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Lorenzo Cappellari

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Lorenzo Cappellari
Università del Piemonte Orientale, CHILD and IZA Bonn

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IZA

P.O. Box 7240
53072 Bonn
Germany

Phone: +49-228-3894-0
Fax: +49-228-3894-180
Email: iza@iza.org

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ABSTRACT

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This paper uses Italian panel data to analyse transition probabilities at the bottom of the earnings distribution during the 1990s. The analytical framework is characterised by the ability to account for the endogeneity of initial conditions, educational attainment and earnings attrition, providing a model that encompasses those applied by previous research. Results show that the three selection mechanisms are endogenous for the estimation of low pay transitions. The data also reveal considerable state dependence, i.e. the experience of low pay is found to raise, per se, the probability of subsequent low pay episodes. Low pay persistence and entry rates are found to be larger among female employees, the low educated, manual workers in small firms and workers from the South relative to otherwise comparable individuals.

JEL Classification: C23, C35, D31, J31

Keywords: low pay, earnings mobility, initial conditions, earnings attrition, education

Lorenzo Callellari
Università del Piemonte Orientale
Via Perrone 18
28100 Novara
Italy
Email: lorenzo.cappellari@eco.unipmn.it

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1. Introduction

Low paid employment has become a major issue for several industrialised nations in recent years. The rise of earnings inequality experienced in those nations has placed the labour incomes of a growing proportion of the workforce below pre-determined 'decency thresholds', prompting both equity and efficiency concerns (see OECD,1996). The Italian labour market also experienced similar trends, with the proportion of low paid workers that has been rising since the mid-1980s and through the first half of the 1990s (see Lucifora, 1998, and Brandolini et al., 2001).

The debate provoked by these stylised facts has stressed the need for a dynamic analytical approach, since only the study of low pay mobility — i.e. of movements into and out of low pay over time — can help in identifying the persistently low paid, providing insights on the urgency and targets of policies designed to fight poverty in the labour market.[1] If low paid jobs are a transitory experience of earnings careers, then inequality is shared amongst individual over their life-cycles and policy measures such as minimum wages might increase rigidity at the lower end of the distribution of earnings without any real impact on poverty alleviation. Conversely, pronounced low pay persistence implies that a fraction of the workforce is excluded from the benefits of economic growth in the long run, calling for adequate policy interventions even in the presence of stable cross-sectional distribution over time.

This paper uses panel data on Italian employees over the 1990s and contributes to the existing literature on low pay mobility by estimating models of low pay transition probabilities that are robust to three distinct sources of endogenous selection which might bias this type of analysis. First, proper allowance is made for the endogeneity

[1] See Atkinson et al. (1992) and Jenkins (2000) for surveys of the earnings mobility and income dynamics literature.

plaguing dynamic panel data models, an issue that in the context of discrete data investigation has come to be known as the 'initial conditions problem' after the work of Heckman (1981a). Second, endogenous attrition from the earnings distribution is controlled for. Finally, also educational attainment is allowed to be endogenous when estimating its impact on low pay mobility, thus tackling the problems pointed out by the vast literature investigating the economic returns to education (see e.g. Card, 1999). The three selection processes and low pay transitions are estimated simultaneously, using multivariate probabilistic models to allow for unobserved heterogeneity.

As for other analyses of individual dynamic outcomes, the assessment of state dependence — the extent to which current states depend upon past ones — is crucial for understanding the mechanisms that generate low pay persistence (Heckman, 1981b). At one extreme, persistence could be induced by individual (observed and unobserved) heterogeneity: in such a circumstance, it is (the lack of) some persistent personal attribute that forces individuals below the low pay threshold over time. Alternatively, individuals might be homogeneous and only differ for having experienced low pay in the past: in this case it is the experience of low pay that causes — *per se* — persistence, what is known as genuine state dependence (GSD henceforth). GSD might arise if low paid jobs induce human capital depreciation, so that low pay spells worsen the chances of finding better paid jobs in the future. Alternatively, GSD could arise when there is asymmetric information between job applicants and employers about the quality of the applicant, and prospective employers use applicants' earnings histories as proxies for their abilities, thereby making low wage offers to those who have been low paid in the past. Similar predictions could stem from other labour market models, such as labour supply — via a reduction of reservation wages for those who experience low pay — or efficiency wages — through effects on morale and productivity. Besides shedding light on labour market functioning, distinguishing between heterogeneity and GSD is relevant for policy making. In the first case, policies targeted according to the factors causing persistence can reduce entrapment into low paid jobs. In the case of GSD policies targeted on 'problem groups' amongst the low paid might be misplaced and general measures such as minimum wages could be a more appropriate tool. The analytical framework developed in this paper allows to test for GSD and to quantify its incidence on overall aggregate state dependence.

The model of this paper encompasses those utilised by previous papers on earnings and income mobility.[2] In particular, it extends the analytical framework developed by Stewart and Swaffield (1999) for the assessment of initial conditions endogeneity by including two additional endogenous selection mechanisms, educational attainment and earnings attrition. The analysis of Stewart and Swaffield has shown that initial conditions are endogenous and that omitting them from models of earnings mobility biases inference about the impact of personal attributes in transition rates; analogous conclusion have been reached by Cappellari (2002) by applying that model to Italian data. Models that study transition probabilities while controlling for the endogeneity of both initial conditions and attritions have been applied by Bingley et al. (1995) and Cappellari and Jenkins (forthcoming) to earnings and households income mobility, respectively, showing that exits from the sample are endogenous for estimating transitions and should not be ignored. Finally, despite the wide interest raised by the literature focussing on estimating returns to education in the presence of endogeneity, the issue is still unexplored in the context of earnings mobility, while one could expect it to be relevant in this case if education has an impact on earnings growth rates. The present paper contributes at filling the gap.

Results confirm the necessity of allowing for the endogeneity of each of the three selection processes. In particular, I find evidence of negative sorting into education, i.e. net of observable attributes individuals with higher education tend to have worse chances of moving out or staying out of low pay relative to the less educated, so that returns to education in terms of mobility increase once the bias is removed. Also, I show that GSD effects are important in shaping low pay transitions. By comparing these results with the ones retrievable by applying the models used in previous papers (which are nested within the model of this paper) I shed light on the consequences of alternative modelling choices.

