*Occupazione e disoccupazione in Italia:*
*misura e analisi dei comportamenti*

Progetto di ricerca cofinanziato dal Ministero per l'Università
e la Ricerca Scientifica e Tecnologica - Assegnazione: 1999
Coordinatore: Ugo Trivellato

# Measuring participation at work in the presence of fallible indicators of labour force state

Erich Battistin, Enrico Rettore, Ugo Trivellato
*Dip. di Scienze Statistiche, Univ. di Padova*

Working Paper n. 26 settembre 2000

Unità locali del progetto:

| | |
|---|---|
| Dip. di Economia "S. Cognetti De Martiis", Univ. di Torino | (coord. Bruno Contini) |
| Dip. di Scienze Economiche, Univ. "Ca' Foscari" di Venezia | (coord. Giuseppe Tattara) |
| Dip. di Metodi Quantitativi, Univ. di Siena | (coord. Achille Lemmi) |
| Dip. di Scienze Statistiche, Univ. di Padova | (coord. Ugo Trivellato) |

Dip. di Scienze Statistiche
via S. Francesco 33, 35121 Padova

# Measuring participation at work when the labour force state is imprecisely observed

Erich Battistin
Institute for Fiscal Studies, London

Enrico Rettore
Department of Statistics, University of Padova

Ugo Trivellato
Department of Statistics, University of Padova

12th April 2002

[1]

**Abstract**

Current labour force counting fits general guidelines set by the International Labour Office (ILO) to classify units in the usual three labour force states - employed, unemployed and out of the labour force. The resulting statistics are known to be sensitive to slight variations in the conventional guidelines *prima facie* consistent with this general guidelines. Exploiting alternative criteria followed by the Italian Statistical Office (ISTAT) up to 1992, we provide some evidence to define critical units whose state is not clearly identified and turns out to depend on the classification itself. To prove how statistics are sensitive to alternative definitions of unemployment, we compare such critical groups to some benchmark groups, namely groups whose classification is not questioned and stable with respect to both ILO and ISTAT guidelines. Conditioning on characteristics known to be relevant for the labour forc-e status allows us to establish which state critical units more likely belong to. An application is presented for a sample of married women from the Italian Labour Force Survey on four survey occasions reflecting the labour market cycle between 1984 and 1995.

*Keywords*: Labour force state, sensitivity analysis, finite mixture models.

## 1 Introduction

This is primarily a paper on counting the labour force. Central statistical agencies classify members of a reference population in the usual three labour force

[1]Research for this paper has been supported by a grant from the Ministry for Education, University and Scientific Research to the project 'Dynamics and inertia in the Italian labour market: databases, measurement and modelling issues'. An earlier version was presented at the 40-th Scientific Meeting of the Italian Statistical Society, Florence, April 26-28, 2000

states - employed, unemployed and out of the labour force - following some general guidelines set by the International Labour Office (ILO). However, they are largely conventional in the way they derive operational rules from these guidelines (Hussmanns, Merhan and Verma, 1990).

As a matter of fact, moving from the elementary information collected in a typical Labour Force Survey (LFS in the following) there is substantial room for different classification rules, all consistent with the ILO guidelines. If the labour force statistics were robust to conceivable variations of the operational rules, there would be no issue at all. If, on the contrary, heads-count results appreciably depend upon the operational rules adopted, then there is a measurement problem for labour market analysts.

Even leaving aside the potential problem for the heads-count, problems might also arise for the structural modelling of labour supply and unemployment. Indeed, at the macro level one might hope that the classification errors induced by an inappropriate set of operational rules cancel out through aggregation or nearly so. But at the micro level moving units from their true state to a wrong one results in a measurement error in the dependent variable of the model - the labour force state - which in principle can severely bias the estimates of the structural parameters. Hausman, Abrevaya and Scott Morton (1998) discuss the effect of classification errors in non-linear models of labour market transitions. A sensitivity analysis for a Double-Hurdle specification of labour supply with unemployment applied to Italian LFS data is in Rettore and Trivellato (1993); the topic is further elabourated in Rettore and Trivellato (1998)[2].

From a different perspective, the salience of the distinction among some labour force states - specifically, unemployment and out of the labour force - might be called into question. For a reduced-form dynamic analysis aimed at testing whether these states are different with respect to the probability of transition to employment see Flinn and Heckman (1983), Gonul (1992) and Jones and Riddell (1999).

In what follows we take for granted that there exist three mutually exclusive and distinct labour states where to classify the population of interest: *employment* ($E$), *unemployment* ($U$) and *out of the labour force* ($OLF$). The actual labour force state of each unit is inferred on the basis of fallible discrete indicators derived from the information collected in a typical LFS. As it will be seen, the approach is fairly general and can be applied to any sensible cross-section sample from a LFS. Our empirical analysis focuses on samples of married women from the Italian LFS, four selected quarters over the period 1984 to 1995.

The state of a large number of units in the population is 'out-of-question', and actually it is not questioned by anyone. This is the case for units reporting either (i) hours of work in the reference period, or (ii) no hours of work, very recent activity for seeking work and immediate availability to work, or (iii) no hours of work and no actual interest/availability to work. Quite reasonably, according to several classification rules across different countries these units are classified as $E$, $U$ and $OLF$, respectively (see Sorrentino, 2000, for a comparison of guidelines in US, Canadian, and European LFSs). We will take such units as *benchmark groups.*

[2]Bound, Brown and Mathiowetz (2001) provide an excellent review of the broader subject of measurement errors in survey data. Particularly, in section 6.5 of their review they focus on unemployment

On the other hand, there is a number of units whose state is not entirely apparent on the basis of available evidence. They are mostly ‘grey’ units at the boundary between the labour force states, which might turn out classified either as $U$ or $OLF$ according to alternative operational criteria. While some of the basic difficulties were spelled out some twenty-five years ago by Shiskin (1976), it is worth noting that recent trends in developed countries’ economies have expanded the spectrum of these dubious situations (see for example Malinvaud, 1986). As far as Italy is concerned, the implications of a sizeable ‘underground economy’ should also deserve attention.

In the following we look at some observable individual characteristics (such as age, education and family composition) known both on theoretical and empirical grounds to influence the labour force state. We compare the ‘grey’ units to the out-of-question groups with respect to such characteristics to check which group they look like the most.

To preview our conclusions, we find very poor evidence to support the common practice of classifying as $OLF$ units with no hours of work, looking for a job but with no recent active steps for seeking work. Rather, according to our results they look quite similar to people participating at work: most of those ‘loose’ job seekers look like the (surely) unemployed, but a non-negligible fraction of them appears to be close to the employed.

The remaining of the paper is organized as follows. Section 2 documents the incidence of classification errors in labour market survey data. Section 3 presents our model specification and discusses the related estimation issues. Section 4 presents the data we used in our analysis while Section 5 contains the results. Section 6 concludes.

## 2 The problem

Current statistics from LFSs rely on conventional definitions to count employed and unemployed people. To improve international comparability of labour force indicators, the ILO provides national statistical offices with recommendations on the definition and measurement of unemployment. These guidelines have become the standards for many countries; consequently, definitions used in labour force surveys are now broadly similar in outline and spirit if not in all of their details.

According to ILO (1983), a subject above a certain age (usually 14 or 15 years) is classified as

- <u>employed</u>, if during the *reference period* s/he worked at least *a bit* (or is not at work for any reason, but is bound to get back to a job s/he has an attachment to);
- <u>unemployed</u>, if (i) during the *reference period* s/he did not work at all, (ii) s/he is looking for a job and *recently* took *specific steps* for seeking work, and (iii) s/he is *immediately available* to work;
- <u>out of the labour force</u> otherwise.

Loosely speaking, according to such guidelines the ‘unemployed’ are units over a certain specified age who are without work, available for work, and actively seeking work. Anyway, there is plenty of room for alternative operational definitions of the three labour force states, depending on how we translate the terms *reference period*, *a bit*, *recently*, *specific steps*, *immediately available* into clear cut rules for classification.

All countries agree that an unemployed person should be without any work at all; that is, employment takes precedence over unemployment. They also agree that unemployed persons should be available for work and actively seeking work. However, countries have chosen to implement these latter two criteria differently, which to an extent limits the comparability of labour force statistics across countries.

