

VARIATION OF MIGRATION BEHAVIOUR IN POPULATION

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Abstract

The purpose of this study is to empirically investigate variation in the migration behaviour across individuals. Both a random parameters logit (RPL) and a standard logit model are employed. The migration models are estimated using a register-based data from Finland. The RPL model proves to be a flexible way to control for random variation in the parameters: the results suggest that many migration parameters do vary within population and that the RPL specification improves statistical fit compared to the standard logit model. The RPL can also give valuable information on the reliability of predictions if computed from a model. Therefore, it can be fruitful to relax the assumption of fixed parameters in a wider range of economic applications.

Keywords: Migration, decision making, random parameters logit, simulation estimation

JEL: J61, R23, C15, C35

1 Introduction

A wide range of the statistical formulations of the migration decision relies on logit and probit formulations. For example, migration decision and wage determination has been seen as joint decision; see e.g. Nakosteen and Zimmer (1980), Axelsson and Westerlund (1998), Tunali (2000); the migration and employment decisions have been modelled jointly; see e.g. Zax (1991). In addition, the migration decisions have been formulated as a decision over several alternatives; see e.g. Falaris (1987), Vijverberg (1995).

Although such models have widened our understanding of the migration phenomenon, they have still imposed a notable restriction: the parameters that enter the migration model are assumed to be non-stochastic and therefore same for all individuals. This assumption implies that different individuals with the same observed characteristics have the same value for each factor entering the migration model. One way to overcome this problem is to interact the *observed* variables with each other, but there can still be *unobserved* factors that influence the migration decision rules. Suppose, for example, that we observe whether an individual's spouse is working or not, but we cannot observe whether the spouse is commuting or not. In this case, it is expected that the effect of having a spouse on the propensity of migration should have a smaller negative (or even positive) effect on migration for an individual whose spouse is commuting than for an individual whose spouse is not commuting. The standard models cannot control for such unobserved effects, but it can be done with random parameters logit models (see e.g. McFadden and Train 2000).¹

The random parameters logit (RPL) generalises a standard logit specification by allowing parameters to vary within population. It can be assumed, for example, that the random parameters have a normal or log-normal distribution and thus it is possible to estimate the moments of such distributions (mean, variance). Hence, the RPL model can be a useful way to test whether and how much the migration parameters of interest vary within the sample population.

The main objective of this empirical paper is to test hypothesis of the variation in the parameters with a data set drawn from Finland. The data set is a one per cent random sample

¹ Random parameters logit ("mixed" logit) models have been used in various applications e.g. in marketing and consumer research (Jain, Vilcassim, and Chintagunta 1994; Train 1998; Brownstone and Train 1999), but, to our knowledge, they have not been applied to migration problems except for Haapanen (2002).

from the Finnish longitudinal census. The primary finding is that RPL model can be a useful way to study the variation of the parameter estimates of interest: the results suggest that many migration parameters do vary within population and that the RPL specification improves statistical fit compared to the standard logit model. The RPL can also give valuable information on the reliability of predictions.

The remainder of this paper is organised as follows. Section 2 specifies random parameters migration model. Section 3 introduces our data. Section 4 gives the results of a standard logit model and then compares them with the results of the estimated random parameters logit model. Finally, section 5 concludes the study.

2 Theoretical model specifications

The theoretical setting of this paper is related to the human capital framework², which is based on the modelling work of Sjaastad (1962), Weiss (1971) and Schaeffer (1985). In it migration is assumed to result from variations in individual economic utility in different locations. Furthermore, an individual is assumed to maximise his or her economic utility. Thus, relocation takes place if the expected economic utility gained from moving exceeds the economic utility achieved by staying in the present location. Heterogeneous individuals possess different utility functions, and consequently encounter differences in the net benefits of living in a specific location.

