Do the 'Working Poors' Stay Poor?
An Analysis of Low-Pay Dynamics in Italy

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Abstract

This paper looks at transition probabilities at the bottom of the Italian earnings distribution using survey panel data from the Bank of Italy. The econometric analysis is characterised by a proper treatment of the 'initial conditions' problem and by the ability to test for 'genuine state dependence', the extent with which past low-pay alters the ceteris paribus chance of experiencing low-wages. Our results indicate that initial conditions are actually endogenous and that overlooking the problem leads to overstate the effect of personal attributes on transition probabilities. Also, genuine state dependence is found to be an important determinant of low-pay persistence, accounting for roughly half of aggregate figures. On the other hand, apart from labour market experience, individual attributes are found to affect on transition probabilities, although to a limited extent.

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

JEL code: J31, D31, C25

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Contents

1. Introduction

The growth of earnings inequality which has characterised many industrialised nations over the last couple of decades (see Gottschalk and Smeeding, 1997, for a survey) has brought the “working poors” issue on the top of the agenda both for policy makers and social analysts. Widening wage differentials raise the probability that labour incomes fall below pre-determined ‘decency threshold’, so that for a growing proportion of labour market participants holding a job may no longer ensure the attainment of adequate living conditions. Equity concerns about the welfare of workers at the bottom of the earnings distribution have inspired proposals of redistributive policy measures such as minimum wages (Freeman, 1996). At the same time, a considerable amount of academic research has been devoted to this subject in order to understand the features of the phenomenon and provide the basis for policy design.

To observe that the likelihood of low-pay increases over time offers only a static picture of the issue. Growing low-pay incidence or earnings dispersion is consistent with either an increase in the volatility of individual earnings or with persistently divergent wage profiles within the life-time distribution of earnings. While observationally equivalent, these two extremes have opposite policy implications. In the first case (growing volatility), the experience of low pay in a given year is a transitory phenomenon, say because individuals have temporarily accepted a low-paid job as a first step into the labour market or because the exposition of labour incomes to product market fluctuations has increased. In this event, the labour market operates a dynamic redistribution of earnings over individual life-cycles. Policy interventions such as minimum wages may well worsen employment probabilities at the bottom of the earnings distribution without any real impact of poverty alleviation in the medium run. At the other extreme, low-pay could be a persistent feature of individual earnings careers and individuals are trapped below the low-pay threshold from one period to the next. In this second case widening wage differentials will turn into a deeper economic - and social - stratification, so that policy aimed at alleviating *labour market poverty* are more urgent. These remarks clarify that persistent low-pay is an issue even when cross-sectional earnings distributions are stable through time.

A thorough assessment of the low-pay issue and - hence - a better framework for policy design thus require the adoption of a dynamic perspective, in turn allowed by the use of panel data on individual wage histories. By enabling researchers to observe individuals' positions within the wage distribution in different time periods, panel data can reveal to what extent low-pay consitutes a trap; put differently, panel data make it possible to move from the analysis of incidence to the analysis of persistence in low-pay, and to quantify the degree of earnings mobility across the low-pay threshold.

Studies of income and earnings mobility have a long and well established tradition (see Shorrocks, 1978, and Hart, 1983, among others). The growth of earnings inequality has revived researchers' interest in distributive issues and several studies have been devoted to the econometric modelling of low-pay transitions and mobility in the recent past, especially in Britain (see Elias and Gregory, 1994, Sloane and Theodossiou, 1996, and Stewart and Swaffield, 1999). The analytical approach proposed in these papers consists in estimating Limited Dependent Variables (LDV) models such as probit or logit for the probability of being low-paid conditional on having been low-paid in the past. In particular, Stewart and Swaffield (S&S henceforth) clarify that such a conditioning on lagged low-pay episodes has to be treated with caution, given its potential endogeneity for current low-pay, the so called *initial conditions problem*. They provide an analytical framework which permits to handle such a problem by jointly estimating conditioning and conditional low-pay probabilities using a bivariate probit model with endogenous switching. Their results point towards the endogeneity of lagged wage states when modelling earnings transition probabilities.

The econometric modelling of low-pay transitions can yield two sets of indications useful for policy purposes (OECD, 1997). First, by quantifying the association between personal attributes and transition probabilities, such models can help in disentangling between short and long run working poors, thus revealing the existence of target groups for policy interventions. Second, their results can be used to analyse the relevance of *genuine* *state dependence*, the impact of past low-pay episodes on the likelihood of experiencing low-pay, holding fixed individual characteristics. In such a case, the sole experience of low-pay alters earnings potential (say via human capital depreciation or bad signalling) and, for this reason, it is the whole pool of working poors which should form the target group for policies.

The present paper will adopt and extend the S&S's analytical framework, using survey panel data from the Bank of Italy for 1993 and 1995. Evidence on low pay and - more in general - earnings dymamics in Italy is still scarce. Contini et al. (1998) estimate LDV models for low-pay transitions in a context with exogenous initial conditions. They show that job mobility and employment in large firms positively influence transitions out of low-pay, while, on the other hand, employment in the service sector and past unemployment episodes favour transitions into low-pay. An international comparison of earnings mobility is proposed by Bigard et al. (1998) where a set of mobility indicators is estimated on French and Italian panel data, showing that the Italian distribution is more rigid, especially at the bottom. Variance components models of earnings with which the dynamics of inequality are decomposed into permanent and volatile components are estimated in Cappellari (2000a), showing that the growth of wage differentials characterising Italy over the 1980s can be ascribed to both components.[1] This paper will contribute to this literature by modelling earnings transitions at the bottom of the distribution, while accounting for endogeneity issues. Results point towards the appropriateness of the econometric framework adopted, initial conditions exogeneity not being supported by the data. Moreover, our estimates indicate that, to a large extent, low-pay persistence may be attributed to state dependence effects. On the other hand, while labour market experience has no effect on transition probabilities, other indicators of labour demand and supply favour low-pay transitions, although to a limited extent.

The rest of the paper is as follows. Section 2 provides a description of the data, dfines the low pay thresholds and looks at aggregate low pay transitions. Section 3 sets out our

[1] Results on both the statics and dynamics of low-pay are reported in Cappellari (2000b). The present paper extends tha dynamic analyses presented there.

model of low-pay dynamics and reports results, whose robustness is investigated in section 4. Section 5 draws some concluding remarks.

2. Data, low-pay definitions and aggregate transition patterns

The data utilised in this paper originate from the panel component of *Survey on Households Income and Wealth* (SHIW), conducted by the Bank of Italy on a biannual basis since 1977, and refer to 1993 and 1995. The sampling unit for interviews is the household. However, questionnaires have a double level design by which information on each household member can be recovered; in particular, increasingly detailed labour market information has been made available in recent waves of the survey. [2]

The characteristics of the data are reported in Table 1. The first two columns refer to the cross-sectional composition of the sample in 1993 and 1995, while the third reports the same features, observed in 1993, for the panel sub-sample linking the two waves, which will be used for estimation. The upper part of the Table illustrates the structure of the whole sample according to individuals' labour force status; 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, about 60% of respondents do not participate into the labour market.[3]

The next part of the Table describes the sample structure for full-time employees with valid wage observations and aged between 18 and 65, which we will focus on in our econometric analysis. The differences in sample composition between the cross-sections

[2] See Brandolini and Cannari (1994) for a general overview of the SHIW and Cannari and Gavosto (1994) for a complete description of the subsection referring to the labour market. The panel component of the survey started in 1989. Panel respondents are randomly sampled among those reporting availability for reinterview (roughly 90% of households interviewed in 1993 reported availability for a new contact). Their proportion, however, has initially been fairly small and approached 50% only in the 1993-1995 sample. Moreover, 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. For example, before 1993 the definition of public sector employees did not cover workers in state schools and national health service, thus excluding a relevant proportion of the public sector workforce. Also, information on the employer's size has been provided only since 1993.

