Chapter 3

Scaling levels of education

3.1 Introduction

Education is an important stratifying mechanism in modern societies (Hout and DiPrete, 2006). For that reason, education is entered in many models as either an explanans or as the explanandum, often by turning education into a metric variable using institutional durations, in other words, the number of years a 'standard student' would take to obtain a diploma for an educational category. The advantage of this way of scaling education is that it has a meaningful metric and that these values can often be easily obtained from official or pseudo-official documents. However, there are also a number of disadvantages. First, it conflates duration with value, which are two related but different concepts. Second, these scales can sometimes lead to a rank order of educational categories that does not conform to *a priori* knowledge about the educational system, thus requiring *ad hoc* corrections. Finally, this way of scaling education leads to constant values of educational categories over time, while there is an influential hypothesis — the credential inflation hypothesis — that the values of educational categories have changed over time. In order to deal with these limitations, in this chapter I will estimate a new scale of education for the Netherlands in the 20$^{\text{th}}$ century. These levels of education are not directly observed, instead one can observe the respondents' educational category and the association between these categories and a number of positive outcomes, for example: a better job, a higher income, or access to more desirable social networks. This chapter will centre around one such positive outcome: the respondent's occupational status. The idea is to create a metric variable of level of education by assigning values to each educational category such that this metric level of education optimally predicts the respondent's occupational status. Notice that this implies a distinction between the scaling of education, that is, the relative values assigned to each educational category, and the effect of the metric education variable on occupational status.

This scale will be used to answer two questions. The first question is: Which values best represent each educational category in the Netherlands? The estimated values of the educational categories are put into perspective by comparing the estimated values with the values from a commonly used *a priori* scale (Ganzeboom and Treiman, 2009) for the relative distances between educational categories in the Netherlands that is based on institutional durations. The second question is: How have the values of the educational categories changed over time? There are two mechanisms through which the values of the educational categories can change: First, educational systems are often subject to reform. Such reforms may lead to changes in values of the educational categories that are treated as equivalent, either formally or in practice. This means that such an educational category before and after the reform should be treated as two distinct categories. Second, changes in the number of individuals with higher levels of education relative to the demand for highly-educated workers could lead to changes in the values of the educational categories. (Rumberger, 1981; Clogg and Shockey, 1984; Van der Ploeg, 1994; Wolbers, 1998; Hartog, 2000; Groot and Maassen van den Brink, 2000; Wolbers et al., 2001). The credential inflation hypothesis predicts that the supply of highly-educated labor has increased faster than the demand for highly-educated labor, thereby leading to a decrease in the value of all educational categories. However, not all forms of credential inflation (or for that matter its opposite, credential deflation) will influence the scale of education. The reason for this is that the scale of education only measures the relative distances between the educational categories. So, if all educational categories are equally affected by credential inflation, then the relative distances between the categories, and thus the scale, will remain unchanged. Credential inflation will only influence the scale of education if it affects some educational categories more than others.

3.2 Previous research

The two questions will be answered by decomposing the association between the respondents' educational categories and occupational status into a metric scale for the level of education and the effect of the level of education on the occupational status. Changes over time in the association between educational categories and labor market outcomes have already been intensely studied as part of the controversy surrounding credential inflation. Credential inflation is the hypothesis that the number of people with higher levels of education has increased faster than the demand for these people. As a consequence, those with higher levels of education start accepting lower jobs, pushing those who would normally take those jobs further down, thus leading to a decrease in the value of all the categories of education. Most research in this area does not distinguish between the effect of education and the scale of education (Rumberger, 1981; Clogg and Shockey, 1984; Van der Ploeg, 1994; Wolbers, 1998; Hartog, 2000; Groot and Maassen van den Brink, 2000). The most commonly used measure of credential inflation is the incidence of overeducation, defined as having attained a higher level of education than is required for the job. The evidence regarding the changes in the rate of overeducation is rather mixed: on the one hand some studies find an increase in the incidence of overeducation (Rumberger, 1981; Clogg and Shockey, 1984; Wolbers, 1998), while on the other hand a meta-analysis of these studies shows that there is little empirical evidence for such a trend, neither internationally nor in The Netherlands (Groot and Maassen van den Brink, 2000). However, studying the incidence of overeducation provides only a partial answer to the questions that are posed in this chapter, as it conflates the scale of education with the effect of education.

