

IMPACT OF EXPECTED EARNINGS ON INTERREGIONAL MIGRATION DECISIONS IN FINLAND

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Abstract

This paper examines the impact of expected earnings on interregional migration decisions in Finland. Using a sample on young adults inhabited in peripheral regions in the beginning of 1994, we estimate selectivity corrected earnings predictions and use them in nested logit migration choice model. Our results indicate that the effects of expected earnings on migration propensity are small but significant. We argue that the direct elasticity of migration propensity to growth-centre region is over twice as large as the direct elasticity of migration propensity to some other peripheral region with respect to changes in earnings in these alternatives.

1. Introduction

In this age of urbanisation, when people are migrating from peripheral regions to growth-centre regions, one may wonder how the migration propensity is affected by the expected earnings. Is migration from peripheral regions driven by higher earnings in growth-centre regions? Would an increase in earnings in peripheral regions reduce geographical shift of workforce from those regions? How elastic is migration propensity from peripheral regions with respect to changes in expected earnings? While being important topics in policy making – say because of regional taxation, these questions have been left unanswered in previous studies.

To answer the question whether and how interregional migration is influenced by earnings expectations, we study young adults originally inhabited in Finnish peripheral regions in the beginning of 1994. Our hypothesis is that individuals choose where to locate on the basis of an evaluation of costs and benefits. To simplify matters we aggregate alternatives and assume that each individual may select among three mutually exclusive alternatives. These alternatives are: (i) not to migrate from peripheral region; (ii) migrate to some other peripheral region; and (iii) migrate to a growth-centre region in 1994.

We measure the benefits associated with choosing a given region by means of earnings one is expected receive in each alternative, along with other things. Since we do not observe expected earnings we have to impute them for each alternative in order to study the role of earnings expectations on interregional migration. In doing so we apply an estimator proposed by Lee (1983) to estimate alternative-specific earnings equations free from sample selection bias. With Lee's method we are able control for possible unobserved factors, which may affect both individual's choice of location and his earnings. These unobserved factors may result in sample selection bias if we try to estimate alternative specific earnings equations by OLS on the basis of the self-selected samples. Thus, the key advantage of sample selection models is that they allow us to investigate potential outcomes in addition to the actual outcomes for decision makers.

Individuals' choice of location is modelled with nested logit model. Nested logit allows us to relax the restrictive independence of irrelevant alternatives assumption that simple multinomial logit (MNL) model imposes (McFadden 1981).¹ This important because

unobserved similarities between alternatives or attributes between migrants may arise, which are not otherwise explicitly controlled for in the model, and hence bias the results.

The general determination of migration are well discussed in the literature. See for example comprehensive surveys by Greenwood (1975; 1985), Shields and Shields (1989), Greenwood *et al.* (1991), and Ghatak *et al.* (1996). Haapanen (1998) examines determinants of migration in the context of growth-centre and peripheral regions. There has been fewer studies on impact of wages on migration choice. Falaris (1987) examine the choice among specific locations and considers impact of regional wages on the destination choice using nested logit. Hughes and McCormick (1994) study destination choice with nested logit as well, but do not control for self-selection. Islam and Choudhury (1990) estimate impact of expected income gains on migration likelihood but does not distinguish between different types of regions.

Remainder of this paper is organised as follows. Section 2 specifies structure of our model. Section 3 introduces our data. Section 4 reports our estimation results along with calculations of direct and cross elasticity of migration with respect to earnings increases in different regions. Section 5 concludes the study.

2. Model Specifications

We apply Lee's (1983) discrete choice model with selectivity in order to calculate expected earnings in all alternatives for each person.² Lee's model can be estimated consistently in two steps described below.

In our migration model, each individual inhabited in peripheral region may select among three mutually exclusive alternatives. He or she can either not to migrate ($j = 1$), migrate to another peripheral region ($j = 2$), or migrate to a growth-centre region ($j = 3$). As usual, the motivating force behind a large class of discrete choice models is the concept of random utility maximisation (see *inter alia* McFadden 1973; 1981; 1984; Ben-Akiva and Lehman 1985).

We assume that individuals have a stochastic utility function which we will write in form:

$$(1) \quad U_j = \alpha'_j w_j + \beta'_j x_j + \varepsilon_j, \quad j = 1, 2, 3$$

where w_j are the expected earnings in alternative j and x_j can be function of individual characteristics, which are invariant across alternatives, and attributes of the alternative j . There may be parameter restrictions on or across α and β 's. The last term in (1) is error term, which determines the structure of the model in more detail. If it has extreme value distribution multinomial logit (MNL) will arise.³ On the other hand, if the error term has generalised extreme value (GEV) distribution nested logit arises. The criterion for choosing alternative k for a given individual is: $U_k > \max U_j$, for all $k \neq j$. Hence U_k is net utility costs associated with choosing state k compared to the optimal choice. Individual subscripts are suppressed except in cases where their omission may cause confusion.