[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 classifying themselves as retired.

and the panel are not dramatic when age, experience and gender are taken into account. 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 some effect on the sample structure and, thence, could drive parameter estimates. While not formally testing for attrition ignorability, evidence supporting the robustness of the paper's results to the sample selection criterion will be provided in Section 4.

Several definitions of low earnings have been adopted in previous studies of low-paid employment. Alternatives proposed range from absolute thresholds defined according to some fixed partition of the wage range or to some legally set minimum wage (Smith and Varvricheck, 1992) to relative discretizations of the distribution based upon quantiles (OECD, 1997). Definitions mixing the two approaches, such as fixed proportions of the median or mean wage, have also been adopted (see S&S among others). In the absence of any precise indication of where the *labour market poverty line* should be set, our analysis will look at different thresholds in parallel and, in particular, the first quintile and the third decile of the cross-sectional earnings distribution of full time dependent workers aged between 18 and 65 will be considered. Both thresholds, being order statistics, guarantee robustness to outliers and avoid problems of updating over time. It must be stressed that these thresholds

[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 implies 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.

are computed from cross-sectional distributions, but will be used to analyse the panel sub-sample: this implies that the proportion of cases falling below the threshold in the estimation sample will not correspond to the quantile's definition and that a worker abandoning, say, the bottom quintile from 1993 to 1995 will not necessarily push another worker below the threshold. In this sense, the definitions adopted mix the absolute and relative approaches.

A further issue is the definition of the wage variable. The available information refers to net annual earnings, inclusive of overtime payments, and, separately, to the monetary value of fringe benefits. In order to look at full earnings, the two variables have been added together, obtaining the take-home net annual wage. This figure has then been normalised to account for heterogeneity in the amount of time worked. In this case, the available information 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. Then, 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, monthly wages will also be analysed in parallel, so that results robustness to this assumption can be verified.

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. Nominal wage growth has been fairly weak either for the mean and the median, while earnings dispersion has basically remained constant. Morever, 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; this last value tends to be lower than the first quintile. The lower panel of Table 2 reports the

[5] Information on the employer's size only refers to private sector employees. Thence, size related differentials will refer to variations in wage transition probabilities within the private sector.

incidence of low-pay, both in the cross-sectional sample and in the panel sub-sample.[6] We can observe how the lowest threshold (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 dispersed. Moreover, when the panel sub-sample is taken into account, low pay incidence decreases under each threshold, indicating that small cells problem is more likely to arise in this case[7]; this evidence also shows that these thresholds are not necessarily relative when applied to the panel.

Table 3 reports aggregate statistics of low-pay dynamics computed on the sub-sample of the continuously employed labour force aged 18-65. The first row in the Table shows to what extent the 1993 low-paid persist in such a status two years later. Low-pay persistence appears to be substantial: 56% of those with earnings below the bottom quintile of the 1993 hourly wage distribution were still low-paid in 1995, while the figure raises to nearly 71% when the threshold is defined in terms of the third decile. Corresponding figures are 61 and 64% for the monthly wage distribution. The second line of the Table reports a measure of raw state dependence in low-pay transition probabilities, i.e. the extent with which they vary according to the conditioning starting state; in particular, we report the difference $prob[L_{95}|L_{93}] - prob[L_{95}|H_{93}]$ (with L and H meaning low- and high-pay, respectively). These figures suggest that the likelihood of low-pay is considerably higher for those who begin the transition below, rather than above, the low-pay threshold, the difference ranging from approximately 50 to 60 percentage points according to the threshold and wage definition considered. Thence, at this aggregate level, state dependence effects seem to play a relevant role in governing low pay transitions.

The lower panel of Table 3 cross-tabulates aggregate low-pay persistence probabilities against observable workers' attributes. Evidence from the table suggests that low-pay

[6] In two cases (third decile of hourly wages in 1995 and bottom quintile of monthly wages in 1995) low-pay incidence exceeds the quantiles definition, a result which reflects the presence of clustering in the data.
[7] This "small cells" problem is the reason which led to the exclusion of 2/3 the median as a low-pay threshold for the econometric analysis. The same problem arises in OECD (1996).

persistence is particularly relevant for females, more recent labour market entrants, those with low educational qualifications, manual workers, private sector workers (especially those in the retail trade, personal services, transport and communication and banking/insurance industries), southern workers and workers in small firms. However, the table also shows that in many cases these frequencies are computed on relatively small numbers of observations, so that it might be difficult to uncover these results in a regression analysis due to small cells problems. Moreover, evidence from these cross-tabulations may result from compositional effects and do not allow us to make *ceteris paribus* statements. We now turn to the assessment of these points.

3. Econometric analysis of low-pay transition probabilities

The detection of aggregate state dependence in Section 2 is not informative about the forces generating it (Heckman, 1981b). On the one hand, it could be the result of workers *heterogeneity*, with the personal characteristics (both observable and unobservable by the researcher) affecting low-pay propensities 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 *genuine 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.[8] The distinction between heterogeneity and genuine state dependence within aggregate persistence has relevant policy implications. In the first case the probability of persisting in low-pay can be influenced by modifying workers' attributes (say via training programs), and income support policies should be targeted on those groups with a poor endowment of the attributes favouring exits from low-

[8] 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-

pay. In the case of genuine state dependence, entrapment into low-pay has less to do with personal attributes, but is determined by the past experience of low pay *per se*. This, in turn, implies that policies aimed at modifying workers attributes may have a limited scope and interventions should be targeted on the whole pool of working poors, rather then on specific sub-groups within it. The econometric model presented in this section will allow us to test for the presence of genuine state dependence and to quantify its relevance.

The specification of an econometric model for individual low-pay transition probabilities requires to analyse the influence of personal characteristics on low-pay probabilities *conditional* on lagged low-pay. As pointed out by Heckman (1981a) and stressed by S&S in the context of low-pay transitions, conditioning on the lagged state cannot be taken as exogenous. Since the wage process under investigation started prior to the sampling period, its initial values 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. In Heckman's (1981a) words, an *initial conditions problem* arises which, if ignored, would lead to biased parameter estimates.

As suggested by S&S, the issue may also be seen 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. Thence, some sort of correction for sample selection is needed. However, as shown by O'Higgins (1994), the limited dependent nature of the transition equation implies that Heckman's correction techniques are not suitable in this context and the two probabilities (starting state and transition) have to be estimated jointly.

3.1 Model specification

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paid jobs induces workers to reduce their reservation wage, thus raising the probability of accepting low-wage

To overcome the initial conditions problem, S&S utilise a bivariate probit model with partial observability of one of the two equations. Here I remove the partial observability hypothesis and extend their approach utilising a bivariate probit model with endogenous switching, i.e. the equivalent of usual endogenous switching models when the "main" equation is itself a probit-type one.[9] As we will see below, the main gain from this extension is the possibility to test for genuine state dependence.