2. Data and descriptive patterns of low pay transitions

The data used in this study originate from the panel component of the Survey on Households Income and Wealth (SHIW), administered by the Bank of Italy since 1977.[3] Interviews have been carried out on an annual basis until 1987 and biannually afterwards, with the exception of 1997, when they were deferred to 1998. The sampling unit is the household, but detailed information is available also at the individual level. Although originally designed as a repeated cross-sections sample, the survey includes a panel sub-sample since 1989. While initially fairly small, the proportion of panel-households (i.e. households sampled in at least two consecutive waves) has increased in

[2] I am discussing regression-type models for earnings transition probabilities. Alternative approaches in the mobility literature are those based on lifetime inequality indices or stochastic processes for individual earnings profiles (see e.g. Buchinsky and Hunt, 1999, and Cappellari, 2004).

[3] See DAlessio and Faiella (2000) for a general description of the survey.

recent waves, being approximately 40 percent since 1993; panel-households are selected randomly from the cross-sectional sample.

This paper utilises the four latest waves of the survey, 1993, 1995, 1998 and 2000. Apart from the aforementioned limited size of the panel sub-sample before 1993, data limitations prevented the extension of the analysis to earlier waves. In particular, information on parental backgrounds has been introduced in the survey only since 1993. As will become clearer later on, these variables play a crucial role in the econometric analysis, implying that the model cannot be estimated on waves preceding 1993. In addition, the structure of the questionnaire changed over time, in particular for what concerns labour market variables, and the selected waves provide a good degree of homogeneity in the available information.

I select full-time employees aged 18-55 if female and 18-60 if male who were not in full-time education and were members of households contributing to the panel sub-sample. The data enable identification of two two-year transitions (1993-1995 and 1998-2000): individuals meeting the selection criteria and with valid earnings at the start of each transition form the estimation sample. Estimation uses 5,931 observations, 54 percent of which contributes to both transitions, remaining proportions being 28 percent (only 1998-2000 transition) and 18 percent (only 1993-1995 transition).

The earnings information available in the SHIW refers to yearly earnings, inclusive of extra-time compensations and fringe benefits, net of income taxes and social security contributions. On the working time side, the survey reports the number of months worked in the year and the number of hours worked on average in a week, including extra-time. No information is available on the number of weeks worked on average in a month. In order to derive hourly earnings, I assume that each individual worked 52/12 weeks per month.[4]

Several definitions of low pay have been proposed by previous studies, with alternatives ranging from some legally set minimum pay (Smith and Varvricheck, 1992) to fixed proportions of median or mean earnings (Stewart and Swaffield, 1999) or to relative definitions based upon quantiles (Gregory and Elias, 1994; OECD, 1996). Here I take the latter approach and, in particular, look at two different deciles in parallel, the second and the third, so that the robustness of results to the choice of a specific threshold can be assessed. Quantiles are computed from the whole SHIW cross-section of full-time employees aged 18-55 if female and 18-60 if male and then applied to a sub-sample, namely members of households in the panel component, implying that a movement —say— out of the poorest fifth of the earnings distribution does not induce a movement in the opposite direction, as would be the case if quantiles were estimated from the balanced earnings sample.

<TABLE 1 AROUND HERE>

Low pay transition matrices computed by pooling data across transitions are reported in Table 1. The first row of the table shows results obtained using the bottom quintile of hourly earnings as cut-off point. The probability of persisting in low pay is 53.47 percent, while that of falling into low pay from higher pay is 6.68, indicating that the chance of being low paid in one year changes substantially depending upon the past. Patterns are confirmed if one considers results for the third decile threshold, reported in the second row. These figures show that the probability of experiencing low pay is characterised by state dependence; using the difference $\Pr(L_t|L_{t-2})$-$\Pr(L_t|H_{t-2})$ (with L_t and

[4] In order to assess the robustness of results to the choice of the earnings variable I also analysed monthly earnings and found results to be pretty similar to those obtained on hourly earnings. Results obtained from

H_t indicating low and high pay in year t, respectively) as a measure of raw (or aggregate) state dependence, Table 1 indicates that it amounts at 47 percentage points when low pay is set at the bottom quintile of the distribution; the corresponding figure for the third decile is 51 percent. The extent to which these figures reflect heterogeneity or GSD (see the discussion in the Introduction) will be investigated in the subsequent sections.

Rows 3 and 4 of the table break down low pay transition rates by level of educational attainment. Low pay persistence drops by roughly one third when comparing individuals with low (less that high school) and high educational attainment, whereas entry rates into low pay drop by nearly two thirds when moving from one sub-sample to the other. These figures suggest that the association between low pay transition and education is rather strong. However it is not possible at this stage of the analysis to attribute any causal interpretation to the result due to both observed and unobserved heterogeneity.

Row 7 of the table enlarges the sample by including also those employees who exit from the earnings distribution during the transition, thus considering the whole estimation sample for the model of the next section. The impact of this inclusion is substantive: 24 percent of those who earn above the low pay threshold in the starting year leave the distribution during the transition, and the figure rises to 40 percent when the initially low paid are taken into account, signalling that earnings attrition might be correlated with initial conditions. Overall, the average (over starting states) rate of exits from the distribution of earnings is approximately 27 percent. Additional insights on patterns of attrition from the earnings distribution are provided in row 8, where destination states of those who exits from the earnings distribution are specified.

monthly earnings are available upon request.

Employees who start from low pay and exit the distribution are more likely to end up in part-time or self-employment, unemployment or to exit from the SHIW sample, when compared to workers initially high paid. Low pay jobs thus seem to be characterised by larger instability compared to high pay jobs; in particular, the evidence about entry rates into unemployment is consistent with the presence of cycles of low pay and unemployment as those singled out by Stewart (2002) for the UK. On the other hand, higher entry rates into retirement from high pay compared to low pay may reflect the life cycle of earnings.

3. The analytical framework

As discussed in the Introduction, the econometric analysis of earnings mobility entails various endogeneity issues. The current section lays out a model that allows estimating mobility equations while taking those issues into account.

