Occupational Status Attainment in the Netherlands, 1920-1990: A Multinomial Logistic Analysis

John Hendrickx; Harry B. G. Ganzeboom

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Status attainment in the Netherlands is analysed using both linear regression and multinomial logistic (MNL) regression for male labour-market cohorts between 1920 and 1990. The quasi row and columns 2 mobility model (Logan, 1983; Goodman, 1979) is included in the MNL model, and a stereotyped ordered regression model (Anderson, 1984; DiPrete, 1990) is used for the covariates. The regression analyses indicate that the effect of father's occupation becomes weaker for later entrants into the labour market and as work experience accumulates. The impact of education is not affected by entry year but only by work experience. The MNL models largely confirm the results of the regression analysis, but show that the weakening impact of father's occupation by entry year and experience is not due to an increased flow between occupational classes, but only to a reduced propensity to immobility.

Introduction

During the past fifty years, the analysis of inter-generational occupational mobility has been an important method for drawing inferences about the openness of society. By studying trends in the ability of parents to affect their offspring's occupational status, sociologists are able to monitor shifts from ascription to achievement, from an emphasis on the individual's social origin to an increasing focus on the individual's personal abilities. Patterns of occupational mobility have been studied with a variety of instruments, both for indexing occupations and for analysing trends and relationships between the variables in the analysis. However, we will show that despite all the time and effort expended on this venture, new techniques and considerations are able to call previous conclusions into question.

Ganzeboom, Treiman, Ultee (1992) summarized the developments in post-war mobility research into three generations of research. In the 1950s, the first generation of mobility researchers (e.g. Glass, 1954; Lipset and Bendix, 1959) examined bivariate tables of father's occupation by son's occupation. Although their research was often highly innovative, the researchers lacked the instruments to provide adequate answers to all of their questions. The second generation of mobility research was launched by Blau and Duncan's (1967) status-attainment model. New elements in this approach were the use of individual-level data instead of mobility tables, well-constructed and reliable scales of socio-economic status (Duncan, 1961) or prestige (Treiman, 1977), and the inclusion of education and other explanatory variables besides father's occupation. The inclusion of education in the model makes it possible to compare the relative strengths of ascription (direct and indirect effects of father's occupation) and achievement (the effects of education). The shift from ascription to achievement has several components and these must be examined separately in order to evaluate changes in the openness of society.

However, although the development of reliable scales of socio-economic status and occupational prestige was an important advance in second generation research, the continuous nature of these scales also became a source of criticism. Researchers such as Featherman and Hauser (1978) and Goldthorpe (1987 (1981)) questioned whether the vertical nature of these scales told the whole story. They found that class schemas based on work and labour-market situations were heterogeneous with regard to attributes such as prestige, income, and education. A categorical mobility approach could also provide more details on the flows between occupational classes than a linear regression status-attainment model.

The preference for categorical scales of occupational class resulted in the third generation of mobility research. Researchers reverted to the analysis of square tables pioneered by the first generation, but now made use of sophisticated log-linear models. These mobility models impose constraints on the parameters for the origin–destination association, both to reduce the number of parameters and to test hypotheses on the nature of mobility. An important feature is their ability to distinguish the propensity to immobility within classes from the strength of flows between classes. Results show that immobility must usually be modelled separately in order to acquire an adequate fit of the model.

On the other hand, the benefits of log-linear mobility models came at a price. Log-linear models can only deal with a limited number of variables, which must be categorical. Grouping variables such as time and country were often included, but other explanatory variables such as education were usually not taken into account (exceptions are Yamaguchi, 1983; Ishida, Müller, and Ridge, 1995). The third-generation research essentially reverted to a bivariate model in which only the total effect of origin on destination was considered. This limitation meant that log-linear mobility analysis could not displace status-attainment research entirely (Treiman and Ganzeboom, 1990; DiPrete and Grusky, 1990).

Fortunately, it is not necessary to make a choice between either linear regression status-attainment or log-linear mobility models and to simply accept the shortcomings of the chosen method. Logan

(1983) showed how the multinomial logistic (MNL) regression model could be used to combine the advantages of the two methods. Special constraints are placed on the effects of father's occupational class on son's occupational class to obtain a detailed but parsimonious description of the mobility process. At the same time, individual-level covariates such as education can be included as in status-attainment models. A further refinement was introduced by DiPrete (1990), who showed how the 'stereotyped ordered regression' (SOR) model could be used to reduce the number of parameters for the covariates, without assuming ordered categories. These advantages brought Ganzeboom, Treiman, and Ultee (1992) to consider these MNL models an important contender for the fourth generation of mobility research.

As it turned out, applications of the MNL approach have failed to materialize, with the exception of work by Breen (1994). This is partly due to the problem of imposing the constraints required by a mobility model, which cannot be done using standard programs for multinomial logistic regression. However, technical difficulties of this nature can usually be overcome if the will is strong enough. And in this case, the technical problems are not as great as they appeared to be. By respecifying the MNL model as a conditional logit model, mobility models can be quite easily incorporated in the MNL framework (Breen, 1994). The conditional logit model[1] is strongly related to the MNL model and produces identical results, but provides more flexibility in imposing constraints.

In this paper we will make use of the MNL approach proposed by Logan (1983) to analyse the structure and trend of status attainment in the Netherlands from 1920 to 1990. We will implement a quasi-RC2 mobility model (Goodman, 1979) for the effects of father's occupation on respondent's occupation, while including education, year of entry into the labour market, and work experience as covariates. By using the SOR model (DiPrete, 1990) we are able to describe the effects of these covariates on respondent's occupation in a single parameter. A comparison between linear regression status-attainment models, log-linear mobility models, and these MNL models will show to what extent this approach can provide new insights. The next paragraph contains our hypotheses on these

trends, based on earlier work by De Graaf and Luijkx (1992, 1993) and Ganzeboom and De Graaf (1984). After a brief description of our data, we proceed with a linear regression analysis of status attainment. These results will serve as a base of comparison for the MNL models. A brief technical discussion of MNL models is then followed by a status-attainment analysis using multinomial logistic regression.

Theoretical Background

Both status-attainment models and mobility models focus on the importance of the ascribed characteristic 'father's occupation' versus the achieved characteristic 'education' on the respondent's occupation. Social origin affects social destination because parents with a higher occupational status have more resources with which to improve their offspring's outcomes in the labour market. Four types of resources can be discerned: financial, intellectual, cultural, and social resources (De Graaf and Luijkx, 1992, 1993). The use of continuous occupational scales entails the implicit assumption that the parent's financial, intellectual, cultural, and social resources form a single vertical dimension that correlates strongly with the occupational scale.

