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(NON-) GRADUATION AND THE EARNINGS FUNCTION : AN INQUIRY ON SELF-SELECTION

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Joop Hartog*, Gerard Pfann**, Geert Ridder***

ABSTRACT

We model schooling careers in the Dutch educational systems (including the decision to drop out) as a discrete sequential choice, in which expected earnings play an important role. Selectivity bias from correlation between the errors in the decision function and the earnings function appears empirically relevant and we correct for it by applying a proper maximum likelihood estimation procedure. The results indicate that drop-outs behave differently from graduates. In the decision functions on schooling careers, expected earnings (based on estimated earnings functions in mid-career) are never significant. Yet, the educational choices appear ex post consistent with choices according to comparative (earnings) advantage.

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* University of Amsterdam, Faculty of Economics, Jodenbreestraat 23, 1011 NH Amsterdam, The Netherlands.

** University of Limburg, Department of Economics, P.O.Box 616, 6200 MD Maastricht, The Netherlands.

*** University of Amsterdam, Interfaculty of Econometrics, Jodenbreestraat 23, 1011 NH Amsterdam, The Netherlands.

I. INTRODUCTION

"Admittedly, no one's allowed to become a full-time student, except for the very few in each town who appear as children to possess unusual gifts, outstanding intelligence, and a special aptitude for academic research. But every child receives a primary education, and most men and women go on educating themselves all their lives during free periods".

Thomas More
Utopia, 1516.

It has long been recognized that individual demand for education should be analyzed in an investment framework. Decisions on the length of education are taken with a view on the expected returns, compared to its opportunity cost. Both returns and cost are broadly defined, and may include non-monetary items. There may be substantial debate about the causal role of education in explaining earnings, but the human capital model is virtually unchallenged when it comes to explaining individual's decisions to participate in extended education. This paper is about such decisions and it will basically adopt the investment framework.

The paper tackles two problems in particular : dropping out and self-selection. In the Dutch educational system, in recent years some 35 % of individuals leaving school do so without graduating from the last school they attended. One may hypothesize that there are two sets of forces behind the drop-out decision, push-factors and pull-factors. Push-factors emphasize the failure interpretation. Despite the earlier expectations, when individuals decided to continue their education, it turns out that they are unable to meet the requirements, for lack of ability, motivation, or whatever reason. Pull-factors emphasize positive elements in the decision : individuals are drawn out of school as they discover that the labor market offers them more favorable returns with a shorter education than initially expected. Taken together, these considerations suggest that one may analyse the drop-out decision quite analogously to the decision to attend a particular type of school. It is the comparison between expected returns and opportunity cost that provides the guideline and there is no fundamental distinction between decisions on completed educations and on partial educations. In this paper, these decisions are indeed analyzed with exactly the same structure, which doesn't rule out that drop-outs and graduates may have different (access to) information.

Selectivity has come to be recognized as an important aspect of educational choices. It seems quite likely a priori that individuals have better information on their abilities and expected rewards to schooling than the outside researcher has. This leads to selectivity in the available observations. Those that actually undertake an education and realize the rewards are different from those that abstain from the education, and whose possible rewards are not observed. Empirical support for this hypothesis was found in US data by Willis and Rosen (1979) and more recently by John Garen (1984). In our model we correct for selectivity bias by allowing for correlation in the errors of earnings functions and decision functions for given levels of education.

If one is only interested in the question of the individuals' schooling decisions, one would do best by collecting data on such decisions and on the explanatory variables as perceived by the individuals when the decision was made. This is the way Kodde proceeded in his recent dissertation about demand for university education in the Netherlands (Kodde, 1985). His data included observations on the individuals' expectations. He found convincing support for the effect of the human capital variables : the expected values of foregone and future earnings, expected probabilities of getting a job with or without the university education.

One may, however, also be interested in the wider question of allocative efficiency through education. In that perspective, one may ask whether schooling decisions taken in the past are efficient in the light of today's information and whether individuals with given education are efficiently allocated. This perspective governs the present research, and provides justification for some fairly bold assumptions that will be made.

However we do not claim that we completely or even adequately cover this problem.

The model to be estimated in this paper can broadly be outlined as follows. The Dutch educational system is distinguished in 4 consecutive levels. For each level (except the lowest), there is the option to drop out or to graduate, and after each level (except the top), there is an option to continue to the next level of education or to stop. For each of the 7 resulting exits from the educational system, we distinguish an earnings equation, containing personal characteristics and labour market variables. Decisions on exits from the educational systems (dropping out, stopping or continuing after graduation) are made on the basis of personal characteristics and on the expected earnings differential between exit (dropping out, stopping after graduation) and continued education. Correlation between error terms in the educational decision functions and the earnings functions, at the same exit level, is allowed and we correct for the implied potential selectivity bias. As stated earlier, any exit is treated on an equal footing : there is no essential distinction between dropping out and finishing after graduation (coefficients may differ of course).

The model is quite ambitious in its attempt to cover all levels of the educational system in the Netherlands, with all the advantages of integrated treatment, at the risk of (complete) failure however. Also, the econometric model is built on a very strong assumption, worth introducing here. We assume that expected earnings for individuals deciding to exit from the school system are equal to the expected earnings, predicted from our estimates derived from realized earnings around age 40. As discussed in detail in section III, the earnings data all refer to individuals of about the same age and it is not possible to consider the entire lifecycle earnings profile. So, essentially, we assume that the lifetime earnings prospects are sufficiently indicated by realized earnings at mid-career. Although this is admittedly a strong assumption, dictated by the lack of better data, it is not without justification. It can certainly be argued that mid-career earnings are a reasonable predictor of lifetime earnings. At that age, individuals have had sufficient time to move towards the job they are suited for, and early career disturbances have been corrected. Obviously however, better data on lifetime earnings would be preferable, but they are not available in the Netherlands for a dataset that also includes sufficient background and ability variables.

II. THE STATISTICAL MODEL

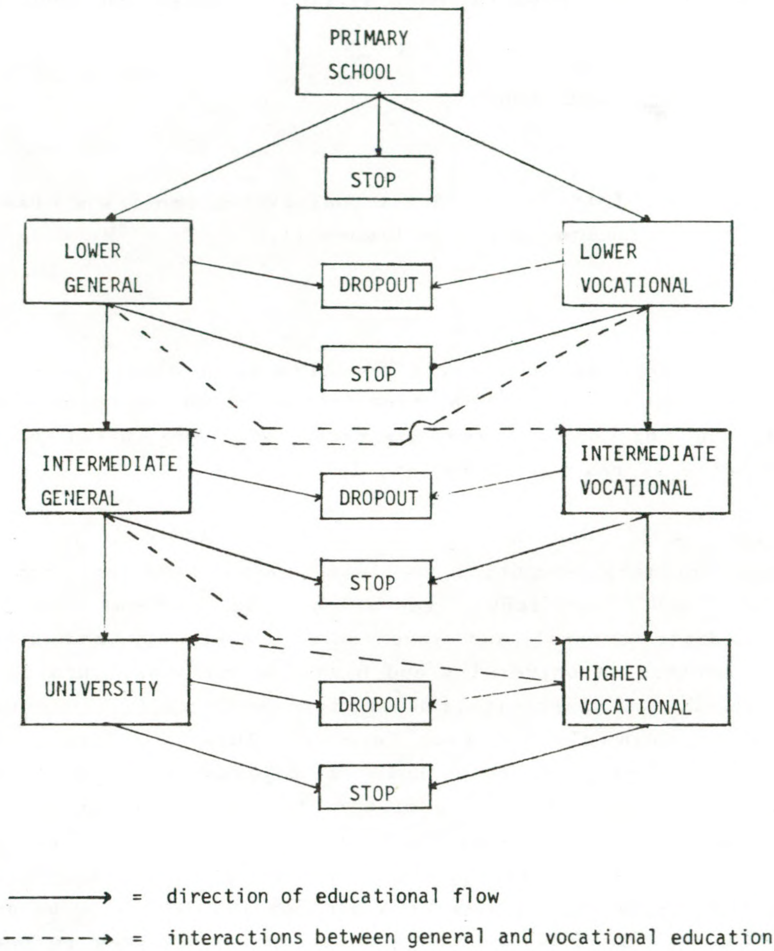
The structure of the Dutch educational system implies a wide range of possible schoolcareers (see figure 1).

