IN - Midwest Houston, TX - South Indianapolis, IN - Midwest Knoxville, TN - South Lakeland, FL - South Los Angeles, CA - West Louisville, KY - South Milwaukee, WI - Midwest Monmouth, NJ - Northeast Norfolk, VA - South Philadelphia, PA - Northeast Pittsburgh, PA - Northeast Riverside, CA - West San Diego, CA - West Spokane, WA - West Syracuse, NY - Northeast Tacoma, WA - West Tampa, FL - South Toledo, OH - Midwest Wichita, KS – Midwest	*16 MSA's (20.5%)* *NE: 0; MW: 6; South: 7; West: 3* Canton, OH - Midwest Charlotte, NC - South Chicago, IL - Midwest Cincinnati, OH - Midwest Columbus, OH - Midwest Detroit, MI - Midwest Greensboro, NC - South Kansas City, MO - South Nashville, TN - South New Orleans, LA - South Pensacola, FL - South Portland, OR - West St. Louis, MO - South Seattle, WA - West Tucson, AZ - West Youngstown, OH - Midwest
Under-compensation 1990	*18 MSA's (23.1%)* *NE: 7; MW: 0; South: 6; West: 5* Allentown, PA - Northeast Bakersfield, CA - West Boise City, ID – West Columbia, SC - South Ft. Lauderdale, FL - South Harrisburg, PA - Northeast Hartford, CT - Northeast Lancaster, PA - Northeast Little Rock, AR - South Melbourne, FL - South Modesto, CA - West New York, NY - Northeast Orlando, FL - South Providence, RI - Northeast Salt Lake City, UT - West San Antonio, TX - South Springfield, MA - Northeast Stockton, CA – West	*17 MSA's (21.8%)* *NE: 2; MW: 2; South: 8; West: 5* Austin, TX - South Baton Rouge, LA - South Boston, MA - Northeast Charleston, SC - South Fresno, CA - West Grand Rapids, MI - Midwest Jackson, MS - South Las Vegas, NV - West McAllen, TX - South Minneapolis, MN - Midwest Phoenix, AZ - West San Francisco, CA - West San Jose, CA - West Sarasota, FL - South Scranton, PA - Northeast Washington, DC - South West Palm Beach, FL - South

relatively low cost. Thus, as the baby-boom generation ages and accumulates wealth, the demand for site specific attributes is expected to increase. The strengthening of this migration response suggests an ongoing improvement in the interregional efficiency of labor markets in the U.S.

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References

Berger, M. C. and G.C. Blomquist. 1992. Mobility and destination in migration decisions: The roles of earnings, quality of life, and housing prices. *Journal of Housing Economics* 2: 37-59.

Blomquist, G. C., M.C. Berger, and J.P. Hoehn. 1988. New estimates of quality of life in urban areas. *American Economic Review* 78: 89-107.

Clark, D.E. 2006. Amenity valuation, incomplete compensation and migration. In: *Environmental Valuation: Interregional and Intraregional Perspectives*, John Carruthers and William Mundy eds. Burlington: Ashgate Publishing.

Clark, D. E., W.E. Herrin, T.A. Knapp, and N.E. White. 2003. Migration and implicit amenity markets: Does incomplete compensation matter? *Journal of Economic Geography* 3: 289-307.

Clark, D. E. and W.J. Hunter. 1992. The impact of economic opportunity, amenities and fiscal factors on age-specific migration rates. *Journal of Regional Science* 32: 349-365.

Evans, A.W. 1990. The assumption of equilibrium in the analysis of migration and interregional differences: A review of some recent research. *Journal of Regional Science* 30(4): 515-532.

Gabriel, S.A. and S.S. Rosenthal. 1999. Location and the effect of demographic traits on earnings. *Regional Science and Urban Economics* 29: 445-461.

Graves, P. E. 1979. A life-cycle empirical analysis of migration and climate, by race. *Journal of Urban Economics* 6: 135-147.

Graves, P. E. and P. Linneman. 1979. Household migration: Theoretical and empirical results. *Journal of Urban Economics* 6: 383-404.

Greenwood, M. J., G.L. Hunt, D.S. Rickman, and G.I. Treyz. 1991. Migration, regional equilibrium, and the estimation of compensating differentials." *American Economic Review* 81: 1382-1390.

Greenwood, M. J. 1985. Human migration: Theory, models and empirical studies. *Journal of Regional Science* 25: 521-544.

Greenwood, M. J. and G.L. Hunt. 1989. Jobs versus amenities in the analysis of metropolitan migration. *Journal of Urban Economics* 25: 1–16.

Henderson, J. V. 1982. Evaluating consumer amenities and interregional welfare differences. *Journal of Urban Economics* 11: 32-59.

Herzog, H. W. and A.M. Schlottmann. 1993. Valuing amenities and disamenities of urban scale: Can bigger be better? *Journal of Regional Science* 33: 145-165.

Hunt, G. 1993. Equilibrium and disequilibrium in migration modelling. *Regional Studies* 27: 341-349.

Knapp, T. A. and P.E. Graves. 1989. On the role of amenities in models of migration and regional development. *Journal of Regional Science* 29: 71-87.

Mueser, P.R. and P.E. Graves. 1995. Examining the role of economic opportunity and amenities in Explanning population redistribution. *Journal of Urban Economics* 37: 176-200.

Rosen, S. 1979. Wage-based indexes of urban quality of life. In: *Current Issues in Urban Economics*. P. Mieszkowski and M. Straszheim eds. Baltimore: Johns Hopkins University.

Roback, J. 1982. Wages, rents, and the quality of life. *Journal of Political Economy* 90: 1257-1278.

Roback, J. 1988. Wages, rents, and amenities: Differences among workers and regions. *Economic Inquiry* 26: 23-41.

Topel, R. H. 1986. Local labor markets. *Journal of Political Economy*. 94: s111-s143.