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Migration Theories and Behavioural Models

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ABSTRACT

This review presents a probabilistic formulation of the decision making process, leading to a rigorous treatment of migration behaviour for projection purposes. These models are developed here at two different levels of aggregation. Aggregate-level models may be applied to migration flows for which the objectively measured characteristics of areas of department and destination act as subjectively measured characteristics and stimuli. They generate quite different population projections than the usual Markov model: sustained cycles may appear or chaotic behaviour may even occur. Individual-level models use event history methods of analysis to introduce a great variety of characteristics of the subject on the decision to move. They lead to projections using microsimulation models. A further step is taken in integrating macro- and microbehavioural models. The use of aggregate and individual characteristics simultaneously leads to more efficient and sophisticated projection models: the factors affecting behaviour at the micro-level cannot be inferred from aggregate studies and conversely.

Key words: migration; behavioural models; population projections; macro and micro approaches; probabilistic models

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INTRODUCTION

The purpose of this paper is not to give a general theoretical view of behavioural models, but rather to present some more precise models which can be used in migration projections, based on behavioural assumptions. These models will give a mathematical formulation of the decision making process, leading to a rigorous treatment of migration behaviour.

Let us first present a general formulation which will be used throughout this paper. First, this formulation will be a probabilistic one: this is an essential condition to carry out projection models. Secondly, these models may be designed for the behaviour of a single individual, but they may also be used to analyse aggregate data. The extrapolation is legitimate only when all the individuals are governed by the same choice mechanisms: otherwise there is an aggregation error (Ginsberg, 1972). We will see later under which conditions such a hypothesis may be considered as verified. Thirdly, the probability of a given type of migration behaviour will be a simultaneous function of the interaction between the stimuli to undertake such a migration and the characteristics of the subject or group submitted to this choice. Such a function may be written thus, as in Fraisse and Piaget (1963):

$$\mathrm{P}(M) = f(S \leftrightarrow C), \tag{1}$$

where $\mathrm{P}(M)$ stands for the probability of migrating, S for the stimuli and C for the characteristics or personality of the individual. The interaction between stimuli and characteristics is represented by the two opposite arrows. This is developed here at two levels of aggregation.

We will first consider homogeneous subpopulations between which migration flows may occur. *Aggregate level models* may be applied to these flows for which the objectively measured characteristics of areas of departure and destination may respectively act as their subjectively measured counterparts and as stimuli. Even if such an approach may be rejected by behavioural purists, as ignoring the aggregation problem (Golledge, 1981), it is an important method of introducing a behavioural perspective in models and more specifically in population projections. We will show how such a perspective may alter usual projections by using a nonlinear model.

We will then consider *individual level models*. Event history methods of analysis, currently used, permit us to give very detailed results on the hazard rate of moving. With these models we are able to introduce a great variety of subjective characteristics and to measure their effect on the decision to move. However, the search process of available destinations and the evaluation of these alternatives will be shown to be more difficult to model for projection purposes. This approach leads to projections using microsimulation models for migratory behaviour, in conjunction with other socio-economic behaviour (family formation, career life-cycle, etc.). These two approaches may lead to contradictory projection results, as one uses aggregate data and the other individual information data. This is an important methodological and even epistemological problem: can one develop methods which are equally valid at different levels of aggregation? Before concluding this paper, we will try to suggest some answers to this fundamental question.

MODELS FOR AGGREGATE POPULATIONS

In order to introduce a behavioural model for aggregate populations, it is necessary to make the hypothesis of invariant behaviour across large population groups: each sub-population, within which we observe the migration process, behaves as a homogenous group; individuals living in the same place are governed by the same choice mechanisms. Such a model may be based on some general behavioural assumptions of the theory of choice (Luce, 1959), applied to a migration choice among alternative destinations.

