AN EXPLICITLY EXPECTATION-BASED APPROACH TO THE STUDY OF INTERCITY MIGRATION

Dae Soo Lee, State University of New York at Farmingdale
Warren C. Sanderson, State University of New York at Stony Brook

ABSTRACT

This paper explores the possibility that explicitly expectation-based variables can help in explaining intercity migration. Using a (forward-looking) financial market variable, stock prices, we examine whether explicitly expectation-based measures are useful in understanding migration flows when added to the more conventional realization-based ones. A conditional multinomial logit model is applied to the 5% Public Use Microdata Samples of the U.S. Census (1990). We compute the SMSA-specific composite stock price indices based on the SMSA's industry composition and each industry's composite stock price index. The estimation results strongly support our explicitly expectation-based approach, providing the way to incorporate financial markets into the migration studies. ***JEL classifications***: C35, J61, R23

INTRODUCTION

The economic approach to understanding intercity[1] migration is one where the potential migrants compare expected utilities of staying in their place of origin with expected utilities of living elsewhere and the utility cost of moving.[2] However, it is difficult to operationalize and test this theory, because we do not have data on what people expect. Hence, the conventional approach is to argue (explicitly or implicitly) that expectations are determined by a linear combination of observable variables. A problem with this procedure is that these observable variables are very imperfect proxies for people's expectations.

For example, suppose United Airlines pays high wages. The current high wage of United Airlines employees does not indicate that the expected utility of those employees is high, if we consider that the airline industry has reduced its employment since September 11, 2001. Furthermore, United Airlines, which has experienced a period of bankruptcy, has renegotiated many labor contracts. The relatively high wage of United employees may be high solely to compensate employees for the above-average risk of near-term employment. Expectations are relevant to understanding migration decisions and could be based on heuristic rules-of-thumbs that are difficult to specify.

One way around the difficulties involved in making strong assumptions about the relationship between observations and expectations is to use explicitly expectation-based variables. Of course, there are no data on the expectations of potential migrants, but there are variables that measure the expected financial health of industries that are concentrated in certain regions. The most obvious of these is stock prices. If economic activity were homogeneous across cities, we would not expect that stock prices would be correlated with intercity movements. But economic activities are not geographically homogeneous.[3] So, it is possible that expectations for the profitability of a city's main employers are also correlated with expectations of the future well-being of potential migrants.

This approach has its own difficulties. Expectations about future profitability, as reflected in stock prices, may or may not be closely correlated with the expectations of potential migrants. Stock prices often fluctuate with other information (such as court decisions[4]) which does not link to firm's production and employment. Migration decisions are based on expectations, which in turn are influenced by many factors that are not visible to the researchers. The question is whether realization-alone based measures incorporate all the relevant information about expectation formulation or whether there remains information in explicitly expectation-based measures that can be exploited.

In this paper, we propose and test the hypothesis that explicitly expectation-based measures are useful in understanding migration flows when added to the more conventional realization-based ones. We do this by estimating two models, one with only realization-based measures and another with both realization-based measures and an explicitly expectation-based measure, stock prices.

The remainder of this paper is organized in the following way. The second section briefly reviews the intercity migration literature. It emphasizes the need for explicitly expectation-based variables and proposes the tentative hypothesis that forward-looking financial variables can contain information correlated with intercity population movements. The third section provides the empirical model. It is a conditional mutinomial logit model[5] that employs 98 alternative choices (one origin SMSA and ninety seven destination SMSAs[6]) in terms of a potential migrant's SMSA residence. The microdata set upon which our empirical work is based is the *5% Public Use Micro Data Sample* derived from the1990 census.[7] The fourth section deals with the creation of the SMSA-specific composite stock price indices. This section shows how to generate the SMSA-specific composite stock prices data, and discuses identification issues. The fifth section analyzes the empirical results and shows that changes in location-specific stock price indices do indeed contain information relevant for understanding intercity migration. The last section summarizes the analytical issues and suggests further studies in this area.

REVIEW OF THE LITERATURE AND HYPOTHESIS

Although there has been no research on employing explicitly expectation-based variables for explaining migration decisions, some earlier literature has implicitly emphasized the necessity for them by utilizing proxies. In the first subsection, we discuss the previous migration studies concerning this issue. Based upon the previous studies, the second subsection suggests our tentative hypothesis.

Review of Previous Studies

Blanco (1964) proposed prospective unemployment as a new migration determinant to test her theory concerning state outmigration rates. Prospective unemployment was defined as the annual rate of change in unemployment which would be expected to occur if workers were not able to migrate between states. It was measured by the difference between the actual rate of change of employment and the natural rate of increase of the working-age population in each state. The paper showed that the change in the level of prospective unemployment was the most important determinant of interstate migration.

Mazek (1969) formulated a job vacancy model and used the term, potential unemployment, as a proxy for job openings. Potential unemployment was defined as the unemployment rate which would exist in a region at the end of the period studied if no in- or out-migration took place during the period. Using 1955-60 inmigration rates for 47 SMSAs, his results supported the importance of potential unemployment on migration. They did not support the importance of income differences.

Olvey (1972) used 1960 census data to analyze the effects of migration determinants, such as wage levels and employment growth (1955-60), on migration. His conclusion was that both long- and short-distance immigrants were more strongly influenced by employment growth than by wage differences or climate (regional amenities).

Greenwood (1975b) added variables such as income growth (1949-59, 1959-69) and employment growth (1950-60, 1960-70) to other migration determinants to explain the migration behavior for the time period of 1955-60 and 1965-70, and corrected for the simultaneity bias in migration models. His finding was that both income growth and employment growth in origin SMSAs had strong negative relationships to outmigration to other SMSAs, whereas they had strong positive relationships to inmigration from other SMSA's.

Stark (1984) and Stark et al. (1989, 1985) developed a theory of relative deprivation on migration by considering the psychic cost of income differences and the income distribution within the reference group. The individual deprivation was an increasing function of the mean excess income as well as the percentage of the persons richer than the individual.[8] Using a proxy for relative deprivation[9] for rural Mexican households that included the information on Mexico-United States migration, Stark et al. (1989) tested the relative deprivation approach. Their findings showed a strong positive correlation between migration propensity and relative deprivation.

More recently, Greenwood et al. (1993) devised the terms, relative employment opportunities (REO), relative wage rate (RWR), and relative wage mix (RWM) in explaining migration.[10] Their empirical results suggested that migration responded to the three economic opportunity variables, although the time patterns of migration responses were different across each of those variables.

