

Migrations, incomes and unobserved heterogeneity

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Abstract

We use panel data to estimate a model of migration decision with unobserved heterogeneity. A household chooses to migrate when the expected income net of moving costs outweighs his income if staying. Incomes and costs are specified as functions of observed characteristics, individual random effects and i.i.d. shocks. Results suggest that a large part of the random component in the income equations is explained by unobserved heterogeneity, idiosyncratic shocks having smaller effects. By contrast, in the moving cost equation, unobserved heterogeneity is negligible. We also find that the effects of unobserved characteristics on income when moving and staying are the same.

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1 Introduction

The literature on migrations usually considers that mobility is an investment in human capital (Sjaastad, 1962). Households migrate only if the life-time expected gains exceed the expected costs. Gains to migration stem from differences in permanent incomes when migrating and when staying at the place of residence. Thus, migrations are related to job opportunities. There may be two main reasons why workers may get different incomes in different areas. First, if local job markets are sufficiently differentiated, the workers' skills can be rewarded differently in each area. Second, a worker may simply find a better match with a particular firm that leads to a wage bonus. In this context, at any point in time, migrants will not be a random sample of households. They will be the households either getting the highest wage bonuses, or having the lowest moving costs. Migration is thus a self-selection process.

Numerous papers analyze the income benefits of migration, taking self-selection into account (Nakosteen and Zimmer, 1980; Robinson and Tomes, 1982; Tunali, 1986; Islam and Choudhouri, 1990; Osberg, Gordon and Lin, 1994; Axelsson and Westerlund, 1998; Tunali, 2000). All these authors use cross-sectional individual data. They estimate income equations related to a move and a stay at the micro level, correcting for the selection effects arising from the choice to migrate or to stay (see Heckman, 1979). This framework allows one to compare the return of observed characteristics on incomes when moving and when staying, and to assess the existence of selection effects.

The use of cross-sectional data is problematic for two reasons. First, one does not observe individual (or household) income trajectories. Permanent income, which should be the right variable to look at in this case, is not observed or even reconstituted. Second, cross-sectional data do not permit to disentangle the effects of unobserved characteristics on income (e.g., returns to unobserved skills) from idiosyncratic shocks on income. This paper is concerned with the latter problem. We use panel data to look at the importance of unobserved heterogeneity in explaining migrations, within the static framework that has been used by the papers quoted above. To follow the previous literature on the subject, the migration decision of a household is modeled as a choice between staying in the current place of residence and moving to another area. Each option is characterized by an income level. When moving, the household incurs some monetary costs (as transportation costs of belongings) and some non monetary costs (as a loss of social network). A household chooses to migrate when a move is associated with an income net of moving costs that is higher than the income if staying. We specify both types of income and the costs as functions of observed characteristics, individual random effects and random shocks. The analysis of random components allows us to assess the relative importance of unobserved skill returns and shocks due to good/bad draws in the income

distribution.

The model is estimated on the French sample of the European Community Household Panel (EHCP), the *Panel Européen des Ménages*, 1994-2000. The panel contains rich information on 7,300 households regarding their socio-demographic characteristics, income, housing and mobility. In particular, it follows people when they move. We adopt a flexible estimation method based on simulation, which allows us to deal with unbalanced panel data and partial information on income for some households (see section 2.1 below). Our approach is related to the job search literature, where longitudinal datasets have been used for a long time to analyze job mobility (e.g. Flinn, 1986).

Compared to previous studies, we are able to assess the relative importance in the income dispersion of unobserved skill returns on the one hand, and shocks due to good/bad draws in the income distribution on the other hand. In fact, unobserved individual heterogeneity explains more than 70% of the total cross-sectional variance of unobservables in the income equations when moving and staying. By contrast, unobserved individual effects are negligible in explaining moving costs.

We also show that the unobserved characteristics that reflect intrinsic capacities of households to obtain higher income (e.g. unobserved skills) have nearly the same returns in the two income equations. Stated differently, the two unobserved individual effects in the income equations when staying and when moving appear to be nearly perfectly correlated and to have the same variance. Conversely, the variance of income shocks is significantly higher when migrating than when staying. Finally, households with unobserved skills leading to higher income also have an individual effect leading to lower moving costs.

Overall, our results suggest that some differences in the return of unobserved skills when moving and staying would not be the main driver of the migration decision. Some shocks like job opportunities or lay-offs would have a larger impact on the migration process. Some observed characteristics (age, diploma, employment status, experience specific to the firm) could also play a role as their returns are found to be different in the two income equations.

The remainder of the paper proceeds as follows. In section 2, we describe the dataset and give some descriptive statistics. In section 3, we present the migration model. Section 4 contains estimation results. Section 5 concludes.

2 The data

We use the longitudinal data from the *Panel Européen des Ménages* (1994-2000) which is the French version of the ECHP. The reason we use the French file instead of the Eurostat file is that it contains more information,

in particular on the residential location of households. These information turn out to be crucial for correctly analyzing mobility. The dataset contains 7,300 households, followed for the period 1994-2000. Households were surveyed once a year around october. When some individuals migrated between two survey dates, their file was transferred to the survey center nearest to their new dwelling. The dataset also contains information on income, jobs, unemployment, education, social relationships, health and housing.

2.1 Sample construction

The observation unit considered here is the household head at a given year.¹ For an interaction between residential mobility and job mobility to be possible, we keep only workers at each date. We exclude individuals declaring themselves on vacation for illness, pregnancy or job conversion, individuals having elective or associative functions, or being on military duty. To avoid transitions between studies and job, we restrict the sample to workers being more than 25 year old. Some other workers are dropped from the sample, because they disappear from the panel between two waves: dead people, emigrants, homeless people, or households with a new address that is unknown. To make interpretations easier, we also select only households consisting of one family with at most two generations (parents and children). More details on the sample construction are given in Appendix A.

The main definition of a *migration* retained here is a residential move to another municipality between two waves of the survey.² We consider that a move takes place when the municipality codes at the two dates are different. For our descriptive statistics, we also define intraurban moves, *interdepartemental* migrations and interregional migrations, as follows. An intraurban move occurs when a household head moves to another dwelling but stays in the same municipality. An interdepartemental migration occurs when the *département* codes at two successive dates are different.³ An interregional move occurs when the region codes at two successive dates are different.

Information on income in the panel comes from the following question asked to the head of the household:

“Considering all the current income of all the household members, what is the monthly amount of net income (social charges excluded) that your

¹For a couple, the household head is the male. For a lone-parent family, the household head is the mother or father of the children.

²A better definition for a move due to job reasons would be an *interdepartemental* migration. However, we do not have enough migration events at the interdepartemental level (see below, Table 3) to estimate all the parameters of our econometric model.

³There are 95 *départements* and 21 regions in metropolitan France. Regions are made of several *départements*.

household has?⁴ If you cannot give an accurate amount, can you at least give an estimation of it?”

Thus, when the household does not know or does not want to disclose his exact income, partial information can be obtained from the follow-up question, in the form of bracket responses. In our context, it seems very important not to discard bracket respondents from the sample, since our model includes income as an endogenous variable. We have no a priori reason to believe that the non-response behaviour on income is not correlated with unobserved quantities intervening in our model, and thus we keep bracket respondents in the sample. Our estimation procedure will explicitly deal with this incomplete information on income for these observations. The identifying hypothesis we make is that bracket respondents provide interviewers the true information, i.e. they indicate the brackets where their income is effectively located. To avoid some problems due to extreme values in the income distribution, we suppress 1% of observations at each tail of the distribution. We thus delete observations for which the monthly income is declared to be under 2,600 french francs, or superior to 54,000 francs. We also delete observations for which income is declared to be in the income brackets ‘3,000 francs and less’ and ‘50,000 francs and above’.

2.2 Descriptive statistics

2.2.1 Which households moved ?

Overall, mobility is low in our sample. The yearly migration rate is only 5.2%, in line with previous studies on France. Table B1 in Appendix B shows the breakdown of our longitudinal sample for several variables used in the subsequent analysis. The yearly migration rate decreases with age, and increases with the education level of the reference person.

The unbalanced feature of our dataset is clear from the figures in Table 1. The panel contains observations on 4,761 households. On those households, 1,716 are observed 7 times (i.e. we observe six yearly transitions). For the other households, we observe fewer transitions.

Table 1: Breakdown of the household sample by number of observed transitions
[Insert Table 1]

Lastly, it is interesting to look at repeated migrations in the sample, since the identification of certain parameters of the model relies on them

⁴“When there are some fluctuations in earnings, only their mean should be considered.”