A Behaviourist Approach

Let us consider an individual making a choice among alternative destinations. We can distinguish between determinants of the intrinsic properties of the response alternatives, and the relationship between these alternatives and the individual's present state (Ginsberg, 1972). Now, let us first suppose that the individual has a perfect view of the attributes of each destination area that s/he might find attractive. If we ignore for the moment the region of origin from which the choice is made, it is possible to show that the probability of choosing alternative j from the others may be written:

$$\text{P (choosing area } j) = \frac{p_j}{\sum_{k=1}^{r} p_k}, \qquad j \in \text{ areas } k = 1, \dots, r, \tag{2}$$

where r is the number of considered regions and p_j represents the specific attractiveness of destination j. It may be measured as a function of different characteristics that prevail there: the extent of unemployment, the mean wage rate, the proportion working in agriculture, etc.

However, the attractiveness of a destination is not independent of the place of origin from which the choice is made. The information that the individuals living in place i may have on p_j will not be perfect and may be modified in some way as a function of different characteristics of the origin. For example, attractiveness may be a function of the proximity of the two places, of the similarity between their occupational structures, etc. If we represent the specific attractiveness of the different areas by a vector $\mathbf{p} = (p_1, p_2, \dots, p_r)$, the modification induced by the region of origin i takes place through a vector operator $f_i(\mathbf{p})$. If we suppose that the operator f_i is independent of the unit of measurement of $\mathbf{p}$ (so that $f_i(k\mathbf{p}) = kf_i(\mathbf{p})$) and that the modified attractiveness of destination j does not depend on the specific attractiveness of other destinations, then the new conditional probabilities of choosing area j, from somebody living in area i, will be

$$\text{P (choosing area } j | \text{living in area } i) = \frac{p_j q_{ij}}{\sum_{k=1}^{r} p_k q_{ik}}, \tag{3}$$

where q_{ij} are considered as stimulus parameters modifying p_j, the specific attractiveness of region j. These parameters are not dependent upon the specific attractiveness of regions other than i or j. Such a hypothesis seems plausible.

The stimulus parameters may be measured as a function of the distance (physical or sociological) between areas i and j and of different characteristics prevailing in area i. Also similar characteristics of area j may be taken into account.

It is clear that these models represent a *behaviourist* approach (Cadwallader, 1989), in which a set of physical stimuli impinge on the individuals in each sub-population to produce an overt migration response, thus generating a relationship between the observable response (number of migrations) and the observable stimuli (characteristics and links between population of origin and population of destination).

Towards more Complex Probabilistic Models

According to the characteristics introduced in these models, different probabilistic models may result, which may be given a clear interpretation.

If we measure the specific attractiveness of region j only by its population, P_j, and the stimulus parameters as a function of the physical distance between i and j, d_{ij}, we can estimate the number of migrants between i and j, M_{ij}, as the product of the probability to choose area j when living in area i, and the population P_i, giving

$$M_{ij} = \frac{P_i P_j f(d_{ij})}{\sum_k P_k f(d_{ik})}, \qquad (4)$$

where $f(d_{ij})$ is a given function of the distance between i and j.[1] This is the usual 'gravity model', which is now grounded in a general behavioural theory rather than upon empirical hypotheses. The parameters of the distance function may be estimated by maximum likelihood procedures or by the method of moments (Ginsberg, 1972).

If we introduce the effect of different socio-economic characteristics of the region of destination in its specific attractiveness, we can write equation (4) in multiplicative form, for example, as

$$M_{ij} = \frac{P_i P_j X_{1j}^{\beta 1} \cdots X_{nj}^{\beta n} f(d_{ij})}{\sum_k P_k X_{1k}^{\beta 1} \cdots X_{nk}^{\beta n} f(d_{ik})}, \qquad (5)$$

where X_{lj} is the lth characteristic of region j and β_l is the corresponding parameter to be determined. For example X_{1j} may be the agricultural labour force, X_{2j} the per cent unemployed, etc., of region j. This model is a version of the economic gravity model which has been widely used in migration studies: for example Lowry (1966), Fotheringham (1991), etc.

A further generalization would be to introduce similar or different socio-economic characteristics of the region of origin, in the stimulus parameters. For example, an individual may have to compare the unemployment rate in his region of origin with the unemployment rate in the region of destination to make a migration choice.