Sorrentino (2000) reviews the interpretation of the ILO guidelines across different countries in US and in Europe. We will exemplify the issue focusing on two approaches, which will be relevant to our empirical analysis. For the sake of brevity, we will call them the 'strict' ILO criterion and the 'mild' ISTAT (the Italian national statistical agency) criterion respectively, for a reason that will be clear from what follows. The 'strict' criterion results from a stringent interpretation of the condition of being actively seeking work and it is currently the criterion suggested by the ILO international guidelines. For a subject to be classified as unemployed one active step must have been taken within the last month. The 'mild' criterion refers to the definition that was followed by ISTAT up to 1992: it only requires that active steps for seeking work be taken, regardless of how far in the past.

Let $T$ be the *true* labour force state and let $R$ be a categorical index summarizing the basic information on the labour force state of each individual in the sample. The categories of $R$ typically summarize subject's activity in the reference period and his/her attachment to work defined by the intensity of the job-search. The classification of each unit into one of the three labour force states is then obtained by suitably grouping the categories of $R$ following some operational criteria.

Columns of Table 1 refer to the categories for $R$ we will consider: overall they are seven, and the definition of each category is reported by row. Category $OCC$ identifies those units who report at least one hour of work in the reference period or those units who have an attachment to a job from which are temporary absent for any reason. According to the evidence so far mentioned, such units are *working* and therefore classified as $E$. Categories $S1$-$S4$ refer to units *actively seeking work* according to the intensity of their search. Category $NS2$ identifies *not searching* units who are definitely not willing to work; $NS1$ refers to 'discouraged' workers, defined as those not looking for a job because either (i) they have been unsuccessfully searching in the past, or (ii) they believe not to be skilled enough or (iii) they believe employers consider them too young or too old [3].

Presumably, conducting an objectively measurable job search is a necessary condition for being classified as unemployed; moreover, those units with a weak attachment to their job and who are not seeking work are likely to be considered not participating the labour market. Using the notation so far introduced, the 'strict' criterion states

$$\begin{array}{ccc} T = E & \Longleftrightarrow & R = OCC, \\ T = U & \Longleftrightarrow & R = S1, \\ T = OLF & & otherwise, \end{array} \tag{1}$$

[3]For a discussion of the criteria for identifying workers, see OECD (1987)

Table 1: Categories of the fallible indicator $R$

| | | *working* | | *actively searching* | | | | *not searching* | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Definitions** | **OCC** | **S1** | **S2** | **S3** | **S4** | | **NS1** | **NS2** | |
| | at least one hour of work in the reference week | X | | | | | | | | |
| | no hours of work in the reference week | | X | X | X | X | X | X | X | |
| | looking for a job and immediately available for work | | X | X | X | X | X | | | |
| | last search undertaken during the last month | | X | | | | | | | |
| | last search undertaken from one to six months ago | | | X | | | | | | |
| | last search undertaken more than six months ago | | | | X | | | | | |
| | no search step undertaken yet (only up to 1992) | | | | | X | | | | |
| | search activity in the future (only after 1992) | | | | | | X | | | |
| | not looking for a job because discouraged | | | | | | | X | | |
| | not looking for a job because not willing to work | | | | | | | | X | |
| **1984** | North | 1636 | 840 | 455 | 54 | 183 | - | 329 | 2052 | *5549* |
| | Center | 429 | 152 | 109 | 28 | 47 | - | 157 | 578 | *1500* |
| | South | 373 | 313 | 200 | 36 | 44 | - | 320 | 864 | *2150* |
| | | *2438* | *1305* | *764* | *118* | *274* | - | *806* | *3494* | *9199* |
| **1990** | North | 1726 | 567 | 362 | 58 | 135 | - | 269 | 1788 | *4905* |
| | Center | 549 | 297 | 203 | 35 | 70 | - | 107 | 520 | *1781* |
| | South | 567 | 925 | 675 | 63 | 106 | - | 384 | 1327 | *4047* |
| | | *2842* | *1789* | *1240* | *156* | *311* | - | *760* | *3635* | *10733* |
| **1993** | North | 671 | 465 | 165 | 62 | - | 27 | 64 | 1405 | *2859* |
| | Center | 375 | 415 | 164 | 71 | - | 8 | 53 | 724 | *1810* |
| | South | 346 | 877 | 404 | 164 | - | 25 | 140 | 1441 | *3397* |
| | | *1392* | *1757* | *733* | *297* | - | *60* | *257* | *3570* | *8066* |
| **1995** | North | 688 | 507 | 163 | 57 | - | 32 | 80 | 1438 | *2965* |
| | Center | 370 | 443 | 236 | 97 | - | 7 | 100 | 813 | *2066* |
| | South | 349 | 947 | 501 | 166 | - | 20 | 234 | 1639 | *3856* |
| | | *1407* | *1897* | *900* | *320* | - | *59* | *414* | *3890* | *8887* |

Table 2: Married women participation and unemployment rates in Italy

| | | Participation | | Unemployment | |
|---|---|---|---|---|---|
| | | *mild* | *strict* | *mild* | *strict* |
| **1984** | North | 0.4618 | 0.4440 | 0.0856 | 0.0488 |
| | Center | 0.4379 | 0.4205 | 0.0726 | 0.0342 |
| | South | 0.3255 | 0.3044 | 0.1372 | 0.0774 |
| | | 0.4289 | 0.4104 | 0.0917 | 0.0508 |
| **1990** | North | 0.5032 | 0.4880 | 0.0610 | 0.0318 |
| | Center | 0.5346 | 0.5075 | 0.0993 | 0.0513 |
| | South | 0.3527 | 0.3127 | 0.2378 | 0.1403 |
| | | 0.4624 | 0.4376 | 0.1095 | 0.0592 |
| **1993** | North | 0.3448 | 0.3331 | 0.0968 | 0.0648 |
| | Center | 0.3767 | 0.3560 | 0.1493 | 0.0996 |
| | South | 0.2531 | 0.2226 | 0.2982 | 0.2022 |
| | | 0.3180 | 0.2973 | 0.1698 | 0.1121 |
| **1995** | North | 0.3457 | 0.3343 | 0.0994 | 0.0686 |
| | Center | 0.3526 | 0.3259 | 0.1747 | 0.1069 |
| | South | 0.2356 | 0.2040 | 0.3189 | 0.2134 |
| | | 0.3049 | 0.2823 | 0.1842 | 0.1188 |

so that, according to the definitions in Table 1, $E = OCC$, $U = S1$ and $OLF = S2 + S3 + S4 + NS1 + NS2$.

On the other hand, the 'mild' criterion states

$$\begin{array}{ccc} T = E & \Longleftrightarrow & R = OCC, \\ T = U & \Longleftrightarrow & R = S1, S2, S3, S4 \\ T = OLF & & otherwise, \end{array} \tag{2}$$

so that $E = OCC$, $U = S1 + S2 + S3 + S4$ and $OLF = NS1 + NS2$.

Although both these rules require a person to be available and actively seeking work to be classified as unemployed, such requirements are interpreted in different ways. The two criteria clearly differ in the way they place the boundary between unemployment and out of the labour force. For both of them, it is out of question that those units presenting either $R = OCC$, $R = S1$ or $R = NS1/NS2$ belong to $E$, $U$ or $OLF$, respectively. What is questioned instead, and where the two criteria are different, is how units presenting the remaining values of $R$ ($S2$,$S3$ or $S4$) are classified.

One might argue that for any practical purpose these two classification systems lead to consistent results. Unfortunately, this is not the case. In Table 2 we present participation and unemployment rates for Italian married women over time (1984, 1990, 1993 and 1995 - second quarter) exploiting the two criteria and controlling for geographic effects (to check the stability of results across different areas). It turns out that the choice of the operational criterion makes the difference, preserving the pattern of unemployment and participation rates over time but attenuating or emphasizing differences across areas [4]. The mis-

[4] Rettore and Trivellato (1993) show that the estimation of a simple model of labour supply with unemployment exploiting the 1984 wave is quite sensitive to the labour force state definition.

classification between unemployed and out of the labour force units appears to be the substantial problem.

