Gross flows from the French labor force survey:a reanalysis

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Summary

This paper reanalyzes gross flow data from the French Labor Force Survey, recently investigated by Thierry Magnac and Michael Visser (1999). They specify a transition model allowing for a specific pattern of classification errors in retrospectively reported labor market states. Their main finding is that neglecting measurement errors leads to an observed labor market which is more dynamic than the true one, and consequently to an underestimation of the average durations spent in labor market states. We question the plausibility of their assumptions. We propose a different model, within a latent class analysis set-up, which explicitly accounts for correlated classification errors over time. The model is applied to correct quarterly gross flows observed in the French labor market: estimated true transitions show higher mobility than observed ones.

I. Introduction

Panel data allow the estimation of gross flows, which are a crucial indicator for labor market analyses. While net flows measure net variations over time in the stock of employed and/or unemployed people, gross flows provide information on the dynamics of the labor market.

Panel data may be obtained by means of various survey strategies, among which are genuine panel surveys (*i.e.*, surveys repeated on a number of occasions on the same units) and cross-section surveys with retrospective questions, or some combination of them (see Duncan and Kalton, 1987, and Trivellato, 1999, among many others).

Measurement (≡classification) errors in the observed state cause some systematic bias in estimated gross flows, thus leading to erroneous conclusions about labor market dynamics.

A large body of literature on classification errors and their impact on gross flow estimation is based on the assumption that errors are uncorrelated over time: the so-called Independent Classification Errors (ICE) assumption, according to which, classification errors produce the observation of spurious transitions and consequently induce an overestimation of changes. However, the ICE assumption is not realistic in many contexts, in which survey design and data collection strategies suggest that measurement errors are correlated over time (see, for example, Skinner and Torelli, 1993, and Singh and Rao, 1995). This is especially true when panel data are collected by retrospective interrogation, because of the effects of memory inaccuracy (Sudman and Brandburn, 1973; Bernard *et al.*, 1984). The main implication of correlated classification errors is that the observed gross flows show a lower mobility than the true ones (van de Pol and Langeheine, 1997).

In this paper we present a model aimed at estimating true labor market gross flows, when observed flows are obtained from panel surveys with mostly retrospective interrogation and are affected by correlated classification errors. We use, as case study, quarterly gross flows from the French Labor Force Survey (FLFS).

Our research was stimulated by the work by Thierry Magnac and Michael Visser, recently published in this *Review* (Magnac and Visser, 1999; henceforth M&V). They estimate labor market transitions in the presence of measurement error, using data collected in three successive waves of the FLFS. Their main finding is that neglecting measurement errors leads to an observed labor market which is more dynamic than the true one, and consequently to an underestimation of the average durations spent in labor market states. These results are puzzling, since the FLFS collects most information on labor market states by means of retrospective questions. The findings of M&V largely depend on their model assumptions, specifically on the postulated pattern of classification errors in retrospectively reported labor market states. We question the plausibility of these assumptions and propose a different model, within a latent class analysis set-up, which explicitly accounts for correlated classification errors.

For the sake of simplicity and in order to reduce the computational burden, we estimate the proposed model according to a simplified formulation of state and time space. We consider a state space restricted to the usual three labor market states – employed, unemployed, and out of the labor force – and analyze quarterly transitions for the period from March 1990 to March 1992. Our main result is that estimated true transitions show higher mobility than observed ones.

The paper proceeds as follows. In section II, the FLFS and sample data used by M&V and in this paper are briefly described. Then the model and estimation strategy of M&V are reviewed: some basic model assumptions are critically discussed, and their plausibility is checked by testing them against less restricted specifications, with evidence not in favor of their models (section III). In section IV, the proposed model is presented and applied to correct quarterly gross flows observed in the French labor market. Lastly, Section V offers some concluding remarks.

II. The French Labor Force Survey

The FLFS, *Enquête Emploi*, is conducted yearly by INSEE, the French national statistical agency. Its reference population is all members of French households aged 15 years or more in the calendar year in which the survey is carried out. It is a rotating panel survey, one-third of the sample being replaced each year.

Information on labor force participation is collected by means of two sets of questions: retrospective interrogation on a reference period composed of the 12 months preceding the interview month, and a question on actual state during the interview month[1]. Respondents are

[1] Our brief description of the survey is restricted to the panel data sets dealt with here.

asked to report their monthly labor condition by filling in a grid in which they classify themselves over one of the following eight categories: self-employed, fixed-term employed, permanently employed, unemployed, on a vocational training program, student, doing military service, other (retired, housewife, *etc.*).

M&V use the information collected in the surveys of January 1990, March 1991 and March 1992 on a sub-group of the cohort sampled in 1990 made up of young people. Their sample consists of 5,247 individuals, who (i) were aged between 19 and 29 years in March 1992 and (ii) participated in all three subsequent survey waves. At each wave, respondents were asked to report their monthly labor market history from the corresponding month of the previous year to the current month. Thus, information on the labor market state in February 1990 is missing, whereas there are two distinct pieces of information on the state occupied in March 1991: one is the concurrent information collected with the March 1991 survey; the other is the retrospective information collected with the March 1992 survey.

M&V distinguish six labor market states: (1) permanent employment, (2) fixed-term employment, (3) training, (4) unemployment, (5) education, and (6) out of the labor force.

III. M&V's Model Revisited

A. M&V's Model and Estimation Strategy

M&V base their model specification and estimation strategy on the following assumptions:

(a) Latent (≡true) transitions between labor market states follow a time-homogeneous first-order Markov process.

(b) The actual reported state is a perfectly reliable source of information, whereas the retrospectively reported states are contaminated by classification errors, with error probabilities fixed *a priori*[2].

(c) (Mis)classifications recorded at time t and $t+d$ are conditionally independent: this is what M&V call the "*d*-step ICE" assumption.