(see section 3 below). As shown in Table 2, only 2.7% of the households move twice or more in the period. This corresponds to 126 observations.⁵

Table 2: Breakdown of the household sample by number of migration events
[Insert Table 2]

2.2.2 Why did households move?

As individuals are followed when they undertake residential moves, it is possible to know their *ex post* motivation for moving. To the question: “For what reason did you move?”, the household head can choose between four options:

1.	“You or another member of the household has found a job here”
2.	“For another reason linked to employment (you wanted to live closer to your workplace)”
3.	“For reasons linked to housing (access to ownership, family enlargement, wants a bigger dwelling, rents)”
4.	“For other reasons (a better environment, to get closer to some family members,...)”

Depending on the type of the move: intraurban, interurban, interdepartemental or interregional, the repartition of reasons reported by moving households differ sensibly as shown in Table 3. Reasons related to housing represent two thirds of answers given by households moving within the same municipality. The corresponding rate is lower for household heads having migrated to another municipality: reasons related to housing then represent only 40% of answers. They remain however the most important reasons invoked by movers. More than 90% of the moves due to reasons related to housing are intradepartemental and, thus, short distance moves.

Reasons related to employment are seldom quoted for intraurban moves (6%). They are second (32%) at the interurban level. They consist not only in the acceptance of a new job (10%) but also gather other job reasons (22%) as the will to live closer to the workplace. More than half of the interurban migrations for job reasons are interdepartemental. At the interdepartemental level, job reasons are the main reasons evoked by migrants for moving. Finally, whatever the type of the move, between 20% and 30% of household heads give other reasons, as the opportunity to live in a better environment or to get closer to a family member.

⁵These statistics were computed on the observations included in our final sample. All observations corresponding to a given household may not be taken into account because some do not meet the sample selection criteria. Moreover, there can be some attrition problems.

Table 3: Ex-post reasons given by household heads
for a move during the period 1994-2000
[*Insert Table 3*]

Interestingly, unemployed and occupied workers do not give the same reasons for migrating to another municipality as shown in Table 4.⁶ As expected, unemployed migrate mainly for job reasons (51%). However, other reasons (environment, family,...) are also quoted very often (43%). Thus, unemployed people may get closer to relatives because they could help them to benefit from cheap housing and/or from a network to find a job more easily. Reasons related to housing are quoted far less often, probably because unemployed are not wealthy enough to increase their housing capital.

Table 4: Ex-post reasons given by household heads, unemployed or occupied,
for an interurban move during the period 1994-2000
[*Insert Table 4*]

2.2.3 Migration and income growth

Table 5 reports yearly income growth and growth rates for interurban migrants and stayers, broken down by age brackets and education level.⁷ On average, income growth is higher for movers (10.6%) than for stayers (6.0%). This result suggests that our explanation for migrations, i.e. job opportunities, is quite relevant at first sight. The gap in income growth between movers and stayers remains when the sample is broken down by diploma of the reference person. Interestingly, the gap is larger for highly educated household heads (e.g. having a college degree) than for low-educated workers. This could be explained by their higher ability to collect information on distant job offers because of their education level (see Schwartz, 1973).⁸ Consequently, they would be able to benefit more from job opportunities.

Breaking down the sample by age bracket reveals that the income growth story is pertinent for young households, but less so for middle-age ones. Income profiles are steeper in the beginning of the life-cycle, and flatten

⁶It should be mentioned that our sample includes only a few unemployed workers migrating to another town: 75 households heads, out of 1036 migrants.

⁷To discard the outliers, we have deleted 1% of the observations at each tail of the income distribution before and after the migration decision to compute these statistics. Note also that the statistics do not take into account observations for those the income is declared in brackets in the years before and after the migration decision.

⁸However, it is not granted from a theoretical point of view that high-educated workers benefit more from a migration than low-educated workers. For instance, it is not the case if the education returns are higher in the area of residence than in other areas.

afterwards. The gap in income growth between movers and stayers decreases with age and eventually becomes negative for workers aged 45 and above.

Table 5: Yearly income growth for interurban migrants and stayers
[Insert Table 5]

More descriptive statistics are given in Appendix B.

3 The model

3.1 General setting

The traditional static model for analyzing migrations in relation to income changes can be described as follows. There exist two areas. A household i is located in one of those areas at date t . This household chooses between staying in his area, in which case he earns an income Y_{it}^n , and migrating to the other area, in which case he earns an income Y_{it}^m . If he migrates, the household incurs a monetary cost C_{it}^0 and a nonmonetary cost C_{it}^1 . The household's utility function depends on the consumption of a composite good and on the non monetary costs. The price of the good is fixed at the national level and is thus common to the two areas.⁹ There are no savings (i.e. the household consumes all his income). The utility, noted U , can then be written as a function of income and non monetary costs (the latter being zero when the household does not move). It is convenient to choose the following functional form:

$$U(Y, C) = \ln Y - \alpha C$$

When the monetary cost is small compared to the income in case of migration, the utility difference between moving and staying approximately writes:¹⁰

$$U(Y_{it}^m - C_{it}^0, C_{it}^1) - U(Y_{it}^n, 0) \approx \ln(Y_{it}^m) - \ln(Y_{it}^n) - \left[\frac{C_{it}^0}{Y_{it}^m} + \alpha C_{it}^1 \right] \quad (1)$$

⁹In this paper, we focus on income as a driver of the migration decision. We abstract from spatial differences in the cost of living, which concern mainly housing prices. These differences could also influence the migration decision.

¹⁰The assumption that monetary costs are small compared to the income of migration has been justified by considering that the static model is a summary of a life-cycle model. Indeed, the income in case of migration approximates the permanent income if the household's situation does not change in the future. Monetary costs then represent their actualized average component at each period, which is usually small.

The household migrates if and only if the utility difference is positive. Equation (1) shows that the migration decision depends on an arbitrage between the income difference and the total (monetary and non monetary) costs.

We now turn to the econometric specification. Income when staying is observed only for stayers and not for migrants. Consequently, we specify an income equation when staying. It writes:

$$\ln(Y_{it}^n) = X_{it}\beta + u_i^n + \varepsilon_{it}^n$$

where X_{it} includes the age of the household head, his highest diploma, his employment status (unemployed or occupied), his tenure in current firm if working and its square, the firm tenure of a possible working spouse and its square, the family type, the number of children, and a dummy for being a foreigner. The term u_i^n captures some unobserved, time-invariant heterogeneity among households. The residual ε_{it}^n captures a shock on income specific to the household that is not observed by the econometrician.

Similarly, income when migrating is observed only for migrants and not for stayers. We thus specify an income equation when migrating:

$$\ln(Y_{it}^m) = X_{it}(\beta + \gamma) + u_i^m + \varepsilon_{it}^m$$

For the sake of simplicity, we explain the income of migration with the same variables as the income when staying. The parameter vector of γ captures the differential returns of these variables on income when the household migrates. As previously, the term u_i^m captures some unobserved heterogeneity among households, and ε_{it}^m captures an idiosyncratic shock on income that is not observed by the econometrician (as for example a new draw in the wage distribution associated to a job offer).

Finally, migration costs (monetary or non monetary) are never observed directly. We specify them as:

$$\frac{C_{it}^0}{Y_{it}^m} + \alpha C_{it}^1 = Z_{it}\delta + u_i^c + \varepsilon_{it}^c$$

where Z_{it} includes the age of the household head, her nationality, his diploma, his employment status, the length of residence, the housing tenure (owner, private sector renter or public sector renter), the type of family and the number of children. The term u_i^c captures some unobserved heterogeneity and ε_{it}^c captures shocks (like the ending of some social relationships) or a change of taste for locations.

We denote M_{it} the dummy variable taking the value 1 when the household migrates and 0 otherwise. The latent econometric model finally writes:

$$\begin{cases} M_{it} = 1_{M_{it}^* > 0} \text{ with } M_{it}^* = \ln(Y_{it}^{m*}) - \ln(Y_{it}^{n*}) - Z_{it}\delta - u_i^c - \varepsilon_{it}^c \\ \ln(Y_{it}^{n*}) = X_{it}\beta + u_i^n + \varepsilon_{it}^n \\ \ln(Y_{it}^{m*}) = X_{it}(\beta + \gamma) + u_i^m + \varepsilon_{it}^m \end{cases}$$

We now turn to the method used to estimate the model.