Accordingly, the questions we aim to provide an answer to in the next section are the following:

- How does the state implied by such classification compare to $T$?
- Is there any way to get 'objective' evidence on the relative merits of alternative labour force counting criteria?
- How much our analysis of labour market is sensitive to the way in which labour force states are conventionally defined?

# 3 Model specification

## 3.1 A model with true states and fallible indicators

Motivated by the evidence reported so far, we proceed to explicitly account for the uncertainty in allocating some categories of $R$ to the states $T$; in other words, we admit that some observed categories are fallible indicators of the true labour force states. We exploit available information on individual characteristics - known to matter for labour force state membership both on theoretical and empirical grounds - to get evidence on the relative merits of existing classification criteria and to shed further light on the relationships between the space of categories and the space of true states.

Let $x$ be the vector of characteristics of each person in the reference population relevant to labour force state membership, and let $f(x)$ be its distribution. A reasonable expectation is that

$$f(x|OCC) \neq f(x|S1) \neq f(x|NS2),$$

since $OCC$, $S1$ and $NS2$ are taken as out-of-question people (employed, unemployed and out of the labour force, respectively) and $x$ appreciably affects the probability of membership in each labour force state (see Table 3-4 below).

The cornerstone of the classification procedure refers to the remaining categories of $R$ ($S2$, $S3$, $S4$ and $NS1$). In fact, our aim is also to investigate the $NS1$ group which, loosely speaking, consists of (or at least includes) the so-called 'discouraged workers'. According to the common practise followed by different classification rules, these units are usually classified as $OLF$ since they miss the 'actively seeking work' condition. It seems anyway interesting to study which out-of-question group they look like the most: whether $NS2$ or $S1$ (or, possibly but unlikely, $OCC$).

If the 'strict' criterion in (1) was right, we should find that the equalities

$$f(x|R) = f(x|NS2) \qquad R = S2, S3, S4, NS1$$

hold, at least approximately. In other words, if people belonging to $S2$, $S3$, $S4$ and $NS1$ were truly out of the labour force, they should look like people taken for sure in this state ($NS2$) with respect to $x$. Analogously, if the 'mild' criterion in (2) was correct, we should find that the equalities

$$\begin{aligned} f(x|R) &= f(x|S1) \qquad R = S2, S3, S4 \\ f(x|R) &= f(x|NS2) \qquad R = NS1 \end{aligned}$$

are approximately satisfied.

There is a third alternative, however, which is somewhere in the middle of the two classification criteria we consider. Categories $S2$, $S3$, $S4$ and $NS1$ might be a mixture of unemployed and out of the labour force units (see Section 3.2 below): in fact, we might find that some units belonging to one of these categories are $x$-similar to units reporting $S1$ (unemployed), some others to units reporting $NS2$ (out of the labour force), and possibly some others to units reporting $OCC$ (employed), thus implying that $f(x|R)$ is a convex combination of $f(x|OCC)$, $f(x|S1)$ and $f(x|NS2)$.

This is exactly what we will be doing. We will rely on the out-of-question categories of $R$ - the ones on which both the 'mild' and the 'strict' criteria agree - and we will seek a weighted mean of the distributions of $x$ within such categories to provide an approximation to $f(x|R)$, $R = S2, S3, S4, NS1$. More formally, the problem may be well formulated in mixture terms by writing

$$f(x|R) = \sum_{s \in T} f(x|s)p(s|R), \qquad R = S2, \ldots, NS1. \tag{3}$$

Note that, in our case, the components of such mixture are identified by means of the *a priori* restrictions implied by similarities in the 'mild' and in the 'strict' classification criteria[5]. In what follows we will describe the estimation strategy to identify the mixture weights characterizing the measurement problem.

## 3.2 Estimation issues

Exploiting the notation defined above, let $T$ be the true unobservable labour force state space consisting of three mutually exclusive and distinct states: $E$, $U$ and $OLF$. Let the outcome of the discrete random variable $R$ be its fallible indicator summarizing available information on employment state. Let also

$$\Im_A = \left\{ f(x|A), A \in \tilde{A} \right\}$$

denote the family of conditional distribution functions of the observable variable $x$ indexed by a point $A$ in a discrete set $\tilde{A}$.

The relationship in (3) states that each member of the family $\Im_R$ belongs to the three dimensional convex hull generated by the family $\Im_T$. The mixing weights $p(T|R)$, i.e. the conditional probability functions of being in state $T$ among people belonging to category $R$, summarize the properties of the measurement instrument.

The probability functions $f(x|R)$, $R = S2, ..., NS1$, are directly identifiable from the available information along with $p(R)$, the observed unconditional distribution of the fallible indicator $R$. Note that if the mixture components $f(x|T)$

[5]Note the similarities of this formulation to the basic idea characterizing a latent class analysis. The components of $f(x|R)$ are correlated because the population under study consists of a mixture of subpopulations (or classes) defined by $T$, within which the variable $x$ is independent from $R$. The identity in (3) follows from the assumption that the observed responses of the manifest variable $x$ are independent from $R$ once latent class membership is accounted for (this is sometimes known as the 'local independence assumption'; see for example Hagenaars, 1990). This assumption implies that all observed relationships amongst the manifest variables $x$ and $R$ are due to their common dependence on the latent variable $T$; once that dependence has been determined, the behavior of the manifest variables is essentially random.

and the weights $p(T|R)$ were identifiable from $f(x|R)$, then the probability to be in each one of the three labour force states would be known, since

$$p(T) = \sum_R p(T|R)p(R), \qquad T = E, U, OLF.$$

In general an identification problem arises. We discuss the identifiability of the parameters of interest when the following relationships between states and fallible indicators hold:

$$\begin{array}{ccc} R = OCC & \Longrightarrow & T = E, \\ R = S1 & \Longrightarrow & T = U, \\ R = NS2 & \Longrightarrow & T = OLF. \end{array} \tag{4}$$

The foregoing relations place some restrictions on the mixing weights, implying with probability one that the sets of people yielding $OCC$, $S1$ and $NS2$ consist only of employed, unemployed and out of the labour force units, respectively. Indeed, from assumptions (4) we derive that

$$p(E|OCC) = p(U|S1) = p(OLF|NS2) = 1,$$

the main implication being that the mixture components are identifiable and are distinct members belonging to the family $\Im_R$, so that $\Im_T \subset \Im_R$ and

$$\begin{array}{rcl} f(x|E) & = & f(x|OCC), \\ f(x|U) & = & f(x|S1), \\ f(x|OLF) & = & f(x|NS2). \end{array} \tag{5}$$

A general, sufficient condition for the identifiability of the weights in (3) is that the set

$$\Im_T = \{f(x|OCC), f(x|S1), f(x|NS2)\}$$

of the mixture components is linearly independent, i.e. that none of them can be written as a linear combination of the remaining ones (Yakowitz and Spragins, 1968). This can be easily checked by testing for the rank of the matrix whose columns are the three component of $\Im_T$ (for a review of methods of inference on the rank of a stochastic matrix see Cragg and Donald, 1997).

The likelihood equations for $p(T|R)$, $R = S2, \ldots, NS1$, can be written by treating the observations as if they are the result of random sampling from a population with probability function as in (3). The EM algorithm is particularly useful for finding the maximum likelihood estimates of the mixing weights in this case (Everitt and Hand, 1981, and Maritz and Lwin, 1989).

Starting with initial trial values $p(T|R)^{(0)}$, new values $p(T|R)^{(1)}$ are obtained by iteration as

$$\begin{array}{rcl} p(T|R,x)^{(1)} & = & \dfrac{f(x|T)p(T|R)^{(0)}}{\sum_s f(x|s)p(s|R)^{(0)}}, \\ p(T|R)^{(1)} & = & \sum_x f(x|R)p(T|R,x)^{(1)}. \end{array}$$

Equations (5) restrict the four distributions $f(x|R)$, $R = S2, \ldots, NS1$, to be convex linear combinations of the elements of $\Im_T$. A test of such restrictions is based on comparing the estimates of $f(x|R)$ implied by the model to the estimates of $f(x|R)$ obtained without imposing any structure. The goodness of fit of this model can then be assessed by means of a likelihood ratio test, based on the differences between observed and expected frequencies.