Let $X(t)$ denote the true labor market state occupied at time t by a sampled individual, $Y(t)$ the corresponding observed state, and $m_{kl}(t) = P(X(t+1) = l \mid X(t) = k)$ the true transition probability between state k and state l from time t to $t+1$, with t=1,…,T−1, where T represents the total number of consecutive months over which an individual is observed.

In addition, let d be an integer variable assuming values between 1 and T−1; $l_{ij}^{d}(t)$ the probability that at time $t+d$ the observed state is j, given that at time t the observed state was i; $a_{lj}(t)$ the probability of observing state j at time t, given that the true state is l; $b_{ik}(t)$ the probability that the true state is k at time t, given that the observed state is i. For t=1,2,…T−d, the d-step ICE assumption implies that:

[2] Error probabilities are also assumed to be state-dependent.

$$l_{ij}^{(d)}(t) = P(Y(t+d) = j \mid Y(t) = i) = \sum_{k,l=1}^{6} b_{ik}(t) m_{kl}^{(d)}(t) a_{lj}(t+d)\,.$$

(3.1)

M&V's estimation method is based on maximization of the pseudo-log-likelihood function:

$$L^d = \sum_{t=1}^{T-d} \sum_{i=1}^{6} \sum_{j=1}^{6} f_{ij}(t, t+d) \log\, l_{ij}^{(d)}(t)\,,$$

(3.2)

where $f_{ij}(t, t+d)$ is the number of units observed in state i at time t and in state j at time t+d.

The unknown parameters to be estimated are transition probabilities m_{kl} (time invariant, because of the stationarity assumption) and the elements of error matrices *A(t)*=[$a_{lj}(t)$] and *B(t)*=[$b_{ik}(t)$]. True and observed states are assumed to coincide at the three survey times denoted by t_1=13 (January 1990), t_2=27 (March 1991) and t_3=39 (March 1992). The following assumption is made for the error probabilities of the retrospectively reported states within each of the three waves:

$$A(t) = I + (Q - I)\frac{(t_i - t)}{12} \qquad \text{for } i = 1, 2, 3 \text{ and } t = t_i - 12, \ldots, t_i\,,$$

(3.3)

where *I* is the identity matrix and *Q* is a matrix of error probabilities[3].

Unknown parameters m_{kl} and *Q* are estimated by a two-stage procedure. First, matrix *Q* is estimated by comparing the two pieces of information on the labor market state in March 1991 and, as stated above, by taking the concurrent information to be error-free (see Table 1): element q_{ij} is the probability that the retrospectively reported (in March 1992) state for March 1991 is j, given that the true state occupied, and declared, one year earlier was *i*. Equation (3.2) is then maximized with respect to m_{kl} [4].

[3] As shown by M&V, p. 467, the elements of matrix *B(t)* are function of the elements of matrix *A(t)*, and thus of *Q*.

[4] An important qualification is that the parameters of the model may be estimated assuming that the ICE condition holds for one particular value of *d*, or that it is possibly valid for several values of *d* at the same time. To test these nested hypotheses, M&V work out a Hausman-type test. In their empirical analyses, they find that the *d*-ICE condition is valid for *d*=18, 24 and 30.

Table 1. – COMPATIBILITY BETWEEN DECLARATIONS OF MARCH 1991 AND MARCH 1992 (row %)*

March 1991	**March 1992**					
	State 1	State 2	State 3	State 4	State 5	State 6
State 1	89.4	4.7	0.8	1.9	1.9	1.3
State 2	20.9	47.5	8.1	12.5	10.4	0.6
State 3	17.4	13.0	51.3	11.3	7.0	0.0
State 4	7.9	3.5	4.7	70.9	4.6	8.4
State 5	0.8	0.5	0.2	0.5	97.3	0.7
State 6	6.0	1.4	0.5	7.0	7.2	77.8

* States: 1 = permanent employment; 2 = fixed-term employment; 3 = training; 4 = unemployment; 5 = education; 6 = out of the labor force.

The general picture emerging from the models estimated by M&V is that neglecting measurement error leads to an overestimation of mobility in the labor market. In addition, the estimates of some transition probabilities are severely biased by classification errors.

B. Discussion of Some Model Assumptions

Evidence from the data studied here and arguments from the literature on measurement errors in panel data cast some doubts on M&V's assumptions, and also on their results. We begin by discussing these assumptions heuristically, and check their plausibility by testing them against less restricted specifications.

First, it should be noted that the observed flows exhibit an apparent seasonal pattern[5], which calls into question the assumption of a time-homogeneous Markov process.

Second, the double information collected for March 1991 provides some crude evidence on response error in the data: 8% of respondents declare a different state in the two surveys, as M&V point out (see also Table 1). But this is by no means conclusive support to the much stronger assumptions made by M&V about the measurement error mechanism, *i.e.*, that the actual reported information is error-free and that retrospective information is contaminated by classification errors which follow a *d*-step ICE assumption and increase linearly with the recall time period.

The FLFS data do not offer any evidence about the assumption that concurrent information is error-free, nor does the literature on measurement errors in surveys definitely support it (Biemer *et al.*, 1991).

As for the *d*-step ICE assumption, it is introduced by M&V in order to weaken the usual (one-step) ICE assumption, on which a large body of the literature on gross flows estimation is based (see, for example, Abowd and Zellner, 1985, and Kuha and Skinner, 1997). According to ICE, (i) classification errors referring to two different occasions are

[5] This is clear from the sequence of the observed monthly flows, not presented here for the sake of space. For example, from June to July we observe that a proportion of people who enter employment and unemployment states is greater than the average, whereas from August to September a proportion greater than the average leaves the employment state, mainly moving to education.

independent of each other conditionally on the true states and (ii) errors only depend on the present true state. Independent classification errors lead to spurious observed transitions and to an overestimation of the amount of gross change in the labor market. Consequently, estimation strategies based on ICE rectify observed labor market dynamics toward stability. Unfortunately, evidence from the cognitive psychology and survey methodology literature suggests that the ICE assumption very often does not hold, especially when information is collected by means of retrospective questions (Sudman and Bradburn, 1973; O'Muircheartaigh, 1996). If this is the case, estimation procedures based on ICE will produce a misleading picture of labor market dynamics.