The study that comes closest to distinguishing between the scale of education and the effect is that by Wolbers et al. (2001), who distinguish between what they call structural change, which corresponds to changes in the scale of education, and change in association, which corresponds to changes in the effect of education. But even though Wolbers et al. (2001) make this distinction in theory, in the end they decide not to apply it in their empirical work. Instead of estimating both the scale and the effect of education, and testing whether or not either has changed over time, they *a priori* fixed the values of the educational categories at the percentage of respondents with at least the same level of education. Their argument for not simultaneously estimating a model with a changing scale of education and changing effect of education is that they claim that this model is not identified (Wolbers et al., 2001, p. 12). However, as I will show in section 3.4, this model is equivalent to a model which includes education as a categorical variable and interacts that categorical variable with time, and is thus identified.

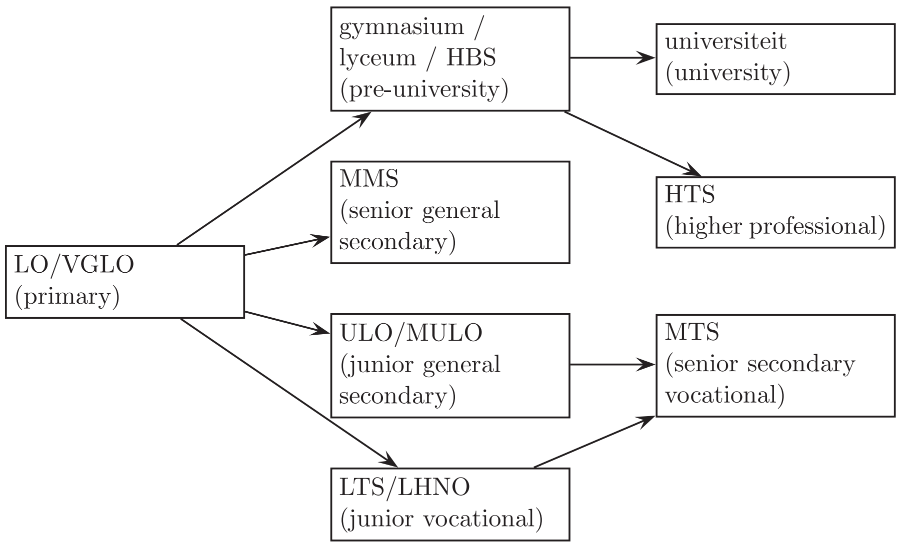
3.3 The Dutch educational system

A short description of the Dutch educational system is given in order to put the scale of education that will be estimated in perspective. This discussion of the Dutch educational system will, in part, be framed as a discussion on what happened before and after the introduction of an important educational reform in 1968 called the Mammoetwet or ‘Mammoth Law’. This does not mean that the Mammoth Law is the only educational reform that occurred during the period under study. It merely means that it was the most comprehensive change to the Dutch educational system. The systems before and after 1968 are presented in Figure 3.1. Although this reform represented a significant change in the system, there are also many features that have remained unchanged. The most important of these is that throughout the twentieth century the educational system in the Netherlands remained a so-called tracked system. Immediately after primary education, students have to choose between four tracks: junior vocational (LBO), junior general secondary (MAVO), senior general secondary (HAVO), and pre-university education (VWO). Within the two lower tracks students can choose to continue to senior secondary vocational education (MBO), higher professional education (HBO) is accessible through HAVO and VWO, while university is accessible through VWO. The abbreviations used above are the names of these levels after 1968, which will be used in this chapter as the generic names for these categories unless it is necessary to refer explicitly to the pre-1968 category.