In modelling earnings determination we assume that at each alternative individual faces semi-log earnings equations:

$$(2) \quad \ln w_j = \gamma'_j z + v_j, \quad j = 1, 2, 3$$

where earnings are function of individual specific characteristics. This is a censored regression in that for a given individual we observe w_j only if this person chooses migration alternative j . By definition the number of earnings equations is equal to the number of migration alternatives. We will assume that the marginal distributions of v_j are normal $N(0, \sigma^2)$.

Because of censoring in earnings, we cannot directly estimate (1). Instead we formulate a 'reduced' form of equations (1) and (2), V_j , where utility V_j is a function of z and x_j . If the error terms are independently and identically distributed with the extreme value distribution, Domencich and McFadden (1975) and Ben-Akiva and Lehman (1985) show that the model implies the multinomial logit probabilities:

$$(3) \quad P_j = \frac{\exp(\omega'_j y_j)}{\sum_{j=1}^3 \exp(\omega'_j y_j)}, \quad j = 1, 2, 3$$

where y_j are the explanatory variables from z and x_j with estimated parameters ω_j and P_j denote the probability of choosing alternative j . In this 'reduced' model we have to assume that ε_j and v_j are uncorrelated across alternatives and people, and that they are uncorrelated with the remaining right-hand-side variables in (1) and (2) in the reduced

form migration equation. We relax these simplifying restrictions when we estimate ‘structural’ migration model by nested logit.⁴

Lee (1983) shows that we can write the conditional mean, on alternative j being chosen, of (2) as

$$(4) \quad w_j = \gamma_j' z - \sigma_j \rho_j [\phi(J(P_j))/P_j] + \xi_j,$$

where $J(P_j) = \Phi^{-1}(P_j)$ involves the inverse of the standard normal distribution, ϕ is the standard normal density function and $E(\xi_j | j \text{ chosen}) = 0$.

We use the estimates of the MNL model to calculate choice probabilities and to form the sample selection correction variables $\phi(J(P_j))/P_j$ for each observation. Then we estimate equation (4) by OLS. This last step gives us consistent estimates of γ_j and $\sigma_j \rho_j$. If some of the estimates of $\sigma_j \rho_j$'s are different from zero there will be evidence of sample selection in the earnings equations. Once we have obtained consistent parameter estimates for the earnings equations, we can use them to calculate predicted, unconditional earnings for each individual in each alternative. We then replace w_j in (1) by predicted earnings \hat{w}_j and estimate the structural version of the migration choice model by nested logit. From the structural equations we obtain estimates of α_j and β_j .

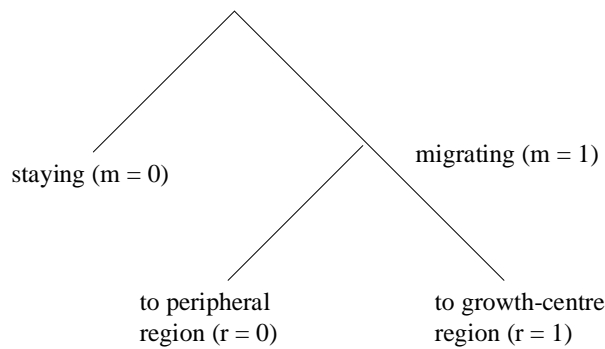


Figure 1. The nested logit structure for migration model

We formulate our structural nested logit model by assuming a natural division of alternatives (see Figure 1). Person chooses whether to migrate from the current peripheral region or not ($m = 1, 0$) and if (s)he does, where to migrate. If $r = 0$, person migrates to some other peripheral region, and if $r = 1$, person migrates to a growth-centre region. Note however that although it is convenient to describe possible choices

with a tree, this does not mean that with nested logit choices have to be made sequentially by the individual. It just means that we are relaxing assumptions on the error terms that the MNL imposes: nested logit allows the variance of the error terms to differ across the groups (migrants vs. stayers), while maintaining the IIA assumption within groups (independent and homoskedastic errors).