Table 2 provides some neat evidence of this, from the very same sample of FLFS data. For simplicity, we use the usual classification of labor market participation into three states: employed (*E*), unemployed (*U*) and out of the labor force (*O*)[6]. For the period February to April 1991, two types of monthly flows are observed: (i) within-wave (WW), when information about labor market states is collected in the same survey, and (ii) between-waves (BW), when information is collected in two different surveys. The differences between WW and BW transition rates appear to be substantial, and are consistently stable across the two monthly transitions. WW transitions describe a remarkably more stable labor market than BW ones. This is an indirect but clear indication that classification errors are correlated over time[7].

The *d*-ICE assumption is introduced by M&V precisely in order to attenuate the inconveniences caused by the ICE one and is motivated in the following terms: "it only requires that (mis)classifications are conditionally independent in a *d*-unit period" (M&V, p. 466). Essentially, the motivation for *d*-ICE assumption is to get results robust against correlated classification errors, while paying a price in terms of efficiency – just a limited fraction of the available sample information is used. Nevertheless, we do not see a convincing rationale for it: it does not explore the pattern of autocorrelated classification errors, and it is coupled with rather strong assumptions about the response error probabilities.

[6] Correspondence with the classification used by M&V is straightforward: *E* comprises their states 1, 2 and 3; *U* consists of state 4; *O* comprises states 5 and 6.

[7] Note that the interpretation of this evidence is not straightforward, as it would have been if BW transitions had resulted from a combination of retrospective and concurrent information respectively, collected in two subsequent survey waves, and if WW transitions had resulted from retrospective information collected within the same survey wave and extending backwards roughly for the same time period (see, *e.g*., Martini, 1989). Given the design of the FLFS, the picture is less clear. Here, WW transition rates result: (i) for February-March 1991 from the survey wave of March 1991, *i.e.***,** from a combination of concurrent (for March) and one-month retrospective information (for February); (ii) for March-April 1991 from retrospective information quite a way back in time (twelve and eleven months respectively), collected from the survey wave of March 1992. Instead, BW transition rates are estimated on the basis of information collected at the two survey waves of March 1991 (for the initial month) and March 1992 (for the final month), that is to say: (i) for February-March, from a combination of one-month retrospective and twelve-month retrospective information; (ii) for March-April, from a combination of concurrent and eleven-month retrospective information. When these features of BW and WW transition rates are taken into account, the evidence from Table 2 does not conflict with the *d*-ICE assumption. However, it clearly points to autocorrelated classification errors.

Table 2. – OBSERVED MONTHLY TRANSITION RATES (%) FROM FEBRUARY TO APRIL 1991*

Monthly transitions**		**EE**	**EU**	**EO**	**UE**	**UU**	**UO**	**OE**	**OU**	**OO**
Feb-Mar	WW	98.19	1.67	0.14	9.11	90.65	0.24	0.28	0.11	99.61
	BW	93.17	3.58	3.25	25.18	65.23	9.59	3.75	1.96	94.29
Mar-Apr	WW	98.60	1.04	0.36	8.89	90.37	0.74	0.24	0.29	99.47
	BW	93.24	3.33	3.43	25.90	63.79	10.31	3.79	2.07	94.14

* States: *E* = employment; U = unemployment; *O* = out of the labor force.
** Transitions: WW = within-wave; BW = between-waves.

Although the fact that, in panel surveys with retrospective questions, memory decay is probably the main cause of response errors[8] is taken into account by M&V, this is done only in part and with a rigid format. M&V do this by combining the *d*-ICE condition with equation (3.3), according to which the probability of incorrect classification increases linearly with the recall time period. Two points deserve attention and, in our view, are far from convincing.

(a) Error probabilities are exogenously determined, on the basis of an entirely *a priori* specification[9].
(b) The combination of the two assumptions above is rather mechanical, with no adequate justification. In addition, it ends up with a pattern of classification errors which does not capture the component of correlation over time.

Thus, it comes as no surprise to find that the final model estimated by M&V corrects labor market dynamics toward stability, like all strategies using the classical ICE assumption.

C. Further Empirical Evidence

In order to provide additional empirical evidence supporting (or possibly confuting) our criticisms to M&V's model and estimation strategy, we tested some nested models, comparing M&V's specification with models in which the time-homogeneity of the latent Markov chain is relaxed or in which measurement errors are set to be free.

Table 3 summarizes estimation and testing results. The forth column contains the corrected number of estimated parameters, *i.e.*, the number of parameters with non-zero

[8] Among the most common effects of memory decay is the tendency for respondents to forget past events and/or to place them wrongly along the time axis (Sudman and Bradburn, 1973). Abundant evidence in the literature indicates that the quality of recall declines as the length of the recall period increases, although this relationship is far from being general and stable. The recall period interacts with other factors, such as salience of the event, type of response task, *etc*. (for broad reviews, see Jabine *et al*., 1984, and Biemer and Trewin, 1997; for meta-analysis questioning the importance of the recall period on data quality, see Mathiowetz, 2000). However, if we restrict ourselves only to the literature on measurement errors in reporting labor market histories, it is quite clear that short spells are often forgotten and that events (*i.e.*, changes of state) are anticipated or postponed on the time axis toward the boundaries of the reference period (see, for example, Martini, 1989, and Ryscavage and Martini, 1990)). The respondent's tendency to shift reported changes in labor market state toward the interview time is called the (forward) "telescoping effect" and the tendency to mechanically report the same condition throughout the whole reference period is called the "conditioning effect" (Eisenhower and Mathiowetz, 1991). The overall result of these effects is to induce correlated classification errors, the magnitude of which increases as the recall period extends.

[9] A sensible alternative would be to formulate a flexible measurement model, *e.g.*, maintaining that errors are an increasing function of recall time, but allowing the functional form to be selected and the parameters to be estimated from the data. We take this approach in our model specification strategy (see section IV).

estimated values. ΔL^2 is the difference in the log-likelihood ratio statistics, and Ddf is the difference in corrected degrees of freedom.