These variables, *prospective unemployment* (Blanco), *potential unemployment* (Mazek), *employment growth* (Olvey), *income growth* and *employment growth* (Greenwood), *relative deprivation* (Stark et al.), *REO*, *RWR*, and *RWM* (Greenwood et al.) are not explicitly expectation-based. Certainly expectations can be based on these variables, but their values are not based on expectations of the future.

The Hypothesis

We would expect there to be a positive relation between the probability of migration between particular SMSAs and an appropriately-defined measure of relative changes[11] in SMSA-specific indices of sectoral stock prices if:(i) there is enough differentiation in the sectoral composition of economic activity across SMSAs at each point of time, and (ii) there is enough temporal differentiation in the sectoral economic activity in the nation to produce meaningful relative (temporal) variations in the SMSA-specific indices, and (iii) the relative changes over time in the SMSA-specific indices are correlated with expectations of future well-being in those SMSAs.

Conditions (i) and (ii) are clearly true. For example, economic activity in Las Vegas is heavily weighted toward the gaming, entertainment, and hotel sectors. Chicago, on the other hand, has a very well-balanced mixed of industries. A comparison of stock price indices produced using the Las Vegas and Chicago mix of industries has shown quite different patterns of change.[12]

Stock prices reflect expectations of future business conditions. It is possible that migrants' expectations of their future living conditions are correlated with stock prices, since both are presumably rational and based on similar information sets that are commonly available to both businesses and migrants.[13] Hence, condition (iii) might be true, and would certainly be an interesting hypothesis to test.

EMPIRICAL MODEL

Our conditional multinomial logit model described in this section is based on Falaris' (1987) application of Lee's (1983) generalized polychotomous choice model with selectivity. We follow Falaris' 5 equation model to specify a random utility function and a wage (or predicted earnings) equation that are used to determine the migration probabilities for each individual.

The only two differences between Falaris' model and our application are as follows. First, Falaris used a nested logit model, whereas our studies is not nested, because we do not consider a hierarchy of locations. Second, in Falaris (1987), the number of wage equations is equal to the number of regions so that the estimated coefficients for each are different across regions. Here, we use a single wage equation to reduce the computational burden, but include SMSA per capita income variable in order to capture important SMSA-specific economic characteristics.[14]

For the conventional approach, we follow Falaris. Our augmented approach simply adds a forward-looking variable, stock prices, to the random utility function.

The Conventional Approach

The utility of a person *I* in the period from *t* to *t+1*, who initially lives in city *i* and who migrates instantaneously to city *j* (j = 1,2,…,n) is given by

$$\begin{aligned} U_{Ij} &= [X'_{Ij}\beta - I(i,j)\cdot Z'_{Ij}\gamma] + e_{Ij} \\ &= K^{1'}_{Ij}\delta + e_{Ij} \end{aligned} \tag{1}$$

where X_{Ij} is vector of variables (that include predicted earnings) for the expected benefit obtained by individual *I*, if *I* were to reside in city *j* in the interval [t, t+1]. Z_{Ij} is vector of variables for the direct and indirect cost incurred by individual *I* in moving from city *i* to city *j* between *t* and *t*+1. $K^{1}_{Ij} \supseteq (X_{Ij}, Z_{Ij})$, and $\delta \supseteq (\beta, \gamma)$. e_{Ij} is the disturbance term that is known to *I*, but not known to the researcher. e_{Ij} is assumed to be *i.i.d. and Gumbel-distributed.*[15] *I(i, j)* is an indicator function such that *I(i,j)*) = 1 if $i \neq j$ (or if he moves), 0 otherwise (or if he does not move). The criterion for migration is that individual *I* moves to city *k* if $U_{Ik} > \max U_{Ij}$ (for *j* = 1,2,3,…, N & $j \neq k$)

The wage equation that predicts individual *I*'s (predicted) earnings in city *j* is specified as

$$ln(y_j) = \alpha_0 + \alpha_1 \cdot sch + \alpha_2 \cdot jexp + \alpha_3 \cdot race + \alpha_4 \cdot sex + \alpha_5 \cdot ln(CY_j) + u_{Ij,} \tag{2}$$

where $u_{Ij} \sim N(0, \sigma_u^2)$. The variable *sch* is individual *I*'s complete schooling years. The variable *jexp*, which equals (*age – sch – 5*),[16] is individual *I*'s job experience. *race* =1 for white, 0 otherwise. *sex* = 1 for man, 0 otherwise. CY_j is per capita money income[17] of city *j* as a proxy for city *j*'s economic activity. Note that this is a censored regression in that we observe y_j only if this individual chooses city *j*. As they are self-selected,[18] it is assumed that e_{Ij} and u_{Ij} are correlated.

Let the migration probability for individual *I* for city *j* be denoted by P_{Ij}. Then, it is specified as

$$P_{Ij} = \frac{e^{K_{Ij}^{1\prime}\delta}}{\sum_{j=1}^{n} e^{K_{Ij}^{1\prime}\delta}} \qquad with \quad \sum_{j=1}^{n} P_{Ij} = 1 \tag{3}$$

where n = 98 (one origin and ninety seven destinations).

Note the disturbance term structure for the random utility function and wage equation together with self-selection scheme. In order to consistently estimate our parameter, we need to respecify the wage equation as

$$ln(y_j) = \alpha_0 + \alpha_1 \cdot sch + \alpha_2 \cdot jexp + \alpha_3 \cdot race + \alpha_4 \cdot sex + \alpha_5 \cdot ln(CY_j) + \sigma\rho \cdot [-\Psi(\Phi^{-1}(P_{Ij}))/P_{Ij}] + uu_{Ij}, \tag{4}$$

where σ is the standard deviation of u, ρ is the correlation coefficient between e_{Ij} and u_{Ij}, Ψ is the probability density function of the standard normal distribution, and Φ^{-1} is the inverse of the cumulative density function of the standard normal distribution. Hence, following Falaris (1987), a two-stage estimation method[19] is applied to get the parameter estimates.

The Augmented Approach

By adding the forward looking variable, stock price indices in equation (1), the random utility for individual *I* for city *j* is specified as

$$\begin{aligned} U_{Ij} &= [X_{Ij}'\beta + \lambda \cdot SP_j - (i,j) \cdot Z_{Ij}'\gamma] + e_{Ij}^2 \\ &= K_{Ij}^{2\prime}\tau + e_{Ij}^2 \end{aligned} \tag{5}$$

where SP_j represents the SMSA *j*-specific composite stock price index. $K_{Ij}^2 \supseteq (X_{Ij}, Z_{Ij}, SP_j)$, $\tau \supseteq (\beta, \gamma, \lambda)$, and e_{Ij}^2 is the disturbance term that is known to *I*, but not known to the researcher. The disturbance term e_{Ij}^2 is also assumed to be *i.i.d. and Gumbel-distributed*.