Although there other nested logit formulations like Daly (1987), we use McFadden's nested logit model, which is a member of generalised extreme value (GEV) family and is consistent with utility maximisation (McFadden 1981; see Koppelman & Wen 1998 for discussion). To simplify notation let the utility of alternative r in nest m be

$$(5) \quad U_{rm} = V_{rm} + \varepsilon_{rm},$$

where $V_{rm} = w_{rm}\alpha_{rm} + x_{rm}\beta_{rm}$ denotes the deterministic component of utility and ε_{rm} denotes the GEV distributed error term. Let P_{rm} denote the probability of choosing migration type m and destination region r . From the rules of conditional probability we know that $P_{rm} = P_{r|m} P_m$, where $P_{r|m}$ is the conditional probability of choosing region r conditional on choosing nest m , and P_m is the marginal probability of choosing nest m of which r is a member.

If we can assume additive separability of deterministic utility and that random term ε_{rm} has the GEV distribution, McFadden derived the nested logit model:

$$(6) \quad P_{r|m} = \frac{\exp(V_{rm}/\mu_m)}{\sum_{j \in R_m} \exp(V_{jm}/\mu_m)} = \frac{\exp(V_{rm}/\mu_m)}{\exp(I_m)},$$

$$P_m = \frac{\exp(\mu_m I_m)}{\sum_k \exp(\mu_k I_k)}, \text{ and } I_m = \ln\left(\sum_{j \in R_m} \exp(V_{jm}/\mu_m)\right),$$

where R_m denote the set of alternatives at level 2 that are connected by branches of the tree to alternative m at level 1. I_m is called the inclusive price of alternative m at level 1 and its parameter μ_m is called inclusive value parameter. Thus, V_m , the utility of nest m is equal to $\mu_m I_m$. If $\mu_m = 1$ for every m then the model collapses to the ordinary multinomial logit model. In our case there is only one free inclusive value parameter. This is because if person does not migrate he cannot choose where migrate and hence the nest is considered degenerate and μ_m will be one.

To sum up, the estimation of the migration choice model proceeds in three steps. First a reduced form multinomial logit model is estimated, where individuals choose between staying in the current peripheral region, migrating to some other peripheral region and migrating to growth-centre region. Then earnings equations are estimated including selectivity correction terms calculated from the reduced form MNL model. Finally, structural nested logit migration model is estimated with predicted earnings entering as additional explanatory variables. Naturally this three step method results in some loss of efficiency.

3. Data

This paper uses a one-percent random sample of population from the Finnish longitudinal census file. Statistics Finland has been combined the population census with various employment registers maintained by labour administration. The socioeconomic status of the sample people and their spouses is well documented: data includes information on personal and family status, past labour market record, and regional characteristics of over 30 000 individuals. The empirical analysis of this study mainly uses data from the post recession years 1994 – 1995, but some of the variables are constructed using information on prior years (1987 – 1993). Especially useful for this study was the fact that we obtained information on individuals' home subregion. The information allows us to divide Finland into 84 subregions (NUTS4, "seutukunnat"), which by and large represent the actual commuting and working areas as well (see Figures 2 – 5).⁵

Peripheral and growth-centre regions are defined with the help of Figures 2 – 5. Figure 2 shows that the net annual migration into Finnish subregions. We can see that there are only few regions that experienced positive net migration in 1996 (see the darkest areas). Comparison of Figures 2 and 3 indicate that destination choices of migrants have often been already populated areas of Finland. Since these growth-centre regions consist of regions of low unemployment and high wage levels, one could call them as prosperous regions and the other regions as depressed regions (see Figures 4 and 5). given these facts we defined the growth-centre regions to include Helsinki and its neighbouring regions (Salo and Porvoo), Tampere, Turku, Vaasa, Jyväskylä, Oulu, and Kuopio. Regions with positive migration flows on the eastern Finland and Riihimäki (north of Helsinki) were not included in growth-centre regions, because they have not shown

consistent positive in-migration flows, and they have higher unemployment and lower wage levels than many growth areas.