Traditionally such migration decisions have been estimated with logit or probit models, for example because their likelihood function can be easily maximised due to a closed-form solution and because their results are convenient to interpret (Ben-Akiva and Lerman 1985). However, to obtain efficient and accurate estimates of the model parameters one should include a specification of the heterogeneity structure in the model: the presence of heterogeneity will alter marginal effects and marginal rates of substitution between choices. We take this perspective in setting out a random parameters logit model that can incorporate the unobserved effects.³

² For example Greenwood (1975; 1985), Shields and Shields (1989), Greenwood *et al.* (1991), and Ghatak *et al.* (1996) review other theoretical alternatives and determinants of migration.

³ The RPL models have taken different forms in different applications but what they have in common is that their commonality arises in the integration of the logit formula over the distribution of unobserved random parameters; see e.g. Jain, Vilcassim, and Chintagunta 1994; Train 1998; Brownstone and Train 1999; McFadden and Train 2000; and Hensher 2001.

We assume that the choice of individual i is made according to the well-known random utility maximisation hypothesis (see e.g. Ben-Akiva and Lerman 1985), where the (indirect) utility of alternative j is the sum of a deterministic component (linear-in-parameters) and a stochastic component. The latter component is further decomposed into a stochastic part that is perhaps heteroskedastic over people, and another stochastic part that is independently, identically distributed (iid) over alternatives and individuals.⁴ In the analysis below, $j = 1$, if an individual stays in the region of origin, and $j = 2$, if he or she moves.

We derive the RPL model by assuming that the utility, $U(i, j)$, that individual i receives given a choice of alternative j is

$$U(i, j) = \alpha_{ji} + \beta_j' x_{ji} + \eta_{ji}' z_{ji} + \varepsilon_{ji}, \quad (3)$$

where α_{ji} is an alternative specific constant (fixed or random), β_j is a vector of fixed parameters and η_{ji} is a parameter vector randomly distributed across individuals (with normalisations: $\alpha_{1i} = \mathbf{0}$, $\beta_1 = \mathbf{0}$ and $\eta_{1i} = \mathbf{0}$). x_{ji} and z_{ji} are sets of explanatory variables that are usually choice-invariant individual specific characteristics (such as age and education).

Furthermore, we assume that the random parameters η follow a general distribution $g(\eta | \Omega)$. Estimation of the RPL model involves estimating the vectors Ω in addition to the fixed parameters as in the standard logit model. In practice, we specify the random parameters as⁵

$$\eta_{ji} = \gamma_j + \sigma_j u_{ji}, \quad (4)$$

where $u_{ji} = N(0, 1)$ and $\eta_{ji} = N(\gamma_j, \sigma_j^2)$ or $\eta_{ji} = \log N(\gamma_j, \sigma_j^2)$. The parameters γ and σ , which represent the mean and standard deviation of η , are estimated. The unobserved disturbance term u is independent standard normal disturbance term.

For each individual, the migration choice probabilities will be

$$P(j | \eta) = \frac{\exp(U(i, j))}{\sum_{j=1}^2 \exp(U(i, j))}, \quad i = 1, \dots, N; \quad j = 1, 2. \quad (5)$$

⁴ McFadden and Train (2000) show that any random-utility model can be approximated to any desired degree of accuracy with a RPL model through appropriate choice of explanatory variables and distributions for the random parameters.

⁵ A number of other error covariance structures can be specified in random parameters logit models (see e.g. Hensher 2001).

If the value of η were known for each individual, the solution to Equation (5) would be straightforward (resulting into the MNL model). However, η is unobserved, although it is drawn from a known joint density function g . Thus, in order to obtain the unconditional choice probabilities for each individual the logit probability must be integrated over all values of η weighted by the density of η :

$$P(j) = \int_{\eta} \frac{\exp(U(i, j))}{\sum_{j=1}^2 \exp(U(i, j))} g(\eta | \Omega) d\eta . \quad (6)$$

Examination of the above equation reveals that the choice probability is a mixture of logit probabilities with g as the mixing distribution. The integrals in Equation (6) cannot be evaluated analytically since it does not have a closed-form solution in general. Therefore, the integrals in the choice probabilities are approximated using a Monte Carlo technique and the resulting simulated log-likelihood function is maximised.

3 Data

In the empirical work data from Finland is used. The data set is a one per cent random sample from the Finnish longitudinal census. The census file is maintained and updated by Statistics Finland. The socioeconomic status of the sample people and their spouses is well documented: the data includes information on personal and family status, past labour market record, and regional characteristics.