A first bias has to do with the estimation of discrete dynamic processes from panel data on individuals, an issue known as the 'initial conditions problem' after the work of Heckman (1981a). The issue arises since identification of transition probabilities requires to condition earnings states on their lagged values: as long as the earnings process is serially correlated and its starting values are unknown to the researcher, the unobservable initial condition will be present in earnings levels at each time period, making lagged states endogenous with respect to current ones.

While the initial conditions problem arises because of missing data before the start of the panel, a second endogeneity issue inherent to the modelling of earnings dynamics can be induced by missing data during the sample period, if attrition from the earnings distribution has some unobserved component that is correlated with unobservables of the mobility process. Earnings attrition can take place because of both panel attrition — i.e. individuals leaving the survey from one interview date to another — or mobility out of employment: while not distinguishing between the two sources of missing data, the model of this paper makes due allowance for endogenous earnings attrition.

The two biases discussed above are due to the dynamic nature of the problem under investigation; a third bias might instead arise because of unobservable correlation between earnings mobility and measures of human capital that typically enter earnings equations, such as educational attainment. A vast literature has developed in recent years highlighting that factors like unobserved ability or family background might bias estimation of the impact of education on earnings (see Card, 1999). While the emphasis of those studies is predominantly on the estimation of earnings levels, it might well be that endogeneity spreads to earnings transitions, as long as education has an impact on earnings growth rates, requiring an assessment of the issue also in models of earnings mobility.

3.1 The model

The earnings mobility model of this paper extends the one proposed by Stewart and Swaffield (1999), where endougenous initial conditions were dealt with, by allowing for the endogeneity of earnings attrition and education. Earnings transitions are analysed by considering individual earnings states at two consecutive waves in year t-2 and t and pooling observations across the two transitions observed. The estimation sample is formed by individuals with valid earnings at the start of each transition.

Let l^*_{it-2} denote a latent low pay propensity for individual i at the start of the transition and be a linear function of a set of observable attributes bundled in the column vector x_{it-2} (with associated parameter vector β) and of a random variable u_{it-2}, assumed to be distributed as a standard normal:[5]

$$l^*_{it-2}=\beta' x_{it-2}+u_{it-2},\ u_{it-2}\sim N(0,1). \tag{1}$$

Whenever l^*_{it-2} exceeds some unobserved value (which can be set equal to zero without loss of generality), individual i is observed in low pay; let $L_{it-2}=\mathrm{I}(l^*_{it-2}>0)$ be a dummy indicating that event.[6] Low pay probabilities at the start of the transition (i.e. the probability of initial conditions) can thus be expressed as $\Pr(L_{it-2}=1)=\Phi(\beta' x_{it-2})$, where $\Phi()$ is the cumulative density function (c.d.f.) of the standard normal variate.

Next, let r^*_{it} indicate the individual latent propensity to persist in the earnings distribution between t-2 and t, specified as:

$$r^*_{it}=\psi' w_{it-2}+\varepsilon_{it},\ \varepsilon_{it}\sim N(0,1) \tag{2}$$

where w_{it-2} is a vector of personal attributes with associated parameter vector ψ and define $R_{it}=\mathrm{I}(r^*_{it}>0)$. Low pay mobility can be observed only for those who remain in the sample at the end of the transition, i.e. if $R_{it}=1$; the probability of that event is $\Pr(R_{it}=1)=\Phi(\psi' w_{it-2})$.

The next process to be specified is educational attainment. One possibility would be to model years of education, which amounts at assuming that returns to educations do not vary with levels of educational attainment. Since the results of Brunello and Miniaci (1999) showed that in Italy returns to education significantly vary with the level of educational attainment, here I take an alternative route and consider a dummy variable signalling whether an individual has reached at least the high school degree, thus allowing returns to differ below and above high school attainment. By letting

[5] One might also think of l^*_{it-2} as a monotonic unspecified transformation of individual earnings, such as the normality assumption holds, see Stewart and Swaffield (1999).
[6] The indicator function $\mathrm{I}(A)$ takes value one whenever its argument is true and zero otherwise.

$$s^*_i=\theta' h_i+\xi_i,\ \xi_i \sim N(0,1) \qquad (3)$$

denote a latent propensity to acquire education and $S_i=I(s^*_i>0)$ indicate attainment at least at the high school level, the probability of holding at least a high school degree can be written as $\Pr(S_i=1)= \Phi(\theta' h_i)$.

Low pay transitions probabilities can be analysed by specifying a relationship for year t low pay propensities conditional on year t-2 earnings states, retention and educational attainment:

$$l^*_{it}=[L_{it-2}\gamma_1'+H_{it-2}\gamma_2']z_{it-2}+v_{it},\ v_{it} \sim N(0,1) \qquad (4)$$

where $H_{it-2}=(1-L_{it-2})$, the vector of personal attributes z_{it-2} includes S_i, the error term differs in nature from the one of year t-2 low pay equation since now conditional earnings are investigated, and the equation is not observed if $R_{it}=0$.[7] Conditionality on lagged pay states is allowed for by letting the whole parameter vector γ switch according to the initial condition. Conditionality on retention, on the other hand, is forced by the fact that the transition equation can not be observed for "earnings attritors", and the sample likelihood will be truncated in those cases. Defined L_{it} the dummy indicator for year t low pay, current low pay probabilities will switch depending upon initial conditions: $\Pr(L_{it}=1)=\Phi(\gamma_1' z_{it-2})L_{it-2}+\Phi(\gamma_2' z_{it-2})H_{it-2}$.

I assume that the error terms of the model equations are jointly distributed as four-variate normal with free correlations, providing a parameterisation of unobserved heterogeneity: unobserved factors that influence earnings transitions are controlled for by estimating their correlations with unobservables that enter the other equations of the model. By assuming that observations are identically and independently distributed (i.i.d.), the sample likelihood can be derived and the relevant parameters —including cross-equations correlation coefficients— estimated.[8] The four-variate normal c.d.f. required for estimation is evaluated using simulation, in particular by adopting the so-called GHK simulator; the estimator employed is thence a Simulated Maximum Likelihood (SML) one. Likelihood contributions are in the Appendix.

Estimation of cross-equation correlation coefficients provides the opportunity for testing the hypothesis of exogeneity of initial conditions, retention and education. In particular, the exogeneity of each of the three processes can be tested by testing that all correlation coefficients involving that process are jointly non significant, so that the corresponding equation can be ignored when estimating the model.