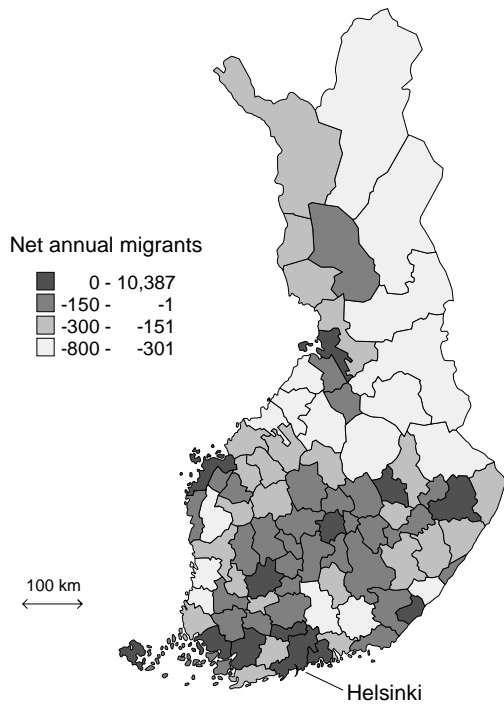


Figure 2. Net annual migrants, 1996

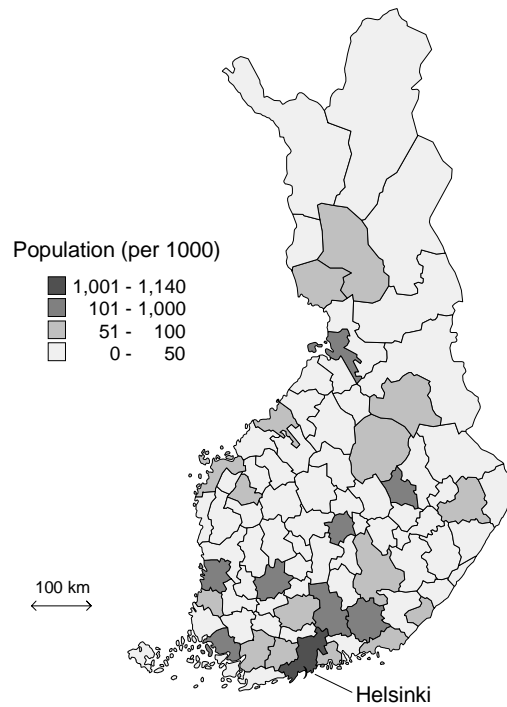


Figure 3. Population, 1996

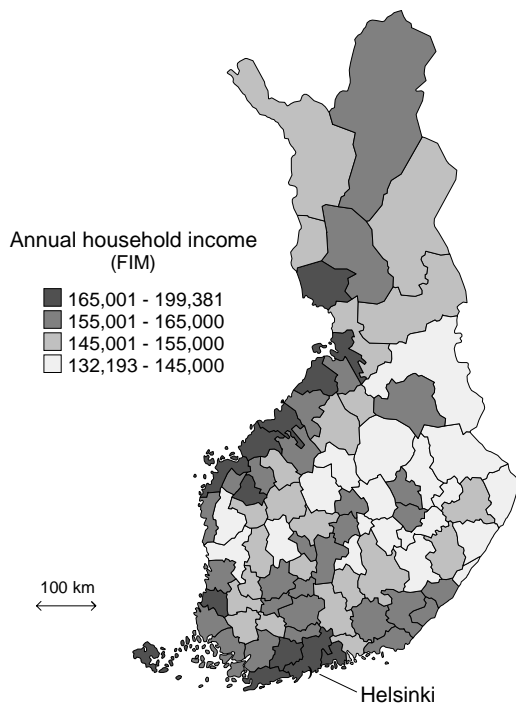


Figure 4. Annual household income (FIM), 1996

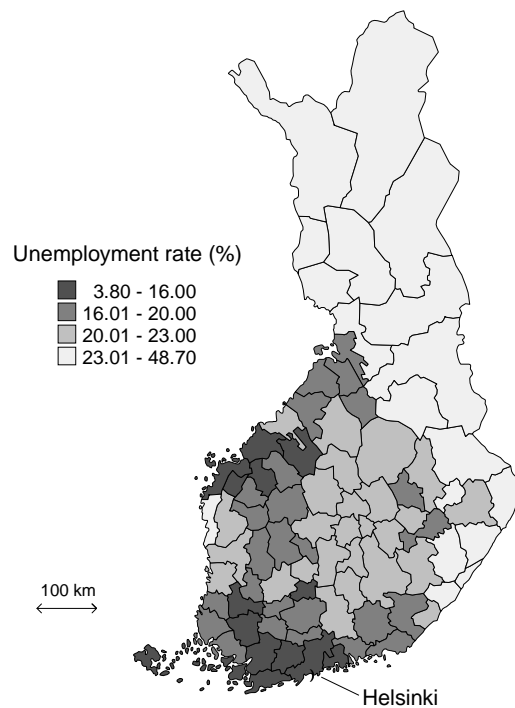


Figure 5. Unemployment rate, 1996

In this paper we define earnings as individuals' annual income from labour plus self-employment income and work-related transfers, such as unemployment insurance and sick pay. In estimation we only use data on 18 – 35 year-olds who had positive earnings in 1993 and 1995 and whose region of origin was one of the peripheral regions in the beginning of 1994. With positive earnings restriction we want to ensure that the people we study are in the labour force and not for example students. Earnings before migration are recorded from 1993, because we cannot identify what was the proportion of annual earnings obtained in the region of origin and destination in 1994. Entrepreneurs are excluded from the sample.