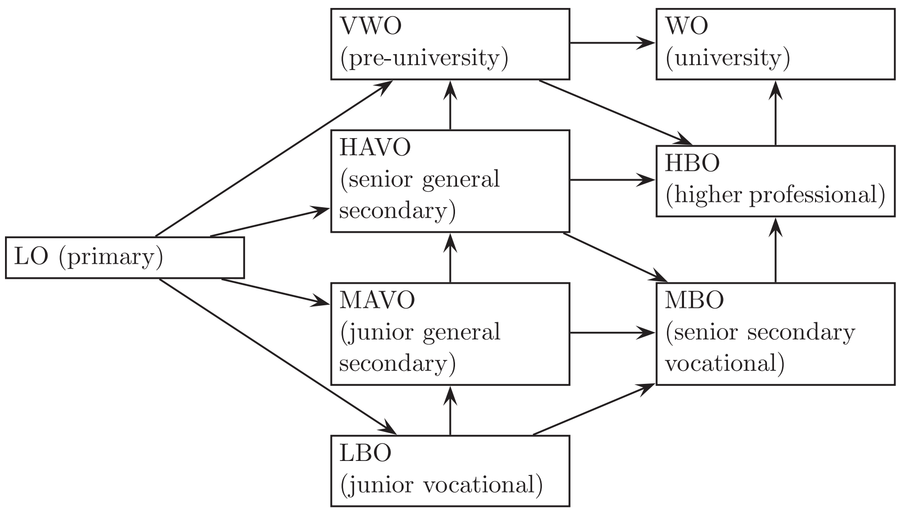
The main differences before and after the reform of 1968 are that it became easier to move between tracks, and that the choice between tracks can be postponed by a year with the introduction of a common and comprehensive first year immediately after finishing primary education, a so-called 'bridge year'. Regarding the scaling of levels of education, the most important changes are that the Mammoth Law fundamentally changed the nature of at least two levels. First, with respect to lower general secondary education (ULO and MULO prior to 1968 and MAVO after 1968), the Mammoth law formalized and encouraged a practice which had already started: initially (M)ULO was intended to be a terminal level, educating its students for non-manual occupations that require more schooling than primary education. The role of (M)ULO then gradually changed to a level that prepares for MBO. Second, a new level of senior general secondary education was created, the HAVO. A similar senior general secondary program (MMS) did exist prior to 1968, but this was a school for girls and intended to be a terminal level of education. The HAVO is intended to prepare for HBO. Based on these developments one would expect that (M)ULO was more valuable than MAVO, and that MMS had a different value than HAVO though the direction of this difference is less clear.

Figure 3.1: The Dutch education system

(a) Before 1968



(b) After 1968



More information about these levels is given in Table 3.1. This table shows the English names for the educational categories, and their Dutch names before and after 1968. In order to get an idea of plausible values of these levels Table 3.1 also reports the institutional duration, the *a priori* scale used in the International Stratification and Mobility File (ISMF) by Ganzeboom and Treiman (2009), and their ISCED classification (UNESCO, 1997). The institutional durations are the number of years a 'normal' student would need to finish this level of education. The *a priori* scale is a measure of the value of each educational category, which uses the institutional duration as a starting point, but applies an *ad hoc* adjustment to make sure that the rank order of each category corresponds to an *a priori* assumption about these values. For the Netherlands this results in an adjustment of the value of MBO. When using institutional years of education, MBO would be assigned a higher value than HAVO and VWO, and is thus ranked above HAVO and VWO. However, obtaining MBO will most likely lead to a blue collar job and obtaining HAVO and VWO will most likely lead to a white collar job, even though both HAVO and VWO are intended as a preparation for further study and not as a preparation for the labor market. For this reason, Ganzeboom and Treiman (2009) apply an *ad hoc* correction by assigning MBO a value between MAVO and HAVO. The metric of the resulting *a priori* scale is called pseudo-years, not only because of this *ad hoc* adjustment, but also because this scale is intended to measure the value of each educational category rather than the duration.

Table 3.1: Conversion of old educational levels into new educational levels

English name	before 1968	after 1968	institutional duration	*a priori* ISMF scale (pseudo-years)	ISCED
primary	LO / VGLO	LO	6 / 7	6	1
junior vocational	LTS / LHNO	LBO	10	9	2C
junior general secondary	ULO / MULO	MAVO	9 / 10	10	2B[a]
senior secondary vocational	MTS	MBO	12 / 14	10.5	3C
senior general secondary	MMS	HAVO	11	11	3B[a]
pre-university	HBS /lyceum / gymnasium	VWO	12	12	3A[a]
higher professional	HTS	HBO	15	15	5B
university	universiteit	WO	16 / 17	17	5A

[a] These programmes were originally intended to be terminal levels of education for most students (so 2C or 3C) but evolved into levels that primarily grant access to subsequent levels of education.