(FIGURE 1)

This structure can be clearly modelled as a choice-tree. This suggests that choice in a tree be modelled as a process of transition through a fixed hierarchy of nodes until a single alternative is reached (McFadden, 1981).

We start with four educational levels. A basic level which contains primary education, a lower level made up from lower general and vocational education, an intermediate level (intermediate general and vocational education), and a higher level, containing university and higher vocational education. It is assumed that participation at any level implies succesfully passing through all previous levels. This is often a formal requirement, as one must hold a diploma of the foregoing educational level to be admitted to the next level. All educational levels, except the basic one, involve two sequential moments of decision. First, a student decides to quit school, and enter the labour market without a diploma (DROPOUT), or he decides to graduate. Secondly, after graduation, he decides to continue studying or to start working (STOP). There are no dropouts at the basic level. It is important to realize that our model is an imposed structure that ignores details of the educational flows. Individuals' careers through the educational system may be quite complex. For example, a dropout from the intermediate general level may try his luck at the lower vocational level. In this paper, we do not use data on actual individual schooling careers. We only use information on the choice of exit and we impose the

FIGURE 1: The Dutch educational system



sequence through the levels. This is motivated by the fact that such a sequence is standard.

During the schooling-period there are six moments of decision (nodes) at most. That leads to seven possible final exits from the educational system (see figure 2).

Let N_j, j = 1, 2, ..., 7, be defined as follows :

N_1 = the number of persons that have left the educational system after primary school.

N_2 = the number of persons that drop out at the lower level.

N_3 = the number of persons that leave school after having finished education on the lower level.

N_4 = the number of persons that drop out at the intermediate level.

N_5 = the number of persons that leave school after having finished education on the intermediate level.

N_6 = the number of persons that drop out at the higher level.

N_7 = the number of persons that graduate at the higher level.

$N = \sum_{j=1}^{7} N_j$ = the total number of persons in the sample.

(FIGURE 2)

Let P_j be the probability of any individual to end up at exit level j. Of course :

$$\sum_{j=1}^{7} P_j = 1 \tag{2.1}$$

If N identical individuals will be distributed independently over the exit levels according to $\{P_j\}$, then the discrete density function of N_j is as follows

$$g(N_1, \ldots, N_7) = \frac{N\,!}{\prod_{j=1}^{7} N_j\,!} \prod_{j=1}^{7} P_j^{\,N_j} \quad \text{if } \sum_{j=1}^{7} N_j = N \tag{2.2}$$

$$= 0 \qquad \text{otherwise.}$$

FIGURE 2: Educational choice-tree

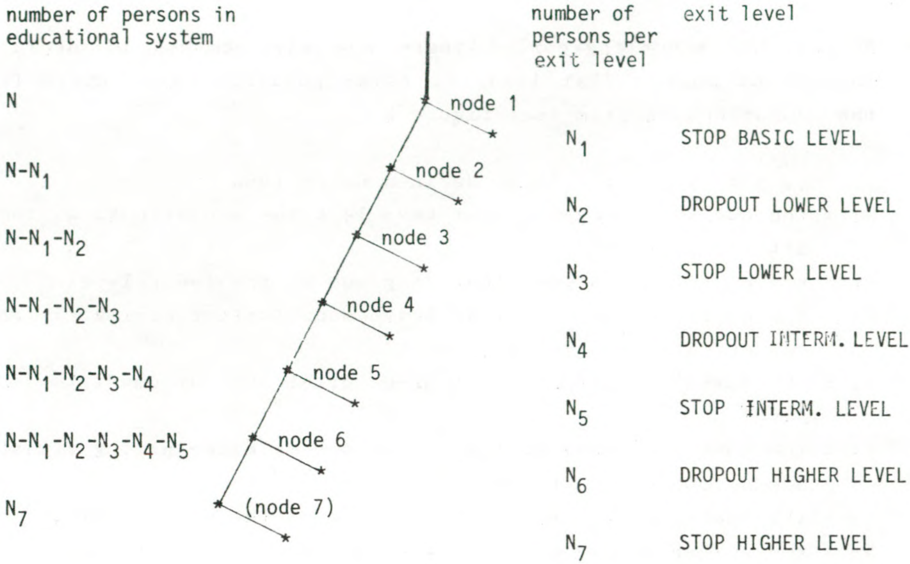
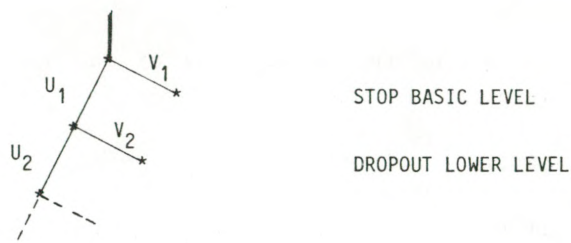


FIGURE 3: Choice-tree with probabilities



The log-likelihoodfunction of the sample becomes

$$(2.3) \qquad L(P_1, \ldots, P_7) \propto \sum_{j=1}^{7} N_j \log P_j .$$

Every branch of the choice-tree of figure 2 indicates the conditional probability of a person choosing that specific path, given he has reached the node preceeding the decision. We define (see figure 3) :

v_j = the probability that a person chooses to end up at exit level j, given he has reached node j,

u_j = the probability that a person decides to continue education, given he has reached node j,

and where $u_j + v_j = 1$.

(FIGURE 3)

The composition of P_j, the probability of finally ending up at exit level j, is given by

$$(2.4a) \qquad P_1 = v_1$$

$$(2.4b) \qquad P_j = v_j u_{j-1} u_{j-2} \ldots u_1, \quad j = 2, \ldots, 6$$

$$(2.4c) \qquad P_7 = 1 - \sum_{j=1}^{6} P_j = u_6 u_5 \ldots u_1$$

From (2.3) we can derive the (unbiased) maximum likelihood estimators of P_j, v_j and u_j :

$$(2.5a) \qquad \bar{P}_j = N_j / N \qquad , j = 1, \ldots, 7$$

$$(2.5b) \qquad \bar{v}_j = (N_j) / (N - \sum_{i=1}^{j-1} N_i) \qquad , j = 1, \ldots, 6$$

$$(2.5c) \qquad \bar{u}_j = (N - \sum_{i=1}^{j} N_i) / (N - \sum_{i=1}^{j-1} N_i) \qquad , j = 1, \ldots, 6$$

We assume that the decision made at node j depends on personal characteristics and social background, and also on the expectation of the difference between income to be earned at exit level j(EY_j) and income to be earned when education will be continued (EYS_j) :

$$(2.6a) \quad P_j = P_j(X,\ EY_j - EYS_j) \quad , j = 1, \ldots, 7$$

$$(2.6b) \quad v_j = v_j(X,\ EY_j - EYS_j) \quad , j = 1, \ldots, 6$$

$$(2.6c) \quad u_j = u_j(X,\ EY_j - EYS_j) \quad , j = 1, \ldots, 6$$

where X is a vector of exogeneous variables, which reflect an individual's characteristics and social background. In order to derive explicit formulations of the decision functions, define I_j as the individual's propensity to choose exit level j, given he is on node j. We assume

$$(2.7a) \quad \underline{I}_j = \gamma'_{1j} X + \gamma_{2j}(EY_j - EYS_j) - \eta_j \quad , j = 1, \ldots, 6$$

$$(2.7b) \quad I_j > 0, \qquad \text{if exit level } j \text{ is chosen}$$

$$(2.7c) \quad I_j \leqq 0, \qquad \text{otherwise,}$$

where η_j is a stochastic error; note that γ_{1j} is a vector and γ_{2j} is a scalar.