3.2 Estimation method

To complete the specification of the model, hypotheses have to be made on the residuals. Two possible estimation strategies are maximum likelihood, on the one hand, and methods of moments on the other hand. The fact that our sample contains only partial information on income for some observations in our sample makes ML more interesting. The counterpart of this choice is that we impose strong, maybe undue, functional restrictions on the distribution of incomes. Nevertheless, our objective in this paper is to start from the framework used in previous studies to show the importance of unobserved heterogeneity. Thus, we stick to the normal specification that has been used before. Note that even under the normality assumption, our specification and data allow us to estimate more relevant parameters than previous studies in the field that used cross-section datasets.

We suppose that the vectors of random terms $U_i = (u_i^c, u_i^n, u_i^m)'$ are i.i.d. and follow a normal law with mean zero. However, we do not make any assumption on the correlations between random effects for a given household. Indeed, some unobserved skills can have an impact both on the income when staying and on the income when moving. In that case the individual random effects in the income equations are correlated. Moreover, unobserved characteristics, like organisational abilities, can also have an effect on the moving costs.

We suppose that the vectors of residuals $\Phi_{it} = (\varepsilon_{it}^c, \varepsilon_{it}^n, \varepsilon_{it}^m)'$ are i.i.d. and follow a normal law with mean zero. For the sake of simplicity, we also consider that at each date t , $U_i \perp \Phi_{it}$, and that the residuals ε_{it}^c , ε_{it}^n and ε_{it}^m are independent. The independence between random shocks for a given household should not be too restrictive. For instance, it is rather unlikely that a lay-off is correlated with the existence of job opportunities in another

From households migrating at one date and not at another, we get some information to identify the covariance of the two income individual random effects because we have for $t \neq t'$:

$$\text{cov}(u_i^n + \varepsilon_{it}^n, u_i^m + \varepsilon_{it'}^m) = \rho_{u^n, u^m} \sigma_{u^n} \sigma_{u^m} \quad (6)$$

Until now, we have shown that the data provide some information for the identification of all the elements in the covariance matrix corresponding to the random terms in the income equations. As we observe the migration decision and the income for stayers, we also get some information to identify:

$$\begin{aligned} & \text{cov}(u_i^n + \varepsilon_{it}^n - u_i^m - \varepsilon_{it}^m - u_i^c - \varepsilon_{it}^c, \varepsilon_{it}^n + u_i^n) \\ &= \sigma_{u^n}^2 - \rho_{u^n, u^m} \sigma_{u^n} \sigma_{u^m} - \rho_{u^n, u^c} \sigma_{u^n} \sigma_{u^c} \end{aligned} \quad (7)$$

Similarly, as we observe the migration decision and the income for movers, we get some information to identify:

$$\begin{aligned} & \text{cov}(u_i^n + \varepsilon_{it}^n - u_i^m - \varepsilon_{it}^m - u_i^c - \varepsilon_{it}^c, \varepsilon_{it}^m + u_i^m) \\ &= \sigma_{u^n}^2 - \rho_{u^n, u^m} \sigma_{u^n} \sigma_{u^m} - \rho_{u^m, u^c} \sigma_{u^m} \sigma_{u^c} \end{aligned} \quad (8)$$

Finally, as we observe the migration decision at two different dates t and t' , we get some information to identify:

$$\begin{aligned} & \text{cov} \left(\begin{array}{l} u_i^n + \varepsilon_{it}^n - u_i^m - \varepsilon_{it}^m - u_i^c - \varepsilon_{it}^c, \\ u_i^n + \varepsilon_{it'}^n - u_i^m - \varepsilon_{it'}^m - u_i^c - \varepsilon_{it'}^c \end{array} \right) \\ &= \sigma_{u^c}^2 + \sigma_{u^n}^2 + \sigma_{u^m}^2 + 2\rho_{u^c, u^n} \sigma_{u^c} \sigma_{u^n} - 2\rho_{u^n, u^m} \sigma_{u^n} \sigma_{u^m} - 2\rho_{u^c, u^m} \sigma_{u^c} \sigma_{u^m} \end{aligned} \quad (9)$$

We have three equations (7), (8), and (9), to recover the three parameters: ρ_{u^c, u^n} , ρ_{u^c, u^m} and σ_{u^c} . Thus, the model does not require any constraint on parameters to be identified.

From this short discussion, it is clear that the most stringent requirement on the data, considering that mobility is low in the sample, is related to the identification of the variance of the individual random effect in the income equation when migrating and the moving cost equation (recall that only 2.7% of the migrants move twice or more in our sample).

3.4 Computation of the likelihood

As seen in section 2, our panel is very unbalanced. Only 36% of the individuals are in our sample all the seven waves. It is thus irrelevant to estimate the model on individuals appearing in all waves only. Our estimation method allows to deal with unbalanced data.

For a household i appearing T_i times in the panel, the contribution to likelihood writes $P(A_{it_1}, \dots, A_{it_{T_i}})$, where t_τ , $\tau \in \{1, \dots, T_i\}$ are the dates at which the household appears in the panel, A_{it} , the event gathering the

information on the income and the migration decision at the date t . At each date, four cases may arise:

- a migration occurs and the exact value of income is known,
- a migration occurs and only the income bracket is known,
- the household does not move and the exact value of income is known,
- the household does not move and only the income bracket is known.

Because of the individual unobserved heterogeneity, events intervening in the likelihood contribution are not independent. However, conditional on the value of the individual heterogeneity terms $U_i \equiv (u_i^c, u_i^n, u_i^m)'$, the events at each date are independent, due to the hypothesis that the idiosyncratic shocks are i.i.d. across periods. We get:

$$\begin{aligned} P(A_{it_1}, \dots, A_{iT_i}) &= E_{U_i} [P(A_{it_1}, \dots, A_{iT_i} | U_i)] \\ &= E_{U_i} [P(A_{it_1} | U_i) \dots P(A_{iT_i} | U_i)] \end{aligned}$$

The probabilities $P(A_{it} | U_i)$ are simple functions of the parameters, involving the density and the cdf of normal laws. However, calculating the likelihood contribution requires integrating over the distribution of U_i . Instead of performing a time-consuming numerical integration of dimension 3, we choose to use simulation.¹¹ We draw $S = 20$ independent realizations of U_i , say $(U_i^1, \dots, U_i^s, \dots, U_i^S)$, and approximate the likelihood contribution by the unbiased and consistent simulator

$$P_i^S = \frac{1}{S} \sum_{s=1}^S P(A_{it_1} | U_i^s) \dots P(A_{iT_i} | U_i^s).$$

The details on the likelihood contributions are relegated to Appendix C.

4 Estimation results

We apply the model to migrations between municipalities of household heads aged 25 and over. According to our descriptive statistics, it would seem better to focus on interdepartemental migrations that seem mostly driven by reasons related to employment, whereas it is not the case for interurban moves. However, interdepartemental mobility is too low in our sample to allow us to estimate all the parameters of the model.

A word of caution is needed at this point to interpret the results. In the real world, there are more than two municipalities (in fact, there are thousands of them). Our model opposes for each individual his own municipality of residence to all other municipalities taken as a whole. Thus, space is not

¹¹See Gourieroux and Monfort (1995) for a comprehensive overview of the simulation methods that have become standard in the mid-nineties.

taken into account in our model. This assumption is necessary to estimate a binary model that does not take into account the choice of a destination when moving. However, this is not a major problem, as we have not introduced municipality characteristics in the model. Another issue is that we do not know exactly when individuals make their migration decision. We only know if they migrated between two survey dates. Consequently, we study the migration decision between two dates t and $t + 1$. Income when moving or staying is then measured at the date $t + 1$. Explanatory variables are measured at the date t to avoid endogeneity problems.

We encountered some convergence problems because the correlation between the two individual income effects was too high. In the initial estimation procedure, the optimization algorithm did not converge and stopped with a correlation of 0.99.¹² Thus, in the sequel we fix this correlation to 1. This amounts to fix:

$$u_i^n = \lambda u_i^m \quad (10)$$

Thus, with this specification, the two random effects are perfectly correlated. However, their variances can differ. Testing for the equality of the two variances amounts to a test of the hypothesis $\lambda = 1$.

We now comment the results. We first focus on those concerning the unobservables as they constitute the main contribution of our paper. We then turn to the coefficients of explanatory variables in the income and moving cost equations.

4.1 Individual heterogeneity and idiosyncratic shocks

Estimation results for parameters related to random terms in the income and moving cost equations are reported in Table 6. We find that individual random effects explain 71% (respectively 79%) of the total variance of unobservables in the income equation when migrating (respectively when staying). By contrast, the individual unobserved heterogeneity is negligible in the moving costs equation: it explains only 1% of the total variance of unobservables.