For many occupations this assumption does not seem untenable. It is reasonable to assume that a low-ranking labourer will have fewer resources of all types compared to a high-ranking professional, in proportion to the difference in rank on the scaling continuum being used. But for occupations such as farmers and the self-employed, this assumption is rather dubious. Parents in these occupations will have high financial resources in the form of a family business, relative to their intellectual, cultural, and social resources. A direct measurement of the different dimensions of parent's resources would be one way to proceed, but this would require new data and only provide information on recent cohorts. An alternative is to proceed with categorical measures of occupational classes that may be assumed to be homogeneous with respect to financial, intellectual, cultural, and social resources.

Similarly, the offspring's occupation can be characterized along several dimensions. As noted above, Featherman and Hauser (1978) found that the occupational classes they used were hetero-geneous with respect to education and income and Goldthorpe (1987 (1981)) found strong overlaps between classes with respect to scores on the Hope–Goldthorpe prestige scale. Evans (1992) used indicators of autonomy, security, prospects, and level of pay to characterize occupations. He found that these indicators did not form a uni-dimensional scale, but that the EGP classification (Erikson, Goldthorpe, and Portocarero, 1979; Erikson and Goldthorpe, 1992) was a good predictor of these attributes. This indicates that scales of occupational class provide a greater depth of information than continuous scales[2] of occupational prestige or socio-economic status.

Parents with greater resources are able to positively affect their offspring's outcomes in the labour market, directly as well as indirectly by providing better educational opportunities. This implies greater association between occupational classes in which parents have more resources and destination classes with higher levels of rewards. However in some instances, parents' resources can have effects of a more discrete nature. This will be the case for farmers and proprietors, where financial resources in the form of a family business will pre-dispose offspring to have the same class as their parents. This necessitates measures of the propensity to immobility as well as of the strength of flows between occupational classes as used in log-linear mobility analyses.

Although offspring of parents with great resources have advantages in the labour market, their head-start has gradually been eroded during the course of this century due to a number of factors which are gathered together under the label of modernization. Modernization refers to forces emanating from technical and economic growth, such as industrialization, bureaucratization, the growth in size of organizations, and the rise of the welfare state. The requirements of the modern work-force, supplemented by government intervention, has led to the broadening of educational opportunities, which reduces the indirect effect of origin via education on destination. The require-ment of efficiency in a free-market economy impedes employment based on ascribed characteris-tics such as family background. Large-scale, bureaucratic organizations also contribute to the waning influence of ascription and the growing

importance of achievement. Since Dutch society underwent a process of modernization during the period being examined, we can expect that ascribed factors such as father's occupation will have had a decreasing impact on respondent's occupation and that achieved factors such as education will have had an increasing impact.

Since we will be examining the respondent's occupation at the time of the interview and not his or her first occupation, it is also necessary to take the impact of work experience into account. During the course of a career, people accumulate human capital and move on to higher jobs (Becker, 1964). However, human capital has a decreasing marginal utility due to the fact that people are less able to absorb new knowledge as they grow older. The effects of work experience will therefore be curvilinear, rising quickly at the beginning, then tapering off. In addition, the effects of education and father's occupation will be greatest at the beginning of a career when the respondent has little human capital. As the respondent accumulates work experience, other factors become less important and the effects of education and father's occupation will gradually decrease.

The considerations above lead us to expect that a class-based approach to status attainment will have advantages over one based on continuous occupational scales in the sense that it will provide new insights. To see whether this is indeed the case, we will perform a status attainment analysis for Dutch labour-market cohorts between 1920 and 1990, first using linear regression, then using multinomial logistic regression models. By dropping education from the multinomial logistic models, we will be able to compare the MNL approach to a log-linear one as well.

For the categorical models, we consider occupational classes to be 'semi-ordered'. Many of the categories can be unambiguously ranked, but the position of some, in particular farm and self-employed occupations, is not entirely clear. We therefore make use of the Stereotyped Ordered Regression (SOR) model, which estimates a scaling metric for occupation, together with the effects of the independent variables (DiPrete, 1990). This approach allows us to think in terms of higher education leading to higher occupations, without specifying in advance which occupational classes

are high and which are low. The SOR model has the added advantage that it estimates a single parameter for the effect of each independent variable, which simplifies interpretation considerably.

For the effect of father's occupation, we use the RC2 mobility model (Goodman, 1979), which estimates a scaling metric for origin as well as destination, together with a single association parameter. In addition to the RC2 model, we also include parameters for the propensity to immobility within each class. This is in keeping with the proposition that certain origin occupations such as farm and self-employed have specific types of resources which increase the probability of immobility in the same class.

Our main interest lies in how the effects of father's occupation and of education on respondent's occupation vary with labour-market cohort and with work experience. The hypothesized impact of modernization on Dutch society and of accumulation of human capital lead to the following two predictions:

- The effects of father's occupation on respondent's occupation will decrease with entry year into the labour market and with work experience.
- The effects of education will increase with entry year, but will decrease with work experience.

These two hypotheses will be tested below, first using linear regression models, then with multinomial logistic and log-linear models. This will allow us to determine whether an MNL modelling using occupational classes has practical rather than merely hypothetical value.

Data

The data consists of 13 nationally representative surveys, conducted in the Netherlands for the year 1958 and at regular intervals in the period 1970–1992. The selection is restricted to male respondents between the ages of 25 and 64 at the time of interview, for whom present occupation and father's occupation were known, resulting in a total of 12,475 cases. In the analyses below, respondent's occupation is the dependent variable, first treated as a continuous measure of socio-economic

Table 1. *Basic statistics for the variables in the analyses*

	Min	Max	Mean	Std
Socio-economic status[a]	19	71	46.2	14.0
Father's socio-economic status[a]	19	71	41.0	13.6
Education	2	20	10.6	3.4
Entry year into the labour market	4	92	57.7	15.1
Work experience	0	54	23.4	12.5

[a]EGP10 scores recoded to mean ISEI values.

status in regression analyses, then as a categorical variable indicating occupational class in multinomial logistic models. In the categorical analyses, a six-category scale based on the EGP classification was used for respondent's and father's occupation (Erikson, Goldthorpe, and Portocarero, 1979; Erikson and Goldthorpe, 1992):

1   Farm labourers
2   Semi- and unskilled manual
3   Skilled manual
4   Self-employed
5   Routine non-manual
6   Controllers

For the regression analyses, the ISEI scale was used[3] (Ganzeboom, De Graaf, and Treiman, 1992).