Earnings for an individual educated up to level j, Y_j, can be explained by X, and a vector Z, reflecting characteristics of the labour market (see Hartog, Van Ophem and Pfann, 1985) :

$$(2.8) \quad \underline{Y}_j = \alpha'_j Z + \beta'_j X + \underline{\varepsilon}_j, \quad , j = 1, \ldots, 7$$

$\underline{\varepsilon}_j$ is a stochastic error. Y_j can only be observed if $I_j > 0$, as it is specific for the exit level.

We apply the rational expectation hypothesis on income at the moment of educational decision. Then it is possible to deduce from the observed income Y_j the mathematical expectation $E(Y_j)$. This assumes that individuals, when making their educational choices, make optimal predictions on the expected earnings given the available information. Admittedly, this is a strong assumption, but it is commonly made in this sort of analysis and indeed had to be adopted to study the efficiency question mentioned in the introduction. So :

$$(2.9) \qquad \underline{Y}_j = E(\underline{Y}_j) + \underline{\varepsilon}_j = \alpha_j' Z + \beta_j' X + \underline{\varepsilon}_j .$$

$E(\underline{Y}_j)$ is the mathematical expectation at the moment of income generation. EY_j and EYS_j are income-expectations at the moments of the educational decision. We will argue below that our labour market variables Z catch compensating variations in wages, to make jobs equally attractive. Then, expected earnings at a given exit level should be taken as earnings for a standardized attractivity, since Z only contains dummies to measure deviations from a reference type of job, we can set the variables Z equal to zero. Hence

$$(2.10) \qquad EY_j = \beta_j' X \qquad , j = 1, \ldots, 7.$$

Characteristic for the decision function I_j is the assumption that someone's propensity to choose exit level j, which is the propensity to participate in the labour market and leave school, depends on personal characteristics, social background and the difference of expected incomes in both alternatives (equation 2.7). It is alo assumed that the choice at node j does not depend on decisions taken at previous nodes :

$$(2.11) \qquad \operatorname{cov}(\underline{\eta}_i, \underline{\eta}_j) = 0, \qquad i \neq j$$

The variation of observed earnings is assumed to be exit level-specific :

$$(2.12) \qquad \operatorname{cov}(\underline{\varepsilon}_i, \underline{\varepsilon}_j) = 0, \qquad i \neq j$$

It will be assumed that the unobserved variations in the schooling decision and in earnings are correlated (see the specifications below). This leads to the selectivity bias that should be taken into account. Overall estimation, by means of Newton-Raphon's iterative maximization procedure, would have been very costly because of the complexity of the simultaneous model's likelihood-function. Therefore, we split the model into two parts and applied stepwise maximization. This leads to inefficient, but consistent estimators. The first part describes the parameter-estimation of exit levels 6 and 7. The second part describes the parameter-estimation of the remaining exit levels.

A : SELF-SELECTION AT THE HIGHER LEVEL OF EDUCATION

At the higher level of education two different earnings functions are relevant :

(2.13) $\underline{Y}_6 = \alpha_6' Z + \beta_6' X + \underline{\varepsilon}_6$, for drop-outs

(2.14) $\underline{Y}_7 = \alpha_7' Z + \beta_7' X + \underline{\varepsilon}_7$, for graduates

and the decision function of node 6

(2.15) $\underline{I}_6 = \gamma_{16}' X + \gamma_{26}' (EY_6 - EYS_6) - \underline{\eta}_6 = W\gamma_6 - \underline{\eta}_6$,

where W contains personal characteristics and the difference in expected incomes.
The expected income of the alternative to exit level 6 equals the expected income of exit level 7 :

(2.16) $EYS_6 = EY_7 = \beta_7' X$

According to the decision made at node 6 we observe for earnings Y :

(2.17) $Y = Y_6$ if $I_6 > 0$
$Y = Y_7$ if $I_6 \leq 0$

We assume

(2.18) $(\varepsilon_6, \varepsilon_7, \eta_6)' \sim N(0, \Sigma_3)$

and jointly with (2.12)

$$\Sigma_3 = \begin{bmatrix} \sigma_{66} & 0 & \sigma_{6\eta} \\ 0 & \sigma_{77} & \sigma_{7\eta} \\ \sigma_{6\eta} & \sigma_{7\eta} & 1 \end{bmatrix}$$

The individual's likelihoodfunction for a higher level student then becomes

(2.19) $L_6 = [\int_{-\infty}^{W\gamma_6} f_6(\varepsilon_6, \eta) d\eta]^{1} * [\int_{W\gamma_6}^{\infty} f_7(\varepsilon_7, \eta) d\eta]^{1-1}$

with $l = 1$ for drop-outs
and $l = 0$ for graduates.
The marginal distribution functions of Y_6 and Y_7 are defined through (2.13), (2.14) and (2.18).
Further

$$(2.20) \qquad f_j(\varepsilon_j,\eta) = f_j(\varepsilon_j) \;.\; f_j(\eta|\varepsilon_j) \qquad j = 6,\ 7$$

This yields

$$(2.21) \qquad L_6 = [f_6(Y) \;.\; \mathrm{Prob}(\eta < W\gamma_6 \mid \underline{\varepsilon}_6 = Y_6 - \alpha_6'Z - \beta_6'X)]^{l} \; * $$
$$[f_7(Y) \;.\; \mathrm{Prob}(\eta \geqq W\gamma_6 \mid \underline{\varepsilon}_7 = Y_7 - \alpha_7'Z - \beta_7'X)]^{1-l}$$

with

$$f_j(Y_j) = \sigma_{jj}^{-\frac{1}{2}} \phi\, (\sigma_{jj}^{-\frac{1}{2}} \;.(Y_j - \alpha_j'Z - \beta_j'X)) \qquad j = 6,\ 7$$

$$\mathrm{Prob}\ (\eta < W\gamma_6 \mid \underline{\varepsilon}_6) = f_6(\eta \mid \varepsilon_6) =$$
$$= \Phi\ [(1 - (\sigma_{6\eta}^2 \;.\; \sigma_{66}^{-1}))^{-\frac{1}{2}} \;.\; \{W\gamma_6 + ((\sigma_{6\eta} \;.\; \sigma_{66}^{-1}) \;.\; (Y_6 - \alpha_6'Z - \beta_6'X))\}]$$
$$\mathrm{Prob}\ (\eta \geqq W\gamma_6 \mid \underline{\varepsilon}_7) = f_7(\eta \mid \varepsilon_7) =$$
$$= 1 - \Phi[(1 - \sigma_{7\eta}^2 \;.\; \sigma_{77}^{-1}))^{-\frac{1}{2}} \;.\; \{W\gamma_6 + ((\sigma_{7\eta} \;.\; \sigma_{77}^{-1}) \;.\; (Y_7 - \alpha_7'Z - \beta_7'X))\}]$$

and where ϕ , Φ are the standard normal density and CDF, respectively.