The variance of the individual random effects in the income equation is quite similar when migrating (.194) and when staying (.177). The equality of these two variances cannot be rejected at a 5% level. As individual random effects in income equations are perfectly correlated, unobserved skills have thus the same return on income when moving and staying. Moreover, as the individual random effect is negligible for moving costs, it implies that unobserved heterogeneity has only little impact on the migration decision.

¹²When we suppress households giving only a bracket response for their income, we obtain convergence. The estimated coefficients are similar to that presented in this section and the correlation between the individual random terms of the two income equations is again estimated at .99.

The variance of income shocks is higher when migrating (.078) than when staying (.047). The two variances are significantly different at the 5% level. This result is conform to intuition and can be explained by important variations in job opportunities in other municipalities that are not observed by the econometrician.

Finally, the individual component in the moving cost equation is negatively correlated with the individual components in the two income equations. Thus, households with unobserved skills driving higher income also have individual unobserved characteristics that lower moving costs, *ceteris paribus*.

In a nutshell, individual unobserved heterogeneity has a key role in the determination of income but it has only a small effect on the migration decision. As a consequence, the mobility process is rather driven by shocks like job opportunities and lay-offs. It may also be influenced by differences in the returns of observables. We examine this alternative in the next subsection.

Table 6: Estimation results: random terms
[Insert Table 6]

The use of panel data allows to estimate the relative contributions of individual unobserved heterogeneity and shocks to the selection bias usually taken into account by Heckman's method in cross-section analysis.

The expected incomes when moving and staying can be decomposed into a component due to observables and a selection bias due to unobservables. We have:

$$\begin{aligned} E[\ln(Y_{it}^n) | M_{it} = 0] &= X_{it}\beta + E[u_i^n + \varepsilon_{it}^n | M_{it} = 0] \\ E[\ln(Y_{it}^m) | M_{it} = 1] &= X_{it}(\beta + \gamma) + E[u_i^m + \varepsilon_{it}^m | M_{it} = 1] \end{aligned}$$

The selection bias terms can be broken down into two parts, involving respectively the unobserved heterogeneity term and the shock term.

Recalling that $M_{it}^* = X_{it}\gamma - Z_{it}\delta + u_i^m - u_i^n - u_i^c + \varepsilon_{it}^m - \varepsilon_{it}^n - \varepsilon_{it}^c$, and denoting $v_{it} = u_i^m - u_i^n - u_i^c + \varepsilon_{it}^m - \varepsilon_{it}^n - \varepsilon_{it}^c$, $\sigma_v^2 = E(v_{it}^2)$, $W_{it} = (Z_{it}\delta - X_{it}\gamma)/\sigma_v$, $\lambda_{it}^n = \frac{\varphi(W_{it})}{\Phi(W_{it})}$, $\mu_u^n = -\frac{\text{cov}(u_i^n, v)}{\sigma_v^2}$, $\mu_\varepsilon^n = -\frac{\text{cov}(\varepsilon_{it}^n, v)}{\sigma_v^2}$, we have:

$$E[u_i^n + \varepsilon_{it}^n | M_{it} = 0] = (\mu_u^n + \mu_\varepsilon^n) \lambda_{it}^n$$

Due to the hypotheses on the correlations of the residuals, we get: $\mu_u^n = -\text{cov}(u_i^n, u_i^m - u_i^n - u_i^c)/\sigma_v^2$ and $\mu_\varepsilon^n = V(\varepsilon_{it}^n)/\sigma_v^2$. Thus, the part of the bias related to income shocks when staying is always positive because of the structure of the model: on average, stayers are the households "getting good draws" in the income distribution when staying. By contrast, the sign

of the bias resulting from individual unobserved heterogeneity depends on the value of the parameters.

Now looking at the income of movers, we have with similar notations:

$$E [u_i^n + \varepsilon_{it}^n | M_{it} = 1] = (\mu_u^m + \mu_\varepsilon^m) \lambda_{it}^m$$

with $\lambda_{it}^m = \frac{\varphi(W_{it})}{1 - \Phi(W_{it})}$, $\mu_u^m = \text{cov}(u_i^m, u_i^m - u_i^n - u_i^c) / \sigma_v^2$ and $\mu_\varepsilon^m = V(\varepsilon_{it}^m) / \sigma_v^2$. The part of the bias related to income shocks when moving is always positive: on average, movers are the households “getting good draws” in the income distribution when moving. Once again, the sign of the bias resulting from individual unobserved heterogeneity depends on the value of the parameters.

Coming to the empirical evaluation of the selection terms, notice that since we have $u_i^m = \lambda u_i^n$, we also have $\mu_u^m = -\lambda \mu_u^n$. As λ is found to be very close to unity, the bias terms associated to unobserved heterogeneity are close in absolute value, but of opposite signs. Table 7 reports the bias terms for movers and stayers, computed from the model estimates. Standard errors are calculated using the delta method. In both cases the bias terms corresponding to unobserved heterogeneity are smaller in absolute value than the bias terms associated with shocks: twice smaller for stayers and four times smaller for movers. Thus, the selection biases measured in cross-section studies (see for instance Tunali, 2000) are mainly driven by shocks like job opportunities or lay-offs. However, in the case of movers the two effects are positive, whereas in the case of stayers, the bias term associated with unobserved heterogeneity is negative. To understand this result, note that $\sigma_v^2 \mu_u^n = -\text{cov}(u_i^n, u_i^m - u_i^n - u_i^c) = -\text{cov}(u_i^n, (\lambda - 1)u_i^n - u_i^c) = -(\lambda - 1)\sigma_{u^n}^2 + \text{cov}(u_i^n, u_i^c)$. The two terms of the sum are negative. For the first term, it is due to a slightly higher variance of the income individual random effect when moving rather than staying. For the second term, it is caused by the negative correlation between the unobserved components of moving costs and income.

To sum up, the self-selection biases in the income equations due to unobservables are mainly driven by shocks. As individual unobserved heterogeneity has a small effect on the decision of migration, it plays only a secondary role in the determination of these biases.

Table 7: Selection bias analysis
[Insert Table 7]

4.2 Income equations

Estimation results for the income equations are reported in Table 8. Column (3) shows the estimates for income when staying. The effect of the explanatory variables usually has the expected sign. The firm tenure of the

household head and the spouse have an inverse U -shaped effect. The higher the diploma of the household head, the higher the income. Age also has a positive effect on income. Individuals living alone have lower income than couples. Foreigners earn less money than natives. The employment status also has an impact on income: when the household head is unemployed, his income is lower than when he works. Finally, households having more children have higher income. The estimated parameters for this equation are very similar to those obtained by OLS on the subsample of stayers for whom we observe the exact value of income, that are given in column (1). The differences worth noticing concern the age effect that is higher in the case of the model and the effect of the employment status that is higher with OLS. Thus selection biases due to migrations and bracket response, as well as individual unobserved heterogeneity, have little impact on the parameter estimates.

Column (4) gives the results for income when moving. We find that the coefficients of explanatory variables when moving are quite different from those of the income equation for stayers. The effect difference is negative for workers that are more than 45 year old: the income is lower when they move than when they stay. It is also negative for household heads born in a foreign country, those having children, those with a low diploma, the unemployed and the women living alone. The firm tenure does not have a U -shape anymore for household heads whereas it is still U -shaped for the spouse, but with a steeper slope. A likelihood ratio test leads to reject the joint nullity of the parameter γ , which measures differences in returns from observed characteristics between staying and migrating. The test statistic is equal to 584.34, whereas the 5% threshold for a $\chi^2(18)$ is 28.87. Thus, observed characteristics appear to have different returns on income for movers and stayers. An OLS regression on the subsample of migrants yields results qualitatively similar to that of the model, as shown in column (3), except for the firm experience that has now a U -shaped effect and for the family structure. However, many effects are quantitatively different. In the case of migrants, selection biases due to migrations and bracket response, as well as individual unobserved heterogeneity, would have a non negligible impact on the parameter estimates.

Table 8: Estimation results, income equations
[Insert Table 8]

4.3 Moving costs equation

Estimation results for the moving costs equation are reported in Table 9. Moving costs are an increasing function of age. They are also higher for households having children aged between 13 and 17, who usually go to high

school. This is not surprising, since a migration can make these children lose their social network and can create réadaptation problems limiting their progression in the school system (Long, 1972 and 1975). The effect of being born in a foreign country is positive but not significant.