The explanatory variables[4] consist of father's occupation, education (measured in years), entry year into the labour market, and years of work experience. Table 1 contains some basic statistics on the variables used in the analyses. The mean values reported in Table 1 were subtracted from education, entry year, and work experience in order to make parameters correspond with the 'average' situation. Since we expect work experience to show diminishing returns with occupation, we also included a quadratic term[5] for experience.

Regression Analyses

These analyses are in large part a replication of a study by De Graaf and Luijkx (1992, 1993), who used largely the same data and similar models. In the models below, respondent's occupation and father's occupation are treated as continuous measures of socio-economic status using the ISEI scale (Ganzeboom, De Graaf, and Treiman, 1992). The hypotheses formulated in the theoretical section

lead to the following model for the impact of father's occupation and of education on respondent's socio-economic status and for the trends of these effects by entry year and work experience:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_1 X_3 + \beta_3 X_1 X_4$$
$$+ \beta_4 X_2 + \beta_5 X_2 X_3 + \beta_6 X_2 X_4 \qquad (1)$$
$$+ \beta_7 X_3 + \beta_8 X_4 + \beta_9 X_4^2$$

where

Y = respondent's socio-economic status;
X_1 = father's socio-economic status;
X_2 = education;
X_3 = entry year into the labour market;
X_4 = work experience.

The parameter β_0 is the intercept and β_1 is the main effect of father's occupation. The parameter β_2 measures the effect of father's occupation by entry year and should be negative according to our first hypothesis. Likewise, our first hypothesis predicts that β_3, which measures the effect of father's occupation by work experience will be negative as well. The second row of equation (1) refers to the effects of education. The main effect of education is contained in β_4, while β_5 and β_6 test whether the effect of education decreases with entry year and work experience respectively. Our second hypothesis predicts that β_5 will be positive, but that β_6 will be negative, as the effect of education dwindles with the progression of the respondent's career.

The remaining parameters in equation 1 are of secondary interest. In the third row, the main effect of entry year is measured by β_7. A positive effect is expected, indicating that higher-status jobs became more prevalent in later cohorts. The last two parameters, β_8 and β_9, contain the linear and quadratic effects of work experience. A curvilinear function

is used, since we expect work experience to have a decreasing marginal utility. A quadratic function is easy to specify, but has the undesirable implication that beyond a certain point, greater experience would lead to lower socio-economic status. The significance of β_9 should be seen only as a test that work experience has decreasing returns, and not interpreted in too literal a fashion.

Results of the Regression Analyses

In addition to our model, we also fitted one in which the effects of education have been omitted. A comparison of the fit of these two models can be used to determine the total impact of education. Table 2 reports the adjusted R^2, unstandardized parameters and t-values for both models. A comparison of the adjusted R^2 of the two models shows that taking education into account more than doubles the proportion of explained variance. The parameters show that father's occupation has a strong effect in both models, but it is reduced by more than a third when education is included. This means that father's occupation has a strong direct effect, as well as a strong indirect effect through education. The effects of father's occupation decrease with both entry year and work experience, as predicted in our first hypothesis.

Education has a strong effect on occupation, which however does not increase with entry year, although it does decrease with work experience. So achievement has not become more important in the Netherlands during the course of this century, although the impact of ascription has decreased. This contradicts findings by De Graaf and Luijkx (1992, 1993), who used much the same data and similar models. The disparity is due to the fact that De Graaf and Luijkx did not include interactions between education and experience and between father's occupation and experience. Because entry year and work experience have a strong negative correlation, allowing effects vary by one variable but not the other can result in misleading conclusions. If the interactions of father's occupation and of education with experience are dropped from model 2, the parameter for father's occupation by entry year becomes weaker but is still significant, while the effect of education by entry year becomes strongly significant, as found by De Graaf and Luijkx.

Entry year has a significant main effect in both models, indicating that occupations with a higher socio-economic status have become more prevalent in the course of time. This effect is considerably stronger in model 1, where the effects of education are not taken into account. Both the linear and quadratic terms of work experience are significant. The negative value of the quadratic term implies that

Table 2. *Unstandardized parameters for the regression analyses*

	Model without education		Regression model	
	Parameter	t-value	Parameter	t-value
Constant	31.733	80.753	38.389	107.185
Father's SES	0.363	41.476	0.207	25.834
Father's SES by entry year	−0.008	−6.969	−0.006	−5.704
Father's SES by experience	−0.006	−4.260	−0.004	−3.037
Education			2.208	62.827
Education by entry year			0.003[a]	0.763[a]
Education by experience			−0.013	−2.374
Entry year	0.443	9.147	0.230	4.865
Experience	0.297	5.107	0.270	4.892
Experience squared	−0.002	−2.310	−0.005	−6.655
Adjusted R^2	0.144		0.355	

[a]Parameter is not significant at 0.05.

work experience has a curvilinear effect which reaches a maximum value[6] at 52 years.

To summarize, the regression analyses show that the effect of father's occupation decreases with both entry year into the labour market and work experience. The effects of education do not increase with entry year, but decrease with work experience. In the next paragraph, we will compare these results with those of a multinomial logistic model in which occupational classes are used, rather than a continuous measure of socio-economic status. This will be preceded by a technical discussion of these models.

Multinomial Logistic Regression Analyses

The regression approach above can be used to test our hypotheses on trends from ascription to achievement, but has the disadvantage that it treats occupation as a continuous variable. A categorical approach is more suitable for dealing with the different types of resources and different dimensions of rewards associated with certain occupations, in particular farmers and the self-employed. We will therefore repeat the analyses using multinomial logistic regression (MNL) models. As discussed in Logan (1983) and more recently in Breen (1994), it is possible to specify models for square tables[7] in an MNL model, while including individual-level covariates such as education. We will also use the non-linear[8] SOR model (DiPrete, 1990) for the individual-level covariates, which will allow us to express their effects in a single parameter. In this way, the main strengths of log-linear mobility analysis and status-attainment regression models can be combined.