Following the same step, we denote the migration probability P_{Ij} as

$$P_{Ij} = \frac{e^{K_{Ij}^{2\prime}\tau}}{\sum_{j=1}^{n} e^{K_{Ij}^{2\prime}\tau}} \qquad with \quad \sum_{j=1}^{n} P_{Ij} = 1 \tag{6}$$

where n=98.

All other processes are the same as in conventional approach. Hence, equation (3) measures the migration probability for conventional approach, whereas equation (6) measures the migration probability for the augmented approach.

By representing the vector of variables, equation (5) will be as follows.

$$U_{Ij} = [X'_{Ij}\beta + \lambda \cdot SP_j - (i,j) \cdot Z'_{Ij}\gamma] + e^2_{Ij} = K^{2\prime}_{Ij}\tau + e^2_{Ij}$$
$$= [\ \beta_1 \cdot ln(y_j) + \beta_2 \cdot ln(N_j) + \beta_3 \cdot ln(Un_j) + \beta_4 \cdot ln(G_j) + \beta_5 \cdot ln(Tax_j) + \beta_6 \cdot ln(Temp_j) + \beta_7 \cdot ln(Empg_j)]$$
$$+ [\lambda \cdot ln(SP_j)] + I(i,j)\ \ [\gamma_0 + \gamma_1 \cdot ln(Dist_{ij}) + \gamma_2 \cdot ln(sch) + \gamma_3 \cdot ln(age) + \gamma_4 \cdot sex + \gamma_5 \cdot race + \gamma_6 \cdot mar$$
$$+ \gamma_7 \cdot kid + \gamma_8 \cdot own\ ] + e^2_{Ij} \tag{7}$$

Hence, equation (1) for the conventional approach does not include SP_j, so that there exists no coefficient λ. Table 1 provides a description of the vector of variables in equation (7), together with their data sources, whereas Table 2 presents the expected signs of our parameter estimates.

Table 1
DESCRIPTION OF THE VARIABLES AND DATA SOURCES

Category	Variable	Description	Data Source
		Ind_I – $City_j$ Variables	
X_{Ij}	y_j	Predicted annual earnings (wage)	See equation (2) and footnote 16.
Z_{Ij}	$Dist_{ij}$	Distance between city i and city j	*Rand McNally*'s *Standard Highway Mileage Guide* (1970, 1985)
		$City_j$'s Variables	
X_{Ij}	N_j	Population size	*Statistical Abstarct of the U.S.* (1985)
X_{Ij}	UN_j	Unemployment rate	*County and City Data Book* (1988) *State and Metro. Area Data Book* (86)
X_{Ij}	G_j	per capita government spending	*County and City Data Book* (1988)
X_{Ij}	Tax_j	per capita tax	*County and City Data Book* (1988)
X_{Ij}	$Temp_j$	yearly mean temperature	*County and City Data Book* (1988) *Statistical Abstarct of the U.S.* (1990)
X_{Ij}	$Empg_j$	employment growth rate (1980–85)	*Employment, Hours, and Earnings, State and Area* 1972–1987 (1989)
-	SP_j	composite stock price index	See below
		Ind_I's Variables	
Z_{Ij}	*sch*	completed schooling years	*5% PUMS* (1990)
Z_{Ij}	*age*	age	*5% PUMS* (1990)
Z_{Ij}	*race*	1 for white, 0 for others	*5% PUMS* (1990)
Z_{Ij}	*sex*	1 for man, 0 for woman	*5% PUMS* (1990)
Z_{Ij}	*mar*	1 for marriage, 0 for single	*5% PUMS* (1990)
Z_{Ij}	*kid*	number of children	*5% PUMS* (1990)
Z_{Ij}	*own*	1 for home owner, 0 otherwise	*5% PUMS* (1990)

Note: 1. *Ind* = individual
2. Except for SP_j, city *j's* variable take the 1985–1986 values that match migration decision period. For SP_j, see the fourth section (Creation of Composite Stock Price Indices for SMSA).
3. Except for *age* and *jexp [age-sch-5]*, individual *I's* variables take the 1989 values, since they are obtained from *PUMS* 1990.
4. *County and City Data Book, State and Metropolitan Area Data Book, PUMS,* and *Statistical Abstract of the United States* are from Bureau of the Census, Department of Commerce.
5. *Employment, Hours, and Earnings; State and Areas 1972-1987* (Mar. 1989) is from Bureau of Labor Statistics, Department of Labor.

Table 2
THE EXPECTED SIGNS OF PARAMETER ESTIMATE

Predicted Earnings Function Parameter	Sign	Utility Function Parameter	Sign
α_0 (Constant)	?	β_1 (Earnings)	+
α_1 (Schooling)	+	β_2 (City Size)	+
α_2 (Job Experience)	+	β_3 (Unemployment Rate)	−
α_3 (Race; White)	+	β_4 (Government Spending)	+
α_4 (Sex; Man)	+	β_5 (Tax Rate)	−
α_5 (Economic Activity)	+	β_6 (Mean Temperature)	+
		β_7 (Employment Growth Rate)	+
		γ_0 (Constant)	−
		γ_1 (Distance)	−
		γ_2 (Schooling Years)	+
		γ_3 (Age)	−
		γ_4 (Sex; Man)	+
		γ_5 (Race; White)	+
		γ_6 (Marriage; Dummy)	−
		γ_7 (Number of Children)	−
		γ_8 (Home Ownership; Dummy)	−
		λ (SMSA Composite Stock Price)	+

CREATION OF COMPOSITE STOCK PRICE INDICES FOR SMSA

Stock prices are influenced by expected future profits and, therefore, are appropriate for testing the hypothesis that there is additional information in this kind of explicitly forward-looking variable, even when traditional factors are taken into account.

First subsection discusses the methodology used in producing the SMSA-specific stock price indices. The possibility of migration causing changes in the SMSA-specific indices is addressed in the second subsection.

