Low-Wage Mobility in the Italian Labour Market

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First draft: November 1998
This version: May 1999

Abstract

This paper uses SHIW panel data for 1993 and 1995 to model individual transition probabilities at the bottom of the Italian wage distribution. The analysis is based on a bivariate probit model with endogenous switching which allows tackling the *initial conditions problem*, i.e. the potential endogeneity of the conditioning starting state. Results show the appropriateness of such a choice: the correlation between state and transition probabilities is significantly different from zero, while overlooking endogeneity leads to overstatement of both size and significance of coefficients in the transition equation. The paper shows that while some factors such as education, sex and geographical location have an effect on low-pay persistence, job related variables are more effective in avoiding falls into low-pay from higher pay. It is also shown how raw persistence involves a considerable share of *true* state dependence, pointing towards the existence of low-pay stigma.

keywords: low-pay; wage mobility; initial conditions problem

JEL code: J31, D31, C25

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1. Introduction

The widening of wage distributions observed in several industrialised economies in recent years is a stylised fact which, as empirical research (see, among others, Juhn *et al.* [1993] and OECD [1996]) has shown, implies the deterioration of the relative position of the less skilled in the wage distribution. Increasing wage inequality thus involves a low-pay issue, with a growing proportion of the labour force earning wages below a given "decency threshold"; such an issue has a relevant political impact which, in some countries, is witnessed by a renewed interest in minimum wage legislations.

Despite being traditionally known as "rigid", the Italian labour market has also been recently characterised by an increasing level of wage inequality. The existing empirical literature has shown that, since the mid-80's, wage differentials markedly grew, especially in favour of high skilled non-manual workers (Erickson and Ichino [1995]; Dell'Aringa and Lucifora [1995]), while, in parallel, the incidence of low-paid jobs has increased (Lucifora [1998]).

Concerns about the level of wage dispersion or low-pay incidence implicitly refer to a static perception of the wage distribution, where the focus of the analysis is the proportion of low-paid workers at a point in time. However, a high degree of low-pay persistence at the individual level constitutes a policy issue even if the distribution is stable over time. In other words, a crucially important aspect is the extent of wage mobility (i.e. changes in wage ranks through time) of the low-paid. A low degree of persistence implies that low-pay is a transitory status of the working career and it may well serve as a (re-) entry point into the labour market which is then abandoned thanks to the acquisition of experience and skills. At the other extreme, if low-pay is a persistent status, workers are trapped in such "bad" jobs for a relevant portion of their career, and the labour market produces inequality in a dynamic sense even if cross-sectional distributions are stable over time.

The analysis of wage mobility requires panel data on individual wages which, thanks to the availability of repeated wage observations for the same worker over time, allow estimation of the parameters of the joint (through time periods) wage distribution and assessment of the degree of persistence of the individual position over a sequence of cross-sectional distributions. Panel data may be utilised to estimate error components models of wages by which the permanent (at the individual level) and transitory components of cross-sectional dispersion can be disentangled; alternatively, they can

be used to follow individual transitions over the classes of the wage distribution through time. This paper takes the latter route and models transition probabilities out from and into low-pay.

Various studies of wage mobility have been devoted to such an econometric modelling of transition probabilities in recent years by treating the outcome mobile/not-mobile by means of discrete response models and conditioning it on a set of personal characteristics and the starting status.[1] However, as pointed out by Bingley *et al.* [1995] and Stewart and Swaffield [1999] (S&S thereafter), some caution should be exerted when performing such an exercise, which, dealing with the analysis of persistence, is prone to the so-called *initial conditions problem* (Heckman [1981a]), i.e. the potential non-exogeneity of the conditioning starting state, and failure to account for the non-random assignment to the starting wage class may bias parameter estimates in the equation for the transition probability.

This paper uses data from the Bank of Italy's *Survey on Households Income and Wealth* (SHIW) and treats the initial condition problem as one of sample selection by means of a bivariate probit model with endogenous switching which extends the model of S&S. Results show that the conditioning initial low-pay state is endogenous and that overlooking such endogeneity systematically leads to overstatement of the size and significance of parameters in the mobility equation. From a policy perspective, the paper shows how, other things equal, labour market experience has no effect on transition probabilities out of low-pay, while some limited effect may be disentangled from other personal characteristics, such as education and gender; on the other hand, job related variables are effective in preventing individuals from falling into low-pay. Moreover, a considerable share of *true* state dependence is found within aggregate persistence probabilities, pointing towards the existence of some low-pay stigma.

The paper is organised as follows. Section 2 describes the 1993 and 1995 waves of the SHIW data, which form the object of the empirical analysis. Section 3 defines the low-pay thresholds and describes the characteristics of low-paid workers in terms of the *ceteris paribus* probability of being low-paid. Section 4 takes into account transitions out from and into the low-pay status: the econometric model of low-wage mobility is set out and results are presented. Section 5 analyses the impact of a more flexible specification

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[1] See, for example, Smith and Vavricheck [1992] and Sloane and Theodossiu [1996]. See also Contini *et al.* [1998] for an application of this kind of approach to Italian data.

of the transition equation, which accounts for the width of transition, on estimated parameters. Section 6 concludes.

2. The data

The data set utilised in this study is drawn from the 1993 and 1995 waves of the SHIW, a micro-data archive set up by the Bank of Italy with the aim of providing information on the economic behaviour of Italian households. Interviews have been conducted on an annual basis since 1977 and biannually from 1987 onwards. Although the sampling unit is the household, increasingly detailed information on labour market variables for individuals within the household has been made available in the recent waves of the survey[2].

The two waves utilised are the latest in the SHIW and various reasons dictated the choice. First of all, given that the focus of this study is the dynamic behaviour of wage earners and of their transitions within the wage distribution through time, the availability of a panel is crucial. A panel sub-section has been introduced in the SHIW data since 1989: however, the proportion of panel households (i.e. those sampled in at least two consecutive waves) has initially been fairly small, approaching 50% only in 1993 and 1995. Secondly, the structure of the questionnaire referring to the labour market varied considerably over time, and the 1993 and 1995 waves provide an acceptable degree of homogeneity in the available information: as an example, the employer size, which we will see to have a considerable effect on the incidence of low-pay, is only available in the two selected waves. Finally, and probably most importantly, in 1993 a subsection on intergenerational mobility was introduced and, in particular, questions on the parents' education and occupation were asked to the spouse and the head of household: as will be clear later, such information plays a central role in the econometric analysis of earnings mobility and its absence from previous waves is the main reason which prevented the extension of the analysis to preceding transitions.

The characteristics of the data are reported in table 1, where the first two columns refer to the sample composition in the 1993 and 1995 waves, while the third reports the same features, observed in 1993, for the panel sub-sample linking the two waves. The upper part of the table illustrates the structure of the whole set of individual observations

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[2] See Cannari and Gavosto [1994] for a full description of the subsection of the survey referring to the labour market.

available under each partition; as we can see, the employees, both full and part-time and accounting for missing wage observations, amount at approximately one fourth of the sample, either in the two cross-sections and in the panel sub-sample. On the other hand, around 60% of the sample do not participate into the labour market.[3] By comparing the two cross-sections with the panel sub-sample, it can be observed how the proportions of students is slightly higher in the latter case, while the opposite is true for the retired, thus reflecting a higher propensity to stay within the household, and thus within sample, for students and inherently higher exit rates for pensioners.

The next panels in the table go on to describe the sample structure for full-time employees with valid wage observations and aged between 18 and 65, which will form the object of the econometric analysis. As can be seen, panel observations are now a smaller proportion relative to cross-sectional observations: the requirement for an observation to stay within the sample is now more demanding, which explains the fact. The differences in the sample composition between the cross-sections and the panel are not dramatic when age, experience and gender are taken into account, although in the first two cases the variable is slightly less disperse in the panel. A difference may instead be observed for what concerns the position in the household, the proportion of children in the panel sub-sample being some 4% lower than the two cross-sections, reflecting a higher propensity to leave the household in this group. Taking into account the other characteristics reported in the table, which basically consist of the wage determinants available in the SHIW data, we can see how, when compared with the two cross-sections, the panel sub-sample tends to be more educated, to hold non-manual jobs (teachers in particular), to be concentrated in the public administration[4] and to be employed in larger firms[5], all characteristics which indicate a stronger labour market attachment. This evidence suggests that panel attrition has an effect on the sample structure, a caveat which has to be taken into account when interpreting the results which follow.[6]

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[3] Given the well known importance of underground jobs in the Italian labour market, this is probably an overestimate. In the analysis which follows, I will consider only those employed on a regular basis and will not take into account individuals which, for example, report a labour income despite classifing themselves as retired.

[4] The classification of sectoral affiliation in the SHIW questionnaire is jointly based on the type of product market and the public/private nature of the employer: this means that the coefficients on the public sector dummies in the next sections have to be interpreted not as public/private differentials, but as differentials between the public sector and the omitted category.

[5] Information on the employer's size only refers to private sector employees.

[6] The issue of attrition is not addressed in this paper. This would require to augment the model with a selection equation for the attrition probability (see Bingley *et al.* [1995]), which implies the availability of suitable instruments, i.e. variables influencing the attrition outcome without a direct effect on wage outcomes.