In a multinomial logistic regression model, the interest lies in how explanatory variable X_k affects the probability π_j that category j of the response variable will be chosen. The probabilities themselves are a non-linear function of the explanatory variables. The model is therefore usually represented in its logit form, in which the log-odds of a respondent having response j versus the reference category J is a linear function of the explanatory variables. The reference category J is typically the highest category, but any category may be used. A standard MNL model can be written as:

$$\log(\pi_j/\pi_J) = \alpha_j + \sum_{k=1}^{K} \beta_{jk} X_k \qquad (2)$$

The fact that all effects are relative to a certain reference category may seem arbitrary. However, the log-odds for occupation j versus occupation j' can be easily derived by:

$$\log(\pi_j/\pi_{j'}) = \log(\pi_j/\pi_J) - \log(\pi_{j'}/\pi_J)$$
$$= \alpha_j - \alpha_{j'} + \sum_{k=1}^{K} (\beta_{jk} - \beta_{j'k}) X_k \qquad (3)$$

In the analyses below, the response variable has six categories relating to the respondent's occupation. An MNL model would then contain five α_j parameters indicating the baseline log-odds of a respondent having occupation j ($j = 1$ to 5) versus occupation 6, for the situation in which all explanatory variables have the value 0. For each explanatory variable X_k, there would be five effect parameters β_k indicating how a unit's increase of the X_k affects the log-odds of response j versus response 6.

For anything more than a small number of explanatory variables, this would soon lead to an unpractical number of parameters. In an analysis such as this, these parameters would also contain a good deal of redundant information, since it can be expected that the pattern of log-odds changes will be similar for explanatory variables like education and experience. More education will increase the probability of becoming a higher controller and lower the probability of become an unskilled manual worker, as will more job experience (although perhaps not as strongly). A method[9] for capturing such response patterns and discarding redundancies is the stereotyped ordered regression (SOR) model (DiPrete, 1990).

The SOR model, developed by Anderson (1984), captures the common pattern of the effects of the K covariates in a scaling metric ϕ_j for the response variable. Two values of the scaling metric are fixed in order to identify the model by letting $\Sigma \phi_j = 0$ and $\Sigma \phi_j^2 = 1$. The strength of the effect of each co-variate can then be expressed through a single parameter β_k, rather than five β_{jk} parameters as in equation 2. A model with the SOR restriction is as follows:

$$\log(\pi_j/\pi_J) = \alpha_j + \phi_j \sum_{k=1}^{K} \beta_k X_k \qquad (4)$$

The interpretation of the ϕ_j metric is best illustrated for a comparison of category j versus category j' of the response variable:

$$\log(\pi_j/\pi_{j'}) = \alpha_j - \alpha_{j'} + (\phi_j - \phi_{j'})\sum_{k=1}^{K}\beta_k X_k \qquad (5)$$

If two scale values ϕ_j and $\phi_{j'}$ have almost the same value, then the explanatory variables will barely affect the odds of a respondent having occupation j versus occupation j'. The greater the difference between ϕ_j and $\phi_{j'}$, the more the odds of having j versus j' is affected the covariates β_k. The magnitude of each β_k parameter shows how strongly it affects the odds of choosing occupation j versus occupation j'. The values of the ϕ_j metric can be expected to increase steadily, given the semi-ordered nature of our dependent variable, but to have unequally spaced intervals. Note that the SOR model does not assume ordered categories, only that the occupational categories can be placed on an underlying continuum with respect to the effects of the covariates X_k.

Using the SOR model, a parsimonious description of the effects of the individual-level covariates can be obtained. The next step is to specify the effects of father's occupation in an appropriate manner. This is done by using a scaling metric σ_i for father's occupation and letting an association parameter μ indicate the strength of the association between origin and destination. This amounts to Goodman's (1979) row and columns model II (RC2):

$$\log(\pi_j/\pi_J) = \alpha_j + \mu\sigma_i\phi_j + \phi_j\sum_{k=1}^{K}\beta_k X_k \qquad (6)$$

The RC2 model can be used to measure how father's occupation affects the odds of a higher versus a lower destination occupation. As rescaled by the σ_i metric in equation 6, father's occupation is comparable to a regular covariate: the higher the score on σ_i, the more father's occupation affects the odds of a higher versus a lower occupation for the respondent. In order to capture the extra propensity to immobility in certain occupations, particularly farming and self-employment, immobility parameters d_i ($i = 1$ to 6) are included as well. These parameters measure the log odds of the respondent having the same versus a different occupation than his father.

Our first hypothesis states that the effects of father's occupation will decrease with both entry

year and work experience. In the categorical models, the effects of father's occupation are divided into two components, i.e. mobility, measured by the μ parameter, and immobility, measured by the d_i parameters. Our theory leads us to expect that both components will decrease with both labour-market cohort and life cycle. We therefore let the origin–destination association parameter μ vary by entry year and experience, but only include interactions between an overall immobility parameter d_0 and entry year and experience.

The considerations result in the following model:

$$\begin{aligned}\log(\pi_j/\pi_J) = &\alpha_j + d_i + d_0 X_3 + d_0 X_4 + \beta_{j1}X_3 \\ &+ \sigma_i\phi_j(\mu_0 + \mu_1 X_3 + \mu_2 X_4) + \phi_j(\beta_2 X_2 \qquad (7) \\ &+ \beta_3 X_2 X_3 + \beta_4 X_2 X_4 + \beta_5 X_4 + \beta_6 X_4^2)\end{aligned}$$

where:

X_2 = education;
X_3 = entry year into the labour market;
X_4 = work experience;
α_j = the intercept term;
d_i = immobility for occupation i;
d_0 = overall immobility;
μ_0 = overall origin–destination association;
μ_1 = origin–destination association by entry year;
μ_2 = origin–destination association by experience;
σ_i = scaling metric for father's occupation;
ϕ_j = scaling metric for respondent's occupation.

In equation 7, the α_j parameters form the intercept term. They indicate the baseline log odds of having occupation j versus occupation 6 (controllers) when all explanatory variables are zero. The effects of father's occupation are represented by multiple model terms. The d_i term measures the propensity to immobility of each occupational category, while μ_0 measures the overall origin–destination association. The terms $d_0 X_3$ and $d_0 X_4$ measure how the overall propensity to immobility changes with entry year and experience respectively, and $\mu_1 X_3$ and $\mu_2 X_4$ measure how origin–destination association changes with entry year and experience.