Stock Price Creation Method

In creating SMSA-specific stock price indices, two types of data we need are: (1) the industry-specific composite stock price index[20] whose computing method is analogous to the method of computing *the Laspeyre's Consumer Price Index*, and (2) the employment share[21] of each industry in each SMSA.

Each city's (SMSA's) composite stock price is derived from a weighted average of each industry's (nation-wide) composite stock price where the weights are employment shares in the city. Suppose city *j* has *J* industries, and among *J*, we observe[22] total K number of industry-specific composite stock prices ($K \subset J$). Suppose further that industry k has M_k representative firms[23] (k=1, 2, … , K).

Then, for city j, the composite stock price formula at year t is specified as

$$SP_{Jt} = \sum_{k=1}^{K} R_{kt}^{j} \cdot CINP_{kt} \tag{8}$$

where

$$R_{kt}^{j} = \frac{emp_{kt}^{j}}{\sum_{k=1}^{K} emp_{kt}^{j}}, and\ \ CINP_{kt} = \frac{\sum_{f=1}^{M_k} p_{ft}^{k} \cdot q_{ft}^{k}}{\sum_{f=1}^{M_k} p_{f0}^{k} \cdot q_{f0}^{k}}$$

Here emp_{kt}^{j} is the *k-th* industry's employment in city j, p_{ft}^{k} the stock price of firm f in the *k-th* industry at year t, q_{ft}^{k} the outstanding shares of of firm f in the *k-th* industry at year t, p_{f0}^{k} the stock price of firm f in the *k-th* industry at the base year, and q_{f0}^{k} the outstanding shares of firm f in the *k-th* industry at the base year. $CINP_{kt}$ is the ratio of the aggregate value of equity in the representative firms in the *k-th* industry in year t to the same value in the base year. From Census data, we can only observe migration from 1985 to 1990. In computing the SMSA-specific stock price indices, we use information about changes between 1984 and 1989, because this is the period in which migration decisions would have been made.

The main source of data for the SMSA-specific composite stock price is the *Standard & Poor's Security Price Index Record* (1992), which contains industry-specific composite stock prices ($CINP_{kt}$), and *PUMS* which contains the information on each individual's industry category as well as his SMSA residence. As *S & P's* security price index doesn't cover all of the industry-specific composite stock prices, missing values[24] are computed by the data from *Moody's Handbook of Common Stocks* (1993).

Table 3 shows both the industry-specific composite stock price indices and SMSA-specific composite stock price indices based on equation (8) together with the names of the selected 98 SMSAs.

Table 3
INDUSTRY- & SMSA-SPECIFIC COMPOSITE STOCK PRICE

R.	Industry	Census Code	SIC Code	$CINP_k$	R.	SMSA	SP_j
1	Broadcast Media	440	483-484	4.3226	1	Las Vegas, NV	2.476
2	Tobacco	130	210	4.0427	2	Reno, NV	2.392
3	Food Store	601-611	541-549	3.8735	3	Greensboro, NC	2.347
4	Entertainment	800-810	781-799	3.8087	4	Orlando, FL	2.266
5	Food	100-121	201-206, 209	3.7149	5	Charlotte, NC	2.244
6	Alcohol	120	208	3.3620	6	Eugene, OR	2.233
7	Glass	250	321	3.2775	7	El Paso, TX	2.228
8	Soft Drink	120	208	3.2519	8	Fresno, CA	2.226
9	Drug	181	283	3.1086	9	Sioux Fall, SD	2.209
10	Textile	132-152	225-239	2.8768	10	Billings, MT	2.205
11	Department Store	591	531	2.7837	11	Richmond, VA	2.190

12	Hotel and Motel	762	701	2.7133	12	Grand Rapid, MI	2.190
13	Paperboard Container	161	265	2.6316	13	Knoxville, TN	2.180
14	Soap and Cosmetics	182	284	2.5850	14	Madison, WI	2.178
15	Furniture	242	250	2.5230	15	Louisville, KY	2.174
16	Chemical	180-191	282-287	2.5168	16	Cincinnati, OH	2.170
17	Shoe Store	630	566	2.5145	17	Nashville, TN	2.165
18	Health Care	812-840	807, 809	2.4162	18	Toledo, OH	2.163
19	Telephone and Telg.	441-442	481-489	2.3790	19	Buffalo, NY	2.157
20	Airline	421	450	2.3697	20	Tampa, FL	2.155
21	Other Publishing	172	272-279	2.3674	21	Montgomery, AL	2.153
22	Computer Service	732	737	2.2348	22	Charleston, WV	2.152
23	Chemical Industrial	192	281-289	2.2104	23	San Antonio, TX	2.148
24	General Merchandise	600	539	2.1406	24	Memphis, TN	2.148
25	Restaurant	641	580	2.1303	25	Spokane, WA	2.145
26	Metal Misc.	300-301	347, 349	2.0970	26	Jacksonville, FL	2.142
27	Paper and Pulp	160-161	261-267	2.0650	27	Fargo, ND	2.138
28	Lumber and Wood	230-241	241-249	2.0650	28	Salt Lake City, UT	2.138
29	Credit Agencies	702	610	1.9737	29	Springfield, MA	2.137
30	S. and C. Union	701	603-606	1.9545	30	Miami, FL	2.135
31	Railroad Equipment	361	374	1.9458	31	Baton Rouge, LA	2.131
32	Railway	400	401	1.9458	32	Atlanta, GA	2.130
33	Aluminum	272	333	1.8926	33	Akron, OH	2.121
34	Newspaper Publishing	171	271	1.8898	34	St. Louis, MO	2.120
35	Automobile	351	371	1.8882	35	Boise, ID	2.119
36	Drug Store	642	591	1.8620	36	New York, NY	2.119
37	Life Insurance	711	630-640	1.8250	37	Columbus, OH	2.119
38	Banking	700	601-602	1.8192	38	Kansas City, MO	2.117
39	Insurance (Property*)	711	630-640	1.7998	39	San Francisco, CA	2.116
40	Metal Product	282-292	341-348	1.7855	40	Albany, NY	2.116
41	Household Appliances	340	363	1.7360	41	Denver, CO	2.114
42	Mining	40	100	1.6727	42	Newark, NJ	2.112
43	Pipeline	422	460	1.6623	43	Des Moines, IO	2.112
44	Gas and Steam Supply	451-452	492-496	1.6623	44	Tucson, AZ	2.112
45	Electrical Equipment	342	361-369	1.6531	45	Los Angeles, CA	2.105
46	Trucking	410	421-423	1.6141	46	Portland, OR	2.104
47	Petroleum Refining	200-201	291-299	1.6006	47	Mobile, AL	2.102
48	Electric Light/ Power	450	491	1.5948	48	Norfolk, VA	2.102
49	Toys(Sporting Goods)	390	394	1.5832	49	Minneapolis, MN	2.101
50	Aircraft (Aerospace)	352, 362	372, 376	1.5574	50	Pittsburgh, PA	2.098
51	Coal	41	120	1.4447	51	Philadelphia, PA	2.096
52	Construction	60	150-170	1.3525	52	Providence, RI	2.094
53	Steel	270-271	331	1.3349	53	Chicago, IL	2.094
54	Ship (Boat) Building	360	373	1.3349	54	Cheyenne, WY	2.092
55	Tire and Tube	210	301	1.3316	55	Milwaukee, WI	2.088
56	Brokerage	710	620, 670	1.3256	56	Lansing, MI	2.087
57	Medical Products	371-382	381-387	1.2928	57	Flint, MI	2.087
58	Watch	381	380	1.2928	58	Jackson, MS	2.086
59	Hospital	831	806	1.2773	59	Indianapolis, IN	2.082
60	Computer	321-322	357	1.1299	60	New Orleans, LA	2.081
61	Machinery	320-312	351-353	1.1011	61	Topeka, KS	2.080
62	Communication Equip.	341	365-366	1.0353	62	Cedar Rapids, IO	2.078
63	Real Estate	712	650-660	0.9485	63	Omaha, NE	2.077
64	Machine Tools	281	342	0.7411	64	Lexington, KY	2.077
65	Oil and Gas Drilling	42	130	0.4862	65	Columbia, SC	2.074
					66	Dallas, TX	2.073
					67	Little Rock, AR	2.070