3. Definition and determinants of the low-pay status

This section deals with the definition of the low pay threshold and with the quantification of the effect of observed workers characteristics on the probability of being low paid at a point in time.

A problem which is inherent to the analysis of low wage employment (and of poverty in general) is the definition of the threshold below which a worker may be considered a low wage earner. In particular, the problem is that of results robustness to the choice of the threshold. Various choices have been adopted in previous studies and, clearly, there are no *a priori* grounds to prefer one with respect to the others; to cope with this issue, here I follow the approach proposed by S&S and, instead of selecting a single threshold, I look at different thresholds in parallel. In particular, I consider the first quintile and the third decile of the wage distribution of full time dependent workers aged between 18 and 65, which have both been used in previous studies (see Asplund *et al.* [1998] and Contini *et al.* [1998] respectively); both thresholds, being based on order statistics, guarantee robustness to outliers and avoid problems of updating over time.

A second issue is the definition of the wage variable. The wage information available in the SHIW data refers to the net annual wage, inclusive of overtime payments, and separately, to the monetary value of fringe benefits: for the purposes of the current analysis, I added them together to form the take-home net annual wage. This figure has then been normalised to account for heterogeneity in the amount of time effectively worked. Under this respect, the information available consists of the number of months effectively worked during the year and in the number of hours (inclusive of extra-time) averagely worked on a weekly basis; no information is available on the average number of weeks per month worked. This implies that to study hourly wages it is necessary to make some assumption on the number of weeks worked per month: here I follow Bardasi [1996] and assume that each individual worked 52/12 weeks each month. However, I also analyse monthly wages in parallel, so that any dramatic change in results between the two definitions can be checked.

Some features of the distribution of hourly and monthly (nominal) wages in the two years considered are reported in the upper panel of table 2. As we can see, nominal wage growth has been fairly weak either at the mean and the median of the distribution

for both wage measures, while wage dispersion has basically remained constant over the period. It can also be noted how the distribution of monthly wages tends to be more compressed, thus suggesting that heterogeneity in hours worked matters. The table also reports the low pay thresholds used in the analysis, and compares them with two thirds of the median wage, another threshold widely adopted in the literature; this last value tends to be lower than the first quintile. The lower panel of table 2 deals with the proportions of workers which are defined as low paid under these three thresholds both in the cross-sectional sample and in the panel sub-sample. A first thing to note is that, in certain cases, the proportion of observations falling below or at a given percentile exceeds the level which one would expect from the percentile's definition, thus indicating the presence of clustering in the data. Secondly, we can observe how the lowest thresholds (2/3 the median) is located around the fiftieth percentile for hourly wages and just above the first decile for monthly wages, again showing how this last variable is less disperse. Finally, when the panel sub-sample is taken into account, the proportion of low-paid workers decreases under each threshold, a fact which is in line with the different structure of this group discussed above.[7]

A simple way of analysing the determinants of the low-pay status is to assess the effect of individual characteristics on the probability of being low-paid and to treat the problem by means of a discrete response model, namely a probit.[8] Let's assume that, in a given year, wages depend on a set of individual and job characteristics:

$$g(w_i) = x_i'\delta + u_i \qquad\qquad (1)$$

where i indexes individuals, w is the nominal wage rate, x_i is a vector containing a constant and a set of wage determinants, d is the vector of associated coefficients and $g(.)$ is a monotonic transformation such that u_i is standard normally distributed over i. Let l be the low-pay threshold and d_i a dummy variable indicating the low-pay event:

$$d_i = \begin{cases} 1 & if \quad w_i \leq \lambda \\ 0 & if \quad w_i > \lambda \end{cases}.$$

Then, the probability that individual i will be low-paid is:

$$prob(d_i = 1) = prob(w_i \leq \lambda) = prob(g(w_i) \leq g(\lambda)) = \Phi(g(\lambda) - x_i'\delta) = \Phi(x_i'\beta) \qquad (2)$$

where Φ is the standard normal c.d.f., the new constant term in $\boldsymbol{b}$ subsumes the difference between g($\boldsymbol{l}$) and the old constant in $\boldsymbol{d}$ and the coefficients associated with the individual characteristics in $\boldsymbol{b}$ are the same as in $\boldsymbol{d}$, but with opposite sign.[9]

Such probit models for the low-pay probability have been estimated on the two SHIW cross-sections both for hourly and monthly wages; results are reported in table 3.[10] Results are reported in terms of marginal effects, i.e. the change in predicted probabilities induced by a marginal change in the explanatory variable. For a continuous variable (say the j-th), these are evaluated as $\phi(\bar{x}'\hat{\beta})\hat{\beta}_j$ (where $\bar{x}$ is the vector of sample means of the explanatory variables and $\boldsymbol{f}$ is the standard normal density function), while for a dummy variable (say the k-th) they're are computed as the change in predicted probabilities as the dummy changes from 0 to 1, all the other variables being evaluated at the sample mean, i.e. $\Phi(\hat{\beta}_k + \bar{x}_{-k}'\hat{\beta}_{-k}) - \Phi(\bar{x}_{-k}'\hat{\beta}_{-k})$, where the *-k* subscript denotes the corresponding vector deprived of the k-th element.

Looking first at each column of the table for hourly wages in isolation, it can be seen how the effect of personal characteristics tends to be in line with what one should expect from standard wage equations. Labour market experience (computed as age minus age at the beginning of the first job) has a non-linear effect on the probability of being low-paid, with the minimum located around 30 years. Educational qualifications have a negative impact on such a probability, with the effect of holding a BA degree which is roughly twice that of having an high school degree, both compared to those without an high school degree. Workers holding a non-manual job have a low-pay probability which is (depending upon the threshold) 10 to 26 percentage points lower when compared with blue collar workers; interestingly, the marginal effect for teachers is even higher than that for high level white collar workers, managers, university professors or magistrates[11], a fact which I will comment on later in the section. The effect of sectoral

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[9] Given that this is a model for the probability of having a low wage, we should expect signs to revert with respect to a wage equation.

[10] The number of observations used in the estimation differs from the figures of table 1 due to missing values in some of the explanatory variables. The same remark applies for the analysis of sections 4 and 5.

[11] Managers, professors and magistrates have been amalgamated with high level white collars because, since they tend not to fall below the threshold, a dummy for this group happens to be a "perfect classifier" and the corresponding parameter not identifiable.

affiliation (with respect to manufacturing) is well determined for the public sector and agriculture, while the retail trade and services sectors display some effect depending upon the threshold or year considered; on the other hand, the employer size plays a clear role in reducing low-pay probabilities. Gender[12] and the region of residence have a significant effect; in particular, in the latter case it is the north-east which tends to have the lowest incidence of low-paid jobs. Finally, while both being married and head of the household significantly reduce the likelihood of low-pay, the presence of dependent (aged less than 14) children in the household has a less clear effect.

Taking now into account the estimates' stability over time, it can be noted how, apart from few exceptions, there are no dramatic differences. In particular, the size of the coefficients on the agriculture dummy drops considerably, while the effect for the retail trade group shows up only in the 1995 wave, which is also true (but only for the lower threshold) for the services sector. It is also interesting to observe how there is some evidence of geographical polarisation in low-pay probabilities over time, with the two northern marginal effects which tend to increase while the one for the centre falls.

Another interesting exercise is to control how estimated marginal effects change as the low-pay threshold is raised from the first quintile to the third decile. The general finding is that absolute values of significant effects tend to increase, while some effects which are non significant under the lower threshold become significant (this is the case for the services sector). This evidence is due to the fact that the bulk of observations which have personal characteristics with a given effect on the low-pay probability is located higher up in the wage distribution.[13]

The second part of table 3 reports the results obtained for the distribution of monthly wages; differences with respect to hourly wages can then be ascribed to heterogeneity in hours supplied. Patterns emerged from the analysis of hourly wages are typically confirmed, but with some remarkable exception. First of all, the marginal effect for teachers is now the weaker (among occupational dummies) in absolute value, thus reverting the occupational ordering emerged from hourly wages. Secondly, a drop ranging from 3 to roughly 10 percentage points depending upon the threshold considered can be observed in the coefficients for the public sector. In both cases, heterogeneity in supply behaviour is determined by institutional factors. Finally, the female disadvantage in the probability of having a low wage is exacerbated in the

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[12] Rather than running a separate regression for each gender, I treat the effect with a dummy, in order to maintain homogeneity with the analysis of transition probabilities in the next section, where the pooling of female and male data has been necessary in order to preserve cells size.

[13] In a separate experiment, I found that (for hourly wages in 1993) the effect of being a blue collar worker on the probability of having a wage below or at a given threshold grows monotonically until the median of the distribution and then falls.

monthly wage distribution, signalling that females tend to offer less hours than men, and the source of heterogeneity has more to do with behavioural factors.