3.2 Identification

In order to aid model identification valid "instruments" are required in the form of variables that affect the selection processes but have no residual effect on earnings transitions. Heckman (1981b) suggests that information prior to labour market entry can be used as instrument for initial conditions. Since 1993 the SHIW has included questions on parental background, and I use a set of dummies for parental education as instruments for initial conditions. In addition, I follow Stewart and Swaffield (1999) and assume that the square of labour market experience, which enters equation (1), does not enter the low pay transition equation, given its interpretation of wage change equation.[9]

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[7] Personal attributes in z_{it-2} are measured at the start of the transition so as to avoid simultaneity between changes in attributes and changes in earnings status.

[8] Such an approach, based on the pooling of observations across transitions, is equivalent to the one of the pooled probit estimator discussed e.g. by Woolridge (2002, chapter 13). The approach yields consistent, though not efficient, parameter estimates, inefficiency arising from the violation of the independence assumption for those individuals who are observed in both transitions. I also experimented using a robust variance estimator that accounts for the presence of repeated observations on the same individual and find no relevant differences in results relative to those presented in the paper. Results obtained using the robust estimator are available upon request.

[9] Including the square of experience in the transition equation did not produce statistically significant estimates of the associated coefficient.

The literature on panel attrition has indicated that variables such as the interviewer's opinion on the quality of the interview or the duration of the interview can serve as instruments for sample attrition (see Zabel, 1998). The SHIW data report such information and the tests for instruments validity (see below) indicated that only the interview climate, as assessed by the interviewer, could be used for identification. Variables such as the interview duration, the household's level of interest in the survey or its understanding of the questions were found to be significant in both the attrition and the transition equations. Missing data could also arise because of movements out of the earnings distribution, say because of transitions into unemployment, self-employment or retirement. In order to control for these phenomena, I include parental background indicators into the retention equation as a way of proxying the strongest labour market attachment of those who survive in the earnings sample during the transition. Finally, also squared labour market experience enters the retention equation, accounting for non-linearities in sample exits rates near to retirement.

In order to identify the effect of educational attainment, I adopt the strategy of Brunello and Miniaci (1999) who used parental background indicators and a dummy taking value 1 for individuals born after 1951 as instruments. The first set of variables should capture tastes and constraints that influence schooling choices. The cohort dummy aims to capture the effect of a major reform in the Italian educational system, namely the liberalisation of access to higher education, which was effective since 1969 and affected students born from 1951 (i.e. those who were 18 at the time of the reform) onwards.[10] In addition to these variables, I also use region of birth as an instrument for education, since it might reflect circumstances that influence human capital

[10] Before 1969 graduates from technical high schools had to undertake an exam for being admitted to college. The reform abolished the admission exam.

accumulation which are not relevant to explain earnings, after the impact of region of residence has been controlled for.

The validity of the identification strategy laid out above can be tested parametrically, using functional form as the identifying restriction.

3.3 State dependence

The structure of the model allows assessing the relevance of state dependence. Aggregate state dependence can be computed from parameter estimates as the difference in average estimated transition probabilities between initial conditions:

$$ASD=\Sigma_{i\in\{Lit\text{-}2=1,Rit=1\}}\Pr(L_{it}=1|L_{it\text{-}2}=1)/\ \Sigma_i L_{it\text{-}2}R_{it} - \Sigma_{i\in\{Lit\text{-}2=0,Rit=1\}}\Pr(L_{it}=1|L_{it\text{-}2}=0)/\ \Sigma_i H_{it\text{-}2}R_{it} \quad (5)$$

providing the estimated analogues of the differences in conditional probabilities resulting from the transition matrices of Section 2. The null hypothesis of absence of genuine state dependence can be tested by testing that coefficient vectors in the conditional low pay equation do not differ across the low pay threshold,, i.e. the impact of personal attributes on current low pay is not affected by past low pay experiences: H_0: $\gamma_1=\gamma_2$. Such a test generalises the one usually adopted in dynamic random effect probit models (see e.g. Arulampalam et al., 2000), where GSD is signalled by the significance of the coefficient associated with the lagged dependent dummy variable: the generalisation consists in the fact that not only the intercept, but the whole parameter vector in the equation for current states is allowed to change depending on lagged states. Finally, an indicator of GSD may be derived as the difference in estimated transition probabilities an average individual would have experienced had she started the transition from below or above the low pay threshold, the average being taken over the balanced sample of earnings recipients:

$$GSD=(\Sigma_i R_{it})^{-1}\Sigma_{i\in\{Rit=1\}}[\Pr(L_{it}=1|L_{it-2}=1)-\Pr(L_{it}=1|L_{it-2}=0)]. \quad (6)$$

Note that since differences in transition probabilities are computed at the individual level, they do not reflect heterogeneity. Again, such a measure generalises the one used in dynamic probit models, i.e. the "marginal effect" associated to the lagged dependent dummy variable.

<TABLE 2 AROUND HERE>

4. Results

Table 2 reports results obtained estimating the model of the last section on the SHIW sample, using alternatively the bottom quintile and the third decile as low pay cut-off points. Explanatory variables for the transition equation included in the *z* vector are a gender dummy, potential labour market experience, the educational attainment dummy S_i, occupational dummies, dummies for industrial affiliation, employer size dummies, regional dummies and a dummy for the 1995-2000 transition. The *x* vector includes gender, experience and its square, occupation, industry, firm size and region indicators, the 1995-2000 transition dummy, the set of parental background dummies and the education dummy. The *w* vector contains all variables included in the *x* vector with the exception of the education dummy (initially found non significant), plus the interview climate indicator. The *h* vector includes a gender dummy, parental background indicators, region of birth, the dummy for cohorts born since 1951 and the 1995-98 transition dummy.[11] All vectors include a constant term.

[11] As instruments for identifying the coefficient on education in the low pay level equation I use the cohort dummy and region of birth; a Wald test for the exclusion of these three variables from the low pay equation produced a χ^2 statistic of 4.32 (p-value=0.2288) for the bottom quintile threshold and of 4.35 (p-value=0.2262) for the third decile one.