					68	Sacramento, CA	2.067
					69	Fort Wayne, IN	2.067
					70	San Diego, CA	2.065
					71	Cleveland, OH	2.061
					72	Syracuse, NY	2.061
					73	Rapid City, SD	2.059
					74	Dayton, OH	2.058
					75	Birmingham, AL	2.056
					76	Austin, TX	2.055
					77	Detroit, MI	2.055
					78	Baltimore, MD	2.053
					79	Albuquerque, WY	2.051
					80	Phoenix, AZ	2.035
					81	Washington, DC	2.035
					82	Duluth, NM	2.033
					83	Rochester, NY	2.033
					84	Oklahoma City, OK	2.027
					85	Raleigh, NC	2.022
					86	Wilmington, DE	2.020
					87	Boston, MA	2.016
					88	Seattle, WA	2.008
					89	Colorado Springs, CO	2.002
					90	Ann Arbor, MI	1.998
					91	Tulsa, OK	1.997
					92	Hartford, CT	1.989
					93	Corpus Christi, TX	1.984
					94	Charleston, SC	1.969
					95	Houston, TX	1.959
					96	Casper, WY	1.957
					97	Wichita, KS	1.907
					98	San Jose, CA	1.903

Note: R.=Ranking
Telg. = telegraph
Property* = property and casualty

Possibility of Identification Issue

The stock price index is measured as the change in the aggregate value of equities in each SMSA over the period 1984—89, whereas migration is measured over the period 1985—1990. As the explanatory variable (stock price) and dependent variable (migration) share virtually the same time period in our model, the direction of causation between stock price (equity value change) and migration might be open to question.

Suppose our contemporaneous stock price data were generated from the change of equity values of *local firms* producing for the local market instead of *big firms* that do nation-wide business; a large inflow of migrants could affect the profits of local firms by lowering wages and increasing the demand for the product in the local market.

Since the industry composite indices, upon which our SMSA composite figures are based, are generated from the equity values of the representative firms which are involved in nation-wide (or multi-national) business activities, or based upon the equity values of a group of large local firms whose locations differ, the industry composite index would not be influenced by the local migration. Therefore, our SMSA composite data obtained from those industry composite indices would also be independent of the local migration flows. This fact enables us to avoid the identification issue and allows us to ignore the causal relationship from migration to our SMSA-specific indices.

ANALYSIS OF THE EMPIRICAL RESULTS

This two-step method, together with the selectivity bias correction for the wage equation, brings us to Tables 4 and 5, which exhibit the estimation results for the wage equation as well as the random utility function (or probability function). We compare the estimation results for conventional variables presented in both the conventional approach and our augmented approach and analyze them in the first subsection. In the second subsection, we discuss the coefficient of the stock price indices and its implications for our hypothesis.

Analysis for Conventional variables in both approaches

First, in the wage equation, $\sigma\rho$, the coefficient for the correction term for selectivity bias is small and statistically significant [0.053** (7.84), 0.052** (7.76)].[25] This implies strong evidence for the existence of selectivity, but the selectivity-corrected estimates of α are almost the same as the uncorrected α's. Thus, the second-stage estimates for the β's and γ's with these consistent α's are almost the same as the first-stage results. All the α's are statistically significant, and within one percent of significance level, among which the estimates on *sch* [0.112** (59.45), 0.112** (59.41)], *sex* [0.643** (66.80), 0.643** (66.80)][26], and $ln(CY_j)$[0.696** (18.09), 0.697** (18.10)] have the highest t-ratios.

As both approaches accommodate most of the determinants of conventional migration studies, the results provide an interesting comparison with other estimates in the conventional migration literature such as Greenwood and Sweetland (1972), and DaVanzo (1983). The results (both estimates and *t*-ratios) are consistent with those from previous studies. Except for the parameter estimate for marriage, all the estimates support the conventional migration theory.

Consider the variables for economic opportunities–predicted earnings (y_j), unemployment rate (Un_j), and employment growth rate ($Empg_j$). First, the estimate and its associated *t*-ratio [1.299* (2.05), 1.920** (8.26)] for y_j support the human capital theory which describes migration as an investment in future expected earnings, as is suggested by Sjaastad (1962) and Becker (1962). Results for unemployment, UN_j [-0.333 (-1.85), -0.249** (-4.32)] also suggest that potential migrants avoid cities whose current economic activity is sluggish. The results for (past) employment growth, $Empg_j$ [0.159 (0.22), 0.166 (0.98)], are not statistically significant, possibly because the 1980-1985 period's was heavily impacted by the second oil price shock.[27] The gravity variables–city population (N_j) and distance ($Dist_{ij}$)–also are important. N_j [0.461** (3.58), 0.431** (18.78)] and $Dist_{ij}$ [-0.708** (-30.15), -0.737** (-39.51)] show strong positive and negative effects, respectively, as the gravity theory suggests.[28]

Consider the city characteristics other than those described above. Migrant responses to government spending (G_j)[0.270 (0.39), 0.205** (3.96)] and tax rate (Tax_j) [-0.393 (-0.56), -0.313** (-6.02)] are in line with expectations, although in the conventional approach the coefficients are not statistically significant. Mean temperature ($Temp_j$) shows a large effect [1.183** (3.62), 1.270** (8.69)] on migration. Temperature's effect may come from the aging domestic population, since older people prefer warmer places. Another explanation comes from growth of high technology industries such as computers and tele-communications . As information processing innovation improves long distance communication, it might partially replace transportation so that environmental advantage might partially replace the geographical advantage held by relatively cold census regions such as the Northeast and the North Central.