3.4 The model

In this chapter I will scale the educational categories to create a metric education variable in such a way that this metric education variable optimally predicts occupational status. A schematic representation of this model is given in equation (3.1).

$$\begin{matrix}\text{occupational} \\ \text{status}\end{matrix} = \begin{matrix}\text{control} \\ \text{variables}\end{matrix} + \begin{pmatrix}\text{effect of} \\ \text{education}\end{pmatrix} \times \begin{pmatrix}\text{scale of} \\ \text{education}\end{pmatrix} \tag{3.1}$$

This equation shows that this model will consist of three elements: a set of control variables, optimally scaled education, and an effect of education. A key characteristic of this model is the separation between the effect of the metric education variable and the scaling of the educational categories. In this model it is possible to allow the effect of education to change over one or more variables, for example time, and keep the scaling constant, to keep the effect constant and allow the scaling to change over one or more other variables, allow both the effect and the scaling to change, or keep both the effect and the scaling constant. This model is known under the name: regression with parametrically weighted explanatory variables (Yamaguchi, 2002). It is a special case of the model for estimating a sheaf coefficient (Heise, 1972), which assumes that the effect of the latent variable — in this case scaled education — remains constant. It is also a special case of the Multiple Indicators and Multiple Causes (MIMIC) model (Hauser and Goldberger, 1971) where the latent variable is assumed to be measured with error. Finally, it is also a linear model imposing a proportionality constraint, where the effects of all educational categories are constrained to change by the same proportion.

The simplest version of this model assumes that both the scaling and the effects remain constant, which is equivalent to the model for estimating a sheaf coefficient (Heise, 1972). In this case, the model is just a reparameterization of a model that includes education as a set of dummy variables. The model will be introduced using a simplified example in which there are no control variables present, and only three levels of education are distinguished: primary, secondary, and tertiary, which can be represented as a set of three dummy variables: prim for primary education, sec for secondary education, and tter for tertiary education. Extensions will be added after this basic model has been discussed. The starting point is a linear model estimating the effect of education on occupational status (occ), representing education as a series of dummy variables. Such a model is shown in equation (3.2), wherein the βs are the regression coefficients and ε is a normally distributed error term. In this model, primary education is the reference category.

$$\mathsf{occ} = \beta_0 + \beta_1 \mathsf{sec} + \beta_2 \mathsf{ter} + \varepsilon \tag{3.2}$$

An unconventional way to interpret model (3.2), but not a new way, is that it simultaneously estimates the scale of a single metric variable representing the level of education, and the effect of this metric variable. A scale of educational levels will measure the relative distances between the educational categories. Such relative distances need two constraints: one to fix the origin of the scale and another to fix the unit of the scale. So, if the value of primary education is fixed to 0 and that of tertiary education to 1, then this will fix the origin at primary education and this will fix the unit at the distance between primary and tertiary education. The scaling will assign the position of secondary education relative to these two levels. This new variable (ed) can be written like equation (3.3):

$$\mathsf{ed} = \underbrace{\gamma_1}_{0} \mathsf{prim} + \gamma_2 \mathsf{sec} + \underbrace{\gamma_3}_{1} \mathsf{ter} \tag{3.3}$$

Whereby, the γs define the scale. The effect of education on occupation can be written as in equation (3.4), whereby the effect of this scaled education is called λ_1.

$$\begin{aligned} \mathsf{occ} &= \beta_0 + \lambda_1 \mathsf{ed} + \varepsilon \\ &= \beta_0 + \lambda_1 (\underbrace{\gamma_1}_{0} \mathsf{prim} + \gamma_2 \mathsf{sec} + \underbrace{\gamma_3}_{1} \mathsf{ter}) + \varepsilon \qquad (3.4) \\ &= \beta_0 + \lambda_1 \gamma_2 \mathsf{sec} + \lambda_1 \mathsf{ter} + \varepsilon \end{aligned}$$