Finally, it seems desirable to analyse i to i moves, or non-movers in area i, separately from i to j moves. For example, it has been shown that inter-metropolitan and intra-metropolitan moves correspond to different patterns, the former being explained largely in terms of the economic and spatial characteristics of the areas, the latter explained in terms of life-cycle and neighbourhood characteristics (Cadwallader, 1992). It is easy to introduce such differences in to the previous models.

How to use these Models for Population Projection

Usual population projections with migration are based on a Markov model which uses constant out-migration rates from regional sub-populations (Rogers and Willekens, 1986). These projections lead to a stable regional distribution in the future (Rogers, 1975).

However, formula (4) may lead us to quite a different approach: we may think that rather than using a constant out-migration rate, it would be better to use a constant index of migration intensity to undertake such population projections. To introduce the time dimension and to keep a probabilist signification, it may be useful to define such an index during a given period (t_0, t_1),[2] as

$$m_{ij} = \frac{M_{ij}}{P_i(t_0) P_j(t_1)}. \qquad (6)$$

Such an index can be interpreted as the probability that two randomly selected individuals alive at the end of the period, one selected among those residing in area i at the beginning of the period and the other among those residing in j at the end of the period, will be identical.

It we suppose that these indices remain constant during the time, we can use them to project each sub-population in the future. For example, for the following period of time (t_1, t_2) we can write

$$P_j(t_2) = P_j(t_1) + \sum_{i \neq j} m_{ij} P_i(t_1) P_j(t_2) - \sum_{i \neq j} m_{ji} P_j(t_1) P_i(t_2) \quad (7)$$

for each region j.
If we define the matrix $\mathbf{M}(\mathrm{t})$ as

$$\mathbf{M}(t_1) = \begin{bmatrix} 1 - \sum_{i \neq 1} m_{i.1} P_i(t) & m_{1.2} P_1(t) & \dots & m_{1.n} P_1(t) \\ m_{2.1} P_2(t) & 1 - \sum_{i \neq 2} m_{i.2} P_i(t) & \dots & m_{2.n} P_2(t) \\ \vdots & \vdots & & \vdots \\ m_{n.1} P_n(t) & m_{n.2} P_n(t) & \dots & 1 - \sum_{i \neq n} m_{i.n} P_i(t) \end{bmatrix} \quad (8)$$

and the vector $\mathbf{P}(t)$ as

$$\mathbf{P}(t) = \begin{bmatrix} P_1(t) \\ P_2(t) \\ \vdots \\ P_n(t) \end{bmatrix}, \quad (9)$$

then relationship (7) can be written in matrix form:

$$\mathbf{M}(t_1)\mathbf{P}(t_2) = \mathbf{P}(t_1). \quad (10)$$

Under the condition that $\mathbf{M}(t)$ has an inverse, the projection model may be written more generally:

$$\mathrm{P}(\mathrm{t}_{n+1}) = [\mathrm{M}(\mathrm{t}_n)]^{-1} \mathrm{P}(\mathrm{t}_n). \quad (11)$$

The peculiarity of this model lies in the fact that it is nonlinear (Courgeau, 1991, 1993). It leads to quite different predicted populations than the previous model, even if the projection period is short. However, more interesting results appear in long-term projections. Unlike the previous model, it no longer leads to a stable regional distribution in the future: sustained cycles may appear, some sub-populations may disappear or chaotic behaviour may even occur, depending on migration intensity values.

The methods should be generalized to apply to populations disaggregated into age-groups. This will permit us to use more homogeneous sub-populations. As we said previously, such an aggregate behavioural model supposes that all the individuals of the same sub-population are governed by the same choice mechanisms. It appears that such a hypothesis is not true for different age-groups and that disaggregation may avoid aggregation errors. The introduction of different socio-economic characteristics in such models needs a more complex formulation, using simultaneous equations. However, this is beyond the scope of the present paper.

To conclude this part of the paper, it is important to stress the extent to which such models may have a great impact on demographic thinking, because they involve a shift in the paradigm from analysing the predictable behaviour of linear models to the investigation of the dynamics of nonlinear models (Keilman, 1993). As we have seen, some nonlinear models may reveal chaotic behaviour, even when they are completely deterministic, leading to unusual demographic projections.