4. The econometric analysis of low-wage transition probabilities

This section takes advantage of the panel nature of the SHIW data to analyse the dynamics of the low-paid status at the individual level. As is well known in the wage mobility literature (see, among others, Atkinson *et al*. [1992] and Gottschalk [1997]), the fact that a portion of the labour force earns a wage falling below a given low-pay threshold at a point in time is only partially informative about the features of the low-pay problem and information is needed on the persistence of individuals in the low-pay condition over time. In particular, the econometric analysis of low-pay persistence can shed light on the personal characteristics of those who are trapped at the bottom of the wage distribution through time and help in designing policy interventions. At the same time it is also important to investigate the forces driving falls into the low-pay status from the upper part of the distribution, in order to focus on those personal characteristics which can guarantee the stability of higher hierarchical positions once reached.

4.1 Aggregate transition probabilities

Before moving on to the econometric analysis of wage mobility, it may be instructive to look at the extent to which low-paid workers persist in their status at the aggregate level; such information is provided in table 4, where raw transition probabilities from the 1993 to the 1995 status are reported both for hourly and monthly wages using the two low-pay definitions of the previous section; the first part of the table restricts the attention to the sample of employees in both years aged between 18 and 65 in 1993. The table points towards a substantial degree of low-pay persistence: 56% of those below the first quintile of hourly wages in 1993 are still low-paid in 1995, and such figure rises to nearly 71% when the threshold is defined in terms of the third decile. Similar figures, 61 and 64% respectively, arise for the monthly wage distribution. On the other hand, the probability of falling into low-pay from the top of the distribution is bounded below 10%.

These figures imply a considerable degree of (raw) state dependence in the conditional probability of being low-paid in 1995: if we use the difference $prob[L_{95}|L_{93}] - prob[L_{95}|H_{95}]$ (with L and H meaning low- and high-pay) as a measure

of state dependence, we can see that it ranges from 50 to 60% depending upon the threshold and wage measure considered.

Although striking, such evidence may well imply different phenomena (Heckman [1981b]). On the one hand, it could be the result of workers heterogeneity, with the personal characteristics determining the low-pay status persisting over time; in this case, it is the difference in such characteristics between workers above and below the low-pay threshold which determines the observed state dependence. At the other extreme, raw figures may be generated by true state dependence, meaning that it is the experience of low-pay which modifies individual tastes or constraints and determines *per se* a higher persistence probability, holding fixed personal characteristics. As pointed out by S&S, true state dependence in low-pay persistence may arise from various models of the labour market. For example, if we think of low-paid jobs as "bad" jobs with no skill content, human capital models of wage determination can predict state dependence as a result of skill deterioration induced by the past experience of low-pay. The same prediction can arise in a signalling contest, where potential employers can use previous wages to make inference on the workers' quality and thus making low-wage offers to applicants who have formerly been low-paid. In addition, we could also think of a job search model where the experience of low-paid jobs induces workers to reduce their reservation wage, thus raising the probability of accepting low-wage offers in the future. Disentangling between heterogeneity and true state dependence is thus a relevant issue in the analysis of low-pay transitions and the econometric analysis in this section will address this point.

Focusing only on those employed in both years could lead to ignore important aspects of the low-pay problem; for example, evidence of a cycle between low-pay and unemployment has been found for the UK (see Stewart [1999]). To shed light on the extent of the phenomenon in the SHIW data, table 4 also considers transitions into other labour market states, namely self-employment, unemployment and retirement, for those aged 18 to 65 in 1993. In each of the four cases, the low-paid have a higher transition probability into both self-employment and unemployment when compared to the higher-paid, with raw state dependence being higher in the latter case. This suggests that low-wage jobs are characterised by a higher instability. On the other hand, a higher transition probability into retirement characterises the high-paid group, a likely effect of the life-cycle of earnings. Taking now into account the first column in each of the four matrices, we can also notice how in three out of four cases the unemployed are more

likely to find a job below, rather than above, the low-pay threshold. This evidence is not enough to make statements about the existence of a cycle between unemployment and low-pay (which would require to observe at least two transitions), but is certainly not against such a hypothesis.

4.2 Model specification

The next step in this section is the construction of an econometric model of low-pay transition probabilities, i.e. the probability of being low-paid in 1995 conditional on the 1993 status; in particular, the object of the analysis will be the impact of personal characteristics, measured at the beginning of the transition[14], on individual transition probabilities. One central issue which arises in this context is that conditioning on the lagged state cannot be treated as exogenous: given that the wage process under investigation started prior to the sampling period its initial conditions are not observable by the researcher while, due to the presence of serial correlation in such a process, they will be embedded in wage levels at each time period, causing lagged wages to be endogenous with respect to current wages. This is the so-called *initial conditions problem* described in Heckman [1981a] and ignoring it can lead to biased estimates in the transition probability equation. The issue may also be thought of as a sample selection problem: if the propensity to be low-paid (or high-paid) in 1993 is not randomly distributed across the sample but depends on the unobservable initial conditions, estimating a transition equation selecting those who start from a low-pay (high-pay) state is endogenous to the transition probability.

This last remark suggests that some sort of correction for sample selection is needed; however, given the limited dependent nature of the transition equation, Heckman's correction techniques are not suitable in this context and the two probabilities (starting state and transition) have to be estimated jointly (O'Higgins [1994]).

To overcome the problem, here I extend the approach proposed by S&S and treat it by means of a bivariate probit model with endogenous switching, i.e. the probit equivalent of usual endogenous switching models.[15] Let's specify the selection equation

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[14] This qualification is aimed at avoiding endogeneity issues between changes in wages and changes in wage determinants.

[15] The model proposed by Stewart and Swaffield assumes partial observability of the arrival wage distribution conditional on the origin wage distribution, which corresponds to model no. 3 in Meng and Schmidt [1981] catalogue of bivariate probit models. An application of the Stewart and Swaffield model is given in section 5.

for the initial state along the lines adopted in section 3 to model the low-pay probability at a point in time:

$$g(w_{i93}) = x_i'\delta + u_i$$

$$d_{i93} = \begin{cases} 1 & if \quad w_{i93} \le \lambda_{93} \\ 0 & if \quad w_{i93} > \lambda_{93} \end{cases}, \tag{3}$$

where the specification of the x-vector differs from table 3, as will be clear later.

Next, suppose that the effect of exogenous variables on the arrival state depends upon the initial state in the following way:

$$\begin{aligned} h_1(w_{i95}) &= z_i'\eta_1 + \varepsilon_{1i} & if \quad d_{i93} = 1 \\ h_2(w_{i95}) &= z_i'\eta_2 + \varepsilon_{2i} & if \quad d_{i93} = 0 \end{aligned}, \tag{4}$$

where $h_j(.)$ is a monotonic transformation such that e_{ji} is standard normally distributed over individuals and z is a subvector of x. Let d_{i95} be a dummy variable indicating the low-pay event in the arrival wage distribution and assume that u and the ε_j's are jointly distributed as a tri-variate normal:

$$\begin{pmatrix} u_i \\ \varepsilon_{1i} \\ \varepsilon_{2i} \end{pmatrix} \sim N_3 \left[\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & & \\ \rho_1 & 1 & \\ \rho_2 & \rho_3 & 1 \end{pmatrix} \right]^{16}.$$

Given the assumptions on the errors distribution, it follows that:

$$\begin{aligned} prob(d_{i95} = 1, d_{i93} = 1) &= \Phi_2(z_i'\gamma_1, x_i'\beta; \rho_1) \\ prob(d_{i95} = 1, d_{i93} = 0) &= \Phi_2(z_i'\gamma_2, -x_i'\beta; -\rho_2) \end{aligned}, \tag{5}$$

where Φ_2 is the bivariate normal cdf, b derives from d in the same fashion of section 3 and analogously for g and h_j; thus the elements of g_1 model the effect of individual characteristics on low-pay persistence, while g_2 captures the effect of the same characteristics on the probability of falling from the upper part of the distribution into low-pay. Note that although these expressions refer to the joint probability, estimation of the

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[16] Note that ρ_3 is not identifiable since it would require observations belonging contemporaneously to both regimes.

g's is based on sub-samples defined according to the starting state and is, in this sense, conditional. Note also that, given the model's structure, only the evaluation of the bivariate normal cdf is required. To derive the correct (i.e. summing to one over the sample of the initially low or high-paid) expression for the conditional probability we need to normalise on the probability of the initial state:

$$prob(d_{i95} = 1 | d_{i93} = 1) = \frac{\Phi_2(z_i'\gamma_1, x_i'\beta; \rho_1)}{\Phi(x_i'\beta)}$$

$$prob(d_{i95} = 1 | d_{i93} = 0) = \frac{\Phi_2(z_i'\gamma_2, -x_i'\beta; -\rho_2)}{\Phi(-x_i'\beta)} \text{,}$$

(6)

which makes clear how the parameters for such transition probabilities can be consistently estimated with a univariate probit on sub-samples defined according to the starting state only if r_j=0, i.e. only if the starting state is exogenous.