## 4 Data

Our plan for the empirical analysis extends to micro-data from the Italian LFS on a sample of married women aged no more than 60 whose husband is no more than 65 years old, on four survey occasions - 1984, 1990, 1993 and 1995, always second quarter - and separately for Northern, Central and Southern Italy [6].

We look at married women because they represent a sub-set of the labour supply quite sensitive to individual characteristics, as well as to labour demand conditions (see Killingsworth and Heckman, 1986). The four sample years were selected to reflect the variability in the business cycle, with 1984 and 1990 years of expansion, 1993 a year of recession, and 1995 a year of slight recovery from the recession (see Altissimo, Marchetti and Oneto, 2000). Besides, the over the period we consider changes in the survey operations and definitions took place, due to an important revision of the Italian LFS (see Casavola and Sestito, 1994, and Trivellato, 1997).

The regional breakdown is intended to capture structural differences in the Italian labour market and the overall economy. Thus, the design, although parsimonious, should allow us to evaluate the performance of the classification results on a sensitive sub-population in contexts diversified in terms of labour market structure, cycle and survey instruments.

Table 1 presents the sample size for each year splitted by the categories of $R$. Because of the just mentioned changes in the LFS, the definition of the residual category $S4$ amongst actively searching units slightly changes since October 1992. While before October 1992 subjects presenting $S4$ are those who report that 'no search step has been undertaken at the moment of the interview', since then they are those reporting they will search in the future among those not seeking work at the interview time[7].

The (admittedly poor) individual variables available from the Italian LFS are: woman's age, woman's education, husband's age, husband's education, number of children and age of the youngest child. In Table 3 and Table 4 we present the descriptive statistics for the above variables, split by area and year and - obviously - by the categorical index $R$. Each $f(x|R)$ we consider is given by the multinomial distribution we obtained discretizing such variables into $k = 27$ cells of reasonable sample size.

The empirical analysis is carried out separately by year and geographic area (North, Center, South), allowing each $f(x|R)$ to be a weighted mean of the three out-of-question distributions, that is allowing $f(x|OCC)$ to take part in the weighted mean. Otherwise stated, we are allowing for the presence of workers in the $S2$, $S3$ and $S4$ groups; we will provide arguments for that when commenting on the empirical results (see Section 6 below).

## 5 Results

To summarize what discussed in Section 3, we can express the relationship between densities referred to true (unobserved) states $f(x|T)$ and densities referred

[6] Note that the lower age limit to enter the labour force in Italy is set at 14

[7] In the following, due to the small sample size characterizing certain cells, we will not deal with any potential effect that might arise from proxy/self reporters (see Blair, Menon and Bickart, 1991). Note, however, that the same analysis applied separately to proxy and self respondents for the first two waves leads to similar sets of estimates.

Table 3: Descriptive statistics for the 1984 and 1990 samples

| | *working* | *actively searching* | | | | *not searching* | | *working* | *actively searching* | | | | *not searching* | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **OCC** | **S1** | **S2** | **S3** | **S4** | **NS1** | **NS2** | **OCC** | **S1** | **S2** | **S3** | **S4** | **NS1** | **NS2** |
| | **North 1984** | | | | | | | **North 1990** | | | | | | |
| W's age | 37.44 | 34.78 | 33.95 | 36.93 | 33.50 | 46.32 | 43.51 | 38.64 | 34.32 | 35.27 | 36.12 | 34.60 | 47.53 | 44.70 |
| H's age | 40.89 | 38.43 | 37.59 | 41.15 | 37.32 | 49.71 | 47.05 | 42.05 | 38.11 | 39.05 | 40.14 | 37.63 | 50.93 | 47.96 |
| W's education | 8.28 | 7.21 | 7.49 | 7.07 | 7.69 | 5.95 | 6.41 | 9.20 | 8.14 | 8.23 | 7.98 | 8.25 | 6.44 | 7.19 |
| H's education | 8.21 | 7.47 | 7.61 | 7.06 | 7.80 | 6.56 | 7.24 | 8.97 | 8.04 | 8.23 | 7.91 | 8.50 | 6.96 | 7.84 |
| Children | 1.32 | 1.34 | 1.35 | 1.50 | 1.20 | 1.07 | 1.54 | 1.34 | 1.22 | 1.30 | 1.55 | 1.33 | 1.14 | 1.51 |
| | **Center 1984** | | | | | | | **Center 1990** | | | | | | |
| W's age | 39.29 | 33.86 | 32.66 | 36.32 | 34.87 | 44.92 | 41.43 | 39.42 | 33.96 | 33.11 | 37.51 | 35.26 | 43.52 | 43.27 |
| H's age | 42.74 | 37.67 | 36.21 | 40.71 | 38.43 | 48.09 | 45.58 | 43.24 | 38.28 | 37.21 | 41.11 | 38.77 | 48.07 | 47.35 |
| W's education | 8.45 | 8.26 | 8.79 | 9.75 | 8.04 | 6.16 | 6.68 | 9.53 | 8.97 | 9.93 | 9.34 | 9.53 | 7.24 | 7.37 |
| H's education | 8.56 | 7.89 | 8.50 | 9.18 | 7.51 | 6.82 | 7.52 | 9.19 | 8.67 | 9.61 | 8.23 | 9.06 | 8.10 | 7.93 |
| Children | 1.43 | 1.46 | 1.32 | 1.54 | 1.45 | 1.11 | 1.57 | 1.49 | 1.38 | 1.39 | 1.57 | 1.29 | 1.40 | 1.51 |
| | **South 1984** | | | | | | | **South 1990** | | | | | | |
| W's age | 38.91 | 32.86 | 32.01 | 32.31 | 33.77 | 41.19 | 39.66 | 39.31 | 32.74 | 32.77 | 33.48 | 34.78 | 41.32 | 39.80 |
| H's age | 42.74 | 37.24 | 36.45 | 36.72 | 37.93 | 44.78 | 43.93 | 43.24 | 37.00 | 37.18 | 38.00 | 37.99 | 45.59 | 43.96 |
| W's education | 8.88 | 8.45 | 8.77 | 10.06 | 8.34 | 5.94 | 6.29 | 9.65 | 8.68 | 8.96 | 10.19 | 8.75 | 6.63 | 7.02 |
| H's education | 8.87 | 7.89 | 8.31 | 10.61 | 7.91 | 6.62 | 6.93 | 9.49 | 8.54 | 8.51 | 8.97 | 8.79 | 7.41 | 7.54 |
| Children | 1.88 | 1.77 | 1.56 | 1.89 | 1.73 | 1.64 | 2.10 | 1.79 | 1.62 | 1.63 | 1.76 | 1.72 | 1.55 | 1.98 |

education refers to 'years of education'