Results tend to be stable across low pay thresholds, supporting the robustness of the conclusions drawn from the model to the choice of the cut-off point. The estimated cross-equation correlation coefficients provide insights on the significance and direction of the three potentially endogenous selection mechanisms. The correlation between unobservables of the initial conditions and retention equations (ρ_1) is negative and statistically significant, indicating a lower retention propensity among the initially low paid relative to the higher paid. The correlation coefficient linking initial conditions and the low pay transition equation (ρ_3) is also negative and significant, a result that already emerged in other studies of low pay transitions (see Stewart and Swaffield, 1999, and Cappellari, 2002). Since this coefficient measures the correlation between unobservables of low pay levels and low pay changes, the negative sign can be interpreted as a symptom of Galtonian regression towards the mean. The correlation of unobservables between the retention and education equations (ρ_4) is positive and significant indicating that the highly educated are less likely to leave the earnings distribution relative to other employees, which might reflect both a stronger labour market attachment and a more stable membership of the SHIW sample. A positive and statistically significant correlation coefficient characterises unobservables in the education and transition equations (ρ_6). The sign of this latter coefficient indicates that the propensity to persist or enter low pay is higher among the highly educated, once the effect of observable attributes has been controlled for. The result is analogous to that of Brunello and Miniaci (1999) who study earnings levels and find that returns to education increase once endogeneity of education is allowed for (see also the discussion later in this section about comparisons of estimates from different models). The reason for returns to increase in their analysis is the sorting of less able individuals into the group with high educational endowment, which leads to underestimate returns when education is treated as exogenous and which is analogous to the higher conditional low pay probabilities found among the highly educated, net of observable attributes (i.e. ρ_6>0). This would be true if, for example, liquidity constraints prevented able pupils from unfavourable family background to make their optimal schooling choices; also, as Checchi et al. (1999) point out, the Italian educational system, based on uniformity of the quality of education, might have failed to provide incentives to invest in education for those pupils.[12]

Assessing the significance of each correlation coefficient in turn does not provide a test for the exogeneity of the three selection processes; what is needed is a test for the joint significance of the coefficients referring to a given selection process. Only when all the coefficients involving one particular selection equation are jointly non significant that equation can be ignored for estimating the earnings transition model. Evidence from such tests of exogeneity is reported in Table 2. For each of the three processes, endogeneity emerges very clearly, the relevant correlation coefficients being jointly highly significant. Overall, the data indicate that the framework adopted in this paper is necessary for tackling the endogeneity issues inherent to the analysis of low pay transitions.

The next set of tests reported in Table 2 refers to the validity of instruments. Parental backgrounds indicators, the interviewer's assessment of the climate of interview and the instruments for education are non significant in the transition

[12] Note that the estimated correlation between low pay levels and education (ρ_2) is not statistically significant at conventional levels. Estimating an usual log-wage regression for year *t*-2 with endogenous educational dummy delivered a negative and significant correlation between the unobservables of education and earnings processes (ρ= -0.167, s.e.(ρ)=0.058) supporting the negative sorting interpretation.

equation, while they appear to be strongly significant in the selection equations. Thus, the data support the validity of the variables selected as instruments.

Sample averages of estimated transition probabilities tend to replicate the aggregate figures shown in Table 1. The associations between personal attributes and low pay transition probabilities are presented in terms of "marginal effects", see the Appendix for details on their computation.[13] Transition probabilities for the stylised individual used as reference in the computation of marginal effects tend to be considerably higher then the average rates. For each model, two columns of marginal effects are presented, the first referring to the transition from low pay to low pay (i.e. based on parameter vector γ_1) the second referring to the transition from high pay to low pay (i.e. based on γ_2). Effects tend to go in the expected directions. For example, females have a probability of persisting or entering low pay which is higher compared to the one of males, between 5 and 16 percentage points. Also, labour market experience reduces conditional low pay probabilities. Education has a strong (causal) impact on transition probabilities: in particular, for the lowest threshold low pay persistence is some 29 percent lower for those who have reached a high school degree relative to those who have not, possibly reflecting the fact that for the highly educated even very low paid jobs can act as a port of entry into the labour market. Also, education has a beneficial effect in preventing drops into low pay from high pay. Marginal effects associated to occupational qualifications also tend to have the expected negative sign, while their significance is considerably low for those who were initially low paid. The public sector dummy displays the same kind of asymmetric effect noted

[13] Some of the observed characteristics are amalgamated at a rather aggregate level, for example in the case of occupation. The choice of the level of aggregation is aimed at avoiding small cells size problems, which are particularly likely to arise in a model of low pay transitions where some of the parameters of interest are estimated conditionally on being low paid.

above for occupation dummies, while marginal effects for private sector industrial affiliation, on the other hand, do not reveal any clear pattern. Conditional low pay probabilities tend to be significantly lower for employees in medium sized private sector firms compared to small firms; when large size firm are taken into account the effect tends to vanish for those who start the transition below the low pay threshold. An asymmetric impact of observed factors on conditional low pay probabilities applies also for regional dummies, but this time in the opposite direction. For example, north-western employees have a probability of low pay persistence that is 9 to 24 percentage points lower than that of workers from the South or Islands, while no significant differential characterises the probability of falling into low pay from higher pay. Finally, conditional low pay probabilities do not vary significantly over transitions.

Results about differences in the impact of personal attributes on conditional low pay probabilities depending upon the initial condition are consistent with the existence of GSD effects. A formal test for the absence of GSD (formulated as equality of parameter vectors in the conditional low pay equation) is reported at the bottom of Table 2. For both low pay thresholds the null hypothesis of equality of coefficients across initial conditions is overwhelmingly rejected. Estimates of the measures of ASD and GSD introduced in Section 3 are also reported. GSD constitutes a substantial share of aggregate figures, the ratio GSD/ASD being around 38 percent for the lower threshold and 46 percent for the higher one. These figures are in line with the ones reported by Stewart and Swaffield (1999) for Britain. Test and measures of state dependence thence indicate that a relevant share of persistence may be ascribed to past low pay experiences, which modify individual tastes or constraints and make more difficult for individuals to move onto the higher part of the distribution, irrespective of personal attributes.