Information on individuals' home region allows us to divide Finland into 85 regions (NUTS4, "seutukunnat"), which by and large represent the actual commuting and working areas as well. Therefore, in the empirical analysis below the dependent variable, *migrate in 1996*, involves a change of home region of residence. Figure 1 illustrates the regional division by showing the net annual migration into the regions. We can see (the darkest-shaded areas) that only a few regions that experienced positive net migration in 1996.⁶

⁶ Information on the home region is recorded on the last day of each year. Hence, we know whether person migrated during a calendar year.

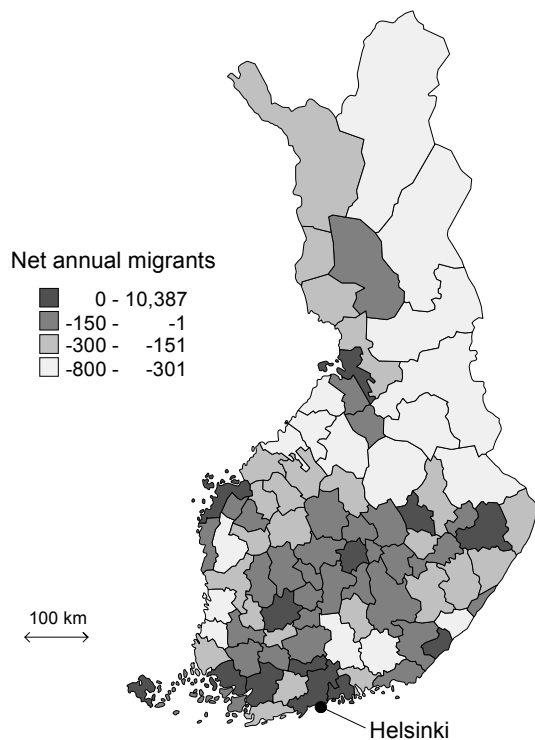


Figure 1. Net annual migrants, 1996

The only restrictions placed on individuals for inclusion in the working sample are that they are between 15 and 64 years of age in 1995, and that information on all variables is complete. After omitting observations with missing information we are left with 33 068 observations, of whom 994 persons (3.01 per cent) migrated in 1996. One could use more a longer panel on observations and observe more migrants. While the small proportion of migrants may work against finding strong statistical evidence, the most recent information likely carries more weight in the worker's prediction of his future.

Table 1 below provides the definitions of the explanatory variables of our empirical migration model, as well as their mean and standard deviation by the migration status. All the explanatory variables are measured before the migration decision is made in 1996. They include a variety of typical factors that have been found to affect migration behaviour (see e.g. Greenwood 1975; 1985; Tunali 2000; Ritsilä 2001). Hence, they control for differences in the human capital, location, labour market status and costs of migration. The differences in the mean values of the explanatory variables in the samples of migrants and stayers are notable.