Table 4: Descriptive statistics for the 1993 and 1995 samples

| | *working* | *actively searching* | | | | *not searching* | | *working* | *actively searching* | | | | *not searching* | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **OCC** | **S1** | **S2** | **S3** | **S4** | **NS1** | **NS2** | **OCC** | **S1** | **S2** | **S3** | **S4** | **NS1** | **NS2** |
| | **North 1993** | | | | | | | **North 1995** | | | | | | |
| W's age | 39.42 | 36.39 | 37.00 | 36.18 | 38.33 | 43.89 | 43.12 | 39.26 | 36.54 | 37.16 | 37.68 | 36.59 | 45.19 | 43.89 |
| H's age | 42.70 | 39.90 | 40.60 | 39.90 | 40.89 | 48.36 | 46.60 | 42.51 | 40.24 | 40.46 | 42.32 | 40.06 | 48.84 | 47.38 |
| W's education | 9.86 | 8.54 | 8.81 | 9.18 | 8.74 | 7.28 | 7.61 | 10.10 | 9.29 | 8.96 | 8.72 | 9.44 | 7.03 | 8.05 |
| H's education | 9.56 | 8.84 | 8.61 | 8.58 | 9.07 | 7.64 | 8.25 | 9.93 | 9.26 | 9.51 | 9.05 | 9.50 | 7.54 | 8.87 |
| Children | 1.26 | 1.29 | 1.26 | 1.47 | 1.04 | 1.30 | 1.53 | 1.22 | 1.26 | 1.30 | 1.53 | 0.84 | 1.29 | 1.45 |
| | **Center 1993** | | | | | | | **Center 1995** | | | | | | |
| W's age | 40.08 | 34.33 | 34.86 | 33.46 | 36.13 | 43.68 | 41.18 | 41.20 | 35.30 | 36.03 | 36.48 | 36.14 | 44.73 | 41.55 |
| H's age | 43.39 | 38.57 | 38.70 | 36.94 | 42.13 | 47.40 | 45.19 | 44.90 | 38.88 | 39.93 | 40.51 | 39.57 | 48.88 | 45.74 |
| W's education | 10.29 | 9.76 | 9.54 | 9.97 | 8.50 | 6.81 | 7.75 | 10.26 | 9.58 | 9.54 | 9.11 | 11.43 | 7.40 | 8.18 |
| H's education | 10.41 | 9.54 | 9.41 | 9.34 | 7.13 | 7.04 | 8.45 | 10.24 | 9.68 | 9.57 | 9.32 | 11.86 | 7.61 | 8.81 |
| Children | 1.43 | 1.39 | 1.38 | 1.54 | 1.88 | 1.51 | 1.57 | 1.44 | 1.42 | 1.44 | 1.46 | 0.71 | 1.56 | 1.53 |
| | **South 1993** | | | | | | | **South 1995** | | | | | | |
| W's age | 39.66 | 33.56 | 34.10 | 32.15 | 35.88 | 39.72 | 38.65 | 40.34 | 34.16 | 34.79 | 35.40 | 37.60 | 40.11 | 38.94 |
| H's age | 43.34 | 37.72 | 38.06 | 37.05 | 39.76 | 44.03 | 42.83 | 44.53 | 38.27 | 38.91 | 39.87 | 42.75 | 44.19 | 43.19 |
| W's education | 10.95 | 8.77 | 8.75 | 9.62 | 7.20 | 7.15 | 7.46 | 11.01 | 9.18 | 9.22 | 9.45 | 7.10 | 7.19 | 7.69 |
| H's education | 10.50 | 8.66 | 8.72 | 9.26 | 6.76 | 7.75 | 8.14 | 10.50 | 8.95 | 9.03 | 9.22 | 7.75 | 7.82 | 8.25 |
| Children | 1.72 | 1.74 | 1.70 | 1.68 | 2.12 | 1.67 | 1.83 | 1.79 | 1.73 | 1.71 | 1.92 | 2.05 | 1.62 | 1.88 |

education refers to 'years of education' to available information $f(x|R)$ through a matrix $\mathbf{P}$. Such matrix contains the mixture weights $p(T|R)$ in the set of equations (3) and therefore it summarizes the properties of the classification instrument.

There are two different kinds of restrictions that might be imposed on the elements of this matrix. The first set of restrictions (more precisely, 0/1 restrictions) directly follows from the common practise of including those units reporting $OCC$, $S1$ and $NS2$ among employed, unemployed and out of the labour force units, respectively, as summarized by (4). This provides an identifying restriction for the vector whose generic element is the density of characteristics $x$ within each state $T$.

The second set of restrictions depends on the classification rule followed in allocating units to $T$, namely - in our case - on the set of *a priori* 0 and 1 restrictions due to the application of the strict criterion (2) and the mild criterion (1)[8].

Given the first set of restrictions, the second set actually contains over-identifying restrictions that in general might be tested. Indeed we will rely on the out-of-question set of restrictions (4) but we will not constrain the weights associated to $R = S2, S3, S4, NS1$. A major implication of such procedure is that we can test the a priori restrictions implied by the two criteria against the data and check which one, if any, is right.

Subsection 5.1 discusses some goodness-of-fit statistics about the model specification adopted, while the estimation results of the weights in $\mathbf{P}$ are presented in Subsection 5.2.

## 5.1 Model fitting

The first issue we deal with is whether, by properly weighting the out-of-question distributions $f(x|OCC)$, $f(x|S1)$ and $f(x|NS2)$, we succeed in getting close to the four distributions $f(x|R)$, $R = S2, S3, S4, NS1$. Any failure thereof should be taken as an evidence that the three states, as defined by the maintained operational criteria, are not enough to fully account for what happens in the labour market. In turn, this could mean either that (i) the maintained operational criteria are not correct or that (ii) the number of true labour force states is larger than three.

Under the null hypothesis of correct model specification, the generic density $f(x|R)$ is equal to a weighted mean of $f(x|OCC)$, $f(x|S1)$ and $f(x|NS2)$, with two weights to be estimated (since there is an obvious adding-to-one restriction). Under the alternative hypothesis, no structure is imposed on $f(x|R)$ so that there are $k-1$ parameters to be estimated (where $k$ is the number of cells in the multinomial distribution we obtained by discretizing $x$). To test the null hypothesis we use a likelihood ratio test resulting in a chi squared distribution with $k-3$ degrees of freedom (under the null).

However, a more careful consideration on this testing procedure is needed. As it is well known, likelihood ratio tests tend to reject the null hypothesis simply because of the large sample size, even though the model is not all that bad. In

[8] For example, by stating that each unit presenting $R = S2, S3, S4$ belongs to $OLF$, the strict criterion implicitly imposes the following restrictions on the weights

$$p(U|S2) = p(U|S3) = p(U|S4) = p(U|NS1) = 0.$$

our particular case, the test would tell us that the approximation provided by the mixture model to $f(x|R)$ and the freely estimated $f(x|R)$ are statistically different, namely that the difference we observe between the two estimates is larger than we should expect due to sampling variability. Nonetheless, if the sample size is large enough, it might well be that we are detecting a statistically significant difference between two quantities which to any practical purpose are quite close. Inspection of the behavior of the $p$-values associated to the likelihood ratio test statistics presented in the next section, conditional on sample size, supports this opinion.

For sensible comparisons of the fitting of the same parametric model across independent samples of different size, we can resort to a variety of suitable goodness of fit statistics, developed in the literature as heuristic indices of model specification. To sensibly compare the goodness-of-fit of two models at different levels of parsimony we need to introduce a penalty for the lack of parsimony.

A penalized version of the log likelihood, with the penalty term depending on both the dimension of the parameter and the sample size, has been proposed by Schwarz (1978). Basically, it is derived as a penalized version of the classical log-likelihood test, where the penalty term is intended to account for over-parametrization and possibly for the sample size (see also Kass and Raftery, 1995). The criterion suggested is derived as the large-sample limit of a bayesian procedure under a special but fairly general class of priors; the rule implied from such a framework is to choose the model so that

$$\ell_\tau - 0.5\tau \log n$$

is maximized, where $\ell_\tau$ is the log-likelihood for the model whose dimension is $\tau$ and $n$ is the sample size. In our case, under the null hypothesis of correct specification in terms of (3) the dimension is $\tau = 2$, i.e. the number of parameters that has to be estimated; under the alternative hypothesis $\tau = k - 1$. It follows that the leading term for the selection between the proposed model and the unconstrained model is (half) the maximum likelihood criterion minus a term resulting from the product of the over-parametrization $(k - 3)$ and the sample size.

Along the same lines, to assess whether the mixture model estimates and the free sample estimates of $f(x|R)$ are very similar, we also considered a correlation-type index. Let $\widehat{f}(x|R)_1$ and $\widehat{f}(x|R)_0$ be the distribution estimates under the alternative and the null hypothesis respectively. They are $k$-dimensional vectors. Let

$$\cos\theta = \frac{\widehat{f}(x|R)_1' \widehat{f}(x|R)_0}{\left\|\widehat{f}(x|R)_1\right\|_2 \left\|\widehat{f}(x|R)_0\right\|_2}$$

be the cosine of the angle between the two vectors. If the mixture model is providing a reasonably good fit to $\widehat{f}(x|R)_1$, then such angle has to be close to zero. Otherwise, it is away from zero. Notice that the cosine, by taking values in the interval $(-1, 1)$, can be interpreted as a correlation coefficient: 1 means perfect agreement between the estimate implied by the mixture model, $\widehat{f}(x|R)_0$, and the unconstrained estimate $\widehat{f}(x|R)_1$; 0 means no agreement at all; -1 means that the model is doing exactly the opposite of the observed distribution.