First of all, let us specify the selection process as a probit equation for the probability of being low-paid in 1993:

$$\begin{aligned} & g(w_{i93}) = x_i'\delta + u_i \\ & u_i \sim N(0,1) \\ & d_{i93} = \mathrm{I}(w_{i93} \leq \lambda_{93}) \\ & i = 1,\ldots,N \end{aligned} \tag{1}$$

where w_{i93} is the nominal wage for worker i in 1993, x_i is a vector of wage determinants with associated parameter vector δ, g(.) is a monotonic unspecified transformation such as the error term u_i is distributed as standard normal, λ_{93} is the low-pay threshold in 1993 and I(A) is an indicator variable equal to 1 whenever A is true and 0 otherwise. Thence:

$$\begin{aligned} prob(d_{i93} = 1) = prob(w_{i93} \leq \lambda_{93}) = prob(g(w_{i93}) \leq g(\lambda_{93})) = \\ \Phi(g(\lambda_{93}) - x_i'\delta) = \Phi(x_i'\beta) \end{aligned} \tag{2}$$

where Φ is the standard normal cumulative density function (c.d.f.), the new constant term in β subsumes the difference between $g(\lambda_{93})$ and the old constant in δ and the coefficients associated with individual characteristics in β are the same as in δ, but with opposite sign.[10]

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offers in the future.

[9] Endogenous switching equations models for continuous variables are set out in Lee (1978).

[10] 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.

It has to be stressed that the use of the specification in (1) does not require any distributional assumption on wages or log-wages. Moreover, the non-linear treatment of the wage variable implicit in (1) corresponds to the idea that the wage process is not continuous, but some break occurs in correspondence of the low-pay threshold. In this way the effect of workers attributes on low-pay probabilities can directly be estimated; to obtain similar effects from usual (log-) wage regressions distributional assumptions would be needed (see Lillard and Willis, 1978). Finally, we could note that the dichotomic treatment of a continuous variable implies a loss of information; its relevance for our analysis will be assessed in Section 4 by means of a more flexible specification of the wage distribution.

Next, let us specify the probability of 1995 wage states *conditionally* on 1993 outcomes:

$$\begin{aligned} &h_1(w_{i95}) = z_i'\eta_1 + \varepsilon_{1i} \qquad \text{if} \quad d_{i93} = 1 \\ &h_2(w_{i95}) = z_i'\eta_2 + \varepsilon_{2i} \qquad \text{if} \quad d_{i93} = 0 \\ &\varepsilon_{ij} \sim N(0,1) \qquad j = 1,2 \\ &d_{i95} = I(w_{i95} \le \lambda_{95}) \end{aligned} \tag{3}$$

where z_i is a sub-vector of x_i.[11,12] Thence, our model allows for genuine state dependence in that the effect of the whole set of personal characteristics is shifted by the experience of low-pay in 1993. The hypothesis of absence of genuine state dependence can then be formulated as $H_0{:}\eta_1=\eta_2$.

Finally, we assume that u and the ε's are jointly distributed as a tri-variate normal:

[11] Personal characteristics in z_i are measured in 1993 in order to avoid endogeneity issues between changes in individuals' attributes and changes in wages.

[12] Kimhi (1999) provides a technical discussion of this of model. O'Higgins (1994) utilise a model which differs from ours in that the restriction $\varepsilon1=\varepsilon2$ is imposed.

$$\begin{pmatrix} u_i \\ \varepsilon_{1i} \\ \varepsilon_{2i} \end{pmatrix} \sim N_3\left[\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & & \\ \rho_1 & 1 & \\ \rho_2 & \rho_3 & 1 \end{pmatrix}\right]. \tag{4}$$

The correlation matrix in (4) deserves some comment. ρ_1 and ρ_2 represent correlation in unobservables between low-pay probabilities in 1993 and (conditional) low-pay probabilities in 1995. Identification of the two coefficients is reached through the panel dimension of our data: they capture the effect of (not necessariliy fixed) individual heterogeneity which generates autocorrelation in the unobservables of the wage process. As we said above, such correlation is the vehicle of the initial condition problem; following S&S, we can test for unobserved heterogeneity and thence initial conditions exogeneity by testing: $H_0 1$: $\rho_1=0$; $H_0 2$: $\rho_2=0$. On the other hand, ρ_3 is not identifiable since it would require observations belonging contemporaneously to both regimes.

Given the assumptions on the errors distribution, a generic likelihood contribution is:

$$\begin{aligned} L_i &= \Phi_2(k_{i95} z_i' \gamma_j, k_{i93} x_i' \beta; k_{i93} k_{i95} \rho_j) \\ k_{it} &= 2d_{it} - 1, \quad t = 93,95 \\ j &= 2 - d_{i93} \end{aligned} \tag{5}$$

where Φ_2 is the bivariate normal c.d.f. and the γ's derive from the η's in the same fashion β derives from δ in (2); thus the elements of γ_1 model the effect of individual characteristics on low-pay persistence, while γ_2 captures the effect of the same characteristics on the probability of falling into low-pay from the upper part of the distribution. Our test of genuine state dependence can then be re-written as: H_0:$\gamma_1=\gamma_2$. Note that although these expressions refer to the joint probability, estimation of the γ_j'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 c.d.f. is required.

It is instructive to look at the "correct" expressions for the conditional low pay probabilities (i.e. summing to one over the sample of the initially low or high-paid):

$$\begin{aligned} prob(d_{i95} = 1 | d_{i93} = 1) &= \Phi_2(z_i'\gamma_1, x_i'\beta; \rho_1) / \Phi(x_i'\beta) \\ prob(d_{i95} = 1 | d_{i93} = 0) &= \Phi_2(z_i'\gamma_2, -x_i'\beta; -\rho_2) / \Phi(-x_i'\beta) \end{aligned} . \tag{6}$$

Conditional probabilities in (6) clarifies how the γ_j vectors can be consistently estimated with a univariate probit on sub-samples defined according to the starting state only if ρ_j=0, i.e. only if the starting state is exogenous.

Estimated parameters from the endogenous switching bivariate probit can be used to compute "marginal effects" on conditional probabilities in (6). However, some caution is required: given that z is a subvector of x, a change in a variable in *z* implies also a change in the corresponding element of *x* and thus in the probability of the conditioning starting state. What we would require is instead a change in the conditional probability holding the past fixed (see S&S). With this aim, and focusing for the exposition's sake on the probability of low-pay persistence, let us define the average predicted probability of initial low-pay as $\hat{\Phi} = \sum_i \Phi(x_i'\hat{\beta}) / N$ and its argument as $\hat{x\beta} = \Phi^{-1}(\hat{\Phi})$; the marginal effect for the k-th dummy variable[13] is then computed as

$$[\Phi_2(\hat{\gamma}_{1k} + \bar{z}_{1-k}'\hat{\gamma}_{1-k}, \hat{x\beta}; \rho_1) - \Phi_2(\bar{z}_{1-k}'\hat{\gamma}_{1-k}, \hat{x\beta}; \rho_1)] / \hat{\Phi} \tag{7}$$

z1 indicating that the average is taken over the relevant sample, the initially low-paid in this case, and the -k subscript denoting the corresponding vector deprived from its k-th element.