Table 1. Variable definitions and descriptive statistics

Variable	Mean (std. dev.)					
	Full sample		Only stayers		Only migrants	
<i>Human capital</i>						
Age	40.067	(13.209)	40.374	(13.149)	30.152	(11.165)
Upper secondary education [†]	0.215	(0.411)	0.211	(0.408)	0.334	(0.472)
Lower academic education [†]	0.084	(0.277)	0.084	(0.277)	0.095	(0.293)
Higher academic education [†]	0.056	(0.230)	0.056	(0.230)	0.065	(0.247)
<i>Location</i>						
Municipal semi-urban [†]	0.154	(0.361)	0.154	(0.361)	0.161	(0.368)
Municipal rural [†]	0.244	(0.430)	0.243	(0.429)	0.289	(0.453)
Growth-centre region [†]	0.446	(0.497)	0.449	(0.497)	0.344	(0.475)
<i>Labour market characteristics</i>						
Travel-to-work unemployment rate	19.820	(4.029)	19.802	(4.029)	20.400	(3.984)
Employed in the last week of 1995 [†]	0.581	(0.493)	0.586	(0.493)	0.426	(0.495)
Commuting [†]	0.052	(0.223)	0.050	(0.218)	0.131	(0.337)
Farmer [†]	0.032	(0.177)	0.033	(0.179)	0.004	(0.063)
Work experience	5.953	(3.548)	6.020	(3.536)	3.795	(3.258)
<i>Migration costs</i>						
Annual wage*10 ⁻⁴	6.539	(7.729)	66.094	(77.694)	42.734	(58.652)
Under school-aged children only [†]	0.104	(0.305)	0.104	(0.305)	0.101	(0.301)
School-aged children [†]	0.295	(0.456)	0.297	(0.457)	0.217	(0.413)
Married [†]	0.671	(0.470)	0.678	(0.467)	0.424	(0.494)
Spouse employed [†]	0.415	(0.493)	0.421	(0.494)	0.209	(0.407)
Homeowner [†]	0.407	(0.491)	0.410	(0.492)	0.295	(0.456)
Living in region of birth [†]	0.529	(0.499)	0.533	(0.499)	0.389	(0.488)
Number of migration events in 1990–95	0.166	(0.481)	0.153	(0.460)	0.574	(0.845)
Number of observations	33 068		32 074		994	

Notes: All variables are measured in 1995 if not otherwise stated. [†]Indicator variable (= if the definition applies, = 0 else). The reference education (municipal; children) is primary school or lower secondary education (urban; no children). Growth-centre regions are Helsinki, Porvoo, Salo, Tampere, Turku, Vaasa, Jyväskylä, Kuopio and Oulu (see Haapanen 2002). Working experience is defined as number of months at work in 1987 – 1995 divided by 10. Annual wage is in Finnish Marks (FIM).

Personal human capital (age, education etc.) is an important factor that contributes to or prevents the decision to move (see e.g. Ritsilä and Ovaskainen 2001). Age is generally viewed as being one of the key personal characteristics in explaining migration. The older the migrant, the fewer will be the years of payoff from the human capital investment in migration, while the cost of migration remains just as high, which helps to explain why migration diminishes with age. In addition, younger individuals are expected to have lower psychical costs, because of fewer local social ties. Education is also a very important personal characteristic in explaining migration. Education is general human capital, which is easily transferable to different locations and which creates employment opportunities. Higher levels of education may thus reduce the risks of migration (Shields and Shields 1989). The reported

mean values support these views: the migrants are younger and have higher educational levels than the stayers.⁷

The mean values of the location variables suggest that migration is more like among individuals living in the rural areas than in the urban areas (see also Axelsson and Westerlund 1998). It is also assumed that the incentives to move from the central areas are low (see also Haapanen and Ritsilä 2001).

Labour market characteristics of individual and region can also affect migration decisions. If local unemployment rate is high, the propensity to move is likely to be high as well, since the probability of job placement is then low (Tervo 2000). Recent work experience and employment may also lower propensity to move, whereas commuting is expected to increase it.

The cost of migration can depend, for example, on the family and housing characteristics, and prior migration experience. Besides affecting the direct costs of moving, marriage and presence of children can indicate the existence of additional local household ties (Mincer 1978). An individual can also be tied to a house and hence it can reduce the probability to move (see e.g. Henley 1998). The cost of moving is likely to increase if individual's spouse is employed or the individual lives in region of birth. Migration propensity is expected to increase with the number of migration events recent past. The cost of migration can also be dependent of the welfare of an individual. The prior expectation is that likelihood of migration decreases as the experienced economic welfare increases (Antolin and Bover 1997). Our measure of welfare is personal annual income subject to state taxation.

4 Estimation results

Table 2 provides the estimation results for a standard logit model, which is used as a comparison for the more advanced random parameters logit model. Parameter estimates and marginal effects (multiplied by 100) are given. All variables enter the model at a five per cent significance level, except for the *travel-to-work unemployment rate* and *work experience* – variables.

⁷ The education variable is defined using the Finnish Standard Classification of Education (31.12.1994).