There were reasons for our sample selection. In our whole sample of peripheral residents 3.06 per cent migrated in 1994 with 1.72 per cent migrating to growth-centre regions.⁶ By concentrating on the young adults we are able to increase the migration propensity to 6.10 per cent with 3.72 per cent migrating to growth-centres in that year. This sample selection is useful because most people migrate while being young, and acceptably because it is performed exogenously with respect to our endogenous variable(s). This sample selection also increases homogeneity of our sample and thus increases non-parametrically reliability of our results within this age group. After these sampling procedures and omitting observations with missing information we are left with 3 061 observations.

Table 1. Descriptive statistics

Variables	Mean (std.dev.)		
	Stayers (N = 2874)	Peripheral migrants (N = 73)	Growth-centre migrants (N = 114)
Sex (male = 1)	0.57	0.49	0.58
Age	28.44 (4.62)	26.49 (4.45)	26.38 (3.94)
Education (1 – 5)	2.21 (1.28)	2.60 (1.47)	3.01 (1.20)
Married (1 = yes)	0.38	0.34	0.20
Home owner (1 = yes)	0.63	0.37	0.29
Work experience	5.99 (3.01)	5.05 (2.77)	4.58 (2.47)
# Employment months in '94	7.88 (4.85)	6.62 (4.66)	7.17 (4.47)
Annual earnings in '93 (FIM)	76.92 (42.73)	67.21 (51.03)	58.45 (46.05)
Annual earnings in '95 (FIM)	92.87 (44.61)	91.67 (47.48)	97.68 (51.36)

Note: Annual earnings in '95 are the predicted values from the MNL selection procedure (Finnish marks). Sample includes young adults originally inhabited in peripheral regions in the beginning of 1994 (18 – 35 year-olds). Working experience is defined as number of months at work in 1987 – 1994 divided by 10.

Before we consider our estimation results we introduce other explanatory variables used in explaining individuals' migration choices. Mean values of the selected explanatory

variables are reported by migration status in Table 1. Looking at Table 1, we can see there are equal number of males and females in the group of peripheral migrants, whereas there are more males in the group of stayers and growth-centre migrants. Migrants are younger than those who decided to stay in the peripheral regions in 1994. Growth-centre migrants are more educated and have less work experience than other migrants and especially those who decided to stay in peripheral regions. Similar pattern goes for home owner and marriage –variables. Table 1 also shows that increase in earnings has been largest in the group of growth-centre migrants. A large proportion of increase in earnings can be explained by marked increase in working month at this age group of young adults – they are two years older and hence more experienced in 1995 than in 1993 – and improvement of the economic conditions in Finland in 1993 – 1995.

However, a clearer picture of earnings distribution can be seen by looking at Figure 6. It illustrates bivariate densities of the earnings in 1993 –1995 by the three migration categories. We have calculated the densities using nonparametric kernel estimation methods (see e.g. Silverman 1986; Wand and Jones 1995). We can see that the distribution earnings of migrants is more dispersed, while the autocorrelation in earnings is more evident within the group of non-migrants. Migration is associated with increase in earnings: there are groups of workers in the sample who had low earnings in 1993 and were able to increase them considerably in 1995. Densities for growth-centre and peripheral migrants also look bit different from each other. Hence the figures give some explanation for the marked increase in earnings in the subsample of migrants.