We now turn to the effect of employment characteristics. Household heads having a higher diploma (more than two years in college) have lower costs than those less educated (no diploma or secondary school diploma). It is probably easier for them to collect information to organize a move and to settle in a new municipality. The employment status (unemployed or occupied) has no significant effect on costs.

Housing characteristics have a significant and important effect on costs. Indeed, the costs increase with the length of residence. This can be due to accumulation of capital specific to the dwelling or to the municipality of residence. Homeowners have higher costs than private sector renters. This expected result reflects the existence of transaction costs (for instance, real estate agency fees) that make the sale of a dwelling particularly expensive in France.¹³ Moreover, costs are higher for public sector renters than for private sector renters. Indeed, for people living in public housing, moving means giving up a rent well under the market rent (Hughes and McCormick, 1981; Le Blanc and Laferrère, 2001).

Table 9: Estimation results, moving costs equation
[Insert Table 9]

To give a concrete idea of the importance of the housing tenure mode on migration costs, we compare the migration probability of workers in a given tenure mode to their predicted migration probability, would they live in the private rental sector. It is important to bear in mind that this thought experiment ignores the possible endogeneity of the tenure mode, in the following sense: households bearing higher moving costs may also choose to own their dwelling more often. This selection, if it exists, is not taken into account in the figures presented here. The different probabilities are approximated with a frequency simulator with 100 replications. Homeowners have an initial migration probability that is very low with a value of 1.83%. Would they be private sector renters, this probability would be nearly four times higher and reach 7.56%. Thus, migration costs related to homeownership appear tremendous. The average migration probability of public sector renters is far higher than that of owners, with a value of 6.27%. Would they be private sector renters, this probability would jump to 9.46%. Consequently, their migration costs appear to be quite important but far lower

¹³Another explanation is that owners can face liquidity constraints because of price fluctuations on the housing market. These fluctuations may prevent them to sell their dwelling rapidly for a price that covers loan repayments.

than those of owners. We also computed the migration probability of the whole sample if all households were private sector renters. It takes the value 9.01%, i.e. 1.8 times the observed probability (5.11%).

5 Conclusion

In this paper, we estimate a standard model of migration decision, based on the difference in incomes when moving to another municipality and staying in the current municipality, net of moving costs. However, the use of panel data allows us to take into account unobserved heterogeneity among households, both in terms of skills and in terms of moving costs, contrary to previous papers in this area of research.

We show that the income dispersion due to unobserved characteristics of households is more important than that of shocks. Unobserved individual heterogeneity explains more than 70% of the total cross-sectional variance of unobservables for incomes. By contrast, the individual heterogeneity is negligible for moving costs.

Unobserved characteristics that reflect an intrinsic capacity of households to obtain higher income (like skills) have nearly the same effects in the two income equations. Conversely, the variance of income shocks is significantly higher when migrating than when staying, probably because of an important heterogeneity in job opportunities. Finally, we find that households with unobserved skills leading to a higher income also have some unobserved characteristics leading to lower moving costs.

Overall, our results suggest that unobserved heterogeneity is not a major driver of the migration decision. The migration process may rather be driven by shocks like job opportunities or some difference in returns on observables like the firm experience.

There exist several promising lines for future research. On the theoretical side, the model could be embedded in a life-cycle utility framework with uncertainty. In fact, migrations are triggered by lifetime income considerations, rather than by the comparison of instantaneous incomes as done here. On the empirical side, it would be interesting to relax some of the parametric assumptions on the distribution of unobserved heterogeneity and shocks. One way of proceeding consists in looking at the covariance structure of incomes, as in Flinn (1986), who tests hypotheses stemming from a structural model of job search by looking at the covariance structure of wages.

Finally, we did not explicitly include space in the model. The migration decision is modeled as a binary choice: to stay or to move. However, there exist several potential destinations of migration, differing by local features of the labour and housing markets, and in terms of amenities. The choice among them could be analyzed more carefully in another paper.

6 APPENDIX

6.1 Appendix A: Sample construction

6.1.1 Appendix A1: Missing values

As often with panel data, missing values and inconsistencies between waves exist for a few observations and have to be dealt with. Some variables concerning characteristics of households that do not vary with time (sex, age, region and country of birth) had missing values. In this case, we use adjacent waves to recover these pieces of information. We do the same for the size of the household, assuming that it does not vary during the period. Missing values concerning the housing tenure are imputed from adjacent waves only when the concerned households did not move. The arrival date in the dwelling is reconstructed when possible using the information on all residential moves. Finally, the professional status, when missing, is imputed using adjacent waves only when the households stayed in the same firm. Overall, imputation concerns only a negligible part of the households. Observations for which there still exist missing values for variables included in the model after these operations are deleted from the sample.

6.1.2 Appendix A2: Correction of municipality codes

We could notice some inconsistencies in the data we used to determine the migration decision to another municipality. For some observations, the municipality codes recorded at two successive waves were different, whereas it was stated that the households had not moved to another dwelling. Using information from adjacent waves, it appears that in the majority of cases, the inconsistency is due to a coding mistake.¹⁴ Indeed, specific questions are asked to individuals that move between two waves. In most cases, when the municipality codes at two adjacent waves differ but it is stated that the households have not moved, these questions are not filled. It is thus rather likely that the households did not move. Moreover, a longitudinal analysis of municipality codes reveals some obvious cases of coding problems (see below for more details).

Consequently, we supposed for our estimations that all the inconsistencies were due to coding mistakes and that the related households had not moved. We tried to assess the maximum bias caused by our hypothesis.

¹⁴This is not surprising since for waves 2, 3 and 4, the survey was not computer-assisted. Paper questionnaires were filled, brought back to INSEE coding units, and coded afterwards. The coding of municipalities was not computer-assisted. On the contrary, for a few households in wave 4 and all households in waves 5, 6 and 7, the survey was collected with a computer-assisted procedure (CAPI). In particular, the municipality was coded directly by the computer during the interview. As a result, the number of inconsistencies regarding the municipality code drops dramatically in waves 5, 6 and 7.

The annual rate of migration we compute for our final sample is 7.6% without any correction, 5.6% when we are able to correct the inconsistencies thanks to a longitudinal analysis, and 5.2% when we make the hypothesis that all inconsistencies are due to coding mistakes. The rate obtained with this hypothesis is close to what could be expected for France (see Baccaïni, 2001).¹⁵ The annual rate of migration for the whole population, computed from the Census, is about to 5.4%. However, this figure is computed using all households, in particular individuals under 25 years old who move more frequently.

We now give more details about the corrections on municipality codes that can be made after a longitudinal analysis. As said before, coding errors appear to explain most of the inconsistencies spotted in the data. To identify the mistakes, we use the *Code Officiel Géographique 1999* that gathers all existing municipalities and their code. The municipality code in France consists in a 5-digit number. The two first digits indicate the département where the municipality is located. The different kinds of mistakes that can be corrected are the following:

- The municipality code at a given wave does not correspond to an existing municipality. We then replace it with the municipality code given at an adjacent wave when it is stated that the individual has not moved between the two waves. It sometimes happens that there is no adjacent wave for this individual. However, some other individuals may have the same no-existing municipality code and an adjacent wave. We then impute a municipality code using this information.

- Two municipality codes differ only by one digit. In that case, if the individual is present at least three waves in the same municipality (i.e. if there are at least three municipality codes that differ only by one digit and two of them are the same), we impute the code given twice to all three waves. If the two codes only appear once, we arbitrarily select one of them and impute it to the other wave for the sake of consistency.

- Two digits are inverted for two municipality codes. Then, one is probably wrong. We use the same method as in the previous case.

- A code corresponds to a municipality whose name is very similar to that of the municipality where the household lived at the previous wave (for instance Colombes instead of Bois-Colombe, Aulnay-sous-Bois instead of Rosny-sous-Bois). When a household lives in the same municipality for a period covering at least three dates, it is easy to identify the code for which there is a mistake.

- In a series of three waves, between two identical municipality codes, there is one different whereas it is stated that the household has not moved.

¹⁵We have not weighted the observations to obtain migration rates representative of the French population. Preliminary results on weighted migration rates computed for the period 1994-1996 are very similar to that obtained with unweighted observations.

In that case, it is likely that the code in the middle is false. We then impute the municipality code of the two extreme waves to the middle wave. Another case, scarcer, exists: between two identical municipality codes, there are two other codes, whereas the household has not moved. This case is treated the same way as the previous one.