<TABLE 3 AROUND HERE>

Results from the endogeneity tests indicate that none of the three selection processes should be ignored when estimating low pay transitions. Insights on the consequences of ignoring endogeneity are provided in Table 3, where results from the estimation of restricted versions of the model are presented, using the bottom quintile as low pay threshold. In particular, I focus on three models that have been estimated by previous papers on earnings mobility and which are nested within the more general framework of this paper. The first column considers the exclusion of the educational attainment equation, yielding the model utilised by Bingley et al. (1995) for earnings mobility and Cappellari and Jenkins (forthcoming) for income mobility. Exogenising education leads to a substantive drop in returns to education (in mobility terms), between 12 and 24 percent in absolute value depending upon the initial condition. Such a finding reflects the positive sign of ρ_6 in Table 2: since the highly educated tend to have a higher unobserved propensity both persist or fall into low pay relative to the low educated, omitting allowance for the bias induces the observed reduction of marginal effects in absolute terms. The finding is in line with what Brunello and Miniaci (1999) reported from estimation of earnings levels equations for Italy. In economic terms, this result could be interpreted as evidence of liquidity constraints which prevent able individuals with unfavourable family background to make their optimal investment in schooling. The second column also excludes the retention equation, leading to the model of Stewart and Swaffield (1999). The most notable difference relative to the model with exogenous education is the rise in size of marginal effects associated to occupation, education and firm size in the low pay entry equation. Cross tabulations (not reported) show that individuals from non-manual occupations, with high education or working for larger firms are more likely to persist in the sample compared to manual or low educated workers from small firms, while Table 2 has shown that those who stay in the sample have larger conditional low pay probabilities relative to earnings attritors. Thence, focussing on a sub-sample –i.e. the "balanced" one– with conditional low pay probabilities larger relative to those of the overall estimation sample leads to underestimate entry rates for groups with high retention propensities. The shift in the estimated ρ_3 (i.e. the Galtonian regression effect) relative to the full model can be interpreted in a similar way. The last column of the table excludes all selection equations, yielding a model of the type estimated, for example, by Contini et al. (1998) on Italian data, and confirms similar comparisons reported by Stewart and Swaffield (1999): ignoring initial conditions endogeneity leads to overstate the impact of observed attributes on low pay transitions. Also, note that the estimated GSD/ASD ratio is now around 50 percent, a consequence of omitting any control for unobserved heterogeneity.

5. Concluding remarks

This paper has used data from the Survey on Household Income and Wealth to analyse the earnings mobility of low paid Italians. In particular models of low pay transition probabilities have been estimated while controlling for endogeneity of initial conditions, earnings attrition and educational attainment.

Results indicate that each of the three selection mechanisms is endogenous and should be properly controlled for. In particular, highly educated individuals are characterised by larger low pay persistence and entry rates relative to otherwise identical workers, as could be the case in the presence of liquidity constraints that prevent able individuals from unfavourable family background to make their optimal schooling choices. As a consequence, ignoring endogeneity of education biases its returns (in terms of low pay mobility) downwards.

The analysis of the relationship between personal attributes and low pay transitions has shown that employees with low educational qualifications, female employees and southern workers have higher risks of being trapped into low pay. The probability of dropping into low pay appears to be associated with manual jobs and with jobs in the private sector metal-manufacturing industry and in small firms.

Results also indicate that state dependence effects play a relevant role in creating low pay traps: it is the experience of low pay which modifies the economic environment faced by individuals, increasing the probability of future low pay experiences irrespective — to some extent — of personal attributes. These findings suggest that entrapment into low pay may not be confined to 'problem groups' of the labour force, pointing towards the need of policies targeted on the whole pool of low paid employees.

Appendix: Likelihood contributions and evaluation of marginal effects.

The model of Section 3 is a four–variate probit with censoring and endogenous switching of one equation. The four equations, given in the text, are:

$l^*_{it-2}=\beta' x_{it-2}+u_{it-2},\ u_{it-2}\sim N(0,1),\ L_{it-2}=\mathrm{I}(l^*_{it-2}>0)$ (A.1) Initial conditions

$r^*_{it}=\psi' w_{it-2}+\varepsilon_{it},\ \varepsilon_{it}\sim N(0,1),\ R_{it}=\mathrm{I}(r^*_{it}>0)$ (A.2) Earnings retention

$s^*_i=\theta' h_i+\xi_i,\ \xi_i\sim N(0,1),\ S_i=\mathrm{I}(s^*_i>0)$ (A.3) Educational attainment

$l^*_{it}=[L_{it-2}\gamma_1'+H_{it-2}\gamma_2']z_{it-2}+v_{it}$ if $R_{it}=1,\ v_{it}\sim N(0,1),\ L_{it}=\mathrm{I}(l^*_{it}>0)$ (A.4) Low pay transition

The low pay transition equation is truncated for observations that leave the sample between t-2 and t (i.e. when R_{it}=0) and allows switching of the parameter vector of interest according to initial conditions.

Errors are assumed to be jointly distributed as four-variate normal with zero mean, unit variances and free correlation coefficients: $(u_{it-2}, \varepsilon_{it}, \xi_i, v_{it},)\sim N_4(0, \Omega)$.

Likelihood contributions take the following form:

$$L_i = [\Phi_4(\Xi_{1i}; \Omega)^{Lit-2}\times\Phi_4(\Xi_{2i}; \Omega)^{Hit-2}]^{Rit}\times\Phi_3(\Xi_{-Lti}; \Omega_{-Lt})^{(1-Rit)} \qquad \text{(A.5)}$$

where Φ_j denotes the j-variate normal c.d.f., Ξ_{ki}, k=1,2, is the vector of index functions for individual i, whose low pay transition component switches according to initial conditions, and the $-Lt$ subscript denotes vectors and matrices deprived of elements referring to the low pay transitions equation.

Computation of multivariate normal distributions is performed by applying the Geweke-Hajivassiliou-Keane (GHK) simulator, yielding a Simulated Maximum Likelihood (SML) estimator.

Tables 2 presents results in terms of marginal effects on estimated low pay persistence (p_{it}) and entry (e_{it}) probabilities:

$$p_{it}=\Phi_4(\Xi_{1i}; \Omega)/\Phi_3(\Xi_{-Lti}; \Omega_{-Lt}) \qquad e_{it} =\Phi_4(\Xi_{2i}; \Omega)/\Phi_3(\Xi_{-Lti}; \Omega_{-Lt}) \qquad \text{(A.6)}$$

The effect considered is the one induced on transition probabilities by changes in the elements of z_{it-2} relative to the reference person described in the text. Note that such changes will, in general, also affect the conditioning events, therefore complicating the interpretation of the effects estimated. In order to circumvent those complications, I fixed the probabilities of conditioning events at their sample averages, using the arguments of those average probabilities into the transition rates given in (A.6).