## 5.2 Estimation results

Tables 5-8 present results from the estimation of probabilities $p(S|R)$ separately by year (1984, 1990, 1993 and 1995) and geographical areas[9]. Because of the change in definitional procedures documented in Section 4, category $S4$ is not directly comparable between waves before and after 1992. Each panel also reports the p-values associated to the likelihood-based test of correct specification, the Schwarz statistic (positive values favor the constrained model while negative ones reject it) and the values of $\cos\theta$.

Results vary over the waves. The null hypothesis of correct specification is nearly always accepted for $f(x|S3)$ both before and after 1992 and it provides a reasonable picture for $f(x|S4)$ particularly for the last two waves. The same hypothesis is instead mostly rejected for $f(x|S2)$ (with the exception of the 1993 wave) and $f(x|NS1)$; overall the specification adopted fits better the data after 1992. The Schwarz statistic is reported in the last row of each panel: apparently the model survives this test with no exception.

The cosine of the angle between actual and fitted data is generally above 85%; not surprisingly, when the sample size is small it is quite away from such value because, due to a large sampling variability, $\widehat{f}(x|R)_0$ and $\widehat{f}(x|R)_1$ take quite different values with high probability, although the corresponding true values might be close each other. As a matter of fact, the cosine turns out reasonably high in most of the instances where the p-value is against the null. Indeed, consider $f(x|S2)$ and $f(x|NS1)$ (the first and fourth columns in each table): almost all the p-values are smaller (sometimes much smaller) than 0.05, a *prima facie* clear evidence against the null. On the other hand, the cosine for $f(x|S2)$ is above 90% and 92% before and after 1992, respectively; values referred to $f(x|NS1)$ are instead above 88% and 83%.

Based on this evidence we decided to accept the mixture model with $OCC$, $S1$ and $NS2$ playing the role of out-of-question groups as a good parsimonious representation of our data.

The main results we find can be summarized as follows. Overall, when the 'mild' ISTAT criterion and the 'strict' ILO criterion disagree, it appears that the former is right. In particular, conditional on the reported evidence that one is (i) not at work, (ii) looking for a job and (iii) immediately available for work, the timing of the last active step for seeking work does not clearly discriminate between U and OLF. More precisely:

- There is no evidence in our data supporting the ILO practice of classifying units presenting $S2$ as $OLF$, with the exception of few cases after 1992. These units are mostly close to individuals belonging to $U$ (the estimated probability ranges from 0.70 to 1).
- The evidence on individuals exhibiting $S3$ is less clear cut, but again apparently they don't look like $OLF$ units. The only apparent pattern is found for Southern Italy, where they are pretty close to $U$ units.
- As for those presenting $S4$, there seems to be some time and geographic variability: before 1992, a relevant fraction of units is close to $OLF$ only

[9] We also checked whether distinguishing between self- and proxy-respondents matters. In fact, the two sets of estimates turned out quite similar. Thus we focus on the results from the overall samples by year and geographical area

Table 5: Estimation results for the 1984 sample

| **North** | **S2** | **S3** | **S4** | **NS1** |
|---|---|---|---|---|
| Employment | 0.1543 | 0.5276 | 0.3016 | 0.0000 |
| Unemployment | 0.8457 | 0.4079 | 0.6984 | 0.0000 |
| Out of the labour force | 0.0000 | 0.0645 | 0.0000 | 1.0000 |
| sample size | 455 | 54 | 183 | 329 |
| p-values | 0.0000 | 0.0304 | 0.0188 | 0.0000 |
| cosine | 0.9628 | 0.8234 | 0.9497 | 0.9209 |
| Schwarz | 42.6550 | 28.5933 | 42.2509 | 14.7611 |
| **Center** | **S2** | **S3** | **S4** | **NS1** |
| Employment | 0.1535 | 0.6724 | 0.3206 | 0.0000 |
| Unemployment | 0.8465 | 0.3276 | 0.6793 | 0.0000 |
| Out of the labour force | 0.0000 | 0.0000 | 0.0001 | 1.0000 |
| sample size | 109 | 28 | 47 | 157 |
| p-values | 0.0415 | 0.0414 | 0.2554 | 0.0000 |
| cosine | 0.8962 | 0.6915 | 0.8365 | 0.8836 |
| Schwarz | 37.6794 | 21.3654 | 32.1464 | 22.8200 |
| **South** | **S2** | **S3** | **S4** | **NS1** |
| Employment | 0.0000 | 0.0829 | 0.1558 | 0.0000 |
| Unemployment | 1.0000 | 0.9171 | 0.6224 | 0.0000 |
| Out of the labour force | 0.0000 | 0.0000 | 0.2218 | 1.0000 |
| sample size | 200 | 36 | 44 | 320 |
| p-values | 0.0252 | 0.2512 | 0.0112 | 0.0000 |
| cosine | 0.9278 | 0.7855 | 0.8093 | 0.9099 |
| Schwarz | 43.9147 | 28.8962 | 24.1398 | 20.7982 |

for southern Italy; after 1992, we observe the same pattern also with respect to the north of Italy. It turns out that half of the considered cases supports the ILO practice of classifying such units as $OLF$. Overall, the largest proportion of units in this category is predicted as $U$.

- People exhibiting $NS1$ are definitely close to $OLF$. The current practice does survive the test here: the so-called 'discouraged workers' look inactive.

# 6 Conclusions

In this paper we have considered the analysis of cross-classified categorical data when the classification process is possibly affected by error. We provided some evidence about the implications of such a problem exploiting data from four waves of the Italian Labour Force Survey covering ten years between mid 1980s and mid 1990s.

National statistical offices infer the real condition with respect to employment exploiting some indicators about the activity (hours of work) and the intensity of the search during the reference period. A classification error might arise because units' classification into employment, unemployment and inactiv-

Table 6: Estimation results for the 1990 sample

| **North** | **S2** | **S3** | **S4** | **NS1** |
|---|---|---|---|---|
| Employment | 0.3026 | 0.3907 | 0.1123 | 0.0000 |
| Unemployment | 0.6974 | 0.5861 | 0.8877 | 0.0000 |
| Out of the labour force | 0.0000 | 0.0232 | 0.0000 | 1.0000 |
| sample size | 362 | 58 | 135 | 269 |
| p-values | 0.0007 | 0.2222 | 0.0385 | 0.0000 |
| cosine | 0.9628 | 0.8416 | 0.9030 | 0.9484 |
| Schwarz | 44.5374 | 34.2523 | 40.0860 | 12.8317 |
| **Center** | **S2** | **S3** | **S4** | **NS1** |
| Employment | 0.1649 | 0.8364 | 0.5449 | 0.1198 |
| Unemployment | 0.8351 | 0.0682 | 0.4551 | 0.0000 |
| Out of the labour force | 0.0000 | 0.0954 | 0.0000 | 0.8802 |
| sample size | 203 | 35 | 70 | 107 |
| p-values | 0.0056 | 0.5920 | 0.0275 | 0.0229 |
| cosine | 0.9301 | 0.8732 | 0.8693 | 0.9451 |
| Schwarz | 41.1918 | 31.7709 | 31.4963 | 36.2122 |
| **South** | **S2** | **S3** | **S4** | **NS1** |
| Employment | 0.0619 | 0.2147 | 0.1967 | 0.0000 |
| Unemployment | 0.9378 | 0.7853 | 0.6677 | 0.0000 |
| Out of the labour force | 0.0004 | 0.0000 | 0.1356 | 1.0000 |
| sample size | 675 | 63 | 106 | 384 |
| p-values | 0.0468 | 0.0614 | 0.0284 | 0.0000 |
| cosine | 0.9773 | 0.8515 | 0.8934 | 0.8987 |
| Schwarz | 59.8244 | 31.9701 | 36.5434 | 21.9665 |

ity depends on conventional definitions to combine those indicators. Different classification rules don't necessarily lead to similar conclusions on the labour market characteristics.

We built on some out-of-question categories to shed some light on those units for which labour market participation depends on the operational rule adopted. Such a procedure allows us to conclude that the general guidelines suggested by the ILO are partially rejected exploiting our data.