- Because two municipalities merged, the code at one date corresponds to a municipality that does not exist anymore. However, at an adjacent date, the code refers to the municipality resulting from the merge. Then, we impute instead of the code corresponding to the municipality that does not exist anymore, the code referring to the municipality resulting from the merge.

- Because a municipality split into two municipalities, one code corresponds to a municipality that does not exist anymore. However, at an adjacent date, the code refers to one of the two municipalities resulting from the splitting. Then, we impute instead of the code corresponding to the municipality that does not exist anymore, the code of the municipality resulting from the splitting observed at an adjacent date.

- The three last numbers of two municipality codes at two adjacent dates are identical whereas the two first (the *département* code) are different. We consider that one of the *département* codes is wrong. We then arbitrarily impute one of the codes with the other.

6.2 Appendix B: Descriptive statistics

Table B1: Descriptive statistics on the migration rate for subsamples

[Insert Table B1]

Table B2: Descriptive statistics on migrants and stayers

[Insert Table B2]

6.3 Appendix C: Computation of the contributions to the likelihood

This Appendix gives further details on the calculation of the likelihood contributions. For a given individual i , we first draw $S = 20$ realizations of $(u_i^c, u_i^n, u_i^m)'$, denoted $U_i^s = (u_i^{cs}, u_i^{ns}, u_i^{ms})'$.¹⁶ An unbiased and consistent simulator of the likelihood contribution writes $P_i^S = \frac{1}{S} \sum_{s=1}^S P(A_{it_1} | U_i^s) \dots P(A_{iT_i} | U_i^s)$ where each event A_{it} , $t \in \{1, \dots, T_i\}$ gathers information on the income and

¹⁶This is done by applying the transformation $U_i^s = Cv_i^s$ to residuals $v_i^s = (v_{i1}^s, v_{i2}^s, v_{i3}^s)'$ drawn once for all in an independent trivariate normal, where C is the Choleski matrix of the current covariance matrix of U_i .

the migration decision at the date t . We thus have to calculate probabilities of the type $P(A_{it} | U_i)$.

- for migrants with a known income value Y_{it}^m :

$$\begin{aligned}
P(A_{it} | U_i) &= P(M_{it} = 1, \ln Y_{it}^{m*} = \ln Y_{it}^m | U_i) \\
&= P\left(\begin{array}{l} \varepsilon_{it}^c - \varepsilon_{it}^m + \varepsilon_{it}^n < X_{it}\gamma - Z_{it}\delta + u_i^m - u_i^n - u_i^c, \\ \varepsilon_{it}^m = \ln Y_{it}^m - X_{it}(\beta + \gamma) - u_i^m \end{array} | U_i \right) \\
&= P\left(\begin{array}{l} \varepsilon_{it}^c - \varepsilon_{it}^m + \varepsilon_{it}^n < X_{it}\gamma - Z_{it}\delta + u_i^m - u_i^n - u_i^c \\ |\varepsilon_{it}^m = \ln Y_{it}^m - X_{it}(\beta + \gamma) - u_i^m, U_i \end{array} \right) \\
&\quad \times P(\varepsilon_{it}^m = \ln Y_{it}^m - X_{it}(\beta + \gamma) - u_i^m | U_i)
\end{aligned}$$

- for migrants with income in the bracket $[x_{it}, y_{it}]$:

$$\begin{aligned}
P(A_{it} | U_i) &= P(M_{it} = 1, \ln Y_{it}^{m*} \in [\ln x_{it}, \ln y_{it}] | U_i) \\
&= P\left(\begin{array}{l} \ln x_{it} - X_{it}(\beta + \gamma) - u_i^m < \varepsilon_{it}^m < \ln y_{it} - X_{it}(\beta + \gamma) - u_i^m, \\ \varepsilon_{it}^c - \varepsilon_{it}^m + \varepsilon_{it}^n < X_{it}\gamma - Z_{it}\delta + u_i^m - u_i^n - u_i^c \end{array} | U_i \right)
\end{aligned}$$

- for stayers with a known income value Y_{it}^n :

$$\begin{aligned}
P(A_{it} | U_i) &= P(M_{it} = 0, \ln Y_{it}^{n*} = \ln Y_{it}^n | U_i) \\
&= P\left(\begin{array}{l} -\varepsilon_{it}^c + \varepsilon_{it}^m - \varepsilon_{it}^n < -X_{it}\gamma + Z_{it}\delta - u_i^m + u_i^n + u_i^c, \\ \varepsilon_{it}^n = \ln Y_{it}^n - X_{it}\beta - u_i^n \end{array} | U_i \right) \\
&= P\left(\begin{array}{l} -\varepsilon_{it}^c + \varepsilon_{it}^m - \varepsilon_{it}^n < -X_{it}\gamma + Z_{it}\delta - u_i^m + u_i^n + u_i^c \\ |\varepsilon_{it}^n = \ln Y_{it}^n - X_{it}\beta - u_i^n, U_i \end{array} \right) \\
&\quad \times P(\varepsilon_{it}^n = \ln Y_{it}^n - X_{it}\beta - u_i^n | U_i)
\end{aligned}$$

- for stayers with income in the bracket $[x_{it}, y_{it}]$:

$$\begin{aligned}
P(A_{it} | U_i) &= P(M_{it} = 0, \ln Y_{it}^{n*} \in [\ln x_{it}, \ln y_{it}] | U_i) \\
&= P\left(\begin{array}{l} \ln x_{it} - X_{it}\beta - u_i^n < \varepsilon_{it}^n < \ln y_{it} - X_{it}\beta - u_i^n, \\ -\varepsilon_{it}^c + \varepsilon_{it}^m - \varepsilon_{it}^n < -X_{it}\gamma + Z_{it}\delta - u_i^m + u_i^n + u_i^c \end{array} | U_i \right)
\end{aligned}$$

References

- [1] Axelsson R. and Westerlund O. (1998), “A panel study of migration, self-selection and household real income”, *Journal of Population Economics*, 126, pp. 113-126.
- [2] Baccaïni B. (2001), “Les migrations en France entre 1990 et 1999. Les régions de l’Ouest de plus en plus attractives”, *INSEE première*, 758.
- [3] Code Officiel Géographique 1999, 13^e Edition, Collection : Nomenclatures et Codes, INSEE.
- [4] Flinn C.J. (1986), “Wages and Job Mobility of Young Workers”, *The Journal of Political Economy*, 94(3), pp. 88-110.
- [5] Gobillon L. et Le Blanc D. (2002), “Should I Stay or Should I Own ? The Impact of Borrowing Constraints on Mobility and Tenure Choice”, CREST Working Paper n°2002-28.
- [6] Gourieroux C., Monfort A. (1995), *Simulation Based Econometric Methods*, Louvain, CORE Lectures Series, Oxford Univ. Press, 174 p.
- [7] Heckman J. (1979), “Sample Selection Bias as a Specification Error”, *Econometrica*, 47(1), pp. 153-162.
- [8] Hughes G. and McCormick B. (1981), “Do Council Housing Policies Reduce Migration Between Regions ?”, *The Economic Journal*, 91, pp. 919-937.
- [9] Islam M. N., Choudhury S. A. (1990), “Self-Selection and Intermunicipal Migration in Canada”, *Regional and Urban Economics*, 20, pp. 459-472.
- [10] Le Blanc, D., A. Laferrère (2001), “The Effects of Public Social Housing on Households’ consumption in France”, *Journal of Housing Economics*, 10, pp. 429-455.
- [11] Lee L. L. (1978), “Unionism and Wage Rates: A simultaneous Equation Model with Qualitative and Limited Dependent Variables”, *International Economic Review*, 19(2), pp. 415-433.
- [12] Lee L. L. (1979), “Identification and Estimation in Binary Choice Models with Limited (Censored) Dependent Variables”, *Econometrica*, 47(4), pp. 977-996.
- [13] Long L. H. (1972), “The Influence of Number and Ages of Children on Residential Mobility”, *Demography*, 9(3), pp. 371-382.