All parameters in model (3.4) can be calculated from the parameters in model (3.2):

$$\begin{aligned} \lambda_1 &= \beta_2 \\ \gamma_1 &= 0 \\ \gamma_2 &= \frac{\beta_1}{\beta_2} \\ \gamma_3 &= 1 \end{aligned}$$

Model (3.4) is thus just a reparameterization of model (3.2), and does not add anything to the model other than an alternative interpretation of the results. This implies that there is no way to test whether a model that separates the effect from the scale is to be preferred over a model consisting only of a set of dummies, as these two models are equivalent. However, this changes when one allows the effect of education to change over other variables while constraining the scaling to remain constant. This implies a testable constraint. This is illustrated by extending the simplified example to allow the effect of education to change over the variable year. The test of an hypothesis involves the comparison of two models, a constrained model and an unconstrained one. The constrained model is represented in equation (3.5), while the unconstrained model includes interaction terms of year with all the dummies as in equation (3.6).

$$\mathsf{occ} = \beta_0 + (\lambda_1 + \lambda_2 \mathsf{year})(\underbrace{\gamma_1}_{0}\ \mathsf{prim} + \gamma_2 \mathsf{sec} + \underbrace{\gamma_3}_{1}\ \mathsf{ter}) + \beta_1 \mathsf{year} + \varepsilon \tag{3.5}$$

$$\begin{aligned} \mathsf{occ} &= \alpha_0 + \alpha_1 \mathsf{year} + \\ &\quad \alpha_2 \mathsf{sec} + \alpha_3\ \mathsf{year} \times \mathsf{sec} + \\ &\quad \alpha_4 \mathsf{ter} + \alpha_5\ \mathsf{year} \times \mathsf{ter} + \varepsilon \end{aligned} \tag{3.6}$$

To facilitate the comparison of the two models, equation (3.5) can be rewritten as equation (3.7):

$$\begin{aligned} \mathsf{occ} &= \beta_0 + \beta_1 \mathsf{year} + \\ &\quad \lambda_1\, \gamma_2 \mathsf{sec} + \lambda_2\, \gamma_2\ \mathsf{year} \times \mathsf{sec} + \\ &\quad \lambda_1 \mathsf{ter} + \lambda_2\ \mathsf{year} \times \mathsf{ter} + \varepsilon \end{aligned} \tag{3.7}$$

If the constrained model is true, then $\alpha_2 = \lambda_1\gamma_2$, $\alpha_3 = \lambda_2\gamma_2$, etc. This implies that

$$\begin{aligned} \frac{\alpha_2}{\alpha_4} &= \frac{\lambda_1\gamma_2}{\lambda_1} = \gamma_2 \\ \frac{\alpha_3}{\alpha_5} &= \frac{\lambda_2\gamma_2}{\lambda_2} = \gamma_2 \end{aligned} \tag{3.8}$$

In other words, the constraint that needs to be imposed on equation (3.6) in order to get equation (3.7) is $\frac{\alpha_2}{\alpha_4} = \frac{\alpha_3}{\alpha_5}$, and it is this constraint that is being tested. This is a proportionality constraint: the effects of educational categories are allowed to change over time, but the proportional distance between the effects are forced to remain equal. The most convenient way of testing this constraint is by comparing the constrained model and the unconstrained model using a likelihood ratio test. Both models are estimated by assuming that ε is normally distributed with a mean of zero and a constant variance. This is a linear regression in the case of the unconstrained model. The constrained model needs to be estimated using maximum likelihood.

This model can be further extended in several ways: first, the model can easily accommodate more than three levels of education, by adding more level dummies. Second, the effect of scaled education can change over more than one variable. Third, the values assigned to each educational category, that is, the scaling of education, can be allowed to change over one or more variables. For instance, one can allow an educational category to have different values before and after an educational reform, and test whether these values are different. Fourth, one can include control variables. This model and all these extensions are implemented in Stata (StataCorp, 2007) as the `propcnsreg` package (Buis, 2007a), which is documented in Technical Materials I.