Table 3. – ALTERNATIVE MODELS FOR MONTHLY FLFS GROSS FLOW ESTIMATION, JANUARY 1989-MARCH 1992

Model*	**Log-likelihood**	**# of estimated parameters**	**Corrected # of estimated parameters**	**Model comparisons**	ΔL^2	**Ddf**	**p-value****
A1	-50,038.86	35	35				
A2	-49,929.50	365	106	A2-A1	218.730	71	>0.005
A3	-49,677.44	425	425	A3-A1	723.840	390	>0.005

* See main text for specifications of various models.
** P-value calculated according to corrected number of degrees of freedom.

Model A1 is one of the final models estimated by M&V: monthly flows among six states in the labor market from January 1989 to March 1992 are considered; latent transitions are assumed to follow a time-homogeneous Markov chain; d is 30 and measurement errors are fixed, as in (3.3). Model A2 relaxes the time-homogeneity of the latent Markov chain, but maintains that transitions between the same calendar months across the three years are equal[10]. In model A3, measurement errors are set free: in order to ensure identifiability, it is only assumed that the error-generating mechanism is the same in the three waves, *i.e.*, errors depend only on the distance, in months, between reference and survey time. The assumption of a time-homogeneous Markov chain is also maintained, since a model with a non-homogeneous unobserved Markov chain and free measurement errors is not identified (Lazarsfeld and Henry, 1968).

Model comparisons by means of conditional testing do not support two crucial assumptions of M&V's models. Relaxing time homogeneity of the first-order latent Markov chain (model A2) shows a significant increase in log-likelihood, which challenges the assumption of stationarity. Comparison of model A3 with A1 shows that the restrictions on the classification error mechanism imposed by M&V cannot be accepted.

This empirical evidence and the above discussion suggest that a different model would be appropriate in estimating true gross flows from the FLFS: a model which overcomes some rigidities of M&V's model – chiefly, the unnecessarily strong assumption of a stationary latent Markov chain – and which accounts for correlated classification errors. In the next section, we specify and estimate such a model within a latent class analysis set-up.

As already pointed out, in order to reduce the computational burden, we carry out our analyses on quarterly transitions[11] among three labor force states – *E*, *U* and *O*, for the period

[10] This specification assumes a dominating constant seasonal component, as inspection of the data suggests. In addition, it avoids having too many unknown parameters to estimate and helps reaching convergence within a reasonable time.

[11] Specifically, we consider quarterly transitions for the months of March, June, September and December.

from March 1990 to March 1992 – *i.e*., for a time-span covering two survey waves[12]. Preliminarily, it is important to ascertain that such a choice does not appreciably alter the pattern of observed transitions. For this purpose, some useful results are given in Table 4. They refer to models which parallel models A1-A3, but differ from them precisely because they only consider three states (models B1-B3, which again deal with monthly transitions) and additionally quarterly transitions (models C1-C3), for the period January 1989-March 1992.

Table 4. – ALTERNATIVE MODELS FOR FLFS GROSS FLOW ESTIMATION AMONG THREE LABOR FORCE STATES, JANUARY 1989-MARCH 1992

Model*	**Log-likelihood**	**# of estimated parameters**	**Corrected # of estimated parameters**	**Model comparisons**	ΔL^2	**Ddf**	**p-value****
B1	-33,026.58	8	8				
B2	-32,931.56	230	165	B2-B1	190.04	78	>0.005
B3	-32,927.68	86	86	B3-B1	197.80	157	>0.005
C1	-10,997.00	8	8				
C2	-10,958.32	84	62	C2-C1	77.36	36	>0.005
C3	-10,963.39	44	44	C3-C1	67.22	64	>0.005

* See main text for specifications of various models.
** P-value calculated according to the corrected number of degrees of freedom.

Model comparison by means of conditional tests (Table 4, last three columns) leads us to reject both the time homogeneity of the latent Markov chain and the specification imposed on measurement errors by M&V, also when the original six labor market states are collapsed to three and when quarterly transitions instead of monthly ones are further considered. Thus, loosely speaking, the results obtained for models A1-A3 carry over to models estimated on quarterly transitions in the three labor market states.

IV. A Model for Correlated Classification Errors in Retrospective Surveys

A. Correlated Classification Errors and Latent Class Modeling

At this point, our purpose is to specify and estimate a model which allows for a seasonal component in true transitions and, based on suggestions from the literature on response errors in surveys and on the empirical findings above, parsimoniously describes the pattern of correlated classification errors.

A convenient framework for formulating our model is provided by latent class analysis, which has already been applied in a number of studies on panel data to separate true changes from observed ones affected by unreliable measurements (van de Pol and Langeheine, 1997; Bassi, Torelli and Trivellato, 1998; Bassi *et al.*, 2000). We devote this sub-section to essential references to such a modeling set-up.

[12] The dimension of the observed contingency table grows dramatically when many polytomous variables are considered simultaneously, and may become very demanding for estimation algorithms. This is the main reason why we estimate our latent class model on a simplified state and time space.

The true labor market state is treated as a latent variable, and the observed one as its indicator. The model consists of two parts: (i) structural, which describes true dynamics among latent variables (*e.g.*, by means of Markov structures); (ii) measurement, which links each latent variable to its indicator(s). Some restrictions incorporating *a priori* information and/or assumptions on the error-generating mechanism are imposed on the parameters of the measurement part

As a starting point, let us consider the simplest formulation of latent class Markov (LCM) models (Wiggins, 1973), which assumes that true unobservable transitions follow a first-order Markov chain. As in all standard latent class model specifications, local independence among the indicators is assumed, *i.e.*, indicators are independent conditionally on latent variables[13].