The log-likelihood function of the model may be written as:

$$\log L = \sum_i \{d_{i93}d_{i95}\log[\Phi_2(z_i'\gamma_1, x_i'\beta; \rho_1)] + d_{i93}(1 - d_{i95})\log[\Phi_2(-z_i'\gamma_1, x_i'\beta; -\rho_1)] + (1 - d_{i93})d_{i95}\log[\Phi_2(z_i'\gamma_2, -x_i'\beta; -\rho_2)] + (1 - d_{i93})(1 - d_{i95})\log[\Phi_2(-z_i'\gamma_2, -x_i'\beta; \rho_2)]\}.$$

(7)

Identification of the transition process in (4) requires restrictions in the form of variables which enter the x-vector but not the z-vector; in the present case we need variables which influence the wage level but, given this, have no direct effect on the wage change. Here I follow S&S's identification strategy and use a set of indicators of the worker' s parental background in terms of her parents education and occupation. As stated in section 2, since 1993 the SHIW questionnaire contains a part on intergenerational mobility, where the spouse and head of household are asked to report, among others, their parents education and occupation. For those workers who are "child" in the interviewed household, the necessary information has directly been recovered from the household questionnaire. Going back to table 2, this means that for 1.58% of the estimation sample (i.e. those who are "other relative or non relative" in the interviewed household) such parental background variables are not available. In order to preserve the sample size, I treated these cases and the ones where the parental background information was "genuinely" missing with dummies for missing information.[17]

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[17] These are, typically, negligible proportions of the sample, reaching at most 4%; only in the case of the mother's occupation the figure rises to 14%.

Besides the parental background indicators, another variable which only enters the selection equation is the square of labour market experience, given the nature of wage change of the transition probability. This implies that the equation for the transition probability is over-identified and that the validity of the parental background variables as instruments can be tested: such tests are presented along with the estimation results.

4.3 Results

Before considering the whole set of results from the switching probit analysis, table 5 compares estimated ML coefficients under the two competing assumptions (i.e. endogeneity *versus* exogeneity) on the conditioning starting state, focusing, for expositional compactness, on the low-pay threshold defined as the bottom quintile of the hourly wage distribution.[18] The table gives a flavour of the kind of bias induced by assuming exogenous initial conditions. First of all it can be noticed that the null hypothesis of exogenous starting state is rejected for both starting states (i.e. low-pay and high-pay), the two correlation coefficients being statistically significant at conventional levels. Taking estimated coefficients into account, it can be observed that the exogeneity hypothesis leads to overestimate both their size and significance. This is true especially in the case of labour market experience, whose effect on the conditional probability of being low-paid vanishes once allowance is made for endogeneity. For the remaining explanatory variables such overestimation is, although less pronounced, also evident; on the whole, results from table 5 confirm similar comparisons reported by S&S and warn against the dangers of assuming exogeneity of initial conditions.

Results from the switching bivariate probit model are given in table 6 for each low-pay threshold and wage definition, both in terms of ML coefficients and associated marginal effects on the conditional probability.[19] By considering correlation coefficients

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[18] Results similar to the ones reported were obtained for the other low-pay and wage definitions. The exogenous starting state estimates are probit models for the 1995 low-pay event estimated on sub-samples defined according to the 1993 position in the wage distribution, i.e. above or below the low-pay threshold.

[19] For each explanatory variable, the marginal effect is given first, followed by the ML estimated coefficient and the asymptotic t-ratios. The computation of marginal effects from the bivariate probit estimates requires some additional caution, given that a change in a variable in z implies also a change in the corresponding element of x and thus in the denominator of the conditional probability. What we would require is instead a change in the conditional probability holding the past fixed (Stewart and Swaffield [1998]). With this aim, and focusing for the exposition's sake on the probability of low-pay persistence, let's define $\hat{\Phi} = \sum_i \Phi(x_i'\hat{\beta})/N$ (N is the sample size) and $\hat{x\beta} = \Phi^{-1}(\hat{\Phi})$; the marginal effect for the k-th dummy variable is then computed as $\dfrac{\Phi_2(\hat{\gamma}_{1k} + \bar{z}_{1-k}'\hat{\gamma}_{1-k}, \hat{x\beta}; \rho_1)}{\hat{\Phi}} - \dfrac{\Phi_2(\bar{z}_{1-k}'\hat{\gamma}_{1-k}, \hat{x\beta}; \rho_1)}{\hat{\Phi}}$, z1 indicating that the

first, it can be observed how, in each case, they are statistically significative at usual confidence levels, thus clearly rejecting the hypothesis of initial conditions' exogeneity. Such parameters are negative; given that they measure the correlation between the probability of having a small wage change and the probability of having a low initial wage, the negative sign is analogous to a negative coefficient estimated in the regression of wage changes on wage levels, i.e. Galtonian regression towards the mean. Note also that, given the structure of the model and, in particular, the uniqueness of the selection equation which models the probability of having an initial low-wage, this is true also for the initially high-paid. Another fact to note is that the identifying restrictions on the parental background variables are supported by the data at usual confidence levels.

Taking the effect of observable characteristics into account, it can be noticed how labour market experience has basically no effect in reducing the conditional probability of having a low-wage. Educational qualifications, on the other hand, have an effect in such direction which tends to be stronger for those starting the transition below the low-pay threshold; the same is true for the female dummy, but with opposite sign. Non-manual jobs and jobs in large firms are instead characteristics which tend to prevent workers from falling into low-pay, while the effect on low-pay persistence is less robust; similar considerations, but only for the hourly wage distribution, apply for the public sector dummy. The agricultural sector dummy seems to favour drops into low-pay for the distribution of monthly wages, thus denoting a certain wage instability for these jobs. On the other hand, holding a job in the service sector positively affects low-pay persistence[20], while no effect is detected on drops from the high-pay area. Such result could arise from those workers which, say in a bank or an insurance company, are on a low-level job career (actually involving manual tasks such as delivering) but do not classify themselves as blue collars. An alternative explanation could be that this service category is broad enough to include cases which markedly differ from the conventional perception of service sector. Finally, the geographical dummy is significative in reducing low-pay persistence, while no effect can be detected for those initially high-paid.

As we saw earlier in this section, one important issue in the dynamic analysis of low-pay is the distinction between true state dependence and heterogeneity within raw

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average is taken over the relevant sample, the initially low-paid in this case. For labour market experience the effect has been computed as that of a discrete change from 20 to 30 years of experience.
[20] Similar results on Italian data are reported by Contini et al. [1998].

persistence probabilities. Estimation results from table 6 enable such a decomposition, which is reported in the last three rows of the table. The row labelled "Estimated state dependence" reports the difference in the conditional probability of being low-pay computable from the estimated model, giving a measure of overall state dependence which is, apart from small differences due to observations with missing values in the explanatory variables excluded from the regression analysis, the same as the aggregate state dependence effect of table 4:

$$ESD = \frac{\sum\limits_{i:di93=1} \dfrac{\Phi_2(z_i\hat{\gamma}_1, x_i\hat{\beta}; \hat{\rho}_1)}{\Phi(x_i\hat{\beta})}}{\sum_i d_{i93}} - \frac{\sum\limits_{i:di93=0} \dfrac{\Phi_2(z_i\hat{\gamma}_2, -x_i\hat{\beta}; -\hat{\rho}_2)}{\Phi(-x_i\hat{\beta})}}{\sum_i (1-d_{i93})}. \qquad (8)$$

The measure of true state dependence has been obtained by computing this same quantity but holding fixed the sample over which it is averaged, i.e. abstracting from heterogeneity in explanatory variables between workers below and above the low-pay threshold in the origin wage distribution. This procedure yields two measures of true state dependence, corresponding to the two sub-samples over which the average is taken, which are reported in the two bottom lines. Such measures are equivalent to "price" effects in a classical Oaxaca decomposition of wage differentials; in terms of true state dependence, the "price" effect captures the extent to which workers with the same observable characteristics are evaluated differently according to their past wage, i.e. the parameters of their environment are changed by the past low-pay experience per se. First of all it can be observed how true state dependence constitutes a considerable share of aggregate state dependence, ranging from 40 to 70%, thus suggesting that low-pay stigma affects wage histories to a meaningful extent. Secondly, true state dependence is higher when the parameters estimates are applied to the sample of the initially low-paid, signalling a higher vulnerability of this group to the factors causing low-pay stigma.

5. Accounting for the width of transitions

As is well recognised by the statistical literature on mobility (see, for example, Boudon [1972]), an important feature of the mobility process is given by the magnitude

of the "jumps" made by those workers abandoning the origin wage class: not only the fact of changing wage rank is important, but also the width of such transitions matters in assessing the degree of distributional mobility.

In terms of the econometric modelling of transition probabilities, accounting for their width can give some indication on the loss of information induced by the dichotomic treatment of the wage variable underlying the switching bivariate probit above. In other words, the model of section 4 considers only one alternative to the low-pay status in the destination wage distribution, and some of the effects significant in affecting low-pay persistence may well result from small wages "pushes", just sufficient to bring individuals above the low-pay threshold.

To get a feeling on the extent of upward movements from the low-pay status, I report below the aggregate transition probabilities from the bottom three deciles of the distribution.