B : SELF-SELECTION AT THE BASIC, LOWER AND INTERMEDIATE LEVEL OF EDUCATION

The expected income for continued education at choice node j, equals

$$(2.22) \qquad EYS_j = E(\underline{\widetilde{Y}}_j \mid \underline{I}_{j+1} > 0) \;.\; v_{j+1} + E(\underline{\widetilde{Y}}_j \mid \underline{I}_{j+1} \leqq 0) \;.\; u_{j+1}$$
$$= \beta_{j+1}'X \;.\; v_{j+1} + EYS_{j+1} \;.\; u_{j+1}, \qquad j = 1,\ \ldots,\ 5$$

where $\widetilde{Y}_j$ is the earnings that come with the choice alternative of exit level j, continuing schooling.
The recursive system (2.22) can be solved by means of (2.10) and

[40] (2.16) :

$$(2.23)\qquad \begin{aligned} EYS_1 &= \beta_2'Xv_2 + \beta_3'Xv_3u_2 + \beta_4'Xv_4u_3u_2 + \beta_5'Xv_5u_4u_3u_2 \\ &\quad + \beta_6'Xv_6u_5u_4u_3u_2 + \beta_7'Xu_6u_5u_4u_3u_2 \\ EYS_2 &= \beta_3'Xv_3 + \beta_4'Xv_4u_3 + \beta_5'Xv_5u_4u_3 + \beta_6'Xv_6u_5u_4u_3 + \beta_7'Xu_6u_5u_3 \\ EYS_3 &= \beta_4'Xv_4 + \beta_5'Xv_5u_4 + \beta_6'Xv_6u_5u_4 + \beta_7'Xu_6u_5u_4 \\ EYS_4 &= \beta_5'Xv_5 + \beta_6'Xv_6u_5 + \beta_7'Xu_6u_5 \\ EYS_5 &= \beta_6'Xv_6 + \beta_7'Xu_6 \end{aligned}$$

To correct for self-selection-bias at exit level j, we assume a bivariate normal distribution of ε_j and η_j:

$$(2.24)\qquad (\varepsilon_j, \eta_j)' \sim N(0, \Sigma_2) \quad \text{with } \Sigma_2 = \begin{bmatrix} \sigma_j^2 & \rho_1\sigma_1 \\ \rho_j\sigma_j & 1 \end{bmatrix}$$

The individual's likelihoodfunction then becomes

$$(2.25)\qquad L_j = [f_j(Y_j)\ .\ \text{Prob}(\eta_j < W_j\gamma_j)]^{l_j} * \text{Prob}(\eta_j \geq W_j\gamma_j)]^{1-l_j},$$

with $l_j = 1$ if exit level j is chosen,
and $l_j = 0$ if one decides to continue schooling.
Further,

$W_j\gamma_j = \gamma_{1j}'X + \gamma_{2j}(EY_j - EYS_j)$,

$f_j(Y_j) = (\sigma_j(2\pi)^{\frac{1}{2}})^{-1} \exp\ (-(2\sigma_j^2)^{-1}\ .\ (Y_j - \alpha_j'Z - \beta_j'X)^2)$,

$\text{Prob}(\eta_j < W_j\gamma_j) = \Phi[(1 - \rho_j^2)^{-\frac{1}{2}}\ .\ (W_j\gamma_j + \frac{\rho_j}{\sigma_j}(Y_j - \alpha_j'Z - \beta_j'X))]$,

and $\text{Prob}(\eta_j \geq W_j\gamma_j) = 1 - \text{Prob}(\eta_j < W_j\gamma_j)$.

III. THE DATASET : BRABANT 83

Some 5800 sixth-graders of primary schools in the province of Noord-Brabant were interviewed to research the interrelation of the social setting, intelligence and school records in 1952. Thirty years later, in 1983, the adresses of about 5000 of them were retrieved and people were asked to cooperate in a detailed investigation on their individual school and labour market career. Fifty percent of them responded and this yielded a sample of 1611 men and 972 women, who are about forty years old, at the time of the 1983 interview (for further details, see Hartog, 1986).

The exogenous variables we used for the parameter estimation of the model can be divided into individual characteristics and social background on the one hand (the X-vector measured in 1952) and labour market characteristics (the Z-vector measured in 1983) on the other hand : SEX is a dummy variable equal to 1 for women, IQ, an ordinal measure of someone's intelligence, officiates as a reflection of inborn talents. JOBPA is a dummy variable that measures the profession of the father in 1952 and serves as a proxy for someone's social background. JOBPA = 0 for lower level employees and self-employed (many of whom were small farmers), JOBPA = 1 for intermediate and higher level employees.

Three joblevel variables and PARTT are the labour market characteristics. JOBLEVEL 1 is a dummy variable for people working at a lower joblevel, JOBLEVEL 2 indicates working at an intermediate joblevel and JOBLEVEL 3 stands for a higher joblevel. The jov levels are determined by linking individuals' job titles with a scale of job level by complexity and required level of knowledge and ability designed by job analysts in the Dutch Department of Labour (details are given in Hartog and Pfann, 1985). In the estimation, JOBLEVEL 1 has been omitted from the Z-vector and serves therefore as the job level reference category. PARTT is a dummy variable for people working parttime.

The endogenous variables are the exit level, running from 1 to 7, and earnings. Earnings is net hourly wages, obtained by dividing reported net earnings by reported hours worked. After removing cases with missing observations 985 wage-earners are left in the sample.

In table 1 we present means and standard deviations of all the variables by educational exit level (instead of using dummies, JOBLEVEL is measured as a cardinal variable from 1 to 3 for this purpose). There are some important regularities. Mean wage rates

Table 1 Means (and standard deviations) of variables by exit level

EXIT LEVEL	N_j/N	N	Y	SEX	IQ	JOBPA	JOBLEVEL	PARTT
1:STOP BASIC LEVEL	.1302	129	10.56	.13	92.55	--	1.59	.12
			(2.4)	(.3)	(11.0)		(.6)	(.3)
2:DROPOUT LOWER LEVEL	.0964	95	11.10	.21	99.14	.14	1.93	.16
			(2.3)	(.4)	(12.7)	(.4)	(.7)	(.4)
3:STOP LOWER LEVEL	.4213	415	11.71	.19	101.56	.08	2.04	.15
			(3.7)	(.4)	(12.6)	(.3)	(.6)	(.4)
4:DROPOUT INTERMEDIATE LEVEL	.0244	24	13.78	.17	108.38	.25	2.25	.21
			(3.0)	(.4)	(12.4)	(.4)	(.7)	(.4)
5:STOP INTERMEDIATE LEVEL	.1279	126	14.40	.28	106.82	.24	2.52	.20
			(4.4)	(.5)	(13.3)	(.4)	(.5)	(.4)
6:DROPOUT HIGHER LEVEL	.0264	26	16.38	.23	113.62	.23	2.73	.23
			(7.6)	(.4)	(12.3)	(.4)	(.5)	(.4)
7:STOP HIGHER LEVEL	.1726	170	18.85	.24	115.02	.38	2.87	.19
			(5.7)	(.4)	(12.1)	(.5)	(.3)	(.4)

and job levels rise monotonically with the educational exit level. The same applies to mean IQ, with the exception of the step between exits 4 and 5 : drop-outs from the intermediate level on average have a higher IQ than those who graduate and finish at that level. It should be noted however, that the overlap in the IQ distributions between exit levels is large, much larger in fact than in the wage rate distributions. Hence, these averages indicate that the schooling system sharpens the distinction between individuals, if one considers the transformation from ability to wage rates. It is worth pointing out at this stage that the observed regularity in wages, IQ and job level indeed supports the ranking of schooling exits as created here. The table also hints at substantial effects of family background. The proportion of individuals whose father had a high level job tends to increase with the educational exit level. It is also remarkable that none of the persons found at the lowest exit level had a father working at the upper part of the social scale.