- [14] Long L. H. (1975), "Does Migration Interfere with Children's Progress in School?", *Sociology and Education*, 48(3), pp. 369-381.
- [15] Nakosteen R. and Zimmer M. (1980), "Migration and Income: The Question of Self-Selection", *Southern Economic Journal*, 46, pp. 840-851.
- [16] Osberg L, Gordon D, Lin Z., (1994), "Interregional migration and interindustry labour mobility in Canada : a simultaneous approach", *The Canadian Journal of Economics*, 27(1), pp. 58-80.
- [17] Robison C., Tomes N. (1982), "Self-Selection and Interprovincial Migration in Canada", 15(3), *The Canadian Journal of Economics*, pp. 474-502.
- [18] Schwartz A. (1973), "Interpreting the Effect of Distance on Migration", *The Journal of Political Economy*, 81(5), pp. 1153-1169.
- [19] Sjaastad L. (1962), "The Costs and Returns of Human Migration", *The Journal of Political Economy*, 70, pp. 80-93.
- [20] Tunali I. (1986), "A general Structure for Models of Double-Selection and an Application to a Joint Migration/Earnings Process with Remigration", *Research in Labor Economics*, 8(B), pp. 235-282.
- [21] Tunali I. (2000), "Rationality of Migration", *International Economic Review*, 41(4), pp. 893-920.

Table 1: Breakdown of the household sample by number of observed transitions

Number of observed transitions	1	2	3	4	5	6
Number of household heads	686 (14.4%)	659 (13.8%)	556 (11.7%)	565 (11.9%)	579 (12.2%)	1716 (36.0%)

A transition is defined as the presence of an individual in the panel for two consecutive years.
The proportion of households for a given number of transitions is in parenthesis.

Table 2: Breakdown of the household sample by number of migration events

Number of migrations	0	1	2	3 and more
Number of Household heads	3919 (82.3%)	716 (15.0%)	107 (2.3%)	19 (0.4%)

The proportion of households for a given number of migrations is in parenthesis.

Table 3: Ex-post reasons given by household heads for a move during the period 1994-2000

Reason for Moving	Intraurban	Interurban	Inter-departmental	Inter-regional
New Job	5 (1%)	102 (10%)	77 (22%)	64 (28%)
Other Reason Related to Job	37 (5%)	230 (22%)	140 (39%)	97 (43%)
Housing	525 (69%)	412 (40%)	57 (16%)	12 (5%)
Other (Environment, Family,...)	191 (25%)	292 (28%)	83 (23%)	55 (24%)

For a given type of move, the proportion of moving households for a given reason is in parenthesis.

Table 4: Ex-post reasons given by household heads, unemployed or occupied, for an interurban move during the period 1994-2000

Reason for Moving	Unemployed	Occupied Workers
New Job	14 (19%)	88 (9%)
Other Reason Related to Job	17 (22%)	213 (22%)
Housing	12 (16%)	400 (42%)
Other (Environment, Family,...)	32 (43%)	260 (27%)

For a given type of move, the proportion of moving households for a given reason is in parenthesis.

Table 5: Yearly income growth for migrants and stayers (in francs)

	Migration	Number	Mean Income Date t	Mean Income Date t+1	Std. dev. Income Date t	Std. dev. Income Date t+1	Difference in income	Average income growth rate
All households	No	15,416	14,446	14,857	7,625	7,777	411	6.03
	Yes	851	13,938	14,571	7,243	7,598	633	10.58
Age bracket								
25-29 year old	No	1,917	11,126	11,877	4,914	5,256	751	10.91
	Yes	288	11,409	12,666	4,651	5,628	1257	17.42
30-34 year old	No	2,312	12,786	13,410	5,836	6,342	623	6.98
	Yes	208	14,453	15,575	6,825	7,379	1123	12.14
35-44 year old	No	5,298	14,505	14,943	7,108	7,259	438	5.70
	Yes	216	16,022	16,236	7,929	8,122	213	6.02
More than 45 year old	No	5,889	16,125	16,318	8,833	8,961	193	4.38
	Yes	139	15,166	14,428	9,394	9,583	-739	1.18
Diploma								
No diploma, secondary or high school diploma	No	5,258	12,408	12,708	6,363	6,450	300	6.01
	Yes	213	12,149	12,531	6,067	6,422	381	8.01
Vocational training certificate	No	6,547	13,383	13,724	6,004	6,107	341	5.55
	Yes	337	12,383	12,530	5,780	5,728	147	6.46
Between one and two years in college	No	1,504	16,571	17,202	7,769	8,106	631	6.11
	Yes	123	14,452	15,838	6,480	5,964	1,386	21.59
Between three and four years in college	No	668	17,736	18,553	9,371	9,495	817	8.48
	Yes	68	16,106	17,161	8,969	8,767	1,055	15.57
More then five years in college, engineer school diploma	No	1,439	22,981	23,703	10,211	10,141	722	7.09
	Yes	110	20,249	21,756	8,997	10,132	1,507	12.81

Observations for which the income is given in brackets were omitted in the calculation of the statistics. Moreover, observations with a present income below 2,600 and above 54,000 francs were not taken into account to avoid some effects of outliers on the mean income.

Table 6: estimation results: random terms

Parameter	Estimate
σ_{ε}^c	0.749*** (0.148)
σ_{ε}^n	0.216*** (0.002)
σ_{ε}^m	0.279*** (0.009)
σ_u^c	0.068*** (0.031)
σ_u^n	0.421*** (0.001)
σ_u^m	0.440*** (0.013)
$\rho_{u,u}^{c,n}$	-0.487*** (0.006)
$\rho_{u,u}^{c,m}$	$=\rho_{u,u}^{c,n}$
$\rho_{u,u}^{n,m}$	Fixed to 1

*** significant at 1% ; **: significant at 5% ; *: significant at 10%.
Standard errors are given in parenthesis.

Table 7: Selection Bias Analysis

	μ_u	μ_{ε}	$\mu_T = \mu_u + \mu_{\varepsilon}$	$\frac{ \mu_{\varepsilon} }{ \mu_u }$
Stayers	- 0.032*** (0.009)	0.068*** (0.016)	0.036** (0.016)	2.13
Movers	0.033*** (0.009)	0.112*** (0.028)	0.146*** (0.033)	4.38

Table 8: Estimation results, income equations

	(1) OLS Subsample of stayers	(2) OLS Subsample of migrants	(3) MODEL Income when staying	(4) MODEL Income when migrating, effect difference
Constant	9.039*** (0.013)	9.108*** (0.046)	9.046*** (0.010)	-0.033 (0.045)
Age				
25-29 year old (reference)				
30-34 year old	0.034*** (0.013)	0.081** (0.038)	0.101*** (0.009)	0.044* (0.031)
35-44 year old	0.090*** (0.012)	0.100** (0.041)	0.182*** (0.009)	0.015 (0.034)
More than 45 year old	0.192*** (0.012)	0.075 (0.047)	0.279*** (0.009)	-0.095*** (0.034)
Country of Birth				
France (reference)				
Other country	-0.081*** (0.010)	-0.120** (0.060)	-0.104*** (0.009)	-0.123*** (0.038)
Existence and employment status of spouse				
Couple, the spouse does not work (reference)				
Couple, the spouse has a job	0.179*** (0.012)	0.226*** (0.050)	0.108*** (0.007)	-0.014 (0.033)
Male living alone	-0.070*** (0.009)	0.016 (0.037)	-0.055*** (0.005)	-0.012 (0.026)
Woman living alone	-0.364*** (0.010)	-0.322*** (0.048)	-0.364*** (0.007)	-0.097*** (0.039)
Number of children	0.049*** (0.003)	0.053*** (0.013)	0.040*** (0.002)	-0.020** (0.010)
Diploma				
No diploma, secondary or high school diploma (reference)				
Vocational training certificate	0.075*** (0.007)	0.003 (0.035)	0.064*** (0.005)	-0.069*** (0.029)
Between one and two years in college	0.390*** (0.011)	0.243*** (0.046)	0.325*** (0.010)	-0.047* (0.036)
Between three and four years in college	0.430*** (0.015)	0.328*** (0.056)	0.364*** (0.011)	-0.055* (0.042)
More than five years in college, engineer school diploma	0.643*** (0.011)	0.540*** (0.046)	0.577*** (0.008)	-0.021 (0.035)
Employment status				
Occupied worker (reference)				
Unemployed	-0.378*** (0.014)	-0.453*** (0.059)	-0.238*** (0.007)	-0.090*** (0.034)
Job duration in current firm of the household head (in years)	0.011*** (0.001)	0.008* (0.005)	0.007*** (0.001)	-0.011*** (0.003)
Squared job duration in current firm of the household head (in years) $\times 10^{-3}$	-0.145*** (0.030)	-0.008 (0.171)	-0.103*** (0.021)	0.274*** (0.097)
Job duration in current firm of spouse (in years)	0.010*** (0.002)	0.025*** (0.010)	0.004*** (0.001)	0.009* (0.006)
Squared job duration in current firm of spouse (in years) $\times 10^{-3}$	-0.123*** (0.055)	-0.763 (0.499)	-0.072** (0.037)	-0.588*** (0.247)
Standard deviation of the residual	0.387	0.406	\	\
Number of observations	16842	919		
R²	0.46	0.43		

*** significant at 1% ; ** : significant at 5% ; * : significant at 1%.

Standard errors are given in parenthesis.