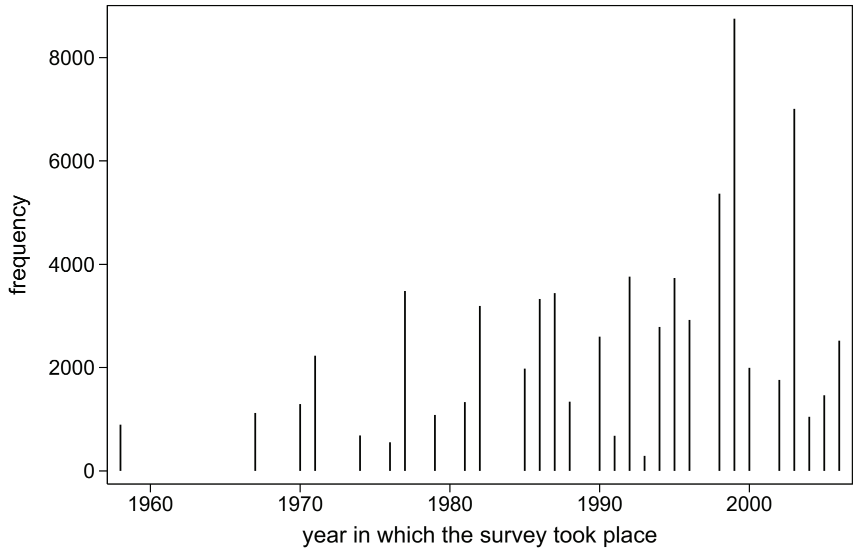
3.5 The data

The model requires data on the respondent's occupational status, the respondent's educational category, and three additional sets of explanatory variables: the control variables, the variables along which the scaling of educational categories is allowed to change, and the variables along which the effect of education is allowed to change. These variables are:

- control variables
  - gender of the respondent,
  - potential experience (age minus institutional duration of education),
  - year in which the survey was held,
  - father's occupational status,
  - two-way interactions of father's occupational status and gender, father's occupational status and year of survey, potential experience and gender, and potential experience and year of survey.
- variables along which the scaling of educational categories is allowed to change
  - whether or not a respondent belongs to the pre-Mammoth or the post-Mammoth cohort, defined as the cohort that was 12 years old before and after 1968 respectively,
- variables along which the effect of education is allowed to change
  - year in which the survey was held, and
  - the gender of the respondent.

The data used in this chapter consists of 54 Dutch surveys that were harmonized as part of the International Stratification and Mobility File (Ganzeboom and Treiman, 2009). The surveys are listed in the appendix to this chapter and described in the data references. Only respondents older than 27 and younger than 65 where used in the analysis. This dataset contains 72,666 respondents who meet this criterion and have complete information on all the covariates. Figure 3.2 shows how these observations are distributed across time. It is important to note that information on the early years is based on only a few points in time.

Figure 3.2: Number of observations per year



The dependent variable is the occupational status of the most recently held occupation, thus it includes homemakers, unemployed, and early retirees who have had a job in the past. The occupations were scaled to represent occupational status according to the International Socio-Economic Index of occupational status [ISEI] (Ganzeboom and Treiman, 2003), which was originally measured on a continuous scale from 10 (low status) to 90 (high status), but is rescaled here to a range between 0 and 1.

The educational category is measured as the highest category attained by the respondent. The eight categories are defined as in Table 3.1 and will be referred to by their post-1968 names. However, some surveys merged some of the educational categories into one or more 'combined categories'. Table 3.2 shows how common this practice has been: a majority of surveys have at least one combined category. The most commonly combined category is HAVO/VWO. This is partly due to the fact that MMS is treated here as the pre-1968 equivalent of HAVO, but it was such a small category that earlier surveys routinely merged that category with pre-university edu-