IV. PARAMETER ESTIMATES

In table 3 the results of the maximization of the likelihood-functions (2.19) and (2.25) are presented. There are three parts, i.e. the parameter estimates of the decision function ($\gamma_1 j, \gamma_2' j$) the earningsfunction (α_j', β_j') and the parameters of the covariance matrix ($_3$ for a higher education, Σ_2 for exit levels 1 to 5).

The expected income of the choice-alternative at node 1 to node 5 (see figure 2) cannot be observed, but is composed of the expected incomes of higher levels and the probabilities to get there. This allows us to perform the maximization in steps, working backwards from the highest level. First the trivariate model of choice of higher education was estimated. The resulting parameter estimates were used to calculate EYS_5. Next, we obtained consistent estimates of the parameters relevant to exit level 5, from which EYS_4 could be computed. And so on.

We have obtained some measures of goodness-of-fit for the model. We get a first indication by computing a quasi-R^2 for the earnings function. The nearer $\tilde{R}^2$ reaches one, the better the actual income earned is approximated by the computed expected income Y^*. Set

$$(4.1) \qquad Y^* = \sum_{j=1}^{7} \hat{P}_j \cdot \hat{\beta}_j' X$$

where $\hat{P}_j$ is calculated from (2.4) using the estimates (as $\hat{\beta}$) from table 3, to calculate the v's and u's. The difference between Y^* and the actual income Y is the earnings residual. Then

$$(4.2) \qquad \tilde{R}^2 = 1 - \frac{\sum_{i=1}^{n} (Y_i - Y_i^*)^2}{\sum_{i=1}^{n} Y_i^2 - n\,\bar{Y}^2} = .618$$

with n = 985 and the sample mean of the actual income Y = 13.25. This is a quite good result if we realise no labour market influences on the composition of Y^* have been taken into account.

An indication of the performance of the model is obtained by comparing predicted and observed exit levels. Predicted exit levels have the highest probability according to the model. The calculations are stratified by observed exit level. For all individuals observed to choose exit level j, exit level j^* is predicted on the basis of their personal characteristics and the estimated coefficients. The prediction is a success if the individual is indeed predicted to choose exit level j. A more tolerant success measure also accepts predicted exit at j-1 and j+1, i.e. an error of one exit level. Notice that in practice such an error may correspond to a substantial difference. Results are given in table 2.

Table 2 Exit level predictions based on the decision functions model (percentage of correct predictions).

Observed exit level j	$j^* = j$	$j^* \in [j-1,j+1]$
STOP BASIC LEVEL	14.0	14.0
DROPOUT LOWER LEVEL	--	94.7
STOP LOWER LEVEL	89.9	89.9
DROPOUT INTERMEDIATE LEVEL	--	70.8
STOP INTERMEDIATE LEVEL	2.4	2.4
DROPOUT HIGHER LEVEL	--	38.5
STOP HIGHER LEVEL	62.9	62.9

The results in table 2 indicate that the success proportions vary quite strongly. The best predictions are for the exits with the highest frequencies : 42 % of the sample stops at the lower level, 17 % at the higher level. Dropouts are 9,2 and 3 % of the sample (at the successive levels) and none of these dropouts are indeed predicted to do so. Judging from the column $j = j^*$, dropouts cannot be distinguished from non-dropouts, while those who stop after graduating from some educational level can be distinguished with some success from those who continue. This indicates that drop-outs are not much different from non-dropouts in terms of the characteristics observed here, and hence, that other variables must be responsible for the decision to drop-out. With the more tolerant measure of succesful prediction in the second column, the success proportions rise, but in particular stopping at basic or intermediate level is still very poorly predicted.

The parameter estimates of the model are reported in table 3. It is clear that many variables have no significant effect. However, in some cases this is a welcome result. The conclusion that, in this sample, sex and father's job level have (virtually) no significant effect on the schooling decisions, is precisely the desired goals of egalitarian policies. Yet, there is some reason for caution here, as other research did find significant effects in these data (e.g. Bakker and Donkers, 1986). With respect to IQ, the marginal effect on the decision function appears to be about equal for the exit levels 1, 3 and 5, i.e. stopping with basic, lower or intermediate education. The effect is substantially smaller for dropping out at lower education and is insignificant for dropping out at intermediate and higher education. This pictures a situation where IQ has an important and fairly uniform effect on the decision to finish education after graduation, but where the drop-out decision depends on other variables. This interpretation is broadened by the observation that significant effects of variables are only found for the stop exits, and not for the dropout exits (with one exception). This mirrors the conclusion above, that other variables are needed to explain the dropout decision. Finally, the finding that the difference in expected earnings nowhere reaches statistical significance is important. Since it is hard to imagine that expected earnings are not relevant for the schooling decisions, we

Table 3 Maximum likelihood estimates of the model (asymptotic t-values in parentheses)

Decision function — EXIT LEVEL

	1 Stop basic	2 drop-out lower	3 stop lower	4 drop-out int.	5 stop interm.	6 drop-out higher
INTERCEPT	1.924 (2.60)**	.363 (.74)	3.069 (7.11)**	.484 (.29)	2.719 (3.77)**	-.284 (-.67)
SEX	-.306 (-.90)	.019 (.11)	-.031 (-.21)	-.578 (-.68)	.340 (1.86)	.230 (.53)
IQ	-.028 (-3.50)**	-.014 (-2.64)**	-.025 (-5.71)**	-.009 (-.99)	-.026 (-3.89)**	-.005 (-.73)
JOBPA	———— a)	.085 (.37)	-.855 (-5.71)**	-.162 (-.68)	-.149 (-.79)	-.495 (-.96)
EY - EYS	.189 (1.44)	.060 (.57)	-.006 (-.11)	-.171 (-1.30)	-.006 (-.18)	.013 (.18)

Earnings function

	1 Stop basic	2 drop lower	3 stop lower	4 drop inter	5 stop inter	6 drop higher	7 stop higher
INTERCEPT	10.847 (6.73)**	9.450 (6.22)**	9.548 (8.37)**	6.178 (1.52)**	5.847 (1.79)	-5.842 (-1.20)	1.455 (.32)
SEX	-2.214 (-1.63)	-2.228 (-2.95)**	-2.387 (-4.10)**	-7.841 (-1.81)	-1.496 (-1.23)	-6.089 (-1.50)	-.381 (-.25)
IQ	.030 (.17)	.010 (.69)	.017 (1.50)	.072 (1.50)	.052 (1.90)	.130 (1.48)	.114 (2.85)**
JOBPA	———— a)	.982 (1.68)	1.880 (3.13)**	1.523 (1.05)	-.045 (-.05)	7.246 (2.65)**	1.086 (1.10)
PARTT	-.825 (-.59)	-.038 (-.05)	-.846 (-1.39)	1.583 (.67)	-.416 (-.31)	9.407 (2.35)*	1.130 (.73)
JOBLEVEL 2	-.471 (-1.14)	.854 (1.82)	.748 (1.68)	2.751 (.72)	3.199 (1.31)	———— a)	———— a)
JOBLEVEL 3	.558 (.69)	2.699 (4.48)**	1.920 (3.34)**	3.290 (.81)	3.947 (1.59)	6.709 (2.76)*	2.759 (2.33)*