Using the notation introduced in section III, if T time-points are considered, then $P(Y(1),...Y(T))$ is the proportion of units observed in a generic cell of the T-ways contingency table. Let us also denote by $v_{l_1}(1) = P(X(1) = l_1)$ the initial state of the latent Markov chain.

For a generic sample individual, a simple LCM model is defined as:

$$P(Y(1) = j_1,..., Y(T) = j_T) = \sum_{l_1=1}^{s} ... \sum_{l_T=1}^{s} v_{l_1}(1) a_{l_1 j_1}(1) \prod_{t=2}^{T} a_{l_t j_t}(t) m_{l_{t-1} l_t}(t-1) \,, \qquad (4.1)$$

where j_t and l_t vary over the possible states occupied in the labor market – in our case, *E*, *U* and *O*, with s=3.

In order to proceed in formulating our model, it is essential to consider the equivalence between latent class and log-linear models. Any latent class model may be expressed as a log-linear one with some unobservable variables (Haberman, 1979). A LCM model may also be specified in the log-linear context through the “modified LISREL approach” proposed by Hagenaars (1990), which extends Goodman’s modified path analysis (Goodman, 1973) to include latent variables[14]. Each conditional response probability in equation (4.1) may be expressed as a function of the log-linear parameters. For example:

$$a_{l_1 j_1}(1) = \frac{\exp(b_{l_1}^{X(1)} + b_{l_1 j_1}^{X(1)Y(1)})}{\sum_{l_1=1}^{3} \exp(b_{l_1}^{X(1)} + b_{l_1 j_1}^{X(1)Y(1)})} \,, \qquad (4.2)$$

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[13] Note that, in the LCM with one indicator per latent variable, the assumption of local independence coincides with the ICE condition.

[14] For an extensive presentation of this approach to categorical causal modeling and for technical details, see Hagenaars (1998).

where $b_{l_1}^{X(1)}$ e $b_{l_1 j_1}^{X(1)Y(1)}$ denote the first- and second-order effects in log-linear parameterization, respectively.

From equation (4.2), it is apparent that any restriction on conditional probabilities may be equivalently imposed on the log-linear parameters. In general, the specification of a model as a product of conditional probabilities has the advantage of more direct interpretation, whereas log-linear parameterization is more flexible and allows more parsimonious models to be specified. The breakdown of conditional probabilities does imply estimation of the entire set of interaction parameters, whereas the modified LISREL approach allows us to specify models in which some higher-order interactions among variables may be omitted or conveniently constrained.

For the model formulated here, we exploit the above equivalence: the higher flexibility of log-linear parameterization allows us to parsimoniously model the correlation of classification errors over time.

B. A Latent Class Model for Quarterly Labor Gross Flows from the FLFS

The information on observed quarterly flows modeled here is shown in Table 5.

Table 5. – OBSERVED QUARTERLY TRANSITION RATES (%) BY TYPE, MARCH 1990 - MARCH 1992*

Quarterly transitions **		***EE***	***EU***	***EO***	***UE***	***UU***	***UO***	***OE***	***OU***	***OO***
Mar1990 – Jun1990	WW	93.03	2.03	1.34	19.94	77.46	2.60	1.37	0.32	98.40
Jun1990 – Sep1990	WW	94.08	4.32	1.60	18.99	79.43	1.58	3.87	3.79	93.34
Sep1990 – Dec1990	WW	93.93	4.39	1.98	24.00	72.47	3.53	1.91	0.80	97.30
Dec1990 – Mar1991	WW	94.77	4.25	0.98	24.53	72.40	3.07	0.98	0.66	98.36
	BW	91.50	4.86	3.64	31.60	56.84	11.56	4.40	2.10	93.50
Mar1991- Jun1991	WW	96.03	3.02	0.95	23.21	74.32	2.47	1.28	0.68	98.04
	BW	91.48	4.63	3.89	35.01	54.20	10.79	4.84	2.14	93.02
Jun1991 – Sep1991	WW	94.29	3.94	1.77	20.93	78.29	0.78	4.71	2.95	92.34
Sep1991 – Dec1991	WW	93.73	4.48	1.79	23.63	74.89	1.48	3.22	1.65	95.13
Dec1991- Mar1992	WW	93.90	4.80	1.30	21.67	76.74	1.59	1.70	0.59	97.71

* States: *E* = employment; U = unemployment; *O* = out of the labor force.
** Transitions: WW = within-wave; BW = between-waves.

Figure 1 presents the path diagram describing some basic features of our model. Here and in the sequel, indicators *Y*(5), *Y*(6), *Y*(7), *Y*(8) and *Y*(9) represent observed states in the five quarters covered by the March 1992 survey (March, June, September and December 1991 and March 1992, respectively); *W*(1), *W*(2), *W*(3), *W*(4) and *W*(5) refer to the sequence of states observed in the preceding survey (March, June, September and December 1990 and March 1991, respectively). As usual, $X(t)$ denotes the true labor market state occupied at time *t*. Figure 1 clearly distinguishes the first-order Markov process among true states $X(t)$ and the measurement sub-model linking indicators *Y*(*t*) and *W*(*t*) to latent states and transitions[15]. It is also apparent that, for eight quarters out of nine, there is only one indicator for each latent variable: only for *X*(5) are there two indicators, *Y*(5) and *W*(5).

[15] As will be explained in the sequel, the oblique arrows in Figure 1 mean that indicators *Y*(*t*) and *W*(*t*) depend on the true transition which occurred between times t and $t+1$.