Transition probabilities from the bottom three deciles of the wage distribution (N=2160)

hourly	1	2	3	4	5	6	7	8	9	10	% 1993
1	44.25	26.44	15.52	3.45	4.60	1.72	2.30	1.15	0.57	0.00	8.06
2	17.58	23.03	26.06	9.70	14.55	3.03	2.42	1.21	2.42	0.00	7.64
3	6.15	18.46	35.90	11.79	13.33	6.15	4.10	2.05	1.03	1.03	9.03
monthly											
1	44.23	28.21	10.26	5.77	1.28	4.49	0.64	4.49	0.00	0.64	7.22
2	18.48	34.24	13.59	16.30	7.07	7.61	1.09	0.54	1.09	0.00	8.52
3	9.19	23.78	15.14	22.70	11.89	8.65	3.24	3.78	0.54	1.08	8.56

As we can see there's considerable variation in the destination states of those who cross the low-pay threshold, and while the bulk of transitions reaches the decile just adjacent the low-pay area, there are some cases (in particular starting from the third decile) in which the median of the distribution is crossed.

A way to investigate the impact of transition width on the parameters of interest is to allow for more than two outcomes in the transition equation; in particular, here I focus only on the transitions of the initially low-paid, adopting the partial observability framework of S&S and extending it by modelling the transition equation as an ordered probit.[21] Let's assume that selection into the starting state is still governed by (3), while the position in the destination wage distribution can only be observed for the initially low-

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[21] Guillotin and Hamouche [1998] model the number of jumps by means of count data models in a framework with exogenous initial conditions.

paid (i.e., only the first part of (4) applies) and is represented by the following discrete ordered indicator:

$$
d_{i95} = \begin{cases}
1 & if & & w_{i95} \leq & \lambda_{95} \\
0 & if & \lambda_{95} & < w_{i95} \leq & \lambda_{95} + \mu_0 \\
-1 & if & \lambda_{95} + \mu_0 & < w_{i95} \leq & \lambda_{95} + \mu_1 \\
-2 & if & \lambda_{95} + \mu_1 & < w_{i95} \leq & \lambda_{95} + \mu_2 \\
-3 & & & otherwise &
\end{cases}
\tag{9}
$$

where the μ's are the first three deciles above the low-pay threshold, while the assumptions on the joint distribution of u_i and e_{1i} are unaltered[22]. The resulting log-likelihood is:

$$
\begin{aligned}
\log L = \sum_i \{ & I(d_{i95} = 1)d_{i93}\log[\Phi_2(z_i\gamma_1, x_i\beta; \rho_1)] + \\
& I(d_{i95} = 0)d_{i93}\log[\Phi_2(\nu_0 + z_i\gamma_1, x_i\beta; \rho_1) - \Phi_2(z_i\gamma_1, x_i\beta; \rho_1)] + \\
& I(d_{i95} = -1)d_{i93}\log[\Phi_2(\nu_1 + z_i\gamma_1, x_i\beta; \rho_1) - \Phi_2(\nu_0 + z_i\gamma_1, x_i\beta; \rho_1)] + \\
& I(d_{i95} = -2)d_{i93}\log[\Phi_2(\nu_2 + z_i\gamma_1, x_i\beta; \rho_1) - \Phi_2(\nu_1 + z_i\gamma_1, x_i\beta; \rho_1)] + \\
& I(d_{i95} = -3)d_{i93}\log[\Phi(x_i\beta) - \Phi_2(\nu_2 + z_i\gamma_1, x_i\beta; \rho_1)] + (1 - d_{i93})\log[\Phi(-x_i\beta)]\},
\end{aligned}
\tag{10}
$$

where the ν_j's $(=h_1(\lambda_{95} + \mu_j))$ are parameters to be estimated and I(A) is a binary indicator which equals 1 when A is true and 0 otherwise.

Results from the estimation of this ordered probit with selectivity are reported in table 7 and are compared with those from a switching bivariate probit with partial observability, i.e. where the polychotomous indicator in (9) is replaced by a binary indicator (1 for w_{i95} below the low-pay threshold and 0 otherwise). A first thing to note is that in each of the cases considered, the null of exogenous initial conditions is rejected at conventional levels, while the validity of the parental background indictors as instruments for the starting state is supported by the data. By comparing the correlation coefficient across the ordered and binary probit models, it can be observed that it is always lower (bigger in absolute value) in the first case. If we recall that a negative value of this parameter reflects the fact that small wage gains are negatively associated with low initial wages, its behaviour across models suggests that in the polychotomous framework low-pay persistence is a relatively worst outcome than in the binary case. On

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[22] The specification in (9) is aimed at maintaining the comparability of $\gamma1$ with the analogous vector estimated from the analysis in section 4.

the other hand, for statistically significant coefficients and associated marginal effects[23] the general finding (a remarkable exception is the dummy for the service sector) is that they decrease in absolute value as we move from the binary to the polychotomous specification of the position in the 1995 wage distribution, meaning that part of such effects was due to small wage "pushes".

6. Summary and conclusions

This paper has utilised panel data from the 1993 and 1995 waves of the Bank of Italy's (SHIW) to analyse the determinants of low-wage mobility.

Defining the low-paid alternatively as those below the bottom quintile or the third decile of the wage distribution, both in hourly and monthly terms, the usual set of wage determinants (human capital, demand side and demographic variables) has been found to have a significant effect on the probability of being low-paid at a point in time.

The analysis has next turned to low-pay dynamics at the individual level. The econometric analysis of low-wage mobility has been based on a bivariate probit model with endogenous switching, which extends the approach previously proposed by Stewart and Swaffield [1999] for the assessment of the initial conditions problem, i.e. the potential endogeneity of the initial low-pay status.

Results show how the hypothesis of exogenous initial conditions can always be rejected, the correlation coefficient between the unobservables in the starting state and transition equations being significantly different from zero. By comparing these results with those from models where the initial status is taken as exogenous, the paper has shown how in this last case the effects of mobility determinants are systematically overstated both in size and significance: this is especially true for labour market experience. Among the other variables controlled for, education, gender, sectoral affiliation to the service sector and geographical location have been found to affect low-pay persistence, while non-manual occupations and jobs in large firms are effective in avoiding falls into low-pay once higher wage positions have been reached, while their

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[23] As for the preceding analysis, such effects refer to variations in the probability of being low-paid in 1995 conditional on low-pay in 1993. Their computation therefore coincides with the one reported in note 19 and, in particular, the conditioning probability is still given by a binary probit for low-pay in 1993. The relevant difference is that now the estimated γ_1 reflects the existence of more than one alternative to the low-pay status in 1995.

effects on low-pay persistence appears to be less robust. This last remark applies also to affiliation to the public sector, but only for the hourly wage distribution.

Estimates from the endogenous switching bivariate probit have been utilised to assess the extent of *true* state dependence within raw transition probabilities: it has been shown that low-pay stigma affects wage profiles to a meaningful extent, between 40 and 70% of raw state dependence, and that the low-paid are more vulnerable to the forces causing true state dependence, thus being more likely to be stigmatised by the experience of low-paid jobs.

Some attempt has also been made to understand the consequences of the binary treatment of the wage variable underlying the endogenous switching model. Using an ordered probit model with endogenous sample selection, it has been shown how, typically, significant effects tend to drop in size, suggesting that their effectiveness is to some extent confined to the quantiles just adjacent the low-pay threshold.

These results show that while factors which are traditionally known as wage determinants have a limited effect on the conditional probability of abandoning the low-pay status, the past experience of low-pay has, *per se*, a considerable impact on future low-pay probabilities, both circumstances which raise concern about the welfare of workers at the bottom of the wage distribution. However, data limitations, in particular the fact that a single transition has been analysed, suggest caution in drawing conclusions and prompt future research on this issue.