Covariance matrix b)

	NIVO 1	NIVO 2	NIVO 3	NIVO 4	NIVO 5	NIVO 6	NIVO 7
Standard deviation	2.152 (15.09)**	1.701 (13.45)**	3.180 (27.68)**	2.754 (5.53)**	4.112 (15.81)**	5.226	6.167
Correlation coeff.	-.239 (-3.55)**	-.138 (-2.57)*	-.354 (-7.29)**	-.388 (-2.28)*	-.332 (-4.09)**	——	——
Variance	——	——	——	——	——	27.330 (3.52)**	38.028 (7.98)**
Covariance	——	——	——	——	——	.085 (.01)	-5.685 (-10.17)**
N	985	856	761	346	322	196	
Max (log L)	-591.15	-462.12	-1470.87	-136.75	-542.86	-673.85	

a) No parameter estimates due to perfect collinearity (no observations).

b) See model for differences in estimation of the covariance matrix.

* = 5 % significant.
** = 1 % significant.

are led to think that the realized earnings used here do not properly measure the expected earnings perceived by the individuals when deciding on schooling. Below, in section V, we will return to these points.

The dominant impression from the estimated earnings function is the small number of variables that have a significant effect. In general, this suggests that holding schooling exit (and age !) constant, the variables used here do not add very much to explaining wage differentials. The effect of sex is only significant at the lower levels. Father's occupational level can have a significant effect on earnings, but this only occurs for two exit levels. Interestingly, at the higher level of education, the earnings boost is larger for dropouts than for graduates. This suggests some compensation effect of family background for educational failure at this level. IQ, while steadily gaining influence for increasing levels of education, only becomes statistically significant at the highest exit level. Job level in fact appears to be the most important variable here, being significant at the two lower level exits and at the two higher level exits. Remarkably, in both cases working at the highest job level boosts wages more for dropouts than for those who graduate (although only at the highest exit the difference seems large enough to be statistically significant).

The bottom part of table 2 presents information on the variance-covariance structure. The variance in the earnings function tends to increase with the exit level. In particular at the highest exit levels, the standard deviation rises faster than expected wages (as calculated in table 4 for the reference case). For the lowest 4 exit levels, the standard deviation is about 20 % of expected wages, at exit level 5 it's about 30 % and it's over 45 % at exits 6 and 7. This is in conformity with other research on earnings. The correlation between errors in the wage equation and in the decision function is positive and highly significant in all but one case (exit level 6). More accurately, there is a positive correlation between the error terms ε_j and $-\eta_j$, where $-\eta_j$ figures in the decision function. This, of course, is an important result. Un observed factors that increase wages for a particular exit correlate positively with unobserved factors that increase the propensity to choose that exit. The correlation is particularly strong at the highest level. The zero-correlation for dropouts from higher education however, is quite remarkable and hard to explain. These strong and positive correlations are convincing support for the existence of self-selection in the education-earnings nexus.

So, the main empirical findings can be summarized as follows. The propensities to choose particular schooling exits are not significantly affected by sex, father's occupational level or differences in expected earnings. There is a discernible effect of IQ on the "regular" exits : finishing after graduation. Dropping out, however, is not (or much less) affected by IQ-scores. In the wage equation, IQ is only significant at the highest exit, while working at the highest job level leads to a larger wage increase for dropouts than for graduates at the lowest and the highest levels of extended education. This might be the effect of unobserved variables. If a dropout manages to reach the highest job level, he has to overcome the hurdles of a shortage in formal education. Hence, he may be expected to have abilities to compensate this shortage, and apparently, even overcompensate. The relevance of unobserved factors is also strongly signalled by the positive correlation between the errors in the wage equation and the exit decision equation.

V. SOME IMPLICATIONS

To see the implications of the model more clearly, and to assess the magnitude of coefficients, marginal effects of variables are calculated from a simple simulation exercise. First, a reference individual is defined : male, with mean IQ (103.6) and with a father working as a lower level employee (JOBPA = 0). The earnings in each exit are calculated from the estimation results in table 3, setting PARTT = 0 (i.e. working full-time) and inserting the expected job level. Using the estimated coefficients for the decision function (table 3), one may calculate the conditional probability of choosing exit level j, given that the individual has reached node j. To calculate expected earnings for not choosing the exit (EYS_j), the exit

TABLE 4 : Marginal effects of explanatory variables on exit probabilities.

4A) conditional probabilities : choosing exit j, given arrival at node j

	1 STOP BASIC	2 DROP LOWER	3 STOP LOWER	4 DROP INT	5 STOP INT	6 DROP HIGHER	7 STOP HIGHER
reference [a] :	.107	.119	.695	.233	.524	.212	
IQ = 92.55	+.074	+.040	+.087	+.041	+.090	+.015	
IQ = 115.02	-.058	-.038	-.104	-.041	-.138	-.017	
JOBPA = 1	-.066	-.008	-.332	-.079	-.076	-.101	
female	-.093	-.037	-.029	+.145	+.105	+.352	
female, parttime	-.098	-.038	-.022	+.164	+.120	+.391	

4B) unconditional probabilities : ending up in exit j

	1 STOP BASIC	2 DROP LOWER	3 STOP LOWER	4 DROP INT	5 STOP INT	6 DROP HIGHER	7 STOP HIGHER
reference [a] :	.107	.106	.546	.055	.096	.015	.054
IQ = 92.55	+.071	+.024	-.008	-.014	-.029	-.005	-.021
IQ = 115.02	-.058	-.029	-.029	+.014	+.015	+.020	+.089
JOBPA = 1	-.066	.000	-.237	+.029	+.110	+.013	+.171
female	-.093	-.025	+.057	+.059	+.022	+.024	-.024
female, parttime	-.098	-.026	+.067	+.063	+.020	+.024	-.028

a) reference individual : male, mean IQ (103.6), father lower level employee or self-employed (JOBPA = 0), predicted earnings include effect of expected job level within each exit. IQ = 92.55 = mean IQ, exit 1; IQ = 115.02 = mean IQ, exit 7.

probabilities just calculated will be used. The procedure can be repeated for different values of the explanatory variables. The results of this exercise are presented in the upper panel of table 4. Knowing the conditional exit probabilities at each node, one may also calculate the unconditional probabilities of finally ending up in each of the exits, by simple multiplication (of equations (2.4)). These results are presented in the lower panel.