Consider the effects of individual characteristics upon migration. Complete schooling years (*sch*) has a strong positive effect with a significant *t*-ratio [1.399** (8.73), 1.507** (16.05)], which implies that more schooling makes the worker more mobile. The age effect on migration [-1.389** (-8.33), -1.529** (-19.27)] is strongly negative and significant, as an older worker's gain associated with migration investment is less than a younger worker's gain.

Home ownership (*own*), as one measure of *location-specific capital*, deters migration incentives [-1.185** (-24.12), -1.257** (-27.46)], as it increases worker's moving costs. The estimate for race [0.184** (3.17), 0.187** (3.32)] is positive and statistically significant, indicating that whites are more mobile than others. The estimate for sex [0.063 (1.54), 0.058 (1.41)] is not statistically significant at the five percent level. The number of children (*kid*) displays a strong and significant negative effect [-0.124** (-5.02), -0.120** (-5.68)] on migration, suggesting that family ties deter migration because of joint decision-making.

Results of Augmented Approach

The estimate for the stock price coefficient [3.220** (7.69)] is strongly positive and statistically significant at the 1 percent level. This suggests that the forward-looking stock price variables are correlated with potential migrants' expectations.

Two different matters could have caused the coefficient of the stock price variable to be statistically insignificant. First, our hypothesis that forward-looking financial variables such as stock prices reflected information about expectation that was not captured in the conventional variables could have been wrong. Second, the methodology of calculating the stock price indices could have been poor. The statistically significant coefficient of the stock price variable then, tends to affirm both our hypothesis and our methodology.

Table 4
THE ESTIMATES FOR WAGE EQUATION

Variable	Coefficient	Conventional Approach Estimate (t-ratio)	Augmented Approach Estimate (t-ratio)
Constant	α_0	1.169** (3.11)	1.160** (3.09)
Sch	α_1	0.112** (59.45)	0.112** (59.41)
jexp	α_2	0.007** (16.07)	0.007** (16.10)
Race	α_3	0.126** (10.15)	0.126** (10.12)
Sex	α_4	0.643** (66.80)	0.643** (66.80)
$ln(Y_j)$	α_5	0.696** (18.09)	0.697** (18.10)
Selectivity	$\sigma\rho$	0.053** (7.84)	0.052** (7.76)

Note: 1. * denotes significance at 5% level, and ** denotes significance at 1% level.
2. *Selectivity* $= -\Psi(\Phi^{1}(P_{Ij}))/P_{Ij}$

Table 5
THE ESTIMATES FOR RANDOM UTILITY FUNCTION (OR PROBABILITY FUNCTION)

		Conventional Approach	Augmented Approach
Variable	**Coefficient**	**Estimate (t-ratio)**	**Estimate (t-ratio)**
Constant	γ_0	-0.293 (-0.30)	0.015 (0.04)
y_j^*	β_1	1.299* (2.05)	1.920** (8.26)
N_j^*	β_2	0.461** (3.58)	0.431** (18.78)
Un_j^*	β_3	-0.333 (-1.85)	-0.249** (-4.32)
G_j^*	β_4	0.270 (0.39)	0.205** (3.96)
Tax_j^*	β_5	-0.393 (-0.56)	-0.313** (-6.02)
$Temp_j^*$	β_6	1.183** (3.62)	1.270** (8.69)
$Empg_j^*$	β_7	0.159 (0.22)	0.166 (0.98)
$Dist_{ij}^*$	γ_1	-0.708** (-30.15)	-0.737** (-39.51)
sch^*	γ_2	1.399** (8.73)	1.507** (16.05)
age^*	γ_3	-1.389** (-8.33)	-1.529** (-19.27)
sex	γ_4	0.063 (1.54)	0.058 (1.41)
race	γ_5	0.184** (3.17)	0.187** (3.32)
mar	γ_6	0.210** (4.03)	0.242** (5.05)
kid	γ_7	-0.124** (-5.02)	-0.120** (-5.68)
own	γ_8	-1.185** (-24.12)	-1.257** (-27.46)
SP_j^*	λ		3.220** (7.69)
FP		-19,200.92	-19,155.06

Note: 1. `*' on the variable means the logarithm form.
2. Coefficients and t-ratios are computed using predicted values of y_j^*.
3. On the estimate, * denotes significance at 5% level, and ** denotes significance at 1% level.
4. $FP = \sum_{I=1}^{48,490} ln\,(P_{Ij})$

CONCLUSIONS

This paper addresses the hypothesis that forward-looking financial variables, such as stock prices, can provide information about the migration process that is not captured by the traditional migration determinants. By comparing the empirical results for conventional approach to those for our augmented approach, we provide a first test of hypothesis and show that it is consistent with observations.

Because this paper is the first to explore the relationship between a (forward-looking) financial variable and migration,[29] further studies are clearly needed to strengthen our confidence in the result. Here are a number of possibilities that come to mind. First, we could explore other time periods. Second, we could consider other financial variables, such as stock futures and home insurance premiums.[30] Third, for the international migration, such financial variables as the country-specific composite stock price indices, the foreign exchange rates (futures), interest rate differentials, or Moody's (or Standard and Poor's) credit ratings could be examined. Fourth, we could consider alternative methodologies for creating the SMSA-specific composite stock price indices.

REFERENCES

Becker, G.S. 1962. "Investment in Human Capital: A Theoretical Analysis." *Journal of Political Economy* 70 (5): 9–49.

Blanco, C. 1964. "Prospective Unemployment and Interstate Population Movement." *Review of Economics and Statistics* 46 (2): 221–222.

Blau, F. D. and Kahn L. M. 1994. "Rising Wage Inequality and the U.S. Gender Gap." *The American Economic Review* 84 (2): 23–28.