The main effects of entry year are contained in the $\beta_{j1}X_3$ term. Note that this term uses the standard response function, rather than the SOR constraint, since we do not necessarily expect entry year to lead to higher occupations. The other covariates do use the SOR constraint and their effects are therefore

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contained in a single parameter. The term $\beta_2 X_2$ contains the main effect of education, and $\beta_3 X_2 X_3$ and $\beta_4 X_2 X_4$ measure how the impact of education changes by entry year and work experience. A curvilinear effect of work experience is modelled by using a linear and a quadratic term $\beta_5 X_4$ and $\beta_6 X_4^2$.

Results of the Multinomial Logistic Analyses

In addition to the postulated model of equation 7, we also fitted three alternative MNL models:

1. *ISEI scores.* This model uses the mean ISEI scores per EGP category as an a priori metric, rather than estimating the σ_i and ϕ_j metrics. A comparison with the postulated model will show whether an estimated metric has more explanatory power than an a priori one.[10]
2. *Education omitted.* This model does not include the effects of education and the interactions of education with entry year and work experience. A comparison of this model with the postulated model shows the total impact of education on respondent's occupation. This model is therefore comparable with a log-linear mobility model using time as a grouping variable. A comparison of the parameters of this model and the postulated model can show how taking education into account affects parameters for the mobility pattern, i.e. whether they only become weaker or whether a different pattern emerges.
3. *Equal scales.* This model uses the same scaling metric ϕ_i for origin as well as destination. This would mean that occupational classes have the same ranking and distances as a resource and as a reward.
4. *Postulated model.*

Evaluating the fit of a multinomial logistic model is not as straightforward as regression or log-linear

models, for which a perfect fit can been defined. An MNL model has a log-likelihood value, which should not be used to test whether the model itself fits the data, but can be used in comparisons between two nested models. A likelihood ratio L^2 statistic can be calculated as $2(ll_2 - ll_1)$, where ll_2 is the log-likelihood of one model and ll_1 is the log-likelihood of a more parsimonious version. This L^2 statistic has a chi-square distribution with the number of degrees equal to the number of parameters that are dropped by the more parsimonious model.

When a large number of cases are used, the normal chi-square test of the L^2 statistic almost always rejects the more parsimonious model, even when parameters dropped by that model have trivial (though statistically significant) values. For such situations, Raftery (1983, 1995) developed the bic statistic. Bic is defined as the log-odds that model 1 versus model 2 is true (the models need not be nested). For large samples, bic can be approximated by:

$$bic = L^2 - df \cdot \log(N) \qquad (8)$$

where N is the sample size.

The bic statistic has been used extensively in log-linear mobility research. A negative bic for a log-linear model means that the model is preferable to the saturated model. Two or more log-linear models can also be compared using the difference in L^2 and df between the models to calculate bic, in which case a negative bic means that the more parsimonious of the two models is preferable. Likewise for multinomial logistic models, a negative bic for the comparison of two models indicates that the more parsimonious of the two is preferable, and a bic of zero or greater means that the more complex MNL model should be chosen.

Table 3 contains the log-likelihood values for the four models fitted here and the L^2, df, and bic values for comparisons of the alternative models with the postulated model. In model 1, the use of ISEI scores

Table 3. *Goodness-of-fit statistics for the multinomial logistic regression models*

Model	Log-likelihood	L^2 vs. model 4	df vs. model 4	bic
1. ISEI scores	−16681	228	8	152
2. Education omitted	−18316	3497	3	3796
3. Equal scales	−16578	20	4	−27
4. Postulated model	−16568			

as an a priori metric saved 8 degress of freedom compared with the postulated model, but the L^2 value of the likelihood test between the two models has a value of 228. The bic value for this comparison has a strongly positive value of 168, indicating that the more extended postulated model should be chosen.

Model 2 omits education in order to evaluate the strength of its impact. The L^2 for a comparison with the postulated model is 3479 with 3 degress of freedom, showing strong effects of education and education by cohort and life cycle. An MNL model has a good deal of explanatory power over a log-linear model in which education is not included. Model 3 uses equal scaling metrics for father's occupation and respondent's occupation. The L^2 statistic for this comparison has a value of 20 with 4 df. This is statistically significant, but that is due to the large number of cases. The bic statistic for this comparison is -27, which indicates that the more parsimonious equal scales model should be chosen. Since equal scaling metrics will simplify the interpretation and the improvement in L^2 for the postulated model is quite small considering the number of cases, we will proceed[11] with the interpretation of model 3.

The parameters of model 3 are presented on the right-hand side of Table 4. On the left are the estimates for the same model but without education. A model without education is comparable to a log-linear mobility model with time as a grouping variable and a comparison of its parameters with those of model 3 can show whether taking education into account will affect the mobility pattern. Conceivably, including education in the model could have an important impact on the parameters for the mobility pattern, e.g. reducing some of the immobility parameters to non-significant values. The parameters for the intercept and the main effects of entry year (which does not use the SOR constraint) have not been included in Table 4 in order to conserve space.

The equal origin–destination scaling metric ϕ_j in panel A of Table 4 shows the optimal scale values for the occupational categories, based on the relationships between respondent's occupation, father's occupation, and the covariates. The estimation procedure used here cannot produce standard errors for the ϕ_j metric, and the Z-values for the remaining parameters are found by treating the ϕ_j scale as

given. However, the L^2 for model 1 using the ISEI scores versus model 3 is 207 with 4 df, with a bic value of 169. The ϕ_j metric therefore deviates significantly from an acceptable a priori metric.

Higher values of ϕ_j indicate that greater amounts of education, work experience, and origin status are required to arrive at destination j. The larger the difference between the ϕ_j scores for two occupations, the more a unit's increase of education or experience affects the odds of someone having the higher of the two occupations. So, for example, in the postulated model one year of education will affect the odds of becoming a controller versus a routine non-manual worker by a factor of $\exp(0.494*(0.744-0.183)) = 1.32$. On the other hand, farmers and skilled manual workers have almost the same score, so the odds of one occupation versus the other are the same no matter how high or low a respondent's education, experience, etc. The scaling metrics also apply to origin status. The higher the score for father's occupation, the more origin status improves the odds of a better occupation, just like a regular covariate such as education or work experience.