Figure 1. – BASIC LCM MODEL OF GROSS FLOWS
FOR 9 TIME POINTS

W(1)   W(2)   W(3)   W(4)   W(5)
↑   Π   ↑   Π   ↑   Π   ↑   Π   ↑
X(1)→ X(2)→ X(3)→ X(4)→X(5)→X(6)→X(7)→X(8)→X(9)
↓ · ↓ · ↓ · ↓ · ↓
Y(5)   Y(6)   Y(7)   Y(8)   Y(9)

The relationships described by the path diagram in Figure 1 may be formulated as in equation (4.3), which breaks down the observed proportion in the generic cell of the 10-way contingency table into the following product of conditional probabilities:

$$P(W(1)=i_1, W(2)=i_2, W(3)=i_3, W(4)=i_4, W(5)=i_5, Y(5)=j_5, Y(6)=j_6, Y(7)=j_7, Y(8)=j_8 Y(9)=j_9)=$$
$$=\sum_{l_1,\ldots l_7=1}^{3} v_{l_1}(1)\prod_{t=1}^{8} m_{l_t l_{t+1}}(t)a_{l_9 j_9}(9)a_{l_8 l_9 j_8}(8)a_{l_7 l_6 j_7}(7)a_{l_6 l_7 j_6}(6)a_{l_5 l_6 j_5}(5)z_{l_5 i_5}(5)z_{l_4 l_5 i_4}(4)z_{l_3 l_4 i_3}(3)z_{l_2 l_3 i_2}(2)z_{l_1 l_2 i_1}(1), \qquad (4.3)$$

where $z_{l_1 l_2 i_1}(1)$ is the probability of observing state i_1 for March 1990 (*W*(1)), given that there was a transition from state l_1 to state l_2 from March 1990 (*X*(1)) to June 1990 (*X*(2)), and similarly for the other conditional response probabilities – those denoted by $z_{l_t l_{t+1} i_t}(t)$, *t*=1,…,4, referring to observed states W(*t*) and those denoted by $a_{l_t l_{t+1} i_t}(t)$, *t*=5,…,8, referring to observed states Y(*t*).

The same relationships implied in Figure 1 may be described in terms of a system of multinomial logit equations. Note, however, that in such parameterization more parsimonious models may be specified (*e.g.*, by imposing that the hierarchical log-linear model does not contain third-order interaction parameters, which are implied by equation (4.3)).

It is important to stress that the auxiliary information at our disposal on the measurement process is not rich at all[16]. Therefore, some assumptions are needed to identify the measurement error mechanism. The final specification of the model combines various pieces of information: obviously, knowledge of the design and measurement characteristics of the FLFS; theoretical considerations and empirical evidence about the pattern of reporting errors in retrospective surveys and the true dynamic process, reviewed in section III; results from specification searches aimed at obtaining a parsimonious and (hopefully) sensible formulation.

[16] Thus, we are very far from the case in which data from reinterview studies are available, collected specifically for information on classification error probabilities. For procedures to correct gross flows based on reinterview data, see Abowd and Zellner (1985), Chua and Fuller (1987), Poterba and Summers (1986) and Singh and Rao (1995).

The set of assumptions of the final model, together with some further comments on the reasons for them, may be summarized as follows (for mathematical formulation, see Appendix).

(a) Quarterly flows among true labor market states follow a first-order non-homogeneous Markov chain, with transition probabilities among the same calendar months in different years set to be equal. Essentially, this specification amounts to assuming a dominant constant seasonal component for labor market dynamics – a pattern convincingly suggested by previous analyses.

(b) As regards the measurement part of the model, it is worth emphasizing again that only for March 1991 are two distinct observations of the labor force state available – concurrent information $W(5)$ and retrospective information $Y(5)$. Thus, we cannot explicitly model dependencies between indicators[17]. One way of accounting for correlated classification errors in our data is to let the indicators depend on latent transitions. That is, we assume that a response given for time t depends on the true transition which occurred between times t and $t+1$ (this is the meaning of the oblique arrows in Figure 1 and of probabilities $z_{l_t l_{t+1} i_t}(t)$ and $a_{l_t l_{t+1} i_t}(t)$; for precise specification, see Appendix). In other words, a sort of forward telescoping effect is postulated, which is sensible in retrospective surveys[18].

(c) In order to incorporate some restrictions suggested by theoretical arguments and empirical findings on the error-generating mechanism, and additionally for reasons of model parsimony, the following further assumptions are imposed on response probabilities.

(c1) In the hierarchical log-linear model formulation, all third-order interaction parameters are excluded.

(c2) For second-order interaction parameters $b_{l_t i_t}^{X(t)W(t)}$, $t=1,\ldots,5$, and $b_{l_t j_t}^{X(t)Y(t)}$, $t=5,\ldots,9$, describing the association between each latent variable and its indicator, a flexible function is specified, such that the probability of erroneously reporting state increases with the distance between reference and survey months.

The specification we move from is:

$$b_{l_t i_t}^{X(t)W(t)} = w_{l_t i_t}^{X(t)W(t)} + d\,(w_{l_t}^{X(t)} f(\Delta t))$$

$$b_{l_t j_t}^{X(t)Y(t)} = w_{l_t j_t}^{X(t)Y(t)} + d\,(w_{l_t}^{X(t)} f(\Delta t)) \,, \qquad (4.4)$$

where $w_{l_t i_t}^{X(t)W(t)}$ and $w_{l_t j_t}^{X(t)Y(t)}$ are parameters measuring the association between each latent variable $X(t)$ and its indicator, which depend on the combination between

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[17] With essentially one indicator per latent state, a model postulating direct effects between indicators would be trivially under-identified.

[18] Proper transitions – *i.e.*, movements from one state to a different one – may easily be wrongly placed in time, because in some cases events really may be difficult to place along the time axis. For example, employees who lost their jobs or retired (transitions *EU* and *EO*) generally take the paid holidays they are entitled to, and may not clearly recall exactly when they left employment. The moment individuals entered the labor force (transitions *OU* and *OE*) may also be hard to recall, especially when they left school (van de Pol and Langeheine, 1997).

observed and true states; d is an indicator function having a value of 1 if the true state is correctly reported, and 0 otherwise; $w_{l_t}^{X(t)}$ are proportionality factors depending on the true state – they account for the fact that the three states E, U and O may be perceived differently by respondents; $f(.)$ is a function of time distance Δt between reference and survey months.