To provide an assessment of this result consider the following model of participation at work with unemployment. Let $w$ be the wage rate the worker can get, which we assume to be known to the worker, at least partly determined by collective bargaining; let $w_m$ be the maximum wage rate an employer is available to pay that worker (employer reservation wage in the following), reflecting worker's productivity. Finally, let $w_r$ be the worker's reservation wage.

If the market wage is larger than the worker's reservation wage, $w > w_r$, the worker participates at work. Conditional on participation at work, if the market wage is larger than the employer's reservation wage, $w > w_m$, the worker is unemployed. On such playground the labour force state is easily defined as

$$T = \{E = (w > w_r, w < w_m); U = (w > w_r, w > w_m); OLF = (w < w_r)\}. \quad (6)$$

Conditional on this model, had we observed $(w, w_r, w_m)$ there would be no room to discuss alternative operational criteria to classify units, since such triple would

Table 7: Estimation results for the 1993 sample

| North | S2 | S3 | S4 | NS1 |
|---|---|---|---|---|
| Employment | 0.3094 | 0.1902 | 0.2326 | 0.0000 |
| Unemployment | 0.6905 | 0.8098 | 0.4885 | 0.0000 |
| Out of the labour force | 0.0001 | 0.0000 | 0.2789 | 1.0000 |
| sample size | 165 | 62 | 27 | 64 |
| p-values | 0.1283 | 0.3752 | 0.2021 | 0.1031 |
| cosine | 0.9206 | 0.8767 | 0.7150 | 0.8969 |
| Schwarz | 43.9936 | 36.1445 | 23.8790 | 32.2012 |
| **Center** | **S2** | **S3** | **S4** | **NS1** |
| Employment | 0.0001 | 0.0000 | 0.0000 | 0.0000 |
| Unemployment | 0.9795 | 1.0000 | 1.0000 | 0.0000 |
| Out of the labour force | 0.0203 | 0.0000 | 0.0000 | 1.0000 |
| sample size | 164 | 71 | 8 | 53 |
| p-values | 0.7110 | 0.1734 | 0.9949 | 0.5033 |
| cosine | 0.9558 | 0.8743 | 0.5227 | 0.9098 |
| Schwarz | 50.2539 | 34.1555 | 8.2334 | 34.3032 |
| **South** | **S2** | **S3** | **S4** | **NS1** |
| Employment | 0.0000 | 0.0000 | 0.0000 | 0.0481 |
| Unemployment | 0.8441 | 1.0000 | 0.4304 | 0.0000 |
| Out of the labour force | 0.1559 | 0.0000 | 0.5696 | 0.9519 |
| sample size | 404 | 164 | 25 | 140 |
| p-values | 0.1336 | 0.0413 | 0.5078 | 0.0006 |
| cosine | 0.9732 | 0.9373 | 0.7408 | 0.8717 |
| Schwarz | 54.8629 | 41.8176 | 23.7314 | 31.0061 |

be enough to provide the exact classification.

Suppose now that this triple uniquely depends on a set of individual characteristics $(x, u)$; in other words, assume that if we observed such characteristics we would be able to infer exactly on the real labour force state through (6). In our exercise we only observe $x$, which is for sure in the generating process of $T$ along with some other unobservables (such as ability or motivation) which we will denote by $u$.

Some caution is therefore necessary in interpreting our empirical results, precisely because of the unobserved heterogeneity component $u$. The results presented above tell us that there exist certain similarities between the $S2, S3, S4, NS1$ groups on the one hand and the $OCC, S1, NS2$ groups on the other, which have been established with respect to $x$. It might well be the case that such groups are different with respect to $u$. To complement and strengthen our evidence, it would be useful extending this analysis to a dynamic setting (see, for example, Poterba and Summers, 1995, and Jones and Riddell, 1999), by studying transition rates from each category of $R$ and seeking for similarities across such transition patterns. Presumably, transitions are affected both by $x$ and $u$, so that conditional on $x$ the state some months before can be taken as a proxy for $u$.

An additional comment refers to an explanation for the evidence that a non-negligible fraction of subjects presenting $S2, S3, S4$ appears to be close to $OCC$.

Table 8: Estimation results for the 1995 sample

| North | S2 | S3 | S4 | NS1 |
|---|---|---|---|---|
| Employment | 0.2887 | 0.3609 | 0.0000 | 0.0000 |
| Unemployment | 0.7113 | 0.5319 | 0.7809 | 0.0000 |
| Out of the labour force | 0.0000 | 0.1072 | 0.2191 | 1.0000 |
| sample size | 163 | 57 | 32 | 80 |
| p-values | 0.3361 | 0.0978 | 0.0340 | 0.0000 |
| cosine | 0.9372 | 0.8429 | 0.7053 | 0.8320 |
| Schwarz | 46.8766 | 31.4344 | 22.1640 | 16.1817 |
| **Center** | **S2** | **S3** | **S4** | **NS1** |
| Employment | 0.0001 | 0.0979 | 0.7957 | 0.0000 |
| Unemployment | 0.8046 | 0.6971 | 0.2043 | 0.0000 |
| Out of the labour force | 0.1953 | 0.2050 | 0.0000 | 1.0000 |
| sample size | 236 | 97 | 7 | 100 |
| p-values | 0.0000 | 0.4853 | 0.9103 | 0.0002 |
| cosine | 0.9620 | 0.9266 | 0.6730 | 0.8805 |
| Schwarz | 9.9918 | 41.9337 | 15.6793 | 25.3711 |
| **South** | **S2** | **S3** | **S4** | **NS1** |
| Employment | 0.0560 | 0.1768 | 0.2060 | 0.0369 |
| Unemployment | 0.8688 | 0.8221 | 0.0000 | 0.0000 |
| Out of the labour force | 0.0751 | 0.0012 | 0.7940 | 0.9631 |
| sample size | 501 | 166 | 20 | 234 |
| p-values | 0.0139 | 0.5173 | 0.4215 | 0.0061 |
| cosine | 0.9669 | 0.9567 | 0.6746 | 0.9298 |
| Schwarz | 52.2453 | 48.4452 | 20.1404 | 40.4933 |

Should we consider them as employed? Clearly, this interpretation is tempting, because it points to the existence of the so called 'underground workers'. If some units don't want to show up as employed, they can purposively lack to mention the hours of work they did during the reference week and conceal themselves in the 'looking for a job' groups, presumably without reporting recent steps for seeking work (thus precisely in $S2$ or $S3$ or $S4$).

This might be the case, of course. But at least two other arguments are relevant, both restraining us from such a strong conclusion. First, the preceding word of caution applies. It might be that $S2, S3, S4$ differ from $OCC$ with respect to $u$. Second, such an evidence might also point to inadequacies of the simple model in (6). Such model asserts that one is unemployed if and only if $w > w_r, w > w_m$. In fact, it might be that there are individuals for whom the condition $w > w_r, w < w_m$ holds, and who are not at work (yet). They are exactly the same as the employed, but they are (still) queuing for a job. Patently, the evidence we obtained might point also to the existence of such type of unemployment.

# References


[1] Altissimo F., Marchetti, D.J. and Oneto, G.P. (2000), 'The Italian Business Cycle: Coincident and Leading Indicators and Some Stylized Facts', Temi di Discussione No. 377, Banca d'Italia - Servizio Studi, Roma.

[2] Bound, J., Brown, C. and Mathiowetz, N. (2001), 'Measurement error in survey data', in J.J. Heckman and E. Leamer (eds.), *Handbook of Econometrics. Vol. 5*, Amsterdam: North-Holland, 3705-3843.