Figure 1 contains a chart of the scaling metrics to assist in their interpretation. In the models both with and without education, farmers would be ranked higher, just under skilled manual workers. If the category of farmers is ignored, then the scale values rise steadily and more or less linearly for the model without education. When education is included, however, a large gap appears between controllers and routine non-manual workers. The scale values for self-employed and routine non-manual workers decrease substantially when education is included, whereas the value for controllers rises. This means that when education is taken into account, controllers derive greater utility from a higher social origin and work experience than when education is not taken into account. Since the scaling metric also applies to social origin, it also means that having a father who is a controller has considerably greater value when education is taken into account than when it is not. This illustrates the value of using a categorical approach, rather than continuous scales of socio-economic status or prestige.

Panel B of Table 4 reports the immobility parameters for each occupational category and the

Table 4. *Parameters for the multinomial logistic regression models*

|	Model 3 w'out eductn.		Model 3	
Panel A: Equal origin–desination scaling metric				
Farmers	−0.294		−0.247	
Semi- and unskilled manual	−0.613		−0.537	
Skilled manual	−0.210		−0.236	
Self-employed	0.177		0.092	
Routine non-manual	0.364		0.183	
Controllers	0.575		0.744	
Panel B: Immobility				
	Estimate	Z-value	Estimate	Z-value
Farmers	2.779	29.031	2.843	29.459
Semi- and unskilled manual	−0.274	−3.965	−0.127[a]	−1.845[a]
Skilled manual	0.437	8.925	0.363	7.172
Self-employed	1.508	17.677	1.591	18.556
Routine non-manual	0.261	3.727	0.518	7.252
Controllers	0.383	6.705	−0.293	−3.363
Immobility by entry year	−0.017	−5.556	−0.018	−5.650
Immobility by experience	−0.017	−4.748	−0.018	−4.858
Panel C: Origin–destination association				
Overall association	1.567	21.201	1.211	13.069
Association by entry year	−0.015[a]	−1.766[a]	0.001[a]	0.160[a]
Association by experience	−0.011[a]	−1.037[a]	0.006[a]	0.560[a]
Panel D: Covariates				
Education			0.494	48.232
Education by entry year			−0.001[a]	−0.435[a]
Education by experience			−0.005	−3.194
Experience	−0.000[a]	−0.111[a]	0.014	3.476
Experience squared	−0.000[a]	−0.618[a]	−0.001	−5.145

[a]Parameter is not significant at 0.05.
Note: Parameters for the intercept and the main effects of entry year have been omitted to conserve space.

trends of overall immobility by entry year and experience. Including or excluding education from the model produces interesting shifts here as well. The fairly strong propensity to immobility for controllers in the model without education becomes significantly negative when education is included in the model. When education is taken into account, the scaling metric shows that sons of controllers have higher odds of achieving a high occupation than a low one, but the immobility parameters show that they have lower odds of

actually becoming a controller. On the other hand, when education is taken into account the immobility parameter for routine non-manual workers increases whereas its origin–destination scale value decreases. Sons of routine non-manual workers are more likely to also become routine non-manual workers when education is taken into account, but less likely to reach a higher versus a lower position.

The immobility parameters for the remaining classes are fairly stable, although the negative
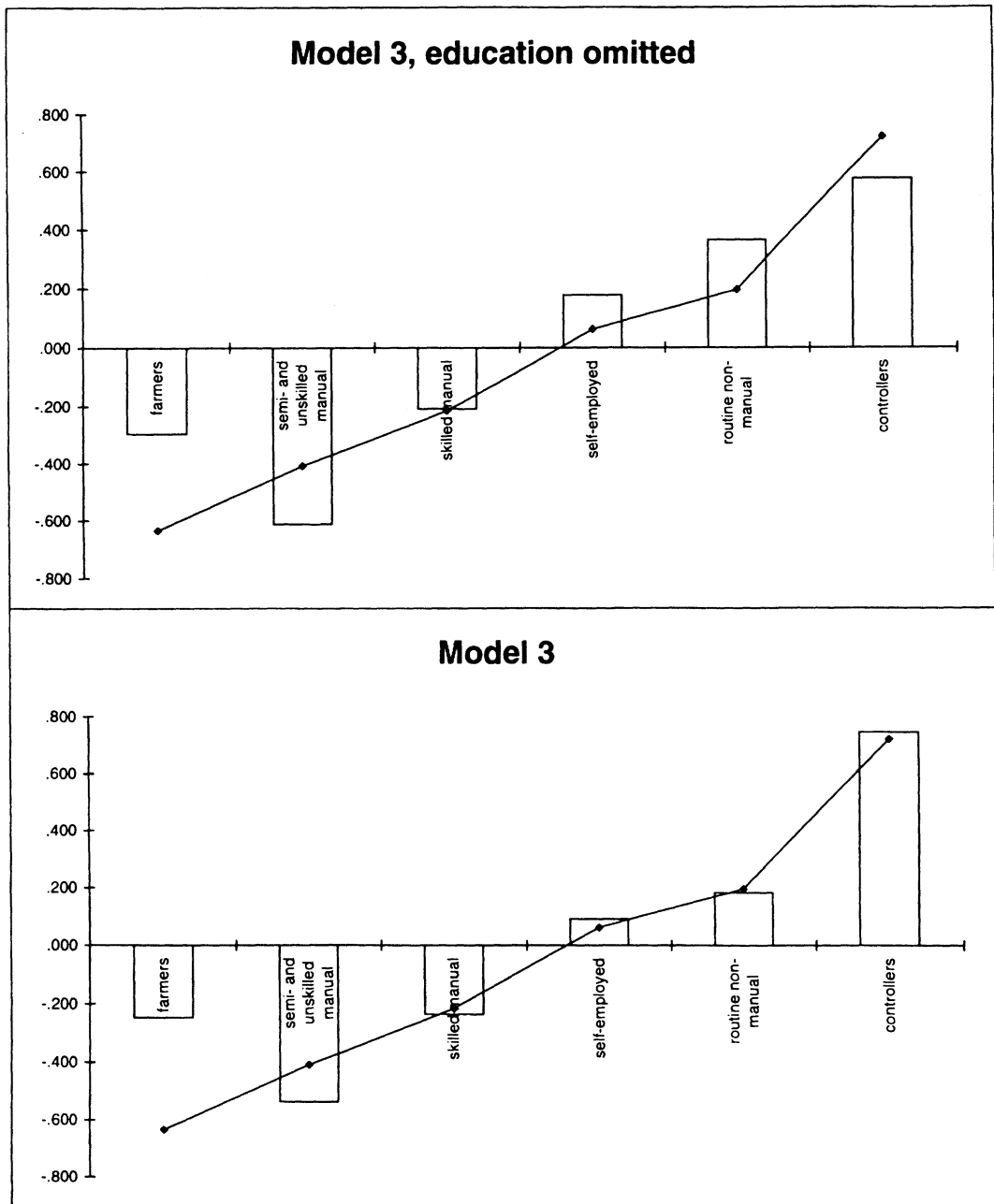
Line represents mean ISEI score per occupational category