Identifying restrictions in the form of variables entering x_i but not z_i - which is to say, variables affecting wage levels but not wage changes - are needed in order to estimate the model. Here I adopt 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. Since 1993 the SHIW questionnaire contains a section 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 "children" in the interviewed household, the necessary information has directly been recovered from the household questionnaire. For those household members not belonging to any of the three categories (1.6% of the estimation sample, see table 1) dummies for missing information have been used.[14]

Besides the parental background indicators, another variable which only enters the selection equation is the square of labour market experience, given the interpretation of wage change equation which can be attributed to (3), i.e. states in 1995 conditional on states in 1993. 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.

3.2 Results

Before considering the whole set of results from the endogenous switching probit analysis, it can be instructive to look at Table 4, which compares ML coefficients estimated under the two competing assumptions (i.e. endogeneity *versus* exogeneity) on the conditioning starting state, thus providing insights on the kind of bias induced by assuming exogenous initial conditions.[15] The first remarkable fact is that the null of exogenous initial conditions is rejected for both starting states (i.e. low-pay and high-pay), the two correlation

[13] For labour market experience (the only continuous variable among regressors) the effect has been computed as that of a discrete change from 10 to 20 years of experience.
[14] These dummies also "cover" observations for which parental background information were genuinely missing. 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%.
[15] The table focuses on the low-pay threshold defined as the bottom quintile of the hourly wage distribution. Results similar to the ones reported were obtained for the other low-pay thresholds 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. The

coefficients being statistically significant at conventional levels. Secondly, both size and significance of estimated coefficients tend to be larger when exogeneity is assumed, especially for labour market experience. The evidence confirms similar comparisons reported by S&S and indicates that overlooking initial conditions endogeneity could produce misleading results on low-pay transitions.

The complete set of results from the switching bivariate probit model is presented in table 5 in terms of "marginal effects" on the conditional low-pay probability, using both low-pay thresholds and wage definitions.

A first relevant result emerging from the table is the validity of our over-identifying restrictions, i.e. the use of parental background indicators to instrument initial conditions. The bottom panel of Table 5 indicates that the exclusion of these variables from the transition equation cannot be rejected at usual confidence levels. On the other hand, they are jointly significant in the selection (i.e. low-pay level) equation.

A second hypothesis we can test is the exogeneity of initial conditions, which - as we saw above - amounts at testing for the significance of the rho's. It can be observed that the null of initial conditions exogeneity is rejected at usual confidence levels in each of the cases considered. We can also note that estimates of these coefficients turn out to be 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. Since the selection equation is the same whatever the conditioning starting state, this holds also for those who begin the transition in the upper part of the distribution.

number of observations used differs from those of tables 1 and 3 due to missing values in some of the explanatory variables.

Taking now the effect of observable characteristics into account[16], it can first be noticed how labour market experience has basically no effect in reducing the conditional probability of having a low-wage. Thence, net of other observable attributes, labour market seniority does not help in escaping the low-pay trap.

Educational qualifications equal or higher than high school degrees, on the other hand, have an effect in such direction which tends to be stronger for those with an initial wage below the low-pay threshold. For example, if we consider the low-pay threshold defined as the bottom quintile of hourly wages, education reduces the conditional low-pay probability by 30% for those who were already low-paid, while for the initially high-paid the figure drops to 2%. Corresponding figures become 13% and 2% if the third decile of monthly wages is analysed.

A similar asymmetric effect can be observed for the female dummy, but with opposite signs, females experiencing a probability of low-pay persistence which is roughly 10 to 20% higher than the males' one.

Holding non-manual jobs has a clearly significant impact in reducing the probability of falling into low-pay from the top of the distribution, 5 to 9% less than manual workers; effects on low-pay persistence, although larger in size, are somewhat less robust in that they are statistically significant in only two cases. Similar remarks apply for the large firms (100 or more employers) dummy, with the reduction in the conditional low-pay probability bounded below 5%; on the other hand, estimated coefficients for small-medium size firms (between 20 and 100 employers) do not appear to be statistically significative.

Affiliation to the public sector reduces the conditional probability of falling into low-pay (-5% compared to private sector manufacturing) when hourly wages are analysed, while the effect vanishes for monthly wages. This evidence is a likely effect of the lower supply of hours per week characterising public sector employment. Considering the other sectoral

[16] Observable characteristics are controlled for at a rather aggregate level; for example, education is captured by a dummy for those with at least a high school degree. This choice is aimed at avoiding small cells problems: as seen in Table 3, groups like managers or college graduated tend not to fall below the low-pay threshold, so that the corresponding dummies happen to be "perfect classifiers" and the associated coefficients are unidentifiable. The pooling of male and female data is also aimed at ensuring an adequate sample size.

dummies (the reference category is private sector manufacturing), the most evident regularity can be observed for the bank-insurance-real estate service sector. In particular, while the effect on low-pay persistence turns out to be positive (between 16 and 27%) and statistically significative (especially for hourly wages), signs revert and both size and significance drop when the effect on falls into low-pay from the upper part of the distribution are taken into account. Results on persistence could arise from those workers which are on a low-level job career (actually involving manual tasks such as delivering) but do not classify themselves as blue collars. These findings also mirror similar results for Italy obtained by Contini et al. (1998) on administrative panel data. Finally, taking the remaining sectoral effects into account, we can notice that no clear pattern seems to arise.

The last group of regressors included in our model refers to region of residence, the reference category being workers living in the centre-south-islands. Low-pay persistence is significantly lower for those living in the north-west (between 13 and 30 percentage points) and in the north-east (between 10 and 14 percentage points), although in this last case statistical significance tends to be lower. On the other hand, regional effects tend to vanish if we consider transition into low-pay from the top of the distribution.

Results from the bivariate switching probit analysis can be used to test for genuine state dependence and to quantify its importance within aggregate persistence. Evidence from this exercise is reported at the bottom of table 5. The row labelled “Estimated state dependence” reports the averge difference in the conditional probability of being low-pay computable from the estimated model:

$$
\begin{aligned}
ESD = {} & \Big\{ \sum_{i:di93=1} \Phi_2(z_i \hat{\gamma}_1, x_i \hat{\beta}; \hat{\rho}_1) / \Phi(x_i \hat{\beta}) \Big\} / \sum_i d_{i93} - \\
& \Big\{ \sum_{i:di93=0} \Phi_2(z_i \hat{\gamma}_2, -x_i \hat{\beta}; -\hat{\rho}_2) / \Phi(-x_i \hat{\beta}) \Big\} / \sum_i (1 - d_{i93})
\end{aligned}
\qquad (8)
$$

providing a measure of overall state dependence which is approximately the same as the aggregate state dependence effect of Table 3. The next row reports the p-value from a LR test of the hypothesis H0:$\gamma 1=\gamma 2$, which we interpret as a test for the presence of genuine state dependence, i.e. the effect of individual characteristics on conditional low-pay probabilities is altered by past low-pay episodes.[17] In each of the four cases the hypothesis is clearly rejected, indicating that past low-pay affects -*ceteris paribus*- the likelihood of low-pay episodes. Finally, the table quantifies the extent of genuine state dependence as the average difference in the conditional low-pay probability each individual would have experienced had she started the transition from above or below the low-pay threshold:

$$GSD = N^{-1}\sum_{i}\{\Phi_2(z_i\hat{\gamma}_1, x_i\hat{\beta};\hat{\rho}_1)/\Phi(x_i\hat{\beta}) - \Phi_2(z_i\hat{\gamma}_2, -x_i\hat{\beta};-\hat{\rho}_2)/\Phi(-x_i\hat{\beta})\} \tag{9}$$

Our results indicate that genuine state dependence is considerable, accounting for roughly half of the observed state dependence. Going back to the economic interpretation and the policy implications of the phenomenon, this evidence suggest that low-pay can have an effect in altering the future development of wage careers and that this could limit the effectiveness of labour market policies aimed at modifying the set of personal attributes causing low-pay. Also, these findings suggest that the whole set of the working poors should be the target for active policies for labour market poverty.