In the fourth column corresponding to the income equation when moving, we give the difference in effect compared to the income equation when staying.

Table 9: estimation results, moving costs equation

	Parameter
Constant	0.737*** (0.160)
Age	
25-29 year old (reference)	
30-34 year old	0.101** (0.047)
35-44 year old	0.165** (0.060)
More than 45 year old	0.185** (0.080)
Country of Birth	
France (reference)	
Other country	0.089 (0.072)
Existence and employment status of a spouse	
Couple, the spouse does not work (reference)	
Couple, the spouse has a job	0.011 (0.037)
Male living alone	-0.021 (0.034)
Woman living alone	0.027 (0.058)
Number of children by age bracket	
No children (reference)	
Less than 4 year old	0.013 (0.035)
Between 4 and 6 year old	-0.021 (0.034)
Between 7 and 12 year old	0.000 (0.025)
Between 13 and 17 year old	0.064** (0.034)
More than 17 year old	-0.012 (0.028)
Diploma	
No diploma, secondary or high school diploma (reference)	
Vocational training certificate	-0.085** (0.028)
Between one and two years in college	-0.170*** (0.058)
Between three and four years in college	-0.256*** (0.075)
More then five years in college, engineer school diploma	-0.188*** (0.060)
Employment status	
Occupied worker (reference)	
Unemployed	0.067 (0.054)
Time spent in the current dwelling (in years)	0.011*** (0.003)
Housing tenure	
Renter, the landowner being another household, an agency or a private firm (reference)	
Renter, the landowner being the employer or a member of the family	0.148*** (0.058)
Renter in the public sector	0.190*** (0.050)
Homeowner	0.561*** (0.102)

*** significant at 1% ; **: significant at 5% ; *: significant at 10%.

Standard errors are given in parenthesis.

Table B1: Descriptive statistics on the migration rate for subsamples

	Number of household heads	Number of migrants	Yearly migration rate
Total	19123	990	5.18%
Age			
25-29 year old	2447	326	13.32%
30-34 year old	2913	239	8.20%
35-44 year old	6430	258	4.01%
More than 45 year old	7333	167	2.28%
Country of Birth			
France	17048	930	5.46%
Other country	2075	60	2.89%
Existence and employment status of a spouse			
Couple, the spouse does not work	4518	213	4.71%
Couple, the spouse has a job	8309	361	4.34%
Male living alone	3259	246	7.55%
Woman living alone	2691	145	5.39%
Number of children			
No child	6004	420	7.00%
One child	4910	262	5.34%
Two children	5295	204	3.85%
Three children and more	2914	104	3.57%
Number of children by age bracket			
Less than four year old	3236	226	6.98%
Four to six year old	3257	187	5.74%
Seven to twelve year old	6806	267	3.92%
Thirteen to seventeen year old	5657	146	2.58%
More than seventeen year old	6349	189	2.98%
Diploma			
No diploma, secondary or high school diploma	6504	250	3.84%
Vocational training certificate	7973	383	4.80%
Between one and two years in college	1914	146	7.63%
Between three and four years in college	842	76	9.03%
More than five years in college, engineer school diploma	1890	135	7.14%
Employment status			
Occupied worker	17836	923	5.17%
Unemployed	1287	67	5.21%
Job duration of the household head in t+1 (in years)			
Less than five years	6359	513	8.07%
Between five and ten years	3352	202	6.03%
Between ten and fifteen years	2514	113	4.49%
More than fifteen years	6898	162	2.35%
Job duration of spouse in t+1 (in years)			
Less than five years	13549	812	5.99%
Between five and ten years	1715	85	4.96%
Between ten and fifteen years	1199	53	4.42%
More than fifteen years	2660	40	1.50%
Time spent in current dwelling (in years)			
Less than five years	7602	661	8.70%
Between five and ten years	4312	200	4.64%
Between ten and fifteen years	2887	67	2.32%
More than fifteen years	4322	62	1.43%
Housing tenure			
Renter, the landowner being another household, an agency or a private firm	4076	494	12.12%
Renter, the landowner being the employer or a member of the family	1060	82	7.74%
Renter in the public sector	3451	224	6.49%
Homeowner	10536	190	1.80%

The observation unit is the household head at a given date.

Table B2: descriptive statistics on migrants and stayers

	All household heads	Stayers	Migrants
Number of observations	19123	18133	990
Dummies taking the value 1 when income is declared in an interval at date t+1, 0 otherwise	0.071 (0.257)	0.071 (0.257)	0.072 (0.258)
Value of income at date t+1 (in francs) when an exact value is declared *	14929 (7965)	14941 (7969)	14713 (7889)
Age	41.248 (9.396)	41.564 (9.311)	35.445 (9.044)
25-29 year old	0.128 (0.334)	0.117 (0.321)	0.329 (0.470)
30-34 year old	0.152 (0.359)	0.147 (0.355)	0.241 (0.428)
35-44 year old	0.336 (0.472)	0.340 (0.474)	0.261 (0.439)
More than 45 year old	0.383 (0.486)	0.395 (0.489)	0.169 (0.375)
Country of Birth			
France	0.891 (0.311)	0.889 (0.314)	0.939 (0.239)
Other country	0.109 (0.311)	0.111 (0.314)	0.061 (0.239)
Existence and employment status of a spouse in t			
Couple, the spouse does not work	0.236 (0.425)	0.237 (0.426)	0.215 (0.411)
Couple, the spouse has a job	0.435 (0.496)	0.438 (0.496)	0.365 (0.482)
Male living alone	0.170 (0.376)	0.166 (0.372)	0.248 (0.432)
Woman living alone	0.141 (0.348)	0.140 (0.347)	0.146 (0.354)
Number of children	1.323 (1.200)	1.340 (1.203)	1.025 (1.108)
Number of children by age bracket			
Less than four year old	0.340 (0.474)	0.166 (0.415)	0.228 (0.459)
Four to six year old	0.417 (0.493)	0.169 (0.408)	0.189 (0.436)
Seven to twelve year old	0.100 (0.300)	0.361 (0.642)	0.270 (0.591)
Thirteen to seventeen year old	0.044 (0.205)	0.304 (0.583)	0.147 (0.437)
More than seventeen year old	0.099 (0.298)	0.340 (0.660)	0.191 (0.504)
Diploma			
No diploma, secondary or high school diploma	0.169 (0.418)	0.345 (0.475)	0.253 (0.435)
Vocational training certificate	0.170 (0.409)	0.419 (0.493)	0.387 (0.487)
Between one and two years in college	0.356 (0.639)	0.098 (0.297)	0.147 (0.355)
Between three and four years in college	0.296 (0.577)	0.042 (0.201)	0.077 (0.266)
More than five years in college, engineer school diploma	0.332 (0.654)	0.097 (0.296)	0.136 (0.343)
Employment status			
Occupied worker	0.067 (0.251)	0.067 (0.251)	0.068 (0.251)
Unemployed	0.933 (0.251)	0.933 (0.251)	0.932 (0.251)
Job duration in firm of the household head in t+1 (in years)	11.697 (10.313)	11.953 (10.356)	7.007 (8.167)
Job duration in current firm of a spouse in t+1 (in years)	4.675 (8.091)	4.810 (8.216)	2.205 (4.668)
Time spent in the current dwelling (in years)	8.900 (8.561)	9.140 (8.631)	4.507 (5.557)
Housing tenure			
Renter, the landowner being another household, an agency or a private firm	0.055 (0.229)	0.054 (0.226)	0.083 (0.276)
Renter, the landowner being the employer or a member of the family	0.180 (0.385)	0.178 (0.382)	0.226 (0.419)
Renter in the public sector	0.213 (0.410)	0.198 (0.398)	0.499 (0.500)
Homeowner	0.551 (0.497)	0.571 (0.495)	0.192 (0.394)

The observation unit is the household head at a given date. Each cell contains the mean of a given variable and in parenthesis, its standard deviation.

* We use only the observations for which an exact value of the income is given., that is to say 16842 observations for stayers and 919 observations for movers.