Figure 1. *Equal origin–destination scaling metrics for the multinomial logistic analysis.*

parameter for semi- and unskilled manual workers becomes non-significant when education is taken into account. There is a very strong propensity to immobility among farmers and a strong propensity among the self-employed, which can be attributed to the inheritance of capital goods by respondents in these categories. The last two rows of panel B show the trends of overall immobility by entry year and

work experience. The overall propensity to immobility declines steadily by both entry year and experience, with almost no differences between the models with and without education.

The parameters for origin–destination association are given in panel C of Table 4. The overall association parameter is strongly significant in both models, but is 23 per cent lower in model 3, where the effects of education are taken into account. Father's occupation has a direct effect on son's occupation, controlling for both immobility and education. The trend parameters for origin–destination association are not significant in either the model without or with education. This indicates that the downward trend of the effect of origin by entry year and experience, which we found in the regression analyses above, must be attributed to changes in the propensity to immobility only. The results of the MNL models show that father's occupation continues to have a strong direct effect on respondent's occupation, which has not diminished in the course of this century and does not decrease during the course of someone's career either.

Panel D contains the parameters of the individual-level covariates. In keeping with the results of the regression analyses, education has a very strong effect, which does not change significantly by entry year but does decrease with work experience. The main effect of work experience has a positive effect and experience squared has a negative parameter, which means that rescaled occupation as a function of work experience follows a curve which slowly rises to a maximum at 33 years, after which the effect starts to decline. The diminishing returns to work experience are stronger in the MNL model than in the regression analysis, where effects peaked after 52 years.

The results of the multinomial logistic models show advantages over both log-linear and linear regression approaches. A log-linear approach that does not take education into account overstates the immobility in the controllers' class and underestimates immobility in the routine non-manual class. Conversely, a log-linear approach overestimates the utility of a routine non-manual origin for attaining a higher position and underestimates the utility of a controller origin. A regression model leads to the conclusion that the impact of father's

occupation decreases with time and work experience, but an MNL model shows that matters are slightly more complicated. It is true that the propensity to have the same occupation as your father has decreased over time, but the strength of flows between different occupational classes has not changed substantially in the course of this century and does not change with work experience. The results also show that continuous measures of socio-economic status fail to capture the unequal barriers between occupational categories. Scaled models of status attainment and mobility, such as stereotyped ordered regression and the row and column model II, are better able to capture the varying magnitudes of these barriers in relationship to explanatory variables such as origin status, education, and work experience.

Conclusions

Logan (1983) and DiPrete (1990) proposed parsimonious multinomial logistic (MNL) models for the analysis of status attainment and mobility that combine the advantages of the linear regression status-attainment and the log-linear mobility approaches. Like log-linear mobility models, these MNL models are able to provide detailed information on the flows between occupational classes. Like linear regression status-attainment models, the MNL models can incorporate individual-level covariates. In this paper, we applied these models in order to determine whether they are able to provide new insights compared to the older approaches.

In comparison to a linear regression approach, the MNL approach shows that the relationship between origin and destination is too complicated to be expressed in a single effect parameter. We found significant propensities to immobility in all occupational categories, with the exception of semi- and unskilled workers, as well as an overall association parameter. In this case, the extra detail provided by an MNL approach led to different substantive conclusions with respect to the growing openness of Dutch society. Whereas a regression approach indicates that the effect of origin on destination decreases with both entry year and experience, the MNL approach shows this is only

due to decreases in the propensity to immobility. The strength of flows between different occupations has remained constant through time.

A key advantage of the MNL approach compared to a log-linear approach is that education can be easily included in the model and its effects expressed through a single parameter. MNL models with and without education provide interesting insights into the effects of education on moves between particular occupational classes. When education is included in the model, the scaled value for controllers increases while that of the self-employed and routine non-manual workers decreases. This shows that education has especially strong effects on the odds of becoming a controller versus some other occupation, and in particular on the odds of controller versus either self-employed or routine non-manual. Log-linear models, therefore, not only overstate the effects of origin on destination, but can also provide incorrect information on the pattern of mobility if education does not affect all destinations equally.

This paper shows that the MNL approach has key advantages. Because occupation is treated as a categorical variable, it is possible to distinguish different components of mobility and test for different trends in each component. Because education is included in the model, it is possible to determine the impact of education on the mobility pattern. The models themselves are no more difficult to estimate or interpret than log-linear mobility models. The MNL approach should be strongly considered for future research on status attainment and mobility.

Notes

1. Conditional logit models are typically used to model the effects of attributes of the alternatives, as well as of respondent attributes, on the respondent's choice between a number of alternatives. For example, Hoffman and Duncan analysed divorced women's choices between remarrying, remaining single and on welfare, and remaining single and working. Along with respondent attributes such as number of children, age, education, and residence, they included attributes of the alternatives such as prospective husband's income, welfare benefits, wage rate, and non-labour income.

Some authors use the term 'conditional logit' to refer to models with individual characteristics only. Others (Agresti, 1991; Maddala, 1983) refer to models with individual and/or choice characteristics as multinomial logistic models on the grounds that both have the same likelihood function. Regardless of one's terminological preferences, programs for conditional logit models require a different organization of the data than programs for multinomial logistic models (Hoffman and Duncan, 1988: 420; Allison and Christakis, 1994: 205). If only respondent attributes are included in the model and only one of the alternatives is used as a reference, then a conditional logit program will produce the same results as a program for multinomial logistic analysis. An advantage of the conditional logit model over the multinomial logistic model is its ability to let certain individual characteristics affect certain choices only. It is this property that allows a mobility model to be specified in a conditional logit model.