Chen, K., Chiang, S., and Leung, S.F. 2003. "Migration, Family, and Risk Diversification." *Journal of Labor Economics* 21 (2): 353–380.

Cushing, Brian. 1986. "Accounting for Spatial relationships in models of interstate population migration." *The Annals of Regional Science* 20 (2): 66-73.

Cutler, D. and Summers, L. 1988. "The Cost of Conflict Resolution and Financial Distress: Evidence from the Texaco-Pennzoil Litigation." *The Rand Journal of Economics* 19 (2): 157–172.

DaVanzo, J. 1983. "Repeat migration in the U.S.; who moves back and who moves on?" *Review of Economics and Statistics* 65 (4): 552–559.

Falaris, E.M. 1987. "A Nested Logit Migration Model with Selectivity." *International Economic Review* 28 (2): 429–443.

Greenwood, M. 1975a. "Research on Internal Migration in the U.S." *Journal of Economic Literature* 13 (2): 397–433.

Greenwood, M. 1975b. "Simultaneity Bias in Migration Models: An Empirical Examination." *Demography* 12 (3): 519–536.

Greenwood, M. and Sweetland, D. 1972. "The Determinants of Migration between Standard Metropolitan Statistical Areas." *Demography* 9 (4): 665–681.

Greenwood, M., Hunt, G., Rickman, D., Treyz, G. 1993. "The Dynamics of U.S. Internal Migration." *The Review of Economics and Statistics* 75 (2): 209–214.

Hunt, G.L. and Mueller, R.E. 2004. "North American Migration: Returns to Skill, Border Effects, and Mobility Costs." *The Review of Economics and Statistics* 86 (4): 988–1007.

Lee, D.S. 1996. *Real and Financial Determinants of Intercity Labor Migration: a multinomial logit model and PUMS data*. Unpublished Doctoral Dissertation, State University of New York at Stony Brook.

Lee, L.F. 1983. "Generalized Econometric Models with Selectivity." (in Notes and Comments) *Econometrica* 51 (2): 507–512.

Mazek, W.F. 1969. "Unemployment and the Efficacy of Migration: The Case of Laborers." *Journal of Regional Science* 9 (1): 101–107.

Mincer, J. 1974. *Schooling Experience and Earnings*. New York, Columbia University Press.

Mincer, J. and Polachek, S. 1974. "Family Investments in Human capital: Earnings of Women." *Journal of Political Economy* 82 (2) Part 2: S76–S108.

Olvey, L. 1972. "Regional Growth and Inter-Regional Migration–Their Patterns of Interaction." *Review of Regional Studies* 2 (2): 139–163.

Sjaastad, L. 1962. "The costs and returns of human migration." *Journal of Political Economy* 70 (5): 80–93.

Stark, O. 1984. "Rural-to-Urban Migration in LDCs: A Relative Deprivation Approach." *Economic Development and Cultural Change* 32 (3): 475-486.

Stark, O. 1991. *The Migration of Labor.* Basil Blackwell, Oxford.

Stark, O., Bloom, E. 1985. "The New Economics of Labor Migration." *The American Economic Review* 75 (2): 173-178.

Stark, O. and Taylor, J.E. 1989. "Relative Deprivation and International Migration." *Demography* 26 (1): 1-14.

Vanderkamp, John. 1971. "Migration flows, their determinants, and the effects of return migration." *Journal of Political Economy* 79 (5): 1012-1031.
.

ENDNOTES

1. In this paper, city is defined as *Standard Metropolitan Statistical Area* (SMSA). Thus, terms such as city and SMSA which will be often used in this paper, are to be read as synonymous.

2. See Sjaastad (1962) and Greenwood (1975a).

3. For example, Boeing and Microsoft produce most of their output in Seattle metropolitan area, whereas Exxon and Texaco do most of their business in the metropolitan areas in Texas. GM and Ford produce most of their output in Detroit or Cleveland SMSAs, whereas hotels and entertainment industries are especially important in the Las Vegas and Orlando SMSAs.

4. Cutler and Summers (1988) showed that the stock prices of Texaco and Pennzoil depended on court information during the period of Texaco-Pennzoil litigation (1984–1988).

5. A more updated estimation procedure has been used in Hunt, G and Mueller R. (2004). They used the nested logit structure, in which the origin is the only one choice for the stay branch and all nonorigin areas are the choice set for mover branch. However, they do not use explicitly expectations-based variables to explain migration.

6. For the names of the selected 98 SMSAs, see Table 3.

7. We wish to thank Rich Robinson of the Consortium for International Earth Science Information Network (CIESIN) for providing the 5% PUMS data in the 1990 census. A random sample of 48,490 observations was drawn from PUMS for use in our empirical work. Furthermore, our paper could be updated with the 5% PUMS data in the 2000 census, which can be found on the website at the site tp2.census.gov/census_2000/datasets/PUMS/FivePercent.

8. Let RD(y) be the relative deprivation function of income y. Then, it is specified as $RD(y) = [1 – F(y)] \cdot E(z – y \mid z > y)$, where z is the income of the richer persons, and F(y) is the cumulative distribution of income y. For more details, see Stark et al. (1989).