4. Sensitivity analysis

The aim of this section is to assess the robustness of our results when two of the assumptions implicitly made in the estimation of the model given by (1), (3) and (4) are, in turn, relaxed. First, we will extend our estimation sample to include those individuals leaving

[17] If one thinks of signalling effects as possible source of state dependence, this is a test for the absence of low-pay stigma, i.e. wage discrimination according to past low-pay status.

the wage distribution during the transition and, second, we will extend our model and allow for a more flexible specification of the wage distribution.

4.1 Accounting for exits from the wage distribution

Estimation of the model of Section 4 is based on the subsample of the continuously (full-time) employed labour force, while those individuals with a valid wage in 1993 but not in 1995 are excluded from the analysis. As long as the propensity to leave the sample of wage earners is correlated with unobservables in the mobility process, such a sample selection rule could lead to biased inference.

A rough indication of how the propensity to exit from the wage distribution varies according to the starting wage status is provided by the left panel of Table 6, which reports destination labour market states for the sample of 1993 wage earners belonging to "panel households" (workers in "non-panel households" are not considered since their exits can be deemed random). Two relevant facts can be observed. First, the propensity to remain within the wage distribution is some 13% higher for those who are high-paid in 1993. Second, conditional on leaving the wage distribution (bracketed figures) destination states differ quite markedly according to starting states. In particular, while the likelihood of unemployment is much higher for those who were previously low-paid, the reverse is true for retirement. Evidence on conditional unemployment probabilities suggests that low-paid jobs are characterised by higher instability, while the difference in transitions into retirement could be an effect of the life cycle of earnings. On the whole, this evidence suggets that results obtained on the "balanced" sample of wage earners should be considered with caution.

To assess the relevance of non-random (wage) attrition for our analysis, here we follow S&S and modify the definition of the 1995 event[18], so that also those leaving the wage

[18] A formal assessment of attrition bias would require to expand our model with a selection equation for sample selection, a task which is beyond the scope of the present paper. In particular, such an expansion would add a dimension to the problem and require computation of trivariate normal integrals. This extended model has been estimated in Cappellari (1999) by means of simulation techniques, showing that attrition is ignorable in our analysis of low-wage transitions on SHIW data.

distribution will be included in the estimation sample; in particular, we re-define the 1995 status as follows:

$$d_{i95} = \begin{cases} I(w_{i95} \leq \lambda_{95} \quad or \quad i \quad is \quad out \quad of \quad the \quad 1995 \quad wage \quad distribution) & if\, d_{i93} = 1 \\ unobservable \quad if \quad d_{i93} = 0 \end{cases} \tag{10.a}$$

while the conditioning equation is still given by (1) (but specified on a larger N) and errors in the conditioning and transition equations are assumed to be jointly distributed as bivariate normal with unit variances and correlation coefficient ρ.

Two aspects of (10.a) must be noted. First, for the 1993 low-paid, being low-paid or not paid in 1995 are treated in the same way (i.e. d_{i95}=1), not going up the wage distribution being the common factor. Second, the partial observability hypothesis characterising the S&S's model is reintroduced for the 1993 high-paid. After all, Table 6 has shown that exits from the wage distribution tend to lead to rather different destinations depending upon the starting wage position. Thence, while it seems reasonable to amalgamate low-pay and no-pay for those who start from low-pay, this does not necessarily hold for those who start from high pay - who are possibly better off in no-pay than in low-pay - and it has been preferred to assume partial observability in this last case.

Our estimation sample has been enlarged to include 567 cases which belonged to "panel households", had a valid wage in 1993 but were either part-time workers, self-employed, entrepreneurs, unemployed, retired, housewives, not observed or had a missing wage in 1995. While for these cases exits from the wage distribution are due to economic or demographic reasons, the rest of the 1993 cross-section of wage earners belong to "non-panel" households and is not observed due to the random sampling scheme, so that it would make no sense to include it in the analysis.

Table 7 contrasts results obtained with this enlarged sample (column 2) with those emerging from estimating the S&S model ($d_{i95}=I(w_{i95}<=\lambda_{95})$ if $d_{i93}=1$, d_{i95} unobservable otherwise; column 1) on the sample of continuously employed workers. Any dramatic change in results would then signal that our conclusions in section 4 are driven by the sample selection rule. Evidence from the table[19] suggests that this is not the case, ML estimates being fairly stable across subsamples. In particular, coefficients which are statistically significant in column 1 do not change considerably when we move to column 2, while other effects tend to be more volatile between the two columns.

Besides its relevance in supporting our analysis of section 4, this evidence could also be interpreted in economic terms by saying that the factors generating low-pay persistence are similar to those driving the low-paid out from the wage distribution, a statement which is in line with the relevance of low-pay/unemployment cycles singled out by Stewart (1999) for the UK.

4.2 Accounting for the width of transitions

As is well recognised by the statistical literature on mobility (see, for example, Shorrocks, 1978), 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 of Section 3. In other words, that model 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 enough to bring individuals above the low-pay threshold. If one views these small pushes as potential sources of measurement errors, then accounting for transitions width allows a more robust assessment of the forces governing the mobility process.

[19] For the sake of compactness, attention is restricted to low-pay defined as the bottom quintile of the hourly wage distribution. Analogous results were obtained adopting the other low wage definitions. This also applies for

The right panel of Table 6 reports aggregate transition probabilities through the deciles of the 1995 hourly wage distribution for those who start the transition from the two bottom deciles (i.e., we are considering the lower threshold). 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 reach the decile just adjacent the low-pay area, a relevant sample proportion do not stop there and, in some cases, the median of the distribution is crossed. This suggests that the impact of transition width on our analysis is worth investigating.

A way to assess the relevance of transition width for the estimation of our model is to allow for more than two outcomes in the transition equation. With this aim, I propose a second extension of the S&S's model. In particular, I use their model with partial observability (1995 outcomes observable only for the 1993 low-paid) but model the transition equation with an ordered probit, rather than with a binary probit as in their case. The reason to assume partial observability is that coefficients in η_2, equation (3), refer to falls into low-pay from the top of the distribution and, hence, the variability of destination outcomes for those who cross the low-pay threshold is limited; consequently, the binary treatment of the wage distribution does not apper to be a demanding assumption.