MODELS FOR INDIVIDUAL BEHAVIOUR

Let us now turn to individual behaviour, using data from detailed surveys. Individual migratory behaviour can be defined as the result of a complex stochastic process, which develops over time, yet is situated within given historical, geographical, economic and social conditions (Courgeau and Lelièvre, 1992). Such migratory behaviour will also be placed in the time and space of an individual's life. The point is to see how an event of a family, economic or other nature experienced by the individual will change the probability of different migratory movements occurring during his or her life-time. We shall, for instance, try to discover how marriage, occupational change, or experience of past moves can influence the decision to move and the choice of the migration destination.

Event History Analysis of the Migration Process

These models may be developed using either a continuous or a discrete time model. We will use here a continuous time formulation which leads to a simple formulation, but which may easily be translated into a discrete time formulation for projection purposes.

Let us consider the duration of stay of an individual, a, as a random variable T_k^a, when $(k-1)$ is the number of previous migrations, and the region of residence during the same period as a random variable I_k^a. The distribution of these random variables may depend on different characteristics of individual a (observed heterogeneity of the population), on different intervening events which could occur during the observed interval (interaction between migration and different demographic or socio-economic events) and on the information the individual may have about different possible destinations. For a given duration t we can define different functions. The most widely used function is the following instantaneous failure rate between areas i and j:

$$m_{ijk}^a(t|x_i^a(t), y_j^a(t)) = \lim_{dt \to 0} \frac{P(T_k^a < t + \mathrm{d}t,\ I_{k+1}^a = j | T_k^a \geqslant t,\ I_k^a = i,\ x_i^a(t),\ y_j^a(t))}{\mathrm{d}t} \tag{12}$$

where $x_i^a(t)$ are different characteristics (heterogeneity and interaction) of the individual a, and $y_j^a(t)$ are sets of information the same individual may have about area j. This is a multivariate model for failure-time data with competing risks. It may be defined more precisely using a non-parametric model (without individual characteristics), a parametric model or a semi-parametric one (with individual characteristics). It is often considered that these characteristics have a multiplicative effect on the instantaneous failure rate, which is the same for the whole population at risk over time (proportional hazard models).

These models are now widely used in demography, sociology, human geography, etc. (see Courgeau and Lelièvre (1992), Davies (1984), Tuma and Hannan (1984) etc.). They represent a *cognitive approach* to human behaviour. In this case we assume that behavioural patterns are not innate or inflexible when the individual is subject to some stimuli, but rather that they can change over an individual's lifetime as a result of what s/he experiences and acquires with time.

How to Create these Models

In order to obtain individual life histories we can use data from retrospective surveys such as, for example, the French survey on family, occupational and migration histories, known as the triple biography ('3B') survey (Courgeau, 1988).

Event history analyses of these surveys will give us detailed estimations of the probability of different demographic or economic events related to the age of the individual, duration of stay in different areas and to various personal characteristics (educational level, social origins, etc.).

For migratory behaviour, we will be able to estimate the probability of migration by rank order, duration of stay and according to the different positions of the individual in the life course just before the time of migration. It will also be possible to use the information the individual may retain on previous places of residence. However, these life history surveys will not give very detailed results on the information an individual living in a given place may have on all the surrounding places.

Other kinds of surveys are necessary to obtain such mental maps (Gould and White, 1986) or to obtain the information individuals living in one area may have on surrounding ones (Cadwallader, 1989). It is, unfortunately, difficult to link these data with event history data. Usually mental maps or information surfaces are place-of-origin-specific ones, without any disaggregation according to the individual life history. In fact, it is evident that they are also individual dependent: a retired person may have a different mental map from that of a young adult, a manager may have a different information surface from that of a factory worker, even when they are living in the same place. In conclusion, it seems important to go further and try to link event history data to individual mental maps and information surfaces. This is a necessary step to obtain more complete information on individuals' lives in time and space.