2. Continuous occupational scales have the added disadvantage of being relatively abstract compared to occupational classes. Scales of occupational prestige can be measured reliably, but it is not altogether clear what is being measured. The concept of prestige entails deference to those with higher prestige and derogation to those with lower prestige, but it is doubtful whether occupational prestige actually measures this. Goldthorpe and Hope (1972) argue that the best interpretation for occupational prestige would be the relative 'goodness' of occupations, on which there appears to be a reasonably stable social consensus. However, this reduces prestige to a rather vague and unsatisfactory concept. Similarly, scales of socio-economic status attempt to optimally associate educational requirements with prospective income. This makes it quite an abstract measure, that is partially tied in with the process of status attainment it is used to model. Neither prestige nor SEI can be discarded as invalid measurements on these considerations, but occupational classes do emerge as less abstract and easier to interpret.

3. For practical reasons, the ISEI scales used in the regression analyses were derived by recoding ten-category EGP scales for respondent's and father's occupation to their mean ISEI values.

4. Entry year and work experience were derived from respondent's age and the year of survey in the following fashion. Entry year is defined as birth year (survey year−age), plus school leaving age (years of education plus 6). Job experience is defined as age, minus school leaving age. In the 1958 survey, age was available in 5-year intervals only. A random component was

therefore added to enhance comparability with the remaining data. These operationalizations of entry year and experience cause the two variables to have a strong negative correlation of -0.869. Due to this strong correlation, both entry year and experience should be included in any interaction effect. For example, a positive effect of education by entry year would be over-estimated if experience were not taken into account, and the effects of education decrease as experience accumulates, as hypothesized above. On the other hand, the strong correlation between entry year and experience could lead to unstable parameter estimates due to collinearity. The collinearity diagnostics produced by programs such as SPSS REGRESSION are not suitable for models containing non-linear terms such as interactions or the quadratic term of experience. For such models, Belsley (1991) suggests iteratively re-estimating the model after applying random perturbations to the variables on which the non-linear transformations are based. This will show how stable the parameter estimates are under small changes in the data. We applied this to X_3 (entry year) and X_4 (experience), using random perturbations in the range -2.5 to 2.5. These perturbations have repercussions for all parameters in the model, since X_1 (father's occupation) and X_2 (education) have interaction effects with X_3 and X_4. After 100 iterations, we found that the impacts on the parameter estimates were quite stable (the results are shown in the Appendix). This is due to the large number of cases (12,475), which allows a high signal-to-noise ratio, despite the high correlations between entry year and experience. The effects of perturbances were evaluated using an SPSS macro written by Ben Pelzer, Manfred te Grotenhuis, and Jan Lammers of the Department of Methodology of the University of Nijmegen. It is available on request from the first author.

5. The quadratic term for experience was created using $(X-m-k)^2$, where X contains the original scores for experience, m is the mean value of experience (23.4), and k is a constant (2.3). By choosing k equal to $b/2$ from the equation $X^2 = a + bX$, the linear and quadratic terms of work experience become orthogonal.

6. The effects of experience are (X_4-m) for the linear term and $(X_4-m-k)^2$ for the quadratic term, where X_4 are the original scores for experience, m is the mean value of experience (23.5), and k is a constant (2.2) which makes the linear and quadratic terms orthogonal. The value of k is equal to $b/2$ from the equation $X_4^2 = a + bX_4$. The maximum of $Y = \beta_8(X_4-m) + \beta_9(X_4-m-k)^2$ can be found by calculating $-\beta_8/(2\beta_9) + m + k$.

7. Mobility models cannot be specified in programs for multinomial logistic regression because of the requirement that one category of the dependent variable be used as reference category for the effects of all independent (dummy) variables. Mobility models usually require different restrictions on the dependent variable, depending on the category of origin. A solution is to specify the MNL model as a conditional logit model (Breen, 1994; Hendrickx, 1995). A conditional logit model allows independent variables to affect only certain categories of the dependent variable, which makes the specification of mobility models quite straightforward.

8. The SOR model and the EQRC2 model used in the MNL models contain both additive and multiplicative model terms. They can be estimated by iteratively estimating conditional logit models, first treating parameters on one side of the multiplication sign as given, and estimating the rest, then estimating the remaining parameters (Breen, 1994; Hendrickx, 1995). Macro programs for estimating these models using the statistical packages SAS or STATA are available at <http://www.socsci.kun.nl/maw/sociologie/J.Hendrickx> or by contacting the first author. The analyses in this paper were conducted using STATA.

9. Another way of reducing the number of parameters in the MNL models could be to use a cumulative logistic model (Agresti, 1990: 322). However, the cumulative logistic model assumes ordered categories, which the SOR model does not. The approach used here is also more flexible, since it allows us to treat occupation as strictly nominal for some variables, such as that of entry year, and impose a SOR constraint for others.

10. The principles on which the ISEI score is based bear some resemblance to the idea behind the SOR model. An SEI measure is designed to optimally link resources (education) with rewards (income) (Ganzeboom, De Graaf, and Treiman 1992: 9), using occupation as an intermediate variable. The SOR model on the other hand, tries to optimally link covariates such as education with occupation, which is treated as an outcome rather than an intermediate variable. The two approaches could yield similar outcomes, in which case the ISEI scores would be preferable due to their better theoretical foundation and simpler interpretation.

11. An objection that might be raised against model 3 is that the SOR constraint imposes a one-dimensional ordering for the occupational categories, even though it does not assume an a priori ordering. To test whether this constraint is acceptable, we

compared the model to a multinomial logistic model using the standard response function and treating father's occupation as a regular categorical variable. The likelihood ratio statistic for a comparison between this model and model 3 is 239 with 75 df, with a bic value of −472. The negative bic indicates that the more parsimonious model 3 is preferable. Indeed, the L^2 value is quite small given the number of cases and degrees of freedom in the comparison shows that the restrictions used in model 3 cause only a very small loss of information.

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Appendix

Table A1. *Effects of random perturbations to entry year and experience on the parameters of the regression analysis*

	Mean	s.d.	Min.	Max.
Constant	38.361	0.015	38.321	38.398
Father's SES	0.207	0.000	0.206	0.207
Father's SES by entry year	−0.006	0.000	−0.007	−0.005
Father's SES by experience	−0.004	0.000	−0.004	−0.003
Education	2.207	0.002	2.203	2.211
Education by entry year	0.003	0.001	0.001	0.005
Education by experience	−0.013	0.001	−0.016	−0.010
Entry year	0.210	0.012	0.178	0.246
Experience	0.270	0.015	0.232	0.310
Experience squared	−0.005	0.000	−0.005	−0.005

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