Let us assume that selection into the starting state is still governed by (1), while the position in the destination wage distribution can only be observed for the initially low-paid (as in (10.a)) and is represented by the following discrete ordered indicator:

$$d^{o}_{i95} = \begin{cases} 1 & if \quad w_{i95} \leq \lambda_{95} \\ 0 & if \quad \lambda_{95} < w_{i95} \leq \lambda_{95} + \mu_0 \\ -1 & if \quad \lambda_{95} + \mu_0 < w_{i95} \leq \lambda_{95} + \mu_1 \\ -2 & if \quad \lambda_{95} + \mu_1 < w_{i95} \leq \lambda_{95} + \mu_2 \\ -3 & otherwise \end{cases} \qquad (10.b)$$

the sensitivity analysis of column 3.

where the μ's are the first three deciles above the low-pay threshold[20]. Errors in the conditioning and transition equations are assumed to be jointly distributed as bivariate normal with unit variances and correlation coefficient ρ. Given these assumptions, likelihood contributions can be written as:

$$L_i = \begin{cases} \Phi_2(z_i\gamma_1, x_i\beta; \rho) & \textit{if} \quad d_{i93} = d^o_{i95} = 1 \\ \Phi_2(\nu_j + z_i\gamma_1, x_i\beta; \rho) - \Phi_2(\nu_{j-1} + z_i\gamma_1, x_i\beta; \rho) & \textit{if} \quad d_{i93} = 1 \quad \textit{and} \quad I(d^o_{i95} = -j) = 1 \\ \Phi(-x_i\beta) & \textit{if} \quad d_{i93} = 0 \end{cases}$$

$$j = 0, \ldots, 3$$
$$\nu_{-1} = 0$$
$$\nu_3 = +\infty$$
$$\nu_{j=} h_1(\lambda_{95} + \mu_{-j}) \qquad \forall j \in \{0,1,2\}$$

(11)

Results from the estimation of this ordered probit with selectivity are reported in the third column of table 7 and can be compared to those in column 1. We can observe how, typically, results tend to be stable between the two columns, but with some remarkable exceptions. In particular, a drop in both size and significance characterises estimated coefficients for the large firms and construction sector dummies, meaning that part of their effects was due short range earnings mobility. On the other hand, the correlation coefficient is now more precisely estimated and remarkably larger in size: the latter finding could signal that persisting in low-pay is now a relatively worst outcome compared to column 1. Apart from these minor changes, estimation of the endogenous switching ordered probit points towards the robustness of our results in Section 3 to the dichotomic treatment of the wage variable.

5. Summary and conclusions

[20] The specification in (10.b) is aimed at maintaining the comparability coefficients in the transition equation with the analogous vector estimated in column 1.

Using survey panel data from SHIW for 1993 and 1995, this paper has shown that the experience of low-pay is a persistent feature of earnings careers in the Italian labour market.

At the aggregate level we have shown that the chance of being trapped below the low-pay threshold during the observed 2 years transition is considerable, between 55 and 70% depending upon the low-pay and wage definitions adopted. Moreover, these aggregate probabilities of transition into low-pay are much higher (between 50 and 60%) compared to the ones faced by workers who are not low-paid at the beginning of the period analysed, suggesting low-pay states depend on past low-pay episodes to a meaningful extent.

These aggregate findings have next been investigated at the individual level. The econometric framework adopted is characterised by a proper treatment of endogeneity problems inherent to dynamic panel analysis (the so called initial conditions problem) and by the ability to test for genuine state dependence, the extent with which past low-pay modify, *per se*, the effect of individual characteristics on conditional low-pay probabilities, holding fixed personal attributes.

Results show that, among observed attributes, potential labour market experience has no effect on low-pay transitions, after initial conditions endogeneity has been dealt with. This indicates that, net of other determinants of labour supply and demand, wage progressions induced by labour market seniority cannot be seen as a mean of alleviating low-pay incidence. On the other hand, gender, education, occupation, the employers size, sectoral affiliation and region of residence present some effect on low-pay transition probabilities, suggesting that there might be some scope for policies targeted according to these attributes.

However, our analysis of genuine state dependence indicates that these policies may not be entirely successful: rouglhy half of observed state dependence is actually generated by the past experience of low-pay itself. Whatever the causes behind this results - stigma effects, human capital deterioration or alterations of search strategies - such an evidence can be interpreted by saying that low-pay persistence is a general problem which affects earnings careers irrespective, to a relevant extent, of personal characteristics. This suggests that policies aimed at coping with labour market poverty should be targeted on the whole pool of working poors: the factors capable of generating earnings progressions within the medium-upper quantiles of the distribution are weakened by the experience of low-pay.

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Table 1: Sample means, standard errors in paretheses

	1993		1995		panel in 1993	
n. obs	24013		23924		10755	
employed	0.24	(0.427)	0.234	(0.423)	0.245	(0.430)
empl. miss.wage/part-time	0.019	(0.138)	0.024	(0.154)	0.019	(0.137)
self-empl.	0.054	(0.226)	0.062	(0.242)	0.052	(0.223)
entrepreneurs	0.024	(0.154)	0.023	(0.151)	0.024	(0.152)
seeking 1st job	0.051	(0.219)	0.043	(0.203)	0.045	(0.208)
unempl.	0.021	(0.144)	0.029	(0.167)	0.022	(0.146)
retired	0.225	(0.418)	0.228	(0.419)	0.204	(0.403)
student	0.189	(0.391)	0.184	(0.387)	0.211	(0.408)
housewife	0.052	(0.222)	0.054	(0.225)	0.053	(0.224)
other	0.124	(0.330)	0.119	(0.324)	0.124	(0.330)
empl 18-65, n.obs	5708		5541		2160	
age	39.056	(10.761)	38.982	(10.794)	39.403	(9.993)
experience	19.277	(11.495)	19.613	(11.604)	19.074	(10.619)
females	0.356	(0.479)	0.367	(0.482)	0.356	(0.479)
head of family	0.525	(0.499)	0.504	(0.500)	0.551	(0.497)
spouse/cohabitant	0.23	(0.421)	0.24	(0.427)	0.248	(0.432)
child	0.222	(0.415)	0.236	(0.425)	0.185	(0.388)
other relative-non relative	0.023	(0.151)	0.02	(0.139)	0.016	(0.124)
no education	0.014	(0.118)	0.01	(0.099)	0.007	(0.086)
elem. education (5 yrs)	0.144	(0.351)	0.123	(0.328)	0.12	(0.325)
junior high (8 yrs)	0.357	(0.479)	0.386	(0.487)	0.327	(0.469)
high school (13 yrs)	0.372	(0.483)	0.364	(0.481)	0.407	(0.491)
ba/bs (17+ yrs)	0.113	(0.317)	0.117	(0.322)	0.138	(0.345)
blue collar	0.441	(0.497)	0.456	(0.498)	0.395	(0.489)
white collar low level	0.38	(0.485)	0.327	(0.469)	0.385	(0.487)
teacher	0.105	(0.306)	0.117	(0.321)	0.136	(0.342)
white collar high level	0.051	(0.219)	0.075	(0.264)	0.057	(0.233)
manag, magistr. prof.	0.024	(0.154)	0.025	(0.156)	0.026	(0.160)
agricolture	0.029	(0.167)	0.024	(0.153)	0.019	(0.138)
other manufacturing	0.28	(0.449)	0.307	(0.461)	0.268	(0.443)
construction	0.058	(0.234)	0.054	(0.226)	0.049	(0.215)
retail trade/ personal e household serv	0.125	(0.331)	0.129	(0.336)	0.105	(0.307)
transp&comm	0.028	(0.166)	0.031	(0.174)	0.023	(0.150)
bank, insurance, real estate	0.063	(0.242)	0.062	(0.242)	0.066	(0.249)
public sector	0.417	(0.493)	0.392	(0.488)	0.47	(0.499)
size<=19	0.421	(0.494)	0.426	(0.494)	0.371	(0.483)
20<=size<=99	0.247	(0.431)	0.224	(0.417)	0.242	(0.428)
100<=size<=499	0.142	(0.349)	0.148	(0.355)	0.167	(0.373)
size>=500	0.19	(0.392)	0.202	(0.402)	0.22	(0.414)
north west	0.243	(0.429)	0.253	(0.435)	0.233	(0.423)
north east	0.21	(0.408)	0.23	(0.421)	0.229	(0.420)
centre	0.23	(0.421)	0.21	(0.407)	0.197	(0.398)
south	0.316	(0.465)	0.308	(0.462)	0.341	(0.474)

note: the distribution of employers size is computed within the private sector

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

	hourly wages		monthly wages	
Descriptive statistics (thousands of lire)	1993	1995	1993	1995
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	1993	1995	1993	1995
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: Descriptive statistics of low-pay persistence and aggregate state dependence (N=2160)