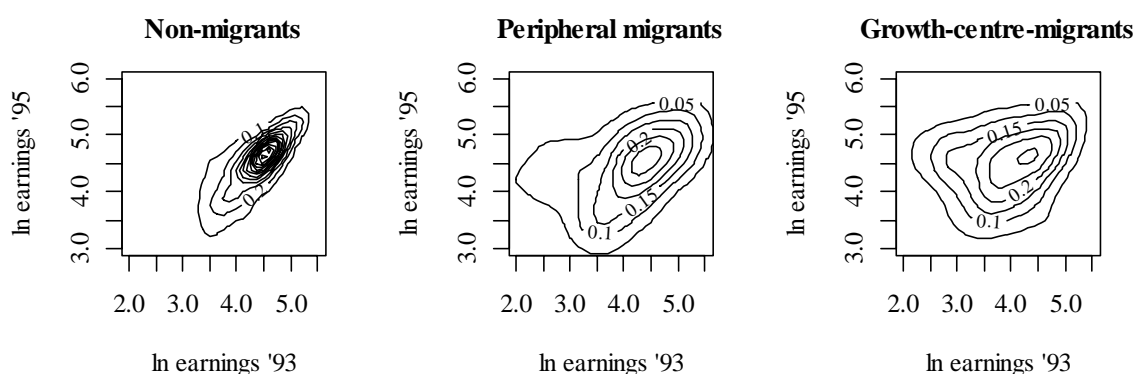


Figure 6. Bivariate density of ln earnings for 18 – 35-year-olds originally inhabited in a peripheral region in the beginning of 1994

4. Estimation Results

We first estimated the reduced form migration model by multinomial logit, where individuals choose between staying in the current peripheral region, migrating to another peripheral region and migrating to a growth-centre region. Then selectivity correction terms we calculated and included in the OLS regressions of $\ln(\text{earnings in 1995})$. Other Mincerian explanatory variables include sex, age, education, work experience, working months, and information on spouse and children, all measured in 1994. Thus we assume that each individual can adequately predict his/her expected earnings in 1995, conditional on his/her characteristics – say education, experience – at moment of migration choice. For the sake of brevity and because these estimation results are just a means to the end of estimating the structural model, these full estimation results are not presented here.⁷ The selectivity corrected earnings equations were not estimated for both sexes separately, because of small number of observations in migration categories.

It is worth reporting the results of the sample selection terms, because significant selection terms would indicate presence of sample selection effects and only their inclusion ensures consistent estimates of other regression coefficients. However, we did not find parameters of the selection terms to be statistically significant. Hence our explanatory variables seem to capture the relevant information of the selection process.⁸ Our sampling strategies also increase the homogeneity of observations and thus reduces possible sample selection effects.

Having calculated the earnings predictions in all three alternatives we estimated structural MNL and nested logit models with full information maximum likelihood.⁹ The estimated utility function parameters specified in equations (1) and (5) are reported in Table 2. The likelihood ratio (LR) tests show that the preferred model specification restricts the earnings parameters α_j to be equal to each other. That is, $\alpha_j = \alpha$ for all j . This hold for the MNL and nested logit specifications. Similarly, Wald test indicates that IV parameter in the nested logit model is not significantly different from one. This means that more parsimonious model would be the MNL (see also log likelihood values). However, by looking at Table 3 elasticities below, this conclusion is somewhat questionable (see discussion below).

We also estimated the nested logit with alternative nesting structures. However, we could not find improvement on the fit of the model. Direct elasticities did not change much either. Instead, the inclusive value parameters were larger than one, which is not necessarily consistent with the utility maximisation (McFadden 1981).¹⁰ Hence, we report the most intuitive model which was introduced with Figure 1.

Table 2. Estimation results of the multinomial logit and nested logit models

Variables	Multinomial logit				Nested logit			
	Staying		Migrating to growth-centre		Staying		Migrating to growth-centre	
Constant	1.964	(0.895)	2.259	(1.136)	2.586	(1.300)	2.749	(1.618)
Predicted annual earnings*10 ⁻⁵	0.246 (0.065)				0.260 (0.086)			
Annual earnings*10 ⁻⁵ in 1993	- 0.014	(0.038)	- 0.136	(0.050)	- 0.052	(0.046)	- 0.203	(0.068)
Sex (1 = male)	- 0.030	(0.268)	0.519	(0.323)	0.065	(0.328)	0.724	(0.441)
Age*10 ⁻¹	0.433	(0.354)	- 0.165	(0.460)	0.534	(0.491)	0.028	(0.666)
Lower academic degree	- 0.739	(0.340)	0.013	(0.425)	- 0.682	(0.423)	0.095	(0.562)
Higher academic degree	- 1.432	(0.453)	0.635	(0.560)	- 1.280	(0.523)	0.873	(0.758)
Spouse's main activity employment	- 0.262	(0.283)	0.093	(0.365)	- 0.219	(0.324)	0.182	(0.462)
Children under 7	0.137	(0.321)	0.046	(0.434)	0.059	(0.432)	- 0.085	(0.622)
7 – 18-year-old children	0.500	(0.388)	- 0.698	(0.544)	0.419	(0.563)	- 0.869	(0.831)
House owner	0.963	(0.255)	- 0.381	(0.336)	0.912	(0.303)	- 0.491	(0.433)
Commuting	- 0.919	(0.284)	- 1.180	(0.365)	- 1.203	(0.362)	- 1.680	(0.541)
Inhabited in a subregion where originally born	0.637	(0.246)	- 0.089	(0.315)	0.610	(0.328)	- 0.124	(0.442)
Working months	- 0.075	(0.035)	- 0.081	(0.050)	- 0.087	(0.043)	- 0.102	(0.063)
Regional population*10 ⁻⁴	- 0.156	(0.147)	- 2.259	(0.351)	- 0.367	(0.294)	- 2.705	(0.667)
IV parameter					0.699 (0.222)			
Log likelihood	- 677.919				- 677.806			
Likelihood ratio index	0.182				0.182			
LR test for equal earnings parameters	1.895 (p = 0.388)				2.227 (p = 0.635)			
Wald test for IV parameter = 1					1.830 (p = 0.176)			
Number of observations	3061				3061			