As the probability of making mistakes increases with the length of the recall period, $f(\Delta t)$ must be an increasing function of Δt. In our case, we chose $f(\Delta t)=exp(\Delta t)$ as the best fit specification, on the basis of L^2, out of a set of possible functions (linear, squared, exponential)[19].

(c3) Parameters $w_{l_t i_t}^{X(t)W(t)}$, $w_{l_t j_t}^{X(t)Y(t)}$, and $w_{l_t}^{X(t)}$ are set constant over time, as well as the association between $W(t)$ and $X(t+1)$ for t=1,..,4, and between $Y(t)$ and $X(t+1)$ for t=5,…,8. These restrictions are consistent with the notion that the measurement properties of properly designed survey instruments are fairly stable over time – a result well established in the literature.

(c4) Lastly, the probability of making mistakes is assumed to be constant for the same month across the various years. The rationale for this assumption again has to do with the concept of the time stability of the measurement properties of the survey instruments, but in a slightly different, more specific sense: it is based on the fact that the survey waves were carried out in the same month of consecutive years – March 1991 and March 1992 -, and on empirical evidence that response errors mainly depend on the period of time elapsing between survey time and the event to be recalled rather than on the calendar month in which the event tool place.

C. Results

The estimated quarterly transition rates from our model are listed in Table 6[20]. When they are compared with the corresponding observed rates in Table 5, overall it emerges that observed transitions are corrected according to expectations. As implied by serially correlated measurement errors in retrospective surveys, true mobility in the French youth labor market is higher than observed mobility.

Table 6. – LCM MODEL: ESTIMATED QUARTERLY TRANSITION RATES (%), MARCH 1990 - MARCH 1992*

Quarterly transitions	EE	EU	EO	UE	UU	UO	OE	OU	OO
Mar – Jun	92.73	4.00	3.27	32.90	57.88	9.21	3.38	1.41	95.21
Jun – Sep	92.91	5.29	1.80	28.20	70.70	1.10	4.63	2.96	92.41
Sep – Dec	93.57	4.52	1.92	24.28	73.15	2.57	2.56	1.21	96.23
Dec – Mar	94.31	4.55	1.15	22.98	74.76	2.27	1.32	0.63	98.05

[19] This choice is in accordance with findings from experimental psychology literature and empirical social research, which indicate that, within short or medium recall periods, the process of memory decay is approximated reasonably well by an exponential function (see, *e.g.*, Sudman and Bradburn, 1973).

[20] Software *lEM* (Vermunt, 1996) was used to estimate the model.

* States: E = employment; U = unemployment; O = out of the labor force.

As regards the measurement part of our LCM model, results are presented in Table 7. First, they show that no errors are made in reporting the concurrent condition (Table 7, last row). Second, they indicate that classification errors are irrelevant for the quarter immediately preceding the survey (Table 7, penultimate row). As for the other reference months, as implied by (4.4) the estimates show that the longer the recall period, the greater probability of answering incorrectly. For transition rates involving recall periods of up to one year (Table 7, first row), the magnitude of flow correction is considerable.

Table 7. – LCM MODEL: ESTIMATED CONDITIONAL RESPONSE PROBABILITIES (%), MARCH 1990 - MARCH 1992*

Reference month	**Conditional response probabilities**								
	$E\|e$	$U\|e$	$E\|u$	$O\|e$	$U\|u$	$O\|u$	$E\|o$	$U\|o$	$O\|o$
March 1990 and 1991 **	95.60	2.06	2.34	17.09	72.42	10.49	2.13	0.87	97.00
June 1990 and 1991 **	97.89	1.34	0.77	7.56	90.48	1.96	1.51	0.77	97.72
September 1990 and 1991 **	99.90	0.06	0.14	0.34	99.48	0.18	0.05	0.02	99.93
December 1990 and 1991 **	100.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	100.00
March 1991 and 1992 ***	100.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	100.00

* Observed states: E = employment; U = unemployment; O = out of the labor force.
True states: e = employment; u = unemployment; o = out of the labor force.
** Retrospective information, collected in survey waves of March 1991 and March 1992, respectively.
*** Concurrent information, collected in survey waves of March 1991 and March 1992, respectively.

We obtain further insights on some features of the latent Markov model, by jointly considering the parameter estimates of the measurement and structural part of the model. Since reported states for December and March are not affected by measurement errors, it comes as no surprise that the December-March estimated transitions basically coincide with observed ones, apart from the averaging induced by the assumption that they do not vary over the two years. In addition, the March-June estimated transitions largely reflect the heavy weight assigned to the information in March 1991 in the BW observed transitions – concurrent, which is thus taken as error-free. For the other transitions, the general pattern outlined above is clear: there is more true dynamics than appear from the observed rates; the more the reference month extends back in time with respect to the survey month, the higher the correction toward mobility; transitions exhibit a definite seasonal pattern.

Table 8 – M&V'S MODEL: ESTIMATED QUARTERLY TRANSITION RATES (%), MARCH 1990 - MARCH 1992*

EE	***EU***	***EO***	***UE***	***UU***	***UO***	***OE***	***OU***	***OO***
97.32	2.28	0.40	13.21	86.20	0.59	2.65	1.54	95.81

* Model specification: monthly flows, time-homogeneous Markov chain, d=18.
States: E = employment; U = unemployment; O = out of the labor force.

For the sake of comparison, we also estimated quarterly transitions from March 1990 to March 1992 with one of the M&V's final models: monthly flows following a first-order time-homogeneous Markov chain, error probabilities fixed as in (3.2), and d=18. Results are listed in Table 8. They clearly describe a labor market which is much more stable than the observed one, and *a fortiori* than that emerging from our analyses[21].

V. Concluding Remarks

This paper reanalyzes gross flow data from the French Labor Force Survey modeled by M&V. Our model shares the same objective as M&V's paper: to correct for measurement errors in retrospectively reported labor market states, for proper estimation of gross flows and transition probabilities. However, our model is based on a rather different specification of the measurement error mechanism and a more flexible pattern of the latent Markov process. Based on arguments from survey methodology literature and on empirical evidence from the same French data set, it accounts for correlated classification errors over time and allows for a seasonal component in the latent Markov process.