Table 2. Standard logit model

Variable	Parameter estimate (s.e.)		Marginal effect*100
Constant	-1.150	(0.243)	
<i>Human capital</i>			
Age	-0.052	(0.004)	-0.140
Upper secondary education	0.327	(0.078)	0.890
Lower academic education	0.435	(0.124)	1.183
Higher academic education	0.689	(0.155)	1.873
<i>Location</i>			
Municipal semi-urban	0.238	(0.104)	0.646
Municipal rural	0.342	(0.093)	0.929
Growth-centre region	-0.456	(0.089)	-1.240
<i>Labour market characteristics</i>			
Travel-to-work unemployment rate	0.016	(0.009)	0.044
Employed in the last week of 1995	-0.282	(0.098)	-0.765
Commuting	1.113	(0.116)	3.024
Farmer	-1.126	(0.514)	-3.061
Work experience	-0.020	(0.014)	-0.054
<i>Migration costs</i>			
Annual wage*10 ⁻⁴	-0.003	(0.001)	-0.076
Under school-aged children only	-0.400	(0.127)	-1.088
School-aged children	-0.282	(0.089)	-0.765
Married	-0.229	(0.097)	-0.623
Spouse employed	-0.483	(0.104)	-1.312
Homeowner	-0.326	(0.084)	-0.887
Living in region of birth	-0.708	(0.074)	-1.924
Number of migration events in 1990–95	0.547	(0.045)	1.485

Notes: Dependent variable: *migrate in 1996*. See Table 1 for variable definitions and descriptive statistics. Sample size: 33068. Log-likelihood: -3761.64. Log-likelihood with constant only: -4462.47. Likelihood ratio index⁸: 0.157.

The estimation results are in accordance with the expectations (see Section 3). We can see, for example, that old people are less likely to migrate than young and that there exists a fairly direct relationship between an individual's years of education and migration. The location variables indicate that migration is more likely among individuals living in the rural areas than in urban areas.

Family status influences migration decisions. Individual's propensity to move is decreased in the presence of children or if the individual is married. Our results also indicate that owning a house reduces individual's probability to move. We did not find gender differences in

⁸ The likelihood ratio index is a measure of fit, defined as $1 - [SLL/SLL(0)]$, where SLL is the value of the simulated log-likelihood at the estimated parameters, and SLL(0) is the maximum value of the log-likelihood subjected to the constraint that all the parameters except the constant term are zeros; see e.g. Maddala 1983, 40; Greene 1997, 891.

migration, which is not surprising given that we have controlled for various household characteristics (Shields and Shields 1989).

However, as discussed above, it is unlikely that parameters of interest are the same for all members of the population. That is why we let some of the parameters to be normal distributed random parameters (see Section 2). The random parameters are selected on the bases of sequential model comparisons starting from simple model where only constant term and one other explanatory variable were entered normally distributed. The model reported in Table 3 proved to be the most parsimonious one.⁹

Table 3. RPL model with normally distributed random parameters

Variable	Parameter estimate, γ (s.e.)		Std. dev. of parameter distribution, σ (s.e.)		Marginal effect*100
Constant	-1.606	(0.409)	1.644	(0.458)	
<i><u>Human capital</u></i>					
Age	-0.068	(0.009)			-0.185
Upper secondary education	0.452	(0.117)			1.229
Lower academic education	0.659	(0.187)			1.793
Higher academic education	1.017	(0.251)			2.764
<i><u>Location</u></i>					
Municipal semi-urban	0.321	(0.142)			0.873
Municipal rural	0.437	(0.130)			1.188
Growth-centre region	-1.399	(0.434)	1.633	(0.461)	-3.802
<i><u>Labour market characteristics</u></i>					
Travel-to-work unemployment rate	0.020	(0.012)			0.053
Employed in the last week of 1995	-0.681	(0.289)	1.055	(0.407)	-1.851
Commuting	1.626	(0.257)			4.420
Farmer	-1.347	(0.608)			-3.662
Work experience	-0.021	(0.019)			-0.057
<i><u>Migration costs</u></i>					
Annual wage*10 ⁻⁴	-0.056	(0.020)	0.038	(0.025)	-0.153
Under school-aged children only	-1.497	(0.792)	1.806	(0.850)	-4.069
School-aged children	-0.415	(0.126)			-1.128
Married	-0.231	(0.130)			-0.627
Spouse employed	-1.294	(0.421)	1.376	(0.460)	-3.516
Homeowner	-0.407	(0.117)			-1.105
Living in region of birth	-0.962	(0.144)			-2.615
Number of migration events in 1990–95	0.817	(0.118)			2.221