[3] Casavola, P. and Sestito, P. (1994), 'L'indagine Istat sulle forze di lavoro', *Lavoro e Relazioni Industriali*, 1, 179-195

[4] Cragg, J. G. and Donald, S.G. (1997), 'Inferring the rank of a matrix', *Journal of Econometrics*, 76, 223-250

[5] Everitt, B.S. and Hand, D.J. (1981), *Finite mixtures distributions*, London: Chapman and Hall

[6] Flinn, C.J. and Heckman, J.J. (1983), 'Are Unemployment and Out of the Labour Force Bahaviorally Distinct Labor Force States?', *Journal of Labor Economics*, 1(1), 28-42

[7] Gonul, F. (1992), 'New Evidence on Whether Unemployment and Out of the Labor Force Represent Behaviorally Distinct States', *Journal of Human Resources*, 27, 329-361

[8] Hagenaars, J.A. (1990), *Categorical Longitudinal Data: Log-linear, Panel, Trend and Cohort Analysis*, Newbury Park: Sage

[9] Hausman, J.A., Abrevaya, J. and Scott Morton, F.M. (1998), 'Misclassifications of a dependent variable in a qualitative response setting', *Journal of Econometrics*, 87, 239-287

[10] Hussmanns, R. Merhan, F. and Verma, S.M. (1990), *Surveys of economically active population, employment, unemployment and underemployment: an ILO manual on concepts and methods*, International Labour Office, Geneva

[11] Jones, S.R.G. and Riddell, W.C. (1999), 'The Measurement of Unemployment: An Empirical Approach', *Econometrica*, 67, 147-162.

[12] Kass, R.E. and Raftery, A.E. (1995), 'Bayes factors', *Journal of the American Statistical Association*, 90, 773-795

[13] Killingsworth, M. and Heckman, J.J. (1986), 'Female labour supply: a survey', in Ashenfelter, O. and Layard, R. (eds), *Handbook of Labor Economics*, Amsterdam: North-Holland, 103-204

[14] Malinvaud, E. (1986), *Sur les statistiques de l'emploi et du chomage*, Paris: La Documentation Francaise

[15] Maritz, J.S. and Lwin, T. (1989), *Empirical Bayes methods*, London: Chapman and Hall

[16] OECD (1987), 'On the Margin of the Labour Force: An Analysis of Discouraged Workers and Other Non-Participants, *Employment Outlook*, OECD, Paris

[17] Poterba, J.M. and Summers, L.H. (1995), 'Unemployment Benefits and Labour Market Transitions: A Multinomial Logit Model with Errors in Classification', *The Review of Economics and Statistics*, 77, 2, 207-216

[18] Rettore, E. and Trivellato, U. (1993), 'A Double-Hurdle labour supply model with fallible indicators of labour force state', *Statistica*, 3, 341-367

[19] Rettore, E. and Trivellato, U. (1998), 'La misura della disoccupazione e la modellazione dell'offerta di lavoro: definizioni a priori e stime dipendenti da modelli a confronto', in E. Giovannini (a cura di), *La misurazione delle variabili economiche e i suoi riflessi sulla modellistica econometrica*, Annali di Statistica, Serie X, vol. 15, Roma: Istat, 127-146

[20] Schwarz, G. (1978), 'Estimating the dimension of a model', *The Annals of Statistics*, 6, 461-464

[21] Shiskin, J. (1976), 'Employment and unemployment: the doughnut or the hole?', *Monthly Labour Review*, 99, 3-10

[22] Sorrentino, C. (2000), 'International unemployment rates: how comparable are they?', *Monthly Labor Review*, 123, 6, 3-20

[23] Trivellato U. (1997), 'Le misure della partecipazione al lavoro nel quadro comunitario', in L. Frey (a cura di), 'Le informazioni sul lavoro in Italia: significato e limiti delle informazioni provenienti dal lato delle famiglie', *Quaderni di Economia del Lavoro*, 59, Milano: Franco Angeli, 9-34

[24] Yakowitz, J.S. and Spragins, J.D. (1968), 'On the identifiability of finite mixtures', *The Annals of Mathematical Statistics*, 39, 209-214

**Working Papers già pubblicati**

1. E. Battistin, A. Gavosto e E. Rettore, *Why do subsidized firms survive longer? An evaluation of a program promoting youth entrepreneurship in Italy*, Agosto 1998.
2. N. Rosati, E. Rettore e G. Masarotto, *A lower bound on asymptotic variance of repeated cross-sections estimators in fixed-effects models*, Agosto 1998.
3. U. Trivellato, *Il monitoraggio della povertà e della sua dinamica: questioni di misura e evidenze empiriche*, Settembre 1998.
4. F. Bassi*, Un modello per la stima di flussi nel mercato del lavoro affetti da errori di classificazione in rilevazioni retrospettive*, Ottobre 1998.
5. Ginzburg, M. Scaltriti, G. Solinas e R. Zoboli, *Un nuovo autunno caldo nel Mezzogiorno? Note in margine al dibattito sui differenziali salariali territoriali*, Ottobre 1998.
6. M. Forni e S. Paba, *Industrial districts, social environment and local growth. Evidence from Italy*, Novembre 1998.
7. B. Contini*, Wage structures in Europe and in the USA: are they rigid, are they flexible?*, Gennaio 1999.
8. B. Contini, L. Pacelli e C. Villosio, *Short employment spell in Italy, Germany and Great Britain: testing the "Port-of-entry" hypothesis*, Gennaio 1999
9. B. Contini, M. Filippi, L. Pacelli e C. Villosio*, Working careers of skilled vs. unskilled workers*, Gennaio 1999
10. F. Bassi, M. Gambuzza e M. Rasera, *Il sistema informatizzato NETLABOR. Caratteristiche di una nuova fonte sul mercato del lavoro*, Maggio 1999.
11. M. Lalla e F. Pattarin, *Alcuni modelli per l'analisi delle durate complete e incomplete della disoccupazione: il caso Emilia Romagna*, Maggio 1999.
12. A. Paggiaro*, Un modello di mistura per l'analisi della disoccupazione di lunga durata*, Maggio 1999.
13. T. Di Fonzo e P. Gennari*, Le serie storiche delle forze di lavoro per il periodo 1984.1-92.3: prospettive e problemi di ricostruzione*, Giugno 1999.
14. S. Campostrini, A. Giraldo, N. Parise e U. Trivellato*, La misura della partecipazione al lavoro in Italia: presupposti e problemi metodologici di un approccio "time use"*, Ottobre 1999.
15. A. Paggiaro e N. Torelli, *Una procedura per l'abbinamento di record nella rilevazione trimestrale delle forze di lavoro*, Ottobre 1999.
16. A. D'Agostino, G. Ghellini e L. Neri*, A Multiple Imputation Method for School to Work Panel Data*, Ottobre 1999.
17. G. Betti, B. Cheli e A. Lemmi, *Occupazione e condizioni di vita su uno pseudo panel italiano: primi risultati, avanzamenti e proposte metodologiche*, Ottobre 1999.
18. B. Anastasia, M. Gambuzza e M. Rasera*, La durata dei rapporti di lavoro: evidenze da alcuni mercati locali del lavoro veneti*, Marzo 2000.
19. F. Bassi, M. Gambuzza e M. Rasera*, Struttura e qualità delle informazioni del sistema NETLABOR. Una verifica sui dati delle Scica delle province di Belluno e Treviso*, Marzo 2000.
20. N. Rosati, *Permanent and Temporary Inequality in Italy in the 1980s and 1990s*, Marzo 2000.
21. G. Betti, B. Cheli e A. Lemmi, *Analisi delle dinamiche di povertà e disoccupazione su uno pseudo panel italiano*, Marzo 2000.
22. A. D'Agostino, G. Ghellini e L. Neri, *Modelli statistici per l'analisi dei comportamenti di transizione scuola lavoro*, Marzo 2000.

23. A. Paggiaro e U. Trivellato*, Assessing the effects of the "Mobility List" programme in an Italian region: do (slightly) better data and more flexible models matter?,* Marzo 2000.
24. F. Bassi, M. Gambuzza, M. Rasera e E. Rettore, *L'ingresso dei giovani nel mercato del lavoro: prime esplorazioni dall'archivio Netlabor*, Giugno 2000.
25. A. D'Agostino, G. Ghellini e L. Neri, *Percorsi di ingresso dei giovani nel mercato del lavoro*, Giugno 2000.
26. E. Battistin, E. Rettore e U. Trivellato, *Measuring participation at work in the presence of fallible indicators of labour force state,* Giugno 2000.

---

Le richieste di working papers vanno indirizzate alla Sig.ra Patrizia Piacentini, Dipartimento di Scienze Statistiche, via C. Battisti 241-243, 35121 Padova, oppure all'indirizzo e-mail patrizia.piacentini@unipd.it.