The model was formulated and estimated within a latent class analysis set-up. Interestingly enough, our results differ substantially from those of M&V. While their model corrects observed flows toward stability, ours does the opposite: estimated true transitions show higher mobility than observed ones. The implications of our findings for the analysis of labor market dynamics, and possibly for policy prescriptions, are far from negligible.

Appendix

The mathematical formulation of the model, resulting from equation (4.3) and assumptions (a)-(c4) in Section IV.B, is given below.

$v_{l_1}(1) = P(X(1) = l_1)$;

$m_{l_t l_{t+1}}(t) = P(X(t+1) = l_{t+1} \mid X(t) = l_t)$ $\quad t = 1,\ldots,8$;

$a_{l_9 j_9}(9) = P(Y(9) = j_9 \mid X(9) = l_9)$;

$a_{l_t l_{t+1} j_t}(t) = P(Y(t) = j_t \mid X(t) = l_t, X(t+1) = l_{t+1})$ $\quad t = 5,\ldots,8$;

$z_{l_5 i_5}(5) = P(W(5) = i_5 \mid X(5) = l_5)$;

$z_{l_t l_{t+1} i_t}(t) = P(W(t) = i_t \mid X(t) = l_t, X(t+1) = l_{t+1})$ $\quad t = 1,\ldots,4$;

l_t, $t = 1,\ldots,9$; j_t, $t = 5,\ldots,9$; i_t, $t = 1,\ldots,5$ vary over *E*, *U* and *O*.

[21] As regards the measurement sub-model, it is interesting to note that M&V's assumption of concurrent error-free information is corroborated by our estimates. However, their *d*-ICE assumption and our specification of the correlated measurement error mechanism are quite divergent, and play a crucial role in producing the substantially different results mentioned above.

(a):

$m_{l_1l_2}(1) = m_{l_5l_6}(5);$

$m_{l_2l_3}(3) = m_{l_6l_7}(6);$

$m_{l_3l_4}(3) = m_{l_7l_8}(7);$

$m_{l_4l_5}(4) = m_{l_8l_9}(8).$

(b)-(c1):

$$a_{l_t l_{t+1} j_t}(t) = \frac{\exp(b_{j_t}^{Y(t)} + b_{j_t l_t}^{Y(t)X(t)} + b_{j_t l_{t+1}}^{Y(t)X(t+1)})}{\sum_{j_t=1}^{3} \exp(b_{j_t}^{Y(t)} + b_{j_t l_t}^{Y(t)X(t)} + b_{j_t l_{t+1}}^{Y(t)X(t+1)})};$$

$$z_{l_t l_{t+1} i_t}(t) = \frac{\exp(b_{i_t}^{W(t)} + b_{i_t l_t}^{W(t)X(t)} + b_{i_t l_{t+1}}^{W(t)X(t+1)})}{\sum_{i_t=1}^{3} \exp(b_{i_t}^{W(t)} + b_{i_t l_t}^{W(t)X(t)} + b_{i_t l_{t+1}}^{W(t)X(t+1)})}.$$

(c2):

$$b_{l_t i_t}^{X(t)W(t)} = w_{l_t i_t}^{X(t)W(t)} + d(w_{l_t}^{X(t)} \exp(\Delta t)) \quad t=1,\ldots,5$$

$$b_{l_t j_t}^{X(t)Y(t)} = w_{l_t j_t}^{X(t)Y(t)} + d(w_{l_t}^{X(t)} \exp(\Delta t)) \quad t=5,\ldots,9.$$

(c3):

$$w_{l_1i_1}^{X(1)W(1)} = w_{l_2i_2}^{X(2)W(2)} = w_{l_3i_3}^{X(3)W(3)} = w_{l_4i_4}^{X(4)W(4)} = w_{l_5i_5}^{X(5)W(5)};$$

$$w_{l_5j_5}^{X(5)Y(5)} = w_{l_6j_6}^{X(6)Y(6)} = w_{l_7j_7}^{X(7)Y(7)} = w_{l_8j_8}^{X(8)Y(8)} = w_{l_9j_9}^{X(9)Y(9)};$$

$$w_{l_1}^{X(t)} = w_{l_2}^{X(t)} = w_{l_3}^{X(t)} = w_{l_4}^{X(t)} = w_{l_5}^{X(t)};$$

$$w_{l_5}^{X/t)} = w_{l_6}^{X(t)} = w_{l_7}^{X(t)} = w_{l_8}^{X(t)} = w_{l_9}^{X(t)};$$

$$b_{l_2i_1}^{X(2)W(1)} = b_{l_3i_2}^{X(3)W(2)} = b_{l_4i_3}^{X(4)W(3)} = b_{l_5i_4}^{X(5)W(4)};$$

$$b_{l_6j_5}^{X(6)Y(5)} = b_{l_7j_6}^{X(7)Y(6)} = b_{l_8j_7}^{X(8)Y(7)} = b_{l_9j_8}^{X(9)Y(8)};$$

$$b_{i_1}^{W(1)} = b_{i_2}^{W(2)} = b_{i_3}^{W(3)} = b_{i_4}^{W(4)} = b_{i_5}^{W(5)};$$

$$b_{j_5}^{Y(5)} = b_{j_6}^{Y(6)} = b_{j_7}^{Y(7)} = b_{j_8}^{Y(8)} = b_{j_9}^{Y(9)}.$$

(c4):

$$a_{l_9 j_9}(9) = z_{l_5 i_5}(5);$$

$$a_{l_8 l_9 j_8}(8) = z_{l_4 l_5 i_4}(4);$$

$$a_{l_7 l_8 j_7}(7) = z_{l_3 l_4 i_3}(3);$$

$$a_{l_6 l_7 j_6}(6) = z_{l_2 l_3 i_2}(2);$$

$$a_{l_5 l_6 j_5}(5) = z_{l_2 l_1 i_2}(1).$$

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