Notes: Dependent variable: *migrate in 1996*. See Table 1 for variable definitions and descriptive statistics. Number of replications for simulated probabilities: 500. Sample size: 33068. Simulated log-likelihood: -3750.53. Log-likelihood with constant only: -4462.47. Likelihood ratio index: 0.160.

⁹ Randomness of a parameter was modelled only if the parameter estimate and the estimated standard deviation showed significance.

A comparison of the RPL model against the standard logit model indicates an important contribution to the overall statistical fit from a less restrictive specification of the unobserved effects: the likelihood ratio index rises substantially compared to the logit model; compare also the log-likelihood of -3750.53 and -3761.64 in the RPL and in the standard logit, respectively.¹⁰ The estimated standard deviations of parameters indicate that migration parameters do vary within the population.

The estimation results are inline with our prior expectations and the standard logit model reported in Table 2. The estimated parameters that enter the non-stochastic portion of utility are generally larger in magnitude in the RPL (Table 3) than in the standard logit (Table 2).¹¹ This is expected, as the scale of utility is determined by the normalisation of the error term. In a standard logit, all stochastic term are absorbed into this one error term. In the RPL model some of the variance in the stochastic portion of the utility is captured in the random parameters. The marginal effects are also in many cases larger than in the standard logit model.

Figure 3 below illustrates the distributions of the estimated random parameters. The figures are computed by generating 33 680 random numbers from the estimated $N(\gamma, \sigma^2)$ distribution. Then the parameter densities are drawn.¹² A consequence of assuming normal distribution for the random parameters is that a parameter can indeed have a sign opposite of expectation for some individuals. For example, the parameter of *spouse employed* is necessarily positive for some individuals, because of its deviation parameter were estimated large and significant in Table 3, although the mean estimate is negative. This can reflect reality or can be an artifact of the assumption of normally distributed parameters. One could specify the parameter density using log-normal distribution instead of normal. Then the density would be strictly positive on one side of zero. However, it could also be too restrictive assumption (see discussion in Section 1).¹³

¹⁰ Likelihood ratio test gives chi-squared (8) statistic 11.11 ($p = 0.08$).

¹¹ Brownstone and Train (1999) and Revelt and Train (1998) have obtained the same result.

¹² A direct plug-in methodology was used to select the optimal bandwidths of the kernel density estimates (Wand and Jones 1995, 71).

¹³ To be more specific, we could assume that each element of η has log-normal distribution, and thus the random parameters could be expressed as $\eta_{ji} = \exp(\gamma_j + \sigma_j u_{ji})$, where γ_j and σ_j represent the mean and