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Table 1: Low pay transition probabilities

	Sample and low pay definition	*destination state* / *origin state*	high pay	low pay	out of the earnings distribution of full time employees								n.obs
					partime	self-empl	unempl.	Housewife	retired	student	other	attrited	
(1)	pooled transitions	high pay	93.32	6.68									3636
	1st quintile	low pay	46.53	53.47									692
(2)	pooled transitions	high pay	90.59	9.41									3221
	3rd decile	low pay	37.22	62.78									1107
(3)	pooled transitions education<High school	high pay	88.86	11.14									1382
	1st quintile	low pay	39.27	60.73									433
(4)	pooled transitions education≥High school	high pay	96.06	3.94									2254
	1st quintile	low pay	58.69	41.31									259
(5)	pooled transitions including attritors	high pay	70.95	5.08	23.96								4782
	1st quintile	low pay	28.02	32.20	39.77								1149
(6)	pooled transitions including attritors	high pay	70.95	5.08	1.48	1.61	1.51	0.44	4.52	0.10	0.79	13.51	4782
	1st quintile	low pay	28.02	32.20	3.22	3.05	6.79	2.44	2.35	0.35	2.26	19.32	1149

Table 2: Results[a] from SML estimation[b] of four-variate probit models for low pay transition probabilities

LOW PAY THRESHOLD	FIRST QUINTILE				THIRD DECILE			
INITIAL CONDITION	LOW PAY		HIGH PAY		LOW PAY		HIGH PAY	
Average prediction	0.554		0.080		0.665		0.099	
Base category[c]	0.794		0.239		0.892		0.310	
Female	0.086	(2.57)	0.118	(3.59)	0.050	(2.98)	0.168	(4.85)
30 years of potential labour market experience	-0.022	(1.19)	-0.039	(3.32)	-0.032	(3.16)	-0.025	(1.71)
Education≥ High school	-0.344	(3.05)	-0.177	(2.85)	-0.330	(4.57)	-0.210	(3.38)
White collar (low level) - Teacher	-0.129	(2.35)	-0.118	(4.30)	-0.073	(2.38)	-0.161	(5.01)
White collar (high level)- Manager-Magistrate-Professor	-0.085	(0.47)	-0.138	(2.85)	0.021	(0.30)	-0.213	(4.07)
Public sector	-0.091	(0.22)	0.159	(4.38)	-0.059	(2.25)	0.231	(4.30)
Agriculture	-0.024	(1.30)	-0.019	(2.19)	-0.065	(1.38)	-0.017	(2.40)
Construction	-0.009	(0.38)	0.053	(0.40)	0.009	(1.76)	0.087	(0.29)
Retail trade	0.069	(0.21)	-0.031	(1.27)	0.020	(0.36)	0.008	(1.68)
Transport and Communication	0.038	(0.91)	0.010	(0.51)	0.045	(0.47)	-0.071	(0.12)
Financial and related services	0.026	(0.59)	-0.023	(0.19)	0.032	(1.36)	0.001	(1.18)
Personal and household services	-0.014	(0.40)	-0.132	(0.32)	-0.094	(0.89)	-0.158	(0.01)
20≤ Firm size≤99	0.002	(0.05)	-0.005	(0.17)	-0.006	(0.27)	-0.056	(1.49)
100≤ Firm size≤499	-0.129	(1.88)	-0.069	(1.91)	-0.046	(1.38)	-0.095	(2.22)
Firm size ≥500	-0.116	(1.11)	-0.110	(3.15)	-0.038	(0.83)	-0.148	(3.67)
North-west	-0.246	(4.07)	-0.043	(1.40)	-0.093	(2.89)	-0.006	(0.17)
North-east	-0.160	(2.99)	-0.051	(1.68)	-0.072	(2.49)	-0.079	(2.21)
Centre	-0.149	(2.86)	-0.014	(0.44)	-0.039	(1.45)	-0.011	(0.31)
Transition 1998-2000	-0.019	(0.51)	0.026	(0.90)	-0.055	(2.38)	0.034	(1.13)
ρ_1(initial conditions-retention)	-0.118		(4.02)		-0.108		(3.84)	
ρ_2(initial conditions-education)	-0.184		(1.34)		0.135		(0.87)	
ρ_3 (initial conditions- low pay transition)	-0.474		(4.59)		-0.376		(3.48)	
ρ_4 (retention-education)	0.077		(2.59)		0.076		(2.55)	
ρ_5 (retention-low pay transition)	0.147		(0.77)		0.118		(0.70)	
ρ_6 (education-low pay transition)	0.362		(2.30)		0.361		(3.09)	

Table 2 (continued)

Low pay threshold	First quintile		Third decile	
Exogeneity of initial conditions ($H0:\rho_1=\rho_2=\rho_3=0;df=3$)	36.66	*0.0000*	33.77	*0.0000*
Exogeneity of retention ($H0:\rho_1=\rho_4=\rho_5=0;df=3$)	21.14	*0.0001*	23.06	*0.0000*
Exogeneity of educational attainment ($H0:\rho_2=\rho_4=\rho_6=0;df=3$)	13.95	*0.0030*	16.70	*0.0008*
Exclusion of instruments from low pay transitions equation (df=24)	17.39	*0.8316*	27.82	*0.2676*
Exclusion of instruments from initial conditions equation (df=8)	29.89	*0.0002*	30.50	*0.0002*
Exclusion of instruments from retention equation (df=9)	19.71	*0.0198*	19.40	*0.0220*
Exclusion of instruments from educational attainment equation (df=11)	460.91	*0.0000*	462.54	*0.0000*
State dependence				
Test (H0: $\gamma1=\gamma2$. df=20)	102.94	*0.0000*	135.68	*0.0000*
ASD; GSD	47.4	17.9	56.6	26.6
Model χ^2(df=107)	2481.18	*0.0000*	2942.42	*0.0000*
Log likelihood	-9861.6675		-10626.201	
Number of observations	5913		5913	