Note: Firstly estimated parameter is given, then followed by asymptotic standard errors in parenthesis. Normalising base category is migrating to periphery.

Before examining probability elasticities with respect to changes in expected earnings, we briefly state the results of the other variables in the models. Because the interpretation of the parameters of the discrete choice models is somewhat problematic, we base our interpretation on (simulated) marginal effects and elasticities (Maddala 1983; Greene 1997). Generally speaking our results are according to prior expectations. Highly educated people are more likely to migrate, especially to growth-centre region. Older people are less likely to migrate. As already Mincer (1978) points out, family considerations appear to influence migration decisions. People are tied to other people and hence individual's migration propensity is decreased in the presence of children. One can also be tied to a house, as it might be the case for house owner and thus reduce one's migration propensity. Commuting increases migration propensity and inhabiting in a subregion where born reduces it. Note that people with higher initial earnings levels are less likely to migrate from the peripheral regions to growth-centre regions.

Table 3. Estimated elasticities with respect to expected earnings

Effect on	Earnings in an alternative		
	Staying	Migrating to periphery	Migrating to growth-centre
<i>Multinomial logit</i>			
Staying	0.013	- 0.023	- 0.089
Migrating to periphery	- 2.008	0.951	- 0.089
Migrating to growth centre	- 2.008	- 0.023	2.307
<i>Nested logit</i>			
Staying	0.268	- 0.002	- 0.006
Migrating to periphery	- 1.996	0.727 ^a	0.023 ^c
Migrating to growth centre	- 1.996	0.006 ^b	1.796 ^d

Notes: ^{a)} The effect can be further decomposed into an effect on choosing to migrate (0.023) and on choosing peripheral region (0.704). ^{b)} Can be decomposed into an effect on choosing to migrate (0.023) and on choosing growth-centre region (- 0.017). ^{c)} Can be decomposed into an effect on choosing to migrate (0.088) and on choosing peripheral region (- 0.066). ^{d)} Can be decomposed into an effect on choosing to migrate (0.088) and on choosing growth-centre region (1.708). Elasticities are calculated at mean values of the explanatory variables. See Koppelman and Wen (1998) for clear elasticity formulas in two level nested logit.

Relaxation of the IIA assumption in the nested logit model can be seen from the direct and cross elasticities reported in Table 3. Table lists estimated elasticities of the estimated probabilities with respect to changes in expected earnings in all alternatives. The elasticities are computed at the sample means. Implication of the IIA assumption can be seen in the table entries: in the MNL model cross elasticities for each attribute

are all equal, while in the nested logit model the IIA property only holds within the branch of migrants.

To interpret the elasticities, suppose a worker in a peripheral region thinks that his earnings would increase in current region by 1 per cent next year, *ceteris paribus*, then it would increase staying propensity by 0.013 (0.268) per cent in (nested) multinomial logit model. Similarly, migration propensity to would decrease by some 2 per cent.

Suppose instead that decision maker assumes that his earnings would increase by 1 per cent by migrating to some other peripheral region, *ceteris paribus*. This would ultimately reduce incentives to stay in current region, but not by much. More importantly, it would increase his migration incentives to peripheral regions by 0.951 (0.727) per cent in our (nested) multinomial logit. Nested logit model allows us to decompose the effect into two parts, as well. It increases person's propensity to migrate (0.023 %) and more importantly it increases persons chances of choosing peripheral region over growth-centre region (0.704 %). Cross elasticities are very small.