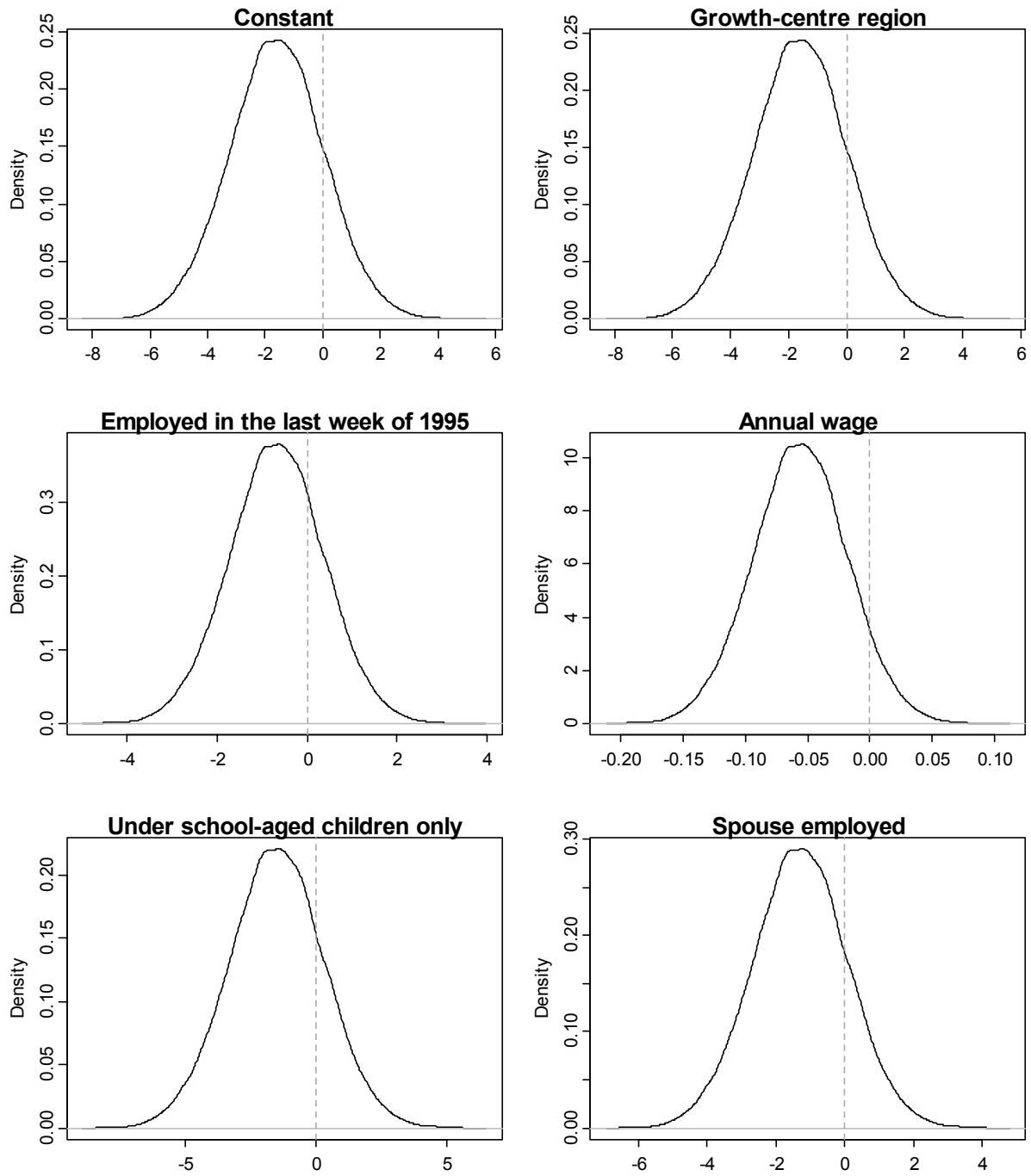


Figure 3. Densities of the random parameters in Table 3

standard deviation of $\ln(\eta)$ that is to be evaluated. The median, mean, and standard deviation of η could be easily calculated using properties of the log-normal distributions; see e.g. Train (1998) and delta method could be used to evaluate the standard errors of such figures; see e.g. Greene (1997).

Naturally we could also be interested in whether the deviation in the random parameters can be explained by other variables. To answer this question, we could reformulate our random parameters as a function of explanatory variables: $\eta_{ji} = \gamma_j + \delta_j' h_i + \sigma_j u_{ji}$, where h_i is the set of individual specific characteristics that influence the mean of the random parameter vector η . However, this analysis has been left for a further study.

5 Conclusion

In this paper we have modelled the migration decision using random parameters logit, which is more general than the standard logit model. We estimated the model specifications using register-based micro data from Finland. Our findings indicated that many estimated parameters do vary within population and the random parameters specification improve fit compared to a migration model estimated by traditional logit. Hence, we conclude that random parameters logit model can be a useful way to study the variation of the parameter estimates of interest. It can also give valuable information on the reliability of the predictions that are computed from an estimated model. Therefore, the results suggest that it might be fruitful to relax the assumption of fixed parameters in a wider range of applications for example in the fields of labour and regional economics.

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