Notes: for each low pay threshold, column headers indicate the initial condition.

a) For explanatory variables marginal effects on conditional low pay probabilities relative to reference individual are reported; see text for computation. Asymptotic t-ratios in parentheses refer to the underlying SML coefficient. Tests statistics are from Wald tests of hypotheses, P-values in italic
b) GHK simulator uses 80 random draws
c) Male, 20 years of potential experience, blue collar worker, private sector manufacturing, firm size <20, lives in the South or Islands, 1993-1995 transition

Table 3: Results[a] from restricted models of low pay transitions

EXOGENEITY OF	EDUCATION (b)				EDUCATION AND RETENTION (c)				EDUCATION. RETENTION AND INITIAL CONDITIONS (c)			
INITIAL CONDITION	LOW PAY		HIGH PAY		LOW PAY		HIGH PAY		LOW PAY		HIGH PAY	
Average prediction	0.533		0.067		0.533		0.067		0.532		0.067	
Base category[d]	0.749		0.179		0.728		0.216		0.755		0.220	
Female	0.064	(1.73)	0.067	(2.74)	0.063	(1.56)	0.002	(2.92)	0.105	(3.43)	0.103	(3.75)
30 years of potential labour market experience	-0.018	(0.91)	-0.028	(2.93)	-0.008	(0.39)	-0.087	(2.73)	-0.062	(3.76)	-0.049	(4.72)
Education≥ High school	-0.106	(2.14)	-0.051	(2.27)	-0.102	(1.98)	-0.106	(2.14)	-0.136	(2.87)	-0.070	(2.75)
White collar (low level) - Teacher	-0.133	(2.28)	-0.093	(4.24)	-0.100	(1.60)	-0.143	(4.12)	-0.204	(3.69)	-0.124	(5.15)
White collar (high level)- Manager-Magistrate-Professor	-0.099	(0.51)	-0.114	(3.13)	-0.032	(0.17)	-0.161	(3.02)	-0.257	(1.25)	-0.147	(3.61)
Public sector	-0.103	(1.37)	0.135	(2.14)	-0.055	(0.75)	0.092	(2.70)	-0.051	(0.73)	0.206	(2.91)
Agriculture	-0.031	(0.46)	-0.014	(0.37)	0.001	(0.01)	-0.062	(0.04)	-0.036	(0.54)	-0.012	(0.26)
Construction	-0.013	(0.27)	0.044	(1.24)	0.001	(0.02)	-0.019	(1.36)	-0.003	(0.05)	0.065	(1.61)
Retail trade	0.072	(0.84)	-0.023	(0.46)	0.088	(0.97)	-0.078	(0.34)	0.065	(0.76)	-0.020	(0.35)
Transport and Communication	0.043	(0.60)	0.004	(0.09)	0.058	(0.78)	-0.054	(0.24)	0.043	(0.61)	0.006	(0.12)
Financial and related services	0.025	(0.34)	-0.024	(0.39)	0.020	(0.26)	-0.087	(0.46)	0.067	(1.02)	0.003	(0.04)
Personal and household services	-0.002	(0.03)	-0.103	(4.35)	0.051	(0.70)	-0.151	(4.20)	-0.155	(2.32)	-0.144	(5.63)
20≤ Firm size≤99	0.003	(0.06)	-0.004	(0.15)	0.033	(0.68)	-0.058	(0.23)	-0.051	(1.14)	-0.030	(1.10)
100≤ Firm size≤499	-0.122	(1.68)	-0.053	(1.82)	-0.096	(1.25)	-0.108	(1.70)	-0.214	(3.01)	-0.092	(2.94)
Firm size ≥500	-0.111	(1.00)	-0.088	(3.15)	-0.048	(0.43)	-0.136	(2.91)	-0.275	(2.49)	-0.129	(4.32)
North-west	-0.270	(4.34)	-0.041	(1.65)	-0.257	(3.86)	-0.098	(1.59)	-0.308	(5.24)	-0.057	(2.06)
North-east	-0.184	(3.25)	-0.048	(2.00)	-0.168	(2.79)	-0.105	(1.91)	-0.216	(3.98)	-0.065	(2.39)
Centre	-0.161	(2.90)	-0.012	(0.46)	-0.159	(2.74)	-0.075	(0.52)	-0.185	(3.47)	-0.021	(0.74)
Transition 1998-2000	-0.048	(1.20)	0.003	(0.14)	-0.030	(0.81)	-0.050	(0.78)	-0.013	(0.38)	0.025	(1.15)

Table 4 (continued)

EXOGENEITY OF	EDUCATION		EDUCATION AND RETENTION		EDUCATION. RETENTION AND INITIAL CONDITIONS	
ρ_1(initial conditions-retention)	-0.109	(3.72)				
ρ_3 (initial conditions- low pay transition)	-0.481	(4.66)	-0.597	(5.89)		
ρ_5 (retention-low pay transition)	0.214	(1.11)				
Exogeneity of initial conditions (df)	36.00 (2)	*0.0000*				
Exogeneity of retention (df)	14.84 (2)	*0.0006*				
State dependence						
Test (H0: γ_1=γ_2. df=20)	130.83	*0.0000*	233.65	*0.0000*		
ASD; GSD	46.6	20.4	46.6	19.9	46.5	23.1
Model χ^2(df)	1916.75 (94)	*0.0000*	1047.65 (65)	*0.0000*	108.47 (19) *0.0000*	306.61 (19) *0.0000*
Log likelihood	-6304.6385		-2426.2081		-420.4844	-735.71963
Number of observations	5913		4316		687	3629

Notes: Low pay defined as the bottom quintile of the earnings distribution. For each model, column headers indicate the initial condition.

a) For explanatory variables marginal effects on conditional low pay probabilities relative to reference individual are reported; see text for computation. Asymptotic t-ratios in parentheses refer to the underlying SML or ML coefficient. Tests statistics are from Wald tests of hypotheses, P-values in italic
b) SML estimator employs a GHK simulator with 75 random draws
c) ML estimator
d) Male, 20 years of potential experience, blue collar worker, private sector manufacturing, firm size <20, lives in the South or Islands, 1993-95 transition