9. Denote RD^i a village household i's relative deprivation. Then $RD^i = AD(Y_i) \cdot P(Y_i)$, where Y_i is the income of household, $AD(Y_i)$ is the mean excess income of households richer than household i, and $P(Y_i)$ is the proportion of the households in the village richer than household i .
10. REO is the average annual employment for the area as reported by the U.S. Bureau of Economic Analysis, but converted from a place-of-work to a place-of-residence basis and expressed relative to the labor force of the area, and relative to a comparable measure for the U.S as a whole. RWR is the average wage rate for the area deflated by an area-specific deflator that includes relative production costs and housing prices, expressed relative to a comparable national measure with area-specific weights. RWM is the average industry-specific wage rates, weighted by each local industry's share of local employment, relative to the same wage and salary measure weighted by each industry's share of national employment.
11. SMSA-specific stock prices used in this paper measure the relative changes in SMSA-specific indices of sectoral stock prices. For more details, see the fourth section (Creation of Composite Stock Price Indices for SMSA).
12. See Table 3.
13. For example, suppose it is predicted that the price of oil would increase if OPEC announced the reduction of the next year's oil production. Then the stock prices of the firms in oil industry would rise with the higher profit expectations, and potential migrants might expect that their future living conditions would be better in such SMSAs as Houston and New Orleans.
14. Falaris (1987) used 7 regions of Venezuela for his analysis, whereas we use 98 SMSAs for our analysis. If we follow Falaris (1987), then we would need 98 wage equations, which would our work beyond our computer resources. The reason why we do not aggregate more is that our analytical focus is on stock prices and most firms whose stock prices are available are located in urban (metropolitan) areas.
15. The Gumbel cumulative distribution function is specified as $F(e|\mu, \eta) = \exp[-\exp(-\mu(e-\eta))]$, where μ is a scale parameter (that is, a measure of dispersion) and η is a location parameter (a measure of central tendency). The primary role of this distribution assumption is to allow the difference of two error terms ($e_{Ij} - e_{Ik}$) to be logistically-distributed. For more details, see Lee (1983).
16. For more details, see Mincer (1974) or Mincer and Polachek (1974).
17. For CY_j, CY_{j86} (1986 income for city j) is used for migration decision period. We synthesize CY_{j86} by $(CY_{j89} + CY_{j83})/2$, since CY_{j86} for all the selected 98 SMSAs cannot be obtained within our data source. The data sources for CY_{j83} are *State and Metropolitan Area Data Book* (1986) and *County and City Data Book* (1988), while the data source for CY_{j89} is *PUMS* (1990).
18. Individual I, who chooses to migrate to city j, may earn more than an observationally identical worker drawn from the sample population.
19. First, the α parameters in the wage equation (2) are estimated with ordinary least squares. The data used in this step are the individual annual (money) income in 1989 (y_j), personal characteristics in PUMS 1990 (as *sch*, *jexp*, *sex*, and *race*), and city j's 1989 annual per capita money income (CY_j) derived from PUMS by classifying and aggregating the individual annual income of 1990 by each SMSA. Second, after we have initial estimates of the α parameters (there may be bias due to self-selection) in (2), we use CY_{j86} and adjusted age (the sample population age minus 3) that better matches the migration decision period, holding other variables value constant, to get an initial fitted value for $ln(y_j)$ representing its value at migration decision time.

Third, this fitted value enters the decision equation (1) to estimate the parameter β's and γ's with the maximum likelihood method for P_{Ij} in equation (3). Fourth, these initial estimates (β's and γ's) in the structural equation (1) and (3) are used to get initial probabilities P_{Ij} with which to estimate the parameters in equation (4) to get consistent α's, and σρ. Fifth, we obtain the selection-corrected income (y_j) by replacing initial α's with these consistent α's. Sixth, we use the selection-corrected income to estimate the parameters in (1) again with the maximum likelihood method for P_{Ij} in (3) to get the consistent estimates of the β's and γ's.

20. This source of this data is the *Standard & Poor's Security Price Index Record* (1992). The index measures the variation (change) in aggregate equity values of selected firms in each industry between the current and base year. Note that a possible stock-split within the time interval requires us to use each firm's equity value instead of its stock price to get industry specific index. Suppose the base year t=0. Then firm f 's stock price at year t, cp_{ft} is specified as $cp_{ft} = p_{ft} \cdot q_{ft} \ / \ p_{f0} \cdot q_{f0}$ where p_{ft} is firm f's stock price at year t, q_{ft} is firm f's outstanding shares at year t, p_{f0} is firm f's stock priceat the base year, q_{f0} is firm f's outstanding shares at the base year. Our industry-specific composite stock price index ($CINP_{kt}$) simply extends this formula.

21. The source of this data is *PUMS 1990*.

22. Public sector and private non-profit institutions such as government, the military, schools, charitable and religious organizations that have no stock price are excluded. Furthermore, important sectors such as wholesalers or (small) business services are excluded because of difficulty in observing their stock prices. The proportion of those that are included ranges from 67 to 72 percent of all the non-farm civilian employment in the SMSAs. Employment in the excluded sectors normally moves in the same direction as employment in the included sectors.

23. The information for M_k is in the *Standard & Poor's Security Price Index Record* (1992).

24. The following industries that we want to include are missing: health care, cement and gypsum, footwear, tire and rubber, mining, photo optical, measurement control, shipyards, and water transport. For the methods to measure those missing variables, see Lee's (1996) unpublished doctoral dissertation.

25. * is for 5% significance level, and ** is for 1% significance level. The first figure is the estimate, and the following figure in the bracket is its t-ratio. The first estimate and its t-ratio is for the conventional approach, and the next is for the augmented approach. This order is consistent in the discussion for the other explanatory variables in this section.

26. In our wage equation, y_j denotes the annual earnings for all men and women with positive income, regardless of whether they work full-time or part-time. The proportion of full-time workers is larger for men than for women. In the previous literature (such as Blau and Kahn (1994)), the wage data is the hourly wage for men and women with the full-time jobs. Because we include both full- and part-time workers, the coefficient on the sex dummy is larger than the estimate of that coefficient from other literature. For this reason, other coefficients could be different as well.

27. For example, with the second oil shock, $Empg_j$ for Detroit was very low (0.4%) during 1980-1985, whereas $Empg_j$ for Houston was very high (5.8%). However, the potential migrants preferred Detroit to Houston during 1985-1990, as the second oil shock disappeared. During 1985-1990, the migration rate from Detroit to Houston was 0.026%, whereas the migration rate from Houston to Detroit was 0.225%

according to *1990 PUMS*. So, employment growth during 1980-85 does not explain migration during 1985-90. This unusual effect is due to the oil shock.

28. The gravity theory says that migration is positively related to the population sizes of the origin and destination regions and negatively related to the distance between the origin and the destination. The representative studies dealing with this theory are Vanderkamp (1979) and Cushing (1986).

29. Although Stark (1991) did not specifically use any financial variable as a migration determinant, he was one of the first to use concepts such as *risk-aversion*, *insurance market*, and *portfolio diversification* (which are often discussed in financial economics), to explain the rural-to-urban family migration. Chen, K., Chiang, S., and Leung, S.F. (2003) applied Stark's theory to explain international migration such as the dependent-oriented migration flows from Hong Kong and Taiwan in the early 1990's.

30. Home insurance premium would be a possible migration determinant, as we consider the migration flows for such SMSAs as New Orleans, Houston, or Miami with frequent natural disaster (Hurricanes).

ACKNOWLEGEMENTS

We are grateful to Mark Montgomery, John Hause, and Roger Folsom for their useful comments to improve the quality of this paper. Special thanks go to the referees of this journal for their excellent and constructive comments.