Table 3.2: Prevalence of combined and not-combined educational categories in the data

educational category	number of surveys	number of respondents
not-combined		
LO	54	13,414
LBO	48	16,773
MAVO	46	9,908
MBO	46	14,763
HAVO	24	1,747
VWO	31	1,550
HBO	50	13,668
WO	51	6,962
combined		
HAVO/VWO	27	4,498
LBO/MAVO	5	1,476
HBO/WO	3	395
HAVO/VWO/MBO	2	478
VWO/MBO	1	511
MAVO/MBO	1	199
LBO/MBO	1	144
MAVO/HAVO	1	88

cation (VWO). An attractive characteristic of the method used here for estimating the scale of education is that it can accommodate surveys with combined educational categories without having to combine the categories from the other surveys, thus using the maximum amount of detail available from each survey. This is done by simply treating these ‘combined levels’ as a separate level whose value needs to be estimated, which can be done by adding dummy variables for the ‘combined levels’. A more parsimonious way of dealing with these ‘combined levels’ is by constraining their value to be equal to the average value of their constituent levels. This constraint will also be tested.

The control variables used while predicting the respondent’s occupational status with the respondent’s education are: father’s occupational status, the respondent’s gender, the respondent’s (potential) years of labor force experience, and the year in which the survey was held. Father’s occupational status is measured — just like the respondent’s occupational status — in ISEI scores that have here been rescaled to range between 0 and 1. The year in which the survey was held is included as an approximation of the period in which the respondents held their occupation. This variable ranges from 1958 to 2006. However, as shown in Figure 3.2, the information for the earlier years is rather sparse. The potential experience in the labor market is approximated using age minus institutional years of education. Time and experience are allowed to have non-linear effects by entering them in the model as restricted cubic splines (Harrell, 2001). This means that the range of time and experience is split up at locations called knots. Experience was given knots at 10, 25 and 35 years of potential experience, and year was given knots at 1980, 1990, and 2000. In the sections after the first knot and before the last knot, third-degree polynomials are estimated. These curves are forced to meet at the knots and have the same first and second derivative at that point. The curve is restricted to be linear before the first knot and after the last knot. This model has the advantage of leading to a smooth curve that is more stable than an (unrestricted) cubic splines (Harrell, 2001). The restricted cubic spline, as used in this chapter, is implemented in Stata 10 (StataCorp, 2007) in the `mkspline` command.

The effect of education is allowed to change over time and gender. Time is represented by the same restricted cubic spline as was used for the control variables. The values of the educational categories are allowed to change depending on whether a respondent belongs to the ‘pre-Mammoth’ cohort or the ‘post-Mammoth’ cohort. These cohorts are defined as whether or not the respondent was 12 years old before or after 1968. This is a rather crude measure as some respondents were already in a ‘Mammoth-like’ system before 1968 because the law was preceded by a large number of experiments. However, the data do not contain a more precise measure of which respondent was educated in which system.

3.6 Results

Eight models are estimated and are described together with their fit statistics in Table 3.3. These models differ from one another in the following ways. Models labeled (a) assume that the values of the educational categories remained constant apart from possible changes introduced by the educational reform in 1968, which corresponds to imposing the proportionality constraint. The models labeled (b) allow the values to change over time and between men and women, which corresponds to entering education as a categorical variable and adding interaction terms of each educational category dummy variable with time and gender. Models 1, 2, and 3 differ from one another with respect to which educational categories changed in value in 1968. Model 1 assumes that all categories changed in value, model 2 assumed that only MAVO and HBO changed in value, while model 3 assumed that none of the values changed in 1968. Model 4 forces the value of the combined categories to be equal to the average

Table 3.3: Fit statistics

model	proportionality constraint	scale of category changes in 1968	value of combined category	df	log-likelihood	BIC
1(a)	yes	all	freely estimated	44	29804.36	-59104.53
1(b)	no	all	freely estimated	101	29947.26	-58762.87
2(a)	yes	MAVO, HBO	freely estimated	38	29803.71	-59170.47
2(b)	no	MAVO, HBO	freely estimated	77	29911.04	-58959.34
3(a)	yes	none	freely estimated	36	29775.72	-59136.87
3(b)	no	none	freely estimated	69	29873.37	-58973.63
4(a)	yes	MAVO, HBO	average	30	29767.00	-59186.66
4(b)	no	MAVO, HBO	average	54	29834.32	-59063.60

Table 3.4: Test proportionality constraint

contrast[a]	BIC difference
1(a):1(b)	341.66
2(a):2(b)	211.12
3(a):3(b)	163.24
4(a):4(b)	123.06

[a] The model numbers refer to Table 3.3

Table 3.5: Model selection

contrast[a]	hypothesis	BIC difference
1(a):2(a)	no change in value of LO, LBO, HAVO, VWO, and WO	65.93
2(a):3(a)	no change in value of all categories	-33.59
2(a):4(a)	values of combined categories constrained to mean	16.20

[a] The model numbers refer to Table 3.3

value of their constituent categories, while models 1, 2, and 3 freely estimate those values.