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Table 1: Sample description

	1993		1995		panel (1993)	
	n.obs/mean	%/s.d.	n.obs/mean	%/s.d.	n.obs/mean	%/s.d.
employed	5768	24.02	5598	23.4	2634	24.49
employed missing wage/part time	468	1.95	578	2.42	206	1.92
self-emloyed	1302	5.42	1492	6.24	564	5.24
entrepreneurs	585	2.44	557	2.33	256	2.38
seek first job	1215	5.06	1029	4.3	487	4.53
unemployed	511	2.13	690	2.88	234	2.18
retired	5401	22.49	5448	22.77	2193	20.39
student	4528	18.86	4400	18.39	2274	21.14
housewife	1247	5.19	1284	5.37	570	5.3
other	2988	12.44	2848	11.9	1337	12.43
Total	24013	100	23924	100	10755	100
Employed 18<=age<=65	5708		5541		2160	
age	39.0555	10.7613	38.9821	10.7944	39.4032	9.99305
experience/10	1.92771	1.14947	1.96128	1.16041	1.90736	1.06188
male	3677	64.42	3510	63.35	1391	64.4
female	2031	35.58	2031	36.65	769	35.6
head of family	2998	52.52	2794	50.42	1191	55.14
spouse/cohabitant	1312	22.99	1328	23.97	536	24.81
child	1265	22.16	1310	23.64	399	18.47
other relative-non relative	133	2.33	109	1.97	34	1.58
no school	81	1.42	55	0.99	16	0.74
elem. school (5 yrs)	824	14.44	679	12.25	260	12.04
junior high (8 yrs)	2035	35.65	2137	38.57	707	32.73
high school (13 yrs)	2123	37.19	2019	36.44	879	40.69
ba/bs (17+ yrs)	645	11.3	651	11.75	298	13.8
blue collar	2515	44.06	2525	45.57	854	39.54
white collar low level	2168	37.98	1814	32.74	832	38.52
teacher	598	10.48	647	11.68	293	13.56
white collar high level	289	5.06	416	7.51	124	5.74
manag,professor,magistrate	138	2.42	139	2.51	57	2.64
agricolture	164	2.87	133	2.4	42	1.94
other manufacturing	1597	27.99	1700	30.68	578	26.76
construction	333	5.84	300	5.41	105	4.86
retail trade	524	9.18	529	9.55	168	7.78
transport & communication	161	2.82	174	3.14	50	2.31
bank insurance	191	3.35	208	3.75	76	3.52
real estate	166	2.91	138	2.49	67	3.1
domestic & other services	191	3.35	188	3.39	59	2.73
public administration	2379	41.69	2171	39.18	1015	46.99
size<=4	470	14.12	484	14.36	145	12.45
5<=size<=19	930	27.94	950	28.19	272	23.35
20<=size<=49	499	14.99	476	14.12	163	13.99
50<=size<=99	324	9.73	280	8.31	107	9.18
100<=size<=499	474	14.24	499	14.81	179	15.36
size>=500	632	18.98	681	20.21	299	25.67
northwest	1389	24.33	1400	25.27	503	23.29
northeast	1200	21.02	1273	22.97	494	22.87
centre	1313	23	1162	20.97	426	19.72
south	1322	23.16	1235	22.29	533	24.68
islands	484	8.48	471	8.5	204	9.44

Table 2: Descriptive statistics of the wage distribution (upper panel) and incidence of low-pay for different thresholds (lower panel)

	hourly wages		monthly wages	
	1993	1995	1993	1995
Descriptive statistics (thousands of lire)				
mean	12.36	12.86	1958.30	2061.47
median	10.82	11.54	1833.33	1916.67
sd logs	0.47	0.45	0.40	0.39
log(90/10)	1.06	1.05	0.87	0.88
2/3 median	7.22	7.69	1222.22	1277.78
first quintile	8.05	8.55	1375.00	1500.00
third decile	8.97	9.62	1500.00	1625.00
Low-pay incidence				
2/3 median	14.02	15.03	11.3	11.19
2/3 median (panel)	10.28	9.58	7.82	6.3
bottom quintile	20.04	20.43	20.08	24.36
bottom quintile (panel)	15.69	14.07	15.74	16.57
third decile	30.2	34	30.17	30.63
third decile (panel)	24.72	24.77	24.31	22.55

Table 3: Probit marginal effects for the probability of being low-paid: hourly wages

Threshold	Bottom Quintile				Third Decile			
	1993		1995		1993		1995	
experience/10	-0.133	(9.59)	-0.108	(7.49)	-0.192	(9.00)	-0.215	(9.28)
experience^2/100	0.024	(7.66)	0.018	(5.92)	0.034	(7.39)	0.036	(7.30)
high school degree	-0.044	(3.64)	-0.045	(3.67)	-0.089	(5.00)	-0.091	(4.68)
ba degree +	-0.085	(4.41)	-0.083	(3.99)	-0.176	(6.17)	-0.187	(5.87)
white collar low-level	-0.097	(8.23)	-0.093	(7.74)	-0.165	(9.65)	-0.188	(10.14)
teachers	-0.103	(5.94)	-0.099	(4.96)	-0.213	(8.17)	-0.260	(9.07)
white collar high level, managers, uni. prof., magistrate	-0.091	(4.63)	-0.101	(5.72)	-0.176	(6.07)	-0.219	(8.31)
public sector	-0.189	(14.20)	-0.202	(14.14)	-0.317	(16.25)	-0.326	(15.04)
agricolture,forests	0.147	(5.08)	0.059	(2.10)	0.140	(3.41)	0.040	(0.91)
constructions	-0.016	(1.04)	0.019	(1.04)	-0.016	(0.64)	0.011	(0.39)
retail trade, household & other services	0.013	(0.98)	0.034	(2.49)	-0.002	(0.11)	0.059	(2.57)
transport e comm.	-0.030	(1.23)	-0.024	(0.97)	-0.030	(0.82)	-0.056	(1.42)
bank, insurance, real estate	0.004	(0.20)	-0.034	(1.70)	-0.061	(2.17)	-0.083	(2.63)
20<=firm size<=99	-0.077	(8.55)	-0.059	(5.69)	-0.132	(8.40)	-0.100	(5.18)
100<=firm size<=499	-0.090	(8.46)	-0.103	(9.56)	-0.174	(9.78)	-0.178	(8.73)
size>=500	-0.118	(11.38)	-0.119	(10.86)	-0.213	(12.69)	-0.245	(13.06)
female	0.096	(8.65)	0.087	(7.58)	0.140	(8.55)	0.137	(7.71)
north-west	-0.068	(6.53)	-0.096	(9.00)	-0.098	(5.88)	-0.100	(5.37)
north-east	-0.080	(7.79)	-0.093	(8.91)	-0.103	(6.06)	-0.133	(7.17)
centre	-0.055	(5.27)	-0.048	(4.22)	-0.064	(3.79)	-0.049	(2.50)
married	-0.074	(5.55)	-0.048	(3.61)	-0.129	(6.79)	-0.077	(3.79)
head of household	-0.050	(4.41)	-0.038	(3.20)	-0.078	(4.69)	-0.076	(4.19)
dependent children	0.015	(1.25)	-0.007	(0.55)	-0.010	(0.60)	-0.053	(2.90)
Number of obs	5673		5522		5673		5522	
chi2(23)	2061.13		1885.99		2494.03		2557.12	
Prob > chi2	0		0		0		0	
Pseudo R2	0.3642		0.3378		0.3594		0.3613	

Table 3 (continued): Probit marginal effects for the probability of being low-paid: monthly wages

Threshold	Bottom Quintile				Third Decile			
	1993		1995		1993		1995	
experience/10	-0.150	(10.55)	-0.192	(10.99)	-0.219	(10.34)	-0.276	(13.11)
experience^2/100	0.027	(8.41)	0.033	(8.76)	0.038	(8.24)	0.048	(10.67)
high school degree	-0.066	(5.26)	-0.072	(4.74)	-0.112	(6.26)	-0.114	(6.30)
ba degree +	-0.099	(5.69)	-0.115	(5.07)	-0.190	(7.41)	-0.176	(6.71)
white collar low-level	-0.099	(7.95)	-0.119	(7.92)	-0.204	(11.85)	-0.165	(9.33)
teachers	-0.072	(3.80)	-0.096	(4.06)	-0.171	(6.66)	-0.134	(4.79)
white collar high level, managers, univ. professor, magistrate	-0.095	(4.43)	-0.154	(7.03)	-0.210	(7.26)	-0.213	(8.26)
public sector	-0.156	(11.20)	-0.174	(9.93)	-0.221	(10.85)	-0.188	(8.85)
agricolture,forests	0.147	(4.85)	0.049	(1.43)	0.142	(3.41)	0.049	(1.20)
constructions	-0.008	(0.44)	0.012	(0.52)	-0.018	(0.71)	0.033	(1.15)
retail trade, household & other services	-0.002	(0.13)	0.014	(0.81)	-0.010	(0.46)	0.010	(0.50)
transport e comm.	-0.049	(1.91)	-0.045	(1.36)	-0.037	(0.96)	-0.086	(2.21)
bank, insurance, real estate	0.009	(0.41)	-0.053	(2.07)	-0.013	(0.41)	-0.059	(1.83)
20<=firm size<=99	-0.077	(7.64)	-0.067	(4.69)	-0.117	(6.97)	-0.084	(4.60)
100<=firm size<=499	-0.097	(8.27)	-0.136	(9.09)	-0.167	(8.67)	-0.164	(8.44)
size>=500	-0.124	(10.47)	-0.159	(10.33)	-0.211	(11.41)	-0.214	(11.18)
female	0.137	(11.57)	0.153	(10.87)	0.200	(11.99)	0.194	(11.70)
north-west	-0.063	(5.77)	-0.100	(7.40)	-0.106	(6.45)	-0.084	(4.95)
north-east	-0.074	(6.77)	-0.108	(7.96)	-0.121	(7.27)	-0.083	(4.84)
centre	-0.056	(5.11)	-0.054	(3.75)	-0.077	(4.64)	-0.025	(1.41)
married	-0.083	(6.08)	-0.088	(5.49)	-0.120	(6.41)	-0.094	(5.06)
head of household	-0.054	(4.63)	-0.058	(4.11)	-0.075	(4.53)	-0.060	(3.62)
dependent children	0.005	(0.36)	-0.007	(0.45)	-0.026	(1.51)	-0.028	(1.62)
Number of obs	5673		5522		5673		5522	
chi2(23)	1929.88		1847.26		2288.77		2074.12	
Prob > chi2	0		0		0		0	
Pseudo R2	0.3405		0.3015		0.3301		0.305	

note: asymptotic t-ratios in parentheses

Table 4: Aggregate transition probabilities between labour market states (L=low-pay, H=high pay, SE=self employment, UN=unemployment, RET=retired)