	Hourly wages				Monthly wages			
	Bottom quintile		Third decile		Bottom quintile		Third decile	
Low-pay persistence: $prob[L_{95} \mid L_{93}]$	56.05		70.79		61.76		64.76	
Raw state dependence: $prob[L_{95} \mid L_{93}] - prob[L_{95} \mid H_{93}]$	49.79		61.13		53.63		55.77	
Low-pay persistence by personal characteristics[a]		# = L93		# = L93		# = L93		# = L93
males	0.543	188	0.679	315	0.565	168	0.569	281
females	0.583	151	0.749	219	0.669	172	0.738	244
potential exp.<=10	0.554	184	0.748	242	0.623	191	0.695	249
10<potential exp.<=20	0.554	65	0.676	108	0.607	61	0.560	109
potential exp.>20	0.565	85	0.669	178	0.598	82	0.631	160
no education	0.400	5	0.778	9	0.400	5	0.571	7
elem. education (5 yrs)	0.625	56	0.734	109	0.667	54	0.717	92
junior high (8 yrs)	0.671	167	0.765	247	0.683	161	0.698	242
high school (13 yrs)	0.376	109	0.621	161	0.513	115	0.568	169
ba/bs (17+ yrs)	0.000	2	0.250	8	0.600	5	0.333	15
blue collar	0.618	246	0.769	381	0.672	229	0.694	353
white collar low level	0.419	86	0.561	139	0.511	94	0.589	141
teacher	0.333	3	0.333	6	0.500	12	0.375	24
white collar high level	0.250	4	0.500	6	0.400	5	0.429	7
manag, magistr. prof.	0.000	0	1.000	2	0.000	0	0.000	0
agricolture	0.636	22	0.655	29	0.533	15	0.667	21
other manufacturing	0.511	133	0.715	207	0.589	129	0.661	186
construction	0.655	29	0.706	51	0.692	26	0.585	41
retail trade	0.632	68	0.860	86	0.704	54	0.786	70
personal e household serv	0.611	18	0.862	29	0.750	20	0.688	32
transp&comm	0.800	5	0.727	11	0.750	4	0.600	5
bank, insurance, real estate	0.625	24	0.893	28	0.667	24	0.821	28
public sector	0.400	40	0.462	93	0.529	68	0.535	142
size<=19	0.665	206	0.818	274	0.707	184	0.780	236
20<=size<=99	0.491	55	0.711	97	0.569	51	0.563	87
100<=size<=499	0.308	26	0.646	48	0.480	25	0.512	41
size>=500	0.167	12	0.500	22	0.250	12	0.526	19
north west	0.403	72	0.628	121	0.458	72	0.580	112
north east	0.554	92	0.732	149	0.611	90	0.699	136
centre	0.508	61	0.734	94	0.635	63	0.688	96
south	0.693	114	0.729	170	0.713	115	0.630	181

notes:
a) #=L93 gives the number of cases falling below the 1993 low-pay threshold

Table 4: Comparison of ML estimates according to differing assumptions on the conditioning starting state (hourly wages, low-pay=bottom quintile)

assumption on initial conditions	Exogenous		Endogenous	
conditioning starting state	Low-pay	High-pay	Low-pay	High-pay
experience/10	-0.212	-0.090	-0.091	-0.027
	(2.925)	(1.677)	(0.799)	(0.492)
education>=high	-0.845	-0.298	-0.726	-0.239
school	(3.723)	(2.025)	(2.945)	(1.660)
female	0.498	0.290	0.338	0.191
	(2.882)	(2.419)	(1.599)	(1.577)
non manual	-0.378	-0.496	-0.235	-0.418
	(1.538)	(3.266)	(0.911)	(2.771)
20<=firm size<100	-0.412	-0.302	-0.171	-0.115
	(1.898)	(1.950)	(0.619)	(0.701)
firm size>=100	-0.733	-0.650	-0.420	-0.431
	(2.718)	(3.914)	(1.188)	(2.425)
public sector	-0.318	-0.857	0.138	-0.608
	(1.122)	(4.791)	(0.324)	(3.199)
agriculture	0.212	0.392	0.109	0.192
	(0.656)	(1.183)	(0.341)	(0.591)
retail trade	0.145	0.260	0.134	0.206
	(0.678)	(1.408)	(0.656)	(1.146)
construction	0.326	-0.040	0.372	-0.017
	(1.141)	(0.191)	(1.363)	(0.085)
bank, insurance,	0.599	-0.362	0.598	-0.303
real estates	(1.770)	(1.222)	(1.834)	(1.064)
transport and	1.257	-0.666	1.319	-0.621
communication	(1.759)	(1.380)	(1.954)	(1.352)
personal & household	0.078	0.074	0.085	0.067
services	(0.219)	(0.250)	(0.249)	(0.232)
north west	-0.761	-0.201	-0.648	-0.165
	(3.692)	(1.513)	(2.848)	(1.273)
north east	-0.326	-0.175	-0.264	-0.151
	(1.733)	(1.333)	(1.387)	(1.183)
constant	0.883	-0.448	0.968	-0.899
	(4.144)	(2.412)	(4.716)	(3.976)
rho			-0.437	-0.551
			(1.467)	(2.670)
Number of obs	334	1814	2148	
Pseudo R2	0.16	0.18	0.29	
model's p-value	0	0	0	

Table 5: Marginal effects[a] for the conditional low-pay probability (N=2148, asymptotic t-ratios in parentheses)