Projections using a Microsimulation Approach

Previous analyses of individual data give us very detailed information on individual migration behaviour according to duration of stay, personal characteristics, different occurrences of events that can change the probability of moving, past migration destinations, etc. However, this information is too intricate to permit the elaboration of standard projection models under an analytical formulation. The use of microsimulation models allows us to obtain an estimation of future regional population, under certain hypotheses. Although microsimulation methods have existed for a long time for migration projections (Hägerstrand, 1957), they focus on very few types of migration behaviour, such as the probability of making a new migration a given number of years after the previous one. We now have very detailed results on migration which can be regarded as the outcome of several interrelated processes which interact in a complex way. These results give us the probabilities (or the rates when using a continuous time approach) that an individual with given characteristics, having experienced certain events (for example, a man working in agriculture, eldest amongst his siblings, married for two years), or having lived in a given place of residence, will undertake a migratory move to a given area of destination a given number of years after a previous move.

We may use these probabilities to simulate the behaviour of each individual from an initial population whose characteristics, past experience and spatial information are given as known at the beginning of the observation. These models will simulate not only the migratory behaviour of individuals, but also other types of demographic behaviour (nuptiality, births, mortality, cohabitation) and occupational behaviour (entry into the labour force, change of occupation).

These microsimulation models are used increasingly to project regional populations or households (Clarke, 1986; Duley and Rees, 1991). They generate very interesting and detailed results which, however, must be interpreted with caution.

First, these models cannot incorporate the whole set of characteristics and interacting phenomena influencing migration behaviour. Since a degree of unobserved heterogeneity always escapes the model, the simulation procedure may lead very quickly to quite different results from those observed in the future. It is possible to introduce unobserved heterogeneity in event history models, but interpretation is highly problematic (Heckman and Singer, 1982; Hobcraft and Murphy, 1986), a matter beyond the scope of this paper. Secondly, we have seen that whilst we have very detailed information on individual characteristics, mental maps and information surfaces are usually estimated at a more aggregate level. We can conclude that our estimations of out-migration flows from an area may be estimated with a better precision than in-migration flows, owing to this imbalance in the quality of available data. Finally, to our knowledge, the properties of these microsimulation models when the duration of the projection increases have not yet been analysed in detail. It would be of great interest to know if problems similar to those observed in macro-models may also occur in these micro-models.

RELATING MACRO- AND MICROBEHAVIOURAL MODELS

So far, we have presented behavioural models which are appropriate at different aggregation levels. Is it possible to relate these levels of aggregation in order to formulate a more efficient projection model? When reading some aggregate level analyses one may be tempted to consider that a sub-population's behaviour is the result of integrating additional patterns of individual behaviour. For example, we can read in Congdon (1991): 'Micro-level models will generally aggregate to generate some form of gravity formulation, especially if such aggregation is performed over relatively homogeneous populations in terms of micro theory'. In our opinion the problem is more complex and requires an answer on both methodological and epistemological grounds.

An answer to this problem may be found if we are working on an individual data set with sufficient sample size, from which we can elaborate both a macro- and microbehavioural model. The macro-model will use the same characteristics as the micro-model, but measured at the aggregate level. We present here some results obtained from theoretical arguments and from our '3B' survey (Courgeau, 1994).

Let us first formulate aggregate models of out-migration from French regions. The out-migration flow from a given region is considered as determined by aggregate characteristics, such as the percentage of population working in agriculture in the area. These aggregate characteristics may

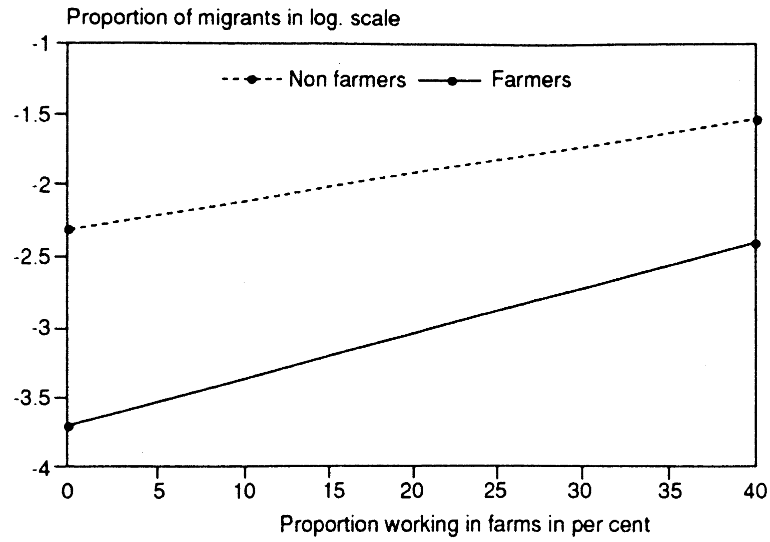

Figure 1. Migrants in log scale as a function of the proportion of farmers. (Source: Courgeau, 1994).