The resulting eight models are compared in Tables 3.4 and 3.5. Table 3.4 gives for each model the test of the proportionality constraint, that is, whether the scale of education has remained constant over time, and Table 3.5 compares the four models with a proportionality constraint against one another. Table 3.4 shows that the differences in the Bayesian Information Criterium (BIC) score[1] is much more than 10 points in favor of the constrained model, which provides "very strong" (Raftery, 1995) or "decisive" (Jeffreys, 1961) evidence in favor of the proportionality constraint. An advantage of BIC differences over tests like the likelihood ratio test is that tests will pick up ever smaller deviations from the null hypothesis as the sample size increases. This is consistent with the logic behind statistical testing, but it also means that statistical tests will pick up substantively irrelevant deviations from the null hypothesis when the sample becomes very large. The comparison of BIC scores avoids this problem. Given that the sample size in this case is approximately 75,000 respondents, the comparison of BIC scores is preferred.

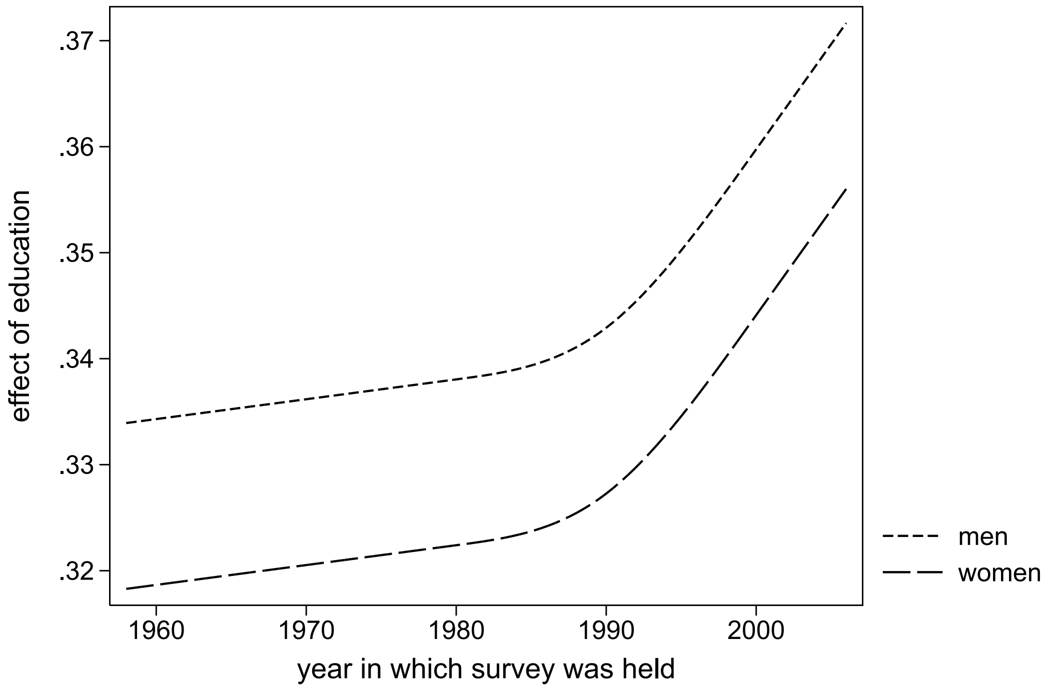
The first two comparisons in Table 3.5 investigate whether the scaling of education was influenced by the implementation of the Mammoth Law in 1968. The first row shows that no evidence was found that the values of LO, LBO, HAVO, VWO, and WO changed before and after the Mammoth law. The second row indicates