The results indicate that exit 3 (stop with a lower level education) is a very important exit, with a high conditional exit probability, as well as a high expected frequency in the final exit distribution. IQ variation have a substantial effect on the conditional exit probabilities. As alternatives to the mean IQ value, the mean of those choosing the lowest exit level and of those choosing the highest level have been inserted. As the standard deviation of the IQ values in the sample equals 14.1, the variations are close to minus and plus one standard deviation. For the lower IQ value, all conditional probabilities of exit increase, and those of extended participation in education decrease, while the converse holds for the higher IQ value. In some cases, the gap between the low-IQ and the high-IQ effect amounts to some 20 percent points. The effect on the unconditional probabilities is generally lower, though still substantial in most cases. The effect of family background (JOBPA) is remarkably large. One should not forget the large dispersion around the coefficients for this effect, however. The effect of gender deviates from the other effects in not being unidirectional (i.e. either upwards or downwards). For females, exit probabilities at the lower levels decrease, and at the higher levels increase. The effect is to increase in particular the final probabilities at the intermediate levels, i.e. 3 and 4. These results are reinforced a little if the effect of working parttime, mainly to females, is added. Hence, the average female is inclined to take higher education levels except for graduating from the highest level. In part this is a direct effect (from the dummy in the decision function), in part it works through different income prospects (compared to males, there's a positive impact at exits 3 and 5, negative impact at the other exits).

The estimation results have also been used to calculate predicted earnings in all exits, separately for individuals chosen to be typical of a particular exit. Thus, for individuals that are observed to have chosen exit j, mean levels of the exogeneous variables are known (IQ, father's occupation, etc.). Given these values, predicted earnings can be calculated for each potential exit, from the estimated coefficients in the earnings function. The effect of the "later" variables PARTT, JOBLEVEL 2 and JOBLEVEL 3 have also been included in the calculations, by giving them their exit specific sample proportion values. This implies that realized values of parttime work and job level have been inserted, while they were obviously unknown at the time the education decision was made (they were ignored in the decision function estimated above). Yet, it makes sense to include these values as an <u>ex post</u> check on efficiency.

A separate calculation is made of the selectivity bias term. Expected earnings may be written as

$$\begin{aligned} E(Y_j) &= x\,\beta_j + E\,\{\varepsilon_j \mid I_j > 0\} \\ &= x\,\beta_j + E\,\{\varepsilon_j \mid \eta_j < W\gamma_j\} \end{aligned}$$

Now, since ε_j and η_j are bivariate normally distributed, we may write (Maddala, 1983, p.367) :

$$E\{\varepsilon_j \mid \eta_j < W\gamma_j\} = -\,\mathrm{covar}(\varepsilon_j, \eta_j)\ \frac{\phi\,(W\gamma_j)}{\Phi\,(W\gamma_j)}$$

The covariance has been estimated, and is taken from table 3 (as the product of correlation coefficient and standard-deviation of ε_j, remembering that $\sigma_\eta = 1$). $\Phi(W\gamma_j)$ is the conditional probability of exit j, given the individual has reached node j, while $\phi(W\gamma_j)$ is the corresponding density. We now set $\Phi(W\gamma_j)$ equal to the observed proportion of individuals at node j who have chosen exit j. It is then straightforward to read the corresponding density ϕ from a table of the standard normal distribution, and to calculate the ratio. The resulting predicted additional earnings for those who are observed to have chosen exit j is presented as "self-selection-effect" in what follows.

Table 5 Predicted wage rates Y_j in each of the exits j for individuals with the mean characteristics of the individuals choosing an actual exit level.

Observed exit	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6	Y_7
1.	13.87	10.62	11.15	13.42	12.06	6.93	12.25
2.	13.06	11.43	11.61	14.24	13.08	9.43	13.47
3.	13.18	11.19	12.65	14.70	13.53	9.60	13.79
4.	13.53	11.85	12.38	18.35	14.23	13.55	15.29
5.	13.35	11.94	12.33	15.34	16.64	13.52	15.46
6.	13.84	12.48	12.76	16.39	15.02	16.14	16.83
7.	14.04	12.88	13.24	16.65	15.19	18.03	25.79
s_i, self-selection effect	.81	.39	.95	2.36	2.22	-.12	8.30
$Y_{ii} - s_i$	13.06	11.04	11.70	15.99	14.42	16.26	17.49

Note : calculated from earnings functions in table 3, setting the dummy variables SEX, JOBPA, PARTT, JOBLEVEL 2 and JOBLEVEL 3 equal to the sample proportions at the observed exit level and IQ equal to the sample mean at the observed exit level (cf table 1, with JOB-LEVEL differentiated).

Predicted earnings are given in table 5. To repeat, these are predicted earnings at all exits, for individuals that are typical of each of the distinguished exits j (i.e. have mean characteristics). Thus, an individual with the mean characteristics of those observed to have chosen exit level 1, has predicted earnings of 13.78 at exit level 1, and 10.62 at exit level 2, and so on. Moreover, as the last two lines indicate, the self-selection effect is .81; ignoring this effect (i.e. setting cov($_j$, $_j$) = 0), would imply predicted earnings at exit level 1 of 13.06 (because of independent errors, predicted earnings at other exits are not affected).

In figure 4, the predicted earnings of table 5 are drawn, excluding the self-selection effect. Three features are worth mentioning. First, it is clear that predicted earnings differentials between the typical individuals are small at exit level 1, and are large at exit level 7 : education increases the effect of existing differences between individuals. Second, the ranking of individuals by exit levels parallels the ranking by predicted earnings. In particular, at the highest exit level, predicted earnings of individuals typically choosing a particular exit level, are ranked in the same way as the exit levels. Those choosing the lowest exit earn the least at the highest exit level. Third, the ranking of typical individuals by predicted earnings is virtually independent of the exit level : the ranking of predicted earnings for typical individuals is virtually the same at each exit level.

In figure 5, the results of table 5 are drawn, now including the self-selection effect. Clearly, the first two features still emerge : earnings differences increase with exit level, and at level level 7, the ranking of predicted earnings matches the ranking of typical individuals by observed exit level. But the third feature, the independence of earnings ranking and exit levels, is not unaffected.
The earnings profiles by exit levels now cross frequently, and it is precisely the self-selection effect that makes predicted earnings in the actually chosen exit the highest of all potential exits (exits 1, 4, 5 and 7). This is strong support and justification for the effort made in modelling the self-selection

FIGURE 4 : Predicted earnings at different exits for individuals who actually choose exit j, j = 1, 2, ..., 7, excluding the self-selection effect.