be considered as the mean values of the characteristics, measured at the individual level as indicator variables: in the previous case, for example this variable will be equal to 1 if the individual is working in agriculture, 0 otherwise. The formulation of individual level models will use these indicator variables.

With such notation it is possible to see in more detail the relationship between the micro- and the macro-models. We found from a theoretical point of view that it is not possible to identify a simple relationship between the parameters of the micro- and the macro-models. We were able to verify from our '3B' data that the correlations between the parameters are very low, leading us to suspect independence between them. Even when introducing these macro- and micro-characteristics simultaneously in a model at the individual level it appears that these two kinds of characteristics may have significant, but separate roles in influencing the probability of migration. An example taken from the '3B' survey permits clarification of a macro- and micro-characteristic on this probability. Farmers will have a very low probability of out-migrating from all regions, compared with other occupational groups. However, if we take into account the proportion of farmers living in each region, we see that an increase in this proportion will raise the probability of out-migration for people living in such areas. As we can see in Figure 1, such a result holds whatever the occupational status of the individual may be.

Such results seem to be contradictory if we suppose that the sub-population behaviour patters are the result of adding individual behaviour patterns. They are no longer contradictory if we suppose that the macro- and micro-characteristics play independent roles in influencing the probability of migration of different individuals. Figure 1 shows the farmers always have a lower migration probability than other occupational groups, whatever the proportion of farmers living in the same region. But when this proportion increases, we observe an increase in the probability of out-migration for farmers as well as others. This last observation is to be linked to the lack of other available occupations outside of farming in these areas, leading to out-migration in order to find a job, as much for those working on farms as those in other occupations. The micro-characteristic affects only the farmer's behaviour; the macro-characteristic affects the whole population of the area.

We can conclude that the factors affecting migration behaviour at the micro-level cannot be inferred from aggregate studies. It would be fallacious to assume that, because the proportion of farmers has been found to influence positively out-migration flows, individual-level migration will be influenced positively by the fact that the individual is a farmer. Analysts using aggregate data may be subject to the ecological fallacy: they attribute to individuals results found at the aggregate level. However, the aggregate parameters may be applied to the whole regional population as affecting their overall probability of migrating. Under these conditions, it will be useful to introduce these aggregate results in projection models using a microsimulation approach. Their effect will be complementary to, and independent of, the individual-level characteristics. The use of aggregate and individual characteristics simultaneously may lead to more efficient projection models.

CONCLUSION

Whilst it has not been possible in this paper to give a general theoretical view of behavioural models, we have been able to present here models at the aggregate and individual levels which can be used in migration projections or microsimulation. We were also able to link these two levels in a more general model. Such an approach raised two important problems which open new areas of research. The first relates to the shift in the paradigm from analysing the predictable behaviour of linear models to the investigation of nonlinear models or microsimulation ones. It is important to explore in more detail the consequences of these models and their demographic explanation. The second relates to the links existing between micro- and macro-behavioural models. The first results need to be generalized to more complex migration models applied to larger samples of individuals, obtained through population registers for example. Further, it is necessary to go beyond a purely individual approach to introduce aggregation levels which could not be considered here: the family level, the household level, etc. New characteristics are to be introduced in these models and the relationship between these different models are to be explored. Such an approach will open up a large research field and may lead to new projection methods for the future.

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NOTES

(1) With this formulation, there must be an M_{ii} term (stayers). Alternatively, we can use another formulation omitting the stayers and similar to Wilson's (1974) destination/origin constrained spatial interaction model.
(2) It may be possible to define an instantaneous migration intensity, so that the model may be a continuous time system (Courgeau, 1991).

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