Hourly wages

threshold=bottom quintile				threshold=third decile			
N=2160	L 95	H 95	% 93	N=2160	L 95	H 95	% 93
L 93	56.05	43.95	15.69	L 93	70.79	29.21	24.72
H 93	6.26	93.74	84.31	H 93	9.66	90.34	75.28
% 95	14.07	85.93		% 95	24.77	75.23	

Monthly wages

threshold=bottom quintile				threshold=third decile			
N=2160	L 95	H 95	% 93	N=2160	L 95	H 95	% 93
L 93	61.76	38.24	15.74	L 93	64.76	35.24	24.31
H 93	8.13	91.87	84.26	H 93	8.99	91.01	75.69
% 95	16.57	83.43		% 95	22.55	77.45	

Hourly wages, L=bottom quintile

N=4096	L 95	H 95	SE 95	UN 95	RET 95	%93
L 93	46.91	36.79	3.21	10.37	2.72	9.95
H 93	5.59	83.76	1.08	2.11	7.46	50.09
SE 93	0.81	1.41	88.48	3.43	5.86	12.17
UN 93	13.02	13.02	9.38	59.90	4.69	4.72
RET 93	0.00	0.21	0.85	0.32	98.62	23.08
% 95	8.18	46.45	12.26	5.41	27.70	

Hourly wages, L=third decile

N=4096	L 95	H 95	SE 95	UN 95	RET 95	%93
L 93	59.72	24.64	2.69	9.32	3.63	15.56
H 93	8.67	81.16	0.99	1.44	7.73	44.48
SE 93	1.01	1.21	88.48	3.43	5.86	12.17
UN 93	18.75	7.29	9.38	59.90	4.69	4.72
RET 93	0.00	0.21	0.85	0.32	98.62	23.08
% 95	14.16	40.48	12.26	5.41	27.70	

Monthly wages, L=bottom quintile

N=4096	L 95	H 95	SE 95	UN 95	RET 95	%93
L 93	51.47	31.86	3.68	10.29	2.70	10.03
H 93	7.27	82.16	0.98	2.11	7.47	50.01
SE 93	0.61	1.62	88.48	3.43	5.86	12.17
UN 93	17.71	8.33	9.38	59.90	4.69	4.72
RET 93	0.00	0.21	0.85	0.32	98.62	23.08
% 95	9.71	44.93	12.26	5.41	27.70	

Monthly wages, L=third decile

N=4096	L 95	H 95	SE 95	UN 95	RET 95	%93
L 93	54.14	29.46	2.71	9.71	3.98	15.43
H 93	8.10	81.98	0.99	1.32	7.60	44.61
SE 93	0.81	1.41	88.48	3.43	5.86	12.17
UN 93	20.83	5.21	9.38	59.90	4.69	4.72
RET 93	0.00	0.21	0.85	0.32	98.62	23.08
% 95	13.05	41.58	12.26	5.41	27.70	

Table 5. Comparison of ML estimates of conditional low-pay probabilities equations under competing assumptions on initial conditions. Bottom quintile of the hourly wage distribution (asymptotic t-ratios in parentheses).

Model for low-pay probability conditional on	Low-pay		High-pay	
Assumption on initial conditions	Endogenous	Exogenous	Endogenous	Exogenous
experience/10	-0.0687	-0.2051	-0.0158	-0.0887
	-(0.6465)	-(2.9220)	-(0.3004)	-(1.6790)
education>=high school	-0.6398	-0.7816	-0.2286	-0.3117
	-(2.6898)	-(3.5180)	-(1.6147)	-(2.1380)
female	0.2423	0.4276	0.1978	0.3192
	(1.2268)	(2.6030)	(1.6943)	(2.7170)
non-manual	-0.1347	-0.2926	-0.4401	-0.5346
	-(0.5511)	-(1.2330)	-(2.9895)	-(3.5580)
firm size>=100	-0.4091	-0.6501	-0.3924	-0.5494
	-(1.4099)	-(2.5290)	-(2.7651)	-(3.8800)
public sector	0.0762	-0.3013	-0.5340	-0.6996
	(0.2285)	-(1.1520)	-(3.5323)	-(4.5840)
agricolture	0.0772	0.2359	0.1064	0.3986
	(0.2472)	(0.7560)	(0.3359)	(1.2080)
bank, insurance, transport& communication retail trade, personal &household serv	0.2572	0.3181	0.0006	0.0431
	(1.5111)	(1.8470)	(0.0043)	(0.2970)
living in the north	-0.3727	-0.4688	-0.1635	-0.1880
	-(2.2171)	-(2.9740)	-(1.6044)	-(1.7760)
constant	0.9524	0.7741	-0.9903	-0.5871
	(5.1484)	(4.2920)	-(5.8353)	-(3.7240)
rho	-0.4583		-0.6468	
	-(1.8010)		-(3.4950)	
n.obs	2148	334	2148	1814
pseudor2	0.2725	0.1329	0.2725	0.1661
pvalue	0.0000	0.0000	0.0000	0.0000

Table 6. Endogenous switching bivariate probit estimated marginal effects* for the conditional low-pay probability: Hourly wages

Low-pay threshold	Bottom quintile		Third decile	
Conditioning starting state	low-pay	high-pay	low-pay	high-pay
experience/10	-0.0300	-0.0015	-0.0294	0.0011
	-0.0687	*-0.0158*	*-0.0768*	*0.0075*
	-(0.6465)	-(0.3004)	-(1.2172)	(0.1503)
education>=high school	-0.2676	-0.0210	-0.0953	-0.0392
	-0.6398	*-0.2286*	*-0.2351*	*-0.2491*
	-(2.6898)	-(1.6147)	-(1.3634)	-(1.9422)
female	0.1053	0.0186	0.1102	0.0492
	0.2423	*0.1978*	*0.2808*	*0.3041*
	(1.2268)	(1.6943)	(1.9274)	(2.7750)
non-manual	-0.0583	-0.0451	-0.1369	-0.0843
	-0.1347	*-0.4401*	*-0.3346*	*-0.4811*
	-(0.5511)	-(2.9895)	-(1.7419)	-(3.6099)
firm size>=100	-0.1706	-0.0288	-0.0404	-0.0455
	-0.4091	*-0.3924*	*-0.0997*	*-0.3495*
	-(1.4099)	-(2.7651)	-(0.5139)	-(2.4608)
public sector	0.0332	-0.0502	-0.0988	-0.0490
	0.0762	*-0.5340*	*-0.2403*	*-0.3150*
	(0.2285)	-(3.5323)	-(1.0579)	-(2.1475)
agricolture	0.0337	0.0103	-0.1531	0.0427
	0.0772	*0.1064*	*-0.3636*	*0.2395*
	(0.2472)	(0.3359)	-(1.3761)	(0.6517)
bank, insurance, transport&	0.1120	0.0001	0.1792	0.0130
communication, retail trade	*0.2572*	*0.0006*	*0.4781*	*0.0831*
personal &household serv				
	(1.5111)	(0.0043)	(3.0072)	(0.6029)
living in the north	-0.1610	-0.0143	-0.1269	-0.0131
	-0.3727	*-0.1635*	*-0.3201*	*-0.0879*
	-(2.2171)	-(1.6044)	-(2.5041)	-(0.9472)
constant	*0.9524*	*-0.9903*	*1.2583*	*-0.9037*
	(5.1484)	-(5.8353)	(7.8214)	-(4.6931)
rho	-0.4583	-0.6468	-0.4690	-0.5307
	-(1.8010)	-(3.4950)	-(2.8237)	-(3.2501)
n.obs	2148		2148	
pseudor2	0.2725		0.258	
pmod	0.0000		0.0000	
phead	0.0665		0.2270	
psel	0.0001		0.0000	
Estimated state dependence	0.4938		0.6104	
True state dependence evaluated at the characteristics of the low-paid	0.3389		0.4161	
True state dependence evaluated at the characteristics of the high-paid	0.1939		0.3040	

*estimated coefficients in italic, asymptotic t-ratios in parentheses, phead is the p-value from a LR test for the exclusion of the instruments in the headline equation, psel is the p-value from a LR test for the inclusion of the instruments in the selection equation, pmod is the model's p-value.