Finally, suppose the decision maker thinks that his earnings would increase by 1 per cent by migrating into a growth-centre region, *ceteris paribus*. This would increase migration propensity to the growth-centre region by 2.307 (1.796) % in our (nested) multinomial logit. Again the figure for nested logit can be decomposed into two parts. It increases person's propensity to migrate (0.088 %) and more importantly it increases persons likelihood of choosing growth-centre over peripheral region (1.708 %). Though, these decomposition effects should be interpreted with caution, as migration decision and destination choice is most likely a simultaneous in nature. Again, cross elasticities are small.

Although these are small effects on already small migration propensities, what is significant is that the direct elasticity of migration propensity to growth-centre region is over twice as large as the direct elasticity of migration propensity to peripheral region with respect to change in expected earnings in these alternatives. Given the expected earnings development in the two types of regions this will further increase migration from peripheral regions. Note that in the MNL model cross elasticities are implausible because average migration and staying probabilities are very different from each other. For example, it is not feasible that a change in earnings person could earn in growth-

centre regions would decrease staying and peripheral migration probabilities by same per cent figure.

5. Conclusions

Aim of was to study is examine whether or not the migration from peripheral regions is driven by larger expected earnings. How elastic is migration propensity from peripheral regions with respect to changes in expected earnings? Would an increase in earnings in peripheral regions reduce geographical shift of workforce from those regions? If that is the case, we could weaken this concentration pattern by increasing earnings of those people who live in peripheral regions for example by lowering personal taxation.

Our results show that migration choices are influenced by expected earnings. That is, higher expected earnings in growth-centre regions are an attraction: the direct elasticity of migration propensity to growth-centre region is over twice as large as the direct elasticity of migration propensity to peripheral region. After controlling for other variables, we argue that in migration choice what matters it not only what you earn today, but also what you are expected to earn in the future.

Some caution must be borne in mind when considering these results. Firstly, expected earnings were predicted with a limited explanatory power. Against this, it may be unreasonable to assume that decision makers have a better expectation of their earnings potential. Secondly, while the nested logit relaxes IIA assumption, it does not allow free correlation structure between error terms like multinomial probit (Daganzo 1979; Weeks 1997) or random parameters logit (McFadden and Train 2000). Having said that, our model still serves as a useful approximation to the problem.

Notes

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¹ The MNL models have several advantages. In particular, it makes estimation of the choice model straightforward, because the log-likelihood function has a global maximum and the probabilities have closed form representations. Unfortunately, this computational tractability comes at a cost. The MNL models assume that the odds ratios are independent of the other alternatives, i.e. P_{ij}/P_{ik} must be independent of the remaining probabilities. The property is termed as independence from irrelevant alternatives (IIA).

² Several previous studies model migration decision and control for sample selection in determination of wages (Nakosteen and Zimmer 1980; Robinson and Tomes 1982; Tunali 1986; Falaris 1987; Islam and Choudhury 1990; Vijverberg 1995; Axelsson and Westerlund 1998), but only Falaris used multinomial choice model.

³ At least four sources can randomness can be listed: unobservable attributes of alternatives, unobservable variations in preferences, measurement errors in the data, or use of instrumental (or proxy) variables (see Ben-Akiva and Lehman 1985, 56 – 57). See McFadden (1981) and Ben-Akiva and Lerman for the assumptions about the distribution of random term that yield the multinomial and the nested logit model.

⁴ Form of the log likelihood is in all cases:

$$\ln L = \sum_{i=1}^n \sum_{j=1}^J \delta_{ij} \ln P_{ij}, \text{ where } \delta_{ij} = 1, \text{ if alternative } j \text{ is selected.}$$

⁵ The subregion of Åland has been excluded, as it has many special characteristics (self-regulation, isolated geographical location, language, small size) distinctive from the rest of the country.

⁶ Corresponding figures for all residents are 2.42 % and 1.20 %. Thus a person inhabited in peripheral region is more likely to migrate than a typical Finn.

⁷ Estimation results are available on request from the author.

⁸ Even if the selectivity parameters were significant their precise interpretation on their sign, however, is problematic (see Dolton and Makepeace 1987).

⁹ The unconditional earnings predictions in the three alternatives were calculated by setting selectivity correction terms equal to zero.

¹⁰ We also tried to estimate HEV model (Bhat 1995), but it did not converge. Another option would have been to use mixed logit proposed by McFadden and Train (2000), but for simplicity we only use MNL and nested logit models.

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