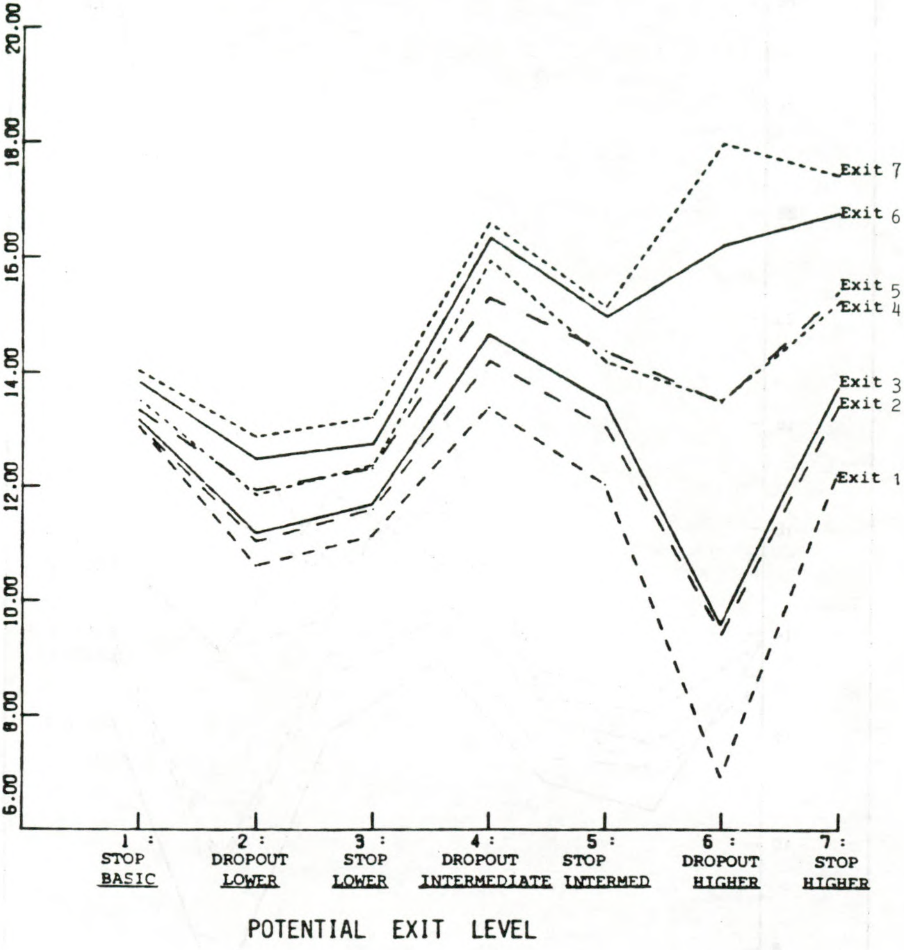
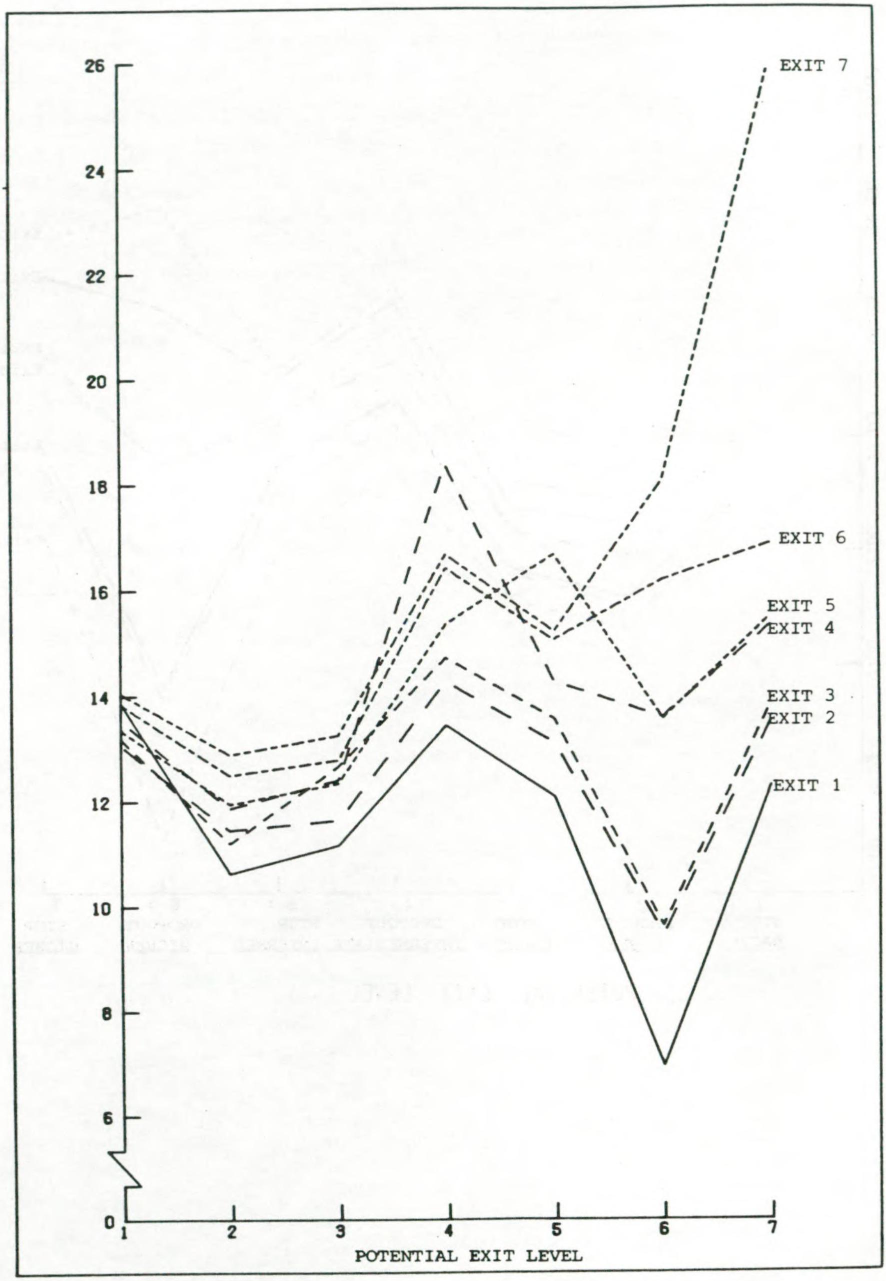


FIGURE 5 : Predicted earnings at different exits for individuals who actually choose exit j, j = 1, 2, ..., 7, including the self-selection effect.



effect in schooling decisions.

The results can also be seen as support for the relevance of comparative advantage : those who choose a particular exit indeed are those who benefit more from that exit than those who do not. Calculations to this effect are presented in table 6. From table 5, we calculated the earnings gain for choosing exit level j+1 over exit level j, for those who actually choose j+1 and for those who actually choose j.

Table 6 : Relative earnings gains from exit levels.

	exit level					
percentage gain earnings exit j+1 over exit j	1	2	3	4	5	6
a) for those choosing j+1	-12.48	13.04	48.22	8.47	7.45	43.03
b) for those choosing j	-23.43	1.66	16.20	-22.45	-18.75	4.27
a) - b)	10.95	11.38	32.02	30.92	26.20	38.76

Clearly, the result is consistently positive, meaning that those who prefer j+1 to j indeed experience a longer earnings gain than those who prefer j to j+1 would have experienced from preferring j+1.

VI. CONCLUSIONS

Given the fact that we utilized data referring to only one point in the career of individuals to model their schooling choices, we have to be very cautious about drawing inferences. Yet, at least tentatively the following conclusions may be offered :

1. In decisions regarding the schooling career (exit levels), predicted earnings differences never had a significant effect.
2. The decision to drop out at any level cannot be treated in unequalified analogy to the decision to continue an education or not after graduating from an educational level.
3. Selectivity bias is an important phenomenon, as the disturbances in the decision functions on exit levels correlate significantly with those in the earnings functions. It is

precisely the self-selection effect that makes the predicted earnings, for all potential exits, highest in the actually chosen exit, in 4 out of 7 cases.

4. The decision functions estimated here are fairly accurate in predicting the decision to stop education at the lower level and to continue the decision to stop education at the lower level and to continue education to graduation from university. Dropping out is never succesfully predicted for those who do drop out.
5. Given the earnings generating characteristics considered here (sex, IQ, father's occupation level, working time, job level), if one groups individuals on the basis of actually observed exit level of education, the predicated earnings differentials between these groups tend to increase with potential exit level. Thus, after grouping individuals, education magnifies earnings inequality.
6. Comparing successive pairs of educational exit levels, observed educational choices are consistent with comparative (earnings) advantage, in the sense that those who in fact prefer exit level j+1 to level j in fact gain more from it than those who prefer j would have gained.

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