Table 6 (continued). Endogenous switching bivariate probit estimated marginal effects*
for the conditional low-pay probability: Monthly wages

Low-pay threshold	Bottom quintile		Third decile	
Conditioning starting state	low-pay	high-pay	low-pay	high-pay
experience/10	-0.0081	-0.0092	-0.0001	0.0017
	-0.0185	*-0.0649*	*-0.0002*	*0.0120*
	-(0.1702)	-(1.3213)	-(0.0038)	(0.2519)
education>=high school	-0.0506	-0.0188	-0.1128	-0.0288
	-0.1153	*-0.1520*	*-0.2421*	*-0.1934*
	-(0.5029)	-(1.2026)	-(1.4731)	-(1.5130)
female	0.1512	0.0468	0.1901	0.0614
	0.3466	*0.3478*	*0.4148*	*0.3814*
	(1.6227)	(3.2913)	(2.8714)	(3.5271)
non-manual	-0.1960	-0.1010	-0.0294	-0.0765
	-0.4496	*-0.6855*	*-0.0633*	*-0.4595*
	-(1.7753)	-(5.1487)	-(0.3591)	-(3.4210)
firm size>=100	-0.1057	-0.0245	-0.0331	-0.0434
	-0.2406	*-0.2231*	*-0.0709*	*-0.3484*
	-(0.9243)	-(1.6194)	-(0.3790)	-(2.4851)
public sector	0.0746	0.0045	-0.0178	-0.0124
	0.1714	*0.0368*	*-0.0382*	*-0.0856*
	(0.6672)	(0.2743)	-(0.2196)	-(0.6314)
agricolture	-0.1585	0.1367	-0.0662	0.0976
	-0.3639	*0.6826*	*-0.1411*	*0.4790*
	-(1.0653)	(2.5969)	-(0.4896)	(1.6337)
bank, insurance, transport&	0.1254	0.0036	0.1015	0.0058
communication, retail trade	*0.2892*	*0.0289*	*0.2223*	*0.0394*
personal &household serv.				
	(1.6499)	(0.2124)	(1.5155)	(0.2818)
living in the north	-0.1997	-0.0107	-0.0635	0.0006
	-0.4597	*-0.0887*	*-0.1370*	*0.0043*
	-(2.7659)	-(0.9624)	-(1.1583)	(0.0468)
constant	*0.9767*	*-1.0374*	*0.8712*	*-1.2046*
	(5.4035)	-(6.6316)	(5.8356)	-(7.4571)
rho	-0.4718	-0.7233	-0.6095	-0.6747
	-(2.0983)	-(4.4092)	-(4.7347)	-(5.5251)
n.obs	2148		2148	
pseudor2	0.2334		0.2232	
pmod	0.0000		0.0000	
phead	0.3963		0.4415	
psel	0.0002		0.0000	
Estimated state dependence	0.5319		0.5567	
True state dependence evaluated at the characteristics of the low-paid	0.3771		0.3944	
True state dependence evaluated at the characteristics of the high-paid	0.2742		0.2860	

*estimated coefficients in italic, asymptotic t-ratios in parentheses, phead is the p-value from a LR test for
the exclusion of the instruments in the headline equation, psel is the p-value from a LR test for the inclusion
of the instruments in the selection equation, pmod is the model's p-value.

Table 7. Comparison between binary and polychotomous specification of the transition equation in models for the probability of low-pay persistence; Hourly wages.

Low-pay threshold	Bottom quintile		Third decile	
Transition equation	Ordered	Binary	Ordered	Binary
experience/10	-0.0096	-0.0314	-0.0081	-0.0287
	-0.0209	*-0.0720*	*-0.0193*	*-0.0746*
	-(0.2592)	-(0.6802)	-(0.3460)	-(1.1814)
education>=high scholl	-0.1960	-0.2694	-0.0776	-0.0942
	-0.4389	*-0.6457*	*-0.1799*	*-0.2315*
	-(2.3251)	-(2.7225)	-(1.1768)	-(1.3428)
female	0.0723	0.1069	0.0717	0.1092
	0.1569	*0.2468*	*0.1698*	*0.2769*
	(0.9882)	(1.2525)	(1.3138)	(1.8992)
non-manual	-0.0401	-0.0598	-0.0977	-0.1364
	-0.0876	*-0.1386*	*-0.2253*	*-0.3320*
	-(0.4494)	-(0.5666)	-(1.3499)	-(1.7307)
firm size>=100	-0.0508	-0.1687	0.0135	-0.0365
	-0.1117	*-0.4051*	*0.0318*	*-0.0898*
	-(0.5258)	-(1.3826)	(0.1855)	-(0.4616)
public sector	0.0776	0.0296	-0.0324	-0.0958
	0.1670	*0.0681*	*-0.0753*	*-0.2321*
	(0.6506)	(0.2046)	-(0.3779)	-(1.0202)
agricolture	-0.1069	0.0356	-0.1814	-0.1551
	-0.2402	*0.0818*	*-0.4049*	*-0.3668*
	-(0.9154)	(0.2617)	-(1.7018)	-(1.3895)
bank, insurance, transport &	0.1313	0.1121	0.2015	0.1813
communication, retail trade personal	*0.2842*	*0.2582*	*0.5047*	*0.4814*
&household serv				
	(1.8887)	(1.5147)	(3.3637)	(3.0362)
living in the north	-0.1604	-0.1646	-0.1234	-0.1280
	-0.3511	*-0.3822*	*-0.2911*	*-0.3213*
	-(2.4687)	-(2.3002)	-(2.5152)	-(2.5201)
constant	*0.9310*	*0.9556*	*1.1624*	*1.2576*
	(5.8346)	(5.1153)	(7.8697)	(7.8328)
ν0	*0.6011*		*0.2818*	
	(7.4652)		(6.5951)	
ν1	*0.8414*		*0.7755*	
	(8.2928)		(9.7521)	
ν2	*1.3376*		*1.0260*	
	(9.2229)		(10.4639)	
rho	-0.5824	-0.4509	-0.5658	-0.4766
	-(3.2373)	-(1.7691)	-(3.8483)	-(2.8700)
n.obs	2148	2148	2148	2148
pseudor2	0.2667	0.3083	0.2612	0.2966
pmod	0.0000	0.0000	0.0000	0.0000
phead	0.7691	0.1579	0.3913	0.0966
psel	0.0001	0.0002	0.0000	0.0000

notes: estimated coefficients in italic, asymptotic t-ratios in parentheses, phead is the p-value from a LR test for the exclusion of the instruments in the headline equation, psel is the p-value from a LR test for the inclusion of the instruments in the selection equation, pmod is the model's p-value.

Table 7 (continued). Comparison between binary and polychotomous specification of the transition equation in models for the probability of low-pay persistence; Monthly wages.

Low-pay threshold	Bottom quintile		Third decile	
Transition equation	Ordered	Binary	Ordered	Binary
experience/10	0.0253	-0.0106	0.0134	0.0024
	0.0534	*-0.0243*	*0.0269*	*0.0051*
	(0.6471)	-(0.2213)	(0.4824)	(0.0797)
education>=high scholl	-0.0670	-0.0534	-0.1160	-0.1097
	-0.1418	*-0.1225*	*-0.2339*	*-0.2327*
	-(0.7299)	-(0.5318)	-(1.6148)	-(1.4205)
female	0.1163	0.1519	0.1414	0.1841
	0.2467	*0.3508*	*0.2879*	*0.3966*
	(1.4354)	(1.6217)	(2.2968)	(2.7268)
non-manual	-0.1192	-0.1966	0.0145	-0.0230
	-0.2529	*-0.4538*	*0.0294*	*-0.0489*
	-(1.2106)	-(1.7816)	(0.1919)	-(0.2777)
firm size>=100	-0.0332	-0.1062	0.0134	-0.0288
	-0.0702	*-0.2433*	*0.0272*	*-0.0610*
	-(0.3367)	-(0.9259)	(0.1694)	-(0.3279)
public sector	0.1121	0.0704	0.0153	-0.0130
	0.2387	*0.1628*	*0.0309*	*-0.0277*
	(1.1304)	(0.6295)	(0.2043)	-(0.1599)
agricolture	-0.2068	-0.1511	-0.1366	-0.0669
	-0.4541	*-0.3482*	*-0.2739*	*-0.1409*
	-(1.5217)	-(1.0169)	-(1.0503)	-(0.4913)
bank, insurance, transport &	0.1435	0.1262	0.1352	0.1041
communication, retail trade personal	*0.3060*	*0.2934*	*0.2794*	*0.2255*
&household serv				
	(1.9380)	(1.6704)	(2.0507)	(1.5451)
living in the north	-0.1473	-0.2004	-0.0585	-0.0644
	-0.3130	*-0.4645*	*-0.1183*	*-0.1371*
	-(2.2156)	-(2.7887)	-(1.1244)	-(1.1662)
constant	*0.8942*	*0.9757*	*0.8653*	*0.8734*
	(5.5909)	(5.3489)	(6.3075)	(5.8800)
ν0	*0.3400*		*0.4527*	
	(6.0658)		(8.4924)	
ν1	*0.7564*		*0.7373*	
	(8.1752)		(10.1046)	
ν2	*0.9782*		*1.1638*	
	(8.8033)		(11.2813)	
rho	-0.5971	-0.4579	-0.6856	-0.6254
	-(3.8866)	-(2.0000)	-(6.3920)	-(4.8878)
n.obs	2148	2148	2148	2148
pseudor2	0.2369	0.2691	0.2193	0.2513
pmod	0.0000	0.0000	0.0000	0.0000
phead	0.1708	0.4830	0.2058	0.3358
psel	0.0003	0.0006	0.0000	0.0000

notes: estimated coefficients in italic, asymptotic t-ratios in parentheses, phead is the p-value from a LR test for the exclusion of the instruments in the headline equation, psel is the p-value from a LR test for the inclusion of the instruments in the selection equation, pmod is the model's p-value.