Wage definition	Hourly wages				Monthly wages			
Low-pay definition	Bottom quintile		Third decile		Bottom quintile		Third decile	
Conditioning starting state	low-pay	high-pay	low-pay	high-pay	low-pay	high-pay	low-pay	high-pay
experience/10	-0.039	-0.003	-0.030	-0.0002	-0.012	-0.009	-0.009	0.001
	(0.799)	(0.492)	(1.238)	(0.026)	(0.237)	(1.290)	(0.305)	(0.168)
education>=high school	-0.298	-0.022	-0.113	-0.031	-0.066	-0.016	-0.136	-0.018
	(2.945)	(1.660)	(1.613)	(1.575)	(0.636)	(1.079)	(1.786)	(1.055)
female	0.145	0.018	0.107	0.046	0.171	0.043	0.202	0.054
	(1.599)	(1.577)	(1.833)	(2.606)	(1.704)	(3.181)	(3.064)	(3.440)
non manual	-0.100	-0.042	-0.159	-0.082	-0.219	-0.093	-0.051	-0.064
	(0.911)	(2.771)	(1.982)	(3.540)	(1.896)	(4.864)	(0.607)	(3.179)
20<=firm size<100	-0.073	-0.009	-0.025	-0.014	-0.014	-0.018	-0.147	-0.018
	(0.619)	(0.701)	(0.358)	(0.585)	(0.128)	(1.137)	(1.822)	(1.008)
firm size>=100	-0.173	-0.030	-0.057	-0.047	-0.081	-0.029	-0.106	-0.041
	(1.188)	(2.425)	(0.639)	(1.950)	(0.616)	(1.738)	(1.088)	(2.245)
public sector	0.060	-0.057	-0.103	-0.054	0.121	-0.006	-0.097	-0.016
	(0.324)	(3.199)	(0.952)	(1.785)	(0.905)	(0.328)	(1.018)	(0.733)
agriculture	0.047	0.020	-0.166	0.043	-0.154	0.127	-0.089	0.086
	(0.341)	(0.591)	(1.474)	(0.655)	(1.006)	(2.500)	(0.659)	(1.575)
retail trade	0.058	0.021	0.138	0.068	0.092	0.021	0.066	0.035
	(0.656)	(1.146)	(1.851)	(1.995)	(0.944)	(0.923)	(0.751)	(1.320)
construction	0.160	-0.001	-0.036	0.018	0.114	-0.002	-0.080	0.042
	(1.363)	(0.085)	(0.423)	(0.545)	(0.919)	(0.089)	(0.813)	(1.357)
bank, insurance,	0.252	-0.021	0.268	-0.035	0.185	-0.034	0.163	-0.026
real estates	(1.834)	(1.064)	(2.585)	(1.087)	(1.323)	(1.217)	(1.245)	(0.867)
transport and	0.458	-0.032	0.080	0.015	0.395	-0.001	0.137	0.047
communication	(1.954)	(1.352)	(0.509)	(0.326)	(1.650)	(0.036)	(0.601)	(1.053)
personal & household	0.037	0.006	0.132	-0.048	0.108	-0.019	-0.127	-0.071
services	(0.249)	(0.232)	(1.196)	(1.153)	(0.738)	(0.554)	(1.093)	(0.013)
nort west	-0.262	-0.013	-0.177	0.000	-0.297	-0.006	-0.131	0.008
	(2.848)	(1.273)	(2.740)	(0.025)	(3.184)	(0.488)	(1.899)	(0.577)
north east	-0.112	-0.012	-0.100	-0.029	-0.140	-0.012	-0.023	-0.008
	(1.387)	(1.183)	(1.649)	(1.797)	(1.697)	(0.939)	(0.365)	(0.588)
constant (ML coeff.)	0.968	-0.899	1.318	-0.862	0.977	-0.981	1.054	-1.216
	(4.716)	(3.976)	(7.053)	(3.512)	(4.840)	(5.439)	(5.809)	(6.285)
rho (ML coeff)	-0.437	-0.551	-0.445	-0.536	-0.502	-0.781	-0.544	-0.728
	(1.467)	(2.670)	(2.538)	(3.051)	(2.151)	(5.893)	(3.827)	(5.547)
pseudor2	0.29		0.27		0.25		0.24	
model's p-value	0		0		0		0	
test 1[b]: p-value	0.0656		0.2282		0.2852		0.4325	
test 2[c] : p-value	0.0025		1.2E-05		0.0032		3.4E-05	
estimated state dependence[a]	0.49		0.61		0.53		0.56	
Test for genuine state dependence H_0:γ1=γ2; p-value	1.6E-05		1.1E-13		1.7E-09		0	
Genuine state dependence[a]	0.21		0.33		0.28		0.31	

Notes:
a) see the text for formulas used in computation
b) significance of instruments in transition equation
c) significance of instruments in selection equation

Table 6: Aggregate transition probabilities out from the wage distribution (left; hourly wages, low-pay=bottom quintile; bracketed figures are conditional on having left the wage distribution) and through the deciles of the wage distribution (right; hourly wages)

Transitions within the wage distribution and to other labour market states					Transition width		
1993 wage status	Low-pay		High-pay		**1993 decile**	1	2
1995 status					**1995 decile**		
low-pay	38.8		5.1		1	44.25	17.58
high-pay	30.4		76.1		2	26.44	23.03
missing wage; part-time	4.9	(15.9)	3.7	(19.7)	3	15.52	26.06
self employed	2.7	(8.8)	1	(5.3)	4	3.45	9.7
entrepreneur	1.2	(3.9)	1	(5.3)	5	4.6	14.55
unemployed	9.2	(29.9)	1.9	(10.1)	6	1.72	3.03
retired	2.2	(7.1)	6.8	(36.2)	7	2.3	2.42
other	0.4	(1.3)	0	(0.0)	8	1.15	1.21
housewife	2.7	(8.8)	0.2	(1.1)	9	0.57	2.42
not observed	7.6	(24.7)	4.3	(22.9)	10	0	0
Total obs	490		2244			174	165

Table 7: Sensitivity analysis (ML coefficients, asymptotic t-ratios in parentheses, bottom quintile of the hourly wage distribution)

Specification of transition equation	(1) Binary	(2) Binary	(3) Ordered
Estimation sample	Valid wage in 1993 and 1995	Valid wage in 1993 and valid wage or out of the wage distribution in 1995	Valid wage in 1993 and 1995
experience/10	-0.094	-0.093	-0.038
	(0.832)	(0.931)	(0.431)
education>=high school	-0.730	-0.558	-0.497
	(2.969)	(2.841)	(2.540)
female	0.343	0.320	0.211
	(1.623)	(1.778)	(1.227)
non manual	-0.238	-0.131	-0.139
	(0.921)	(0.597)	(0.681)
20<=firm size<100	-0.175	-0.191	-0.157
	(0.632)	(0.825)	(0.701)
firm size>=100	-0.420	-0.386	-0.155
	(1.175)	(1.338)	(0.601)
public sector	0.128	0.067	0.152
	(0.302)	(0.196)	(0.459)
agriculture	0.111	0.171	-0.268
	(0.348)	(0.610)	(0.991)
retail trade	0.129	0.141	0.140
	(0.629)	(0.787)	(0.772)
construction	0.370	0.339	0.165
	(1.355)	(1.413)	(0.698)
bank, insurance, real estates	0.594	0.447	0.498
	(1.816)	(1.595)	(1.768)
transport and communication	1.325	1.156	0.959
	(1.959)	(2.014)	(1.650)
personal & household services	0.093	0.147	0.116
	(0.272)	(0.503)	(0.393)
nort west	-0.654	-0.580	-0.563
	(2.894)	(3.096)	(3.051)
north east	-0.270	-0.277	-0.253
	(1.426)	(1.654)	(1.533)
constant (ML coeff.)	0.972	1.191	0.968
	(4.715)	(6.736)	(5.373)
m1			0.626
			(7.241)
m2			0.876
			(7.962)
m3			1.394
			(8.759)
rho (ML coeff)	-0.430	-0.372	-0.550
	(1.437)	(1.382)	(2.523)
Number of obs	2148	2715	2148
Pseudo R2	0.33	0.32	0.28
model's p-value	0	0	0
test 1[a]: p-value	0.1583	0.3418	0.7352
test 2[b] : p-value	0.0025	0.0016	0.0015

a) significance of instruments in transition equation
b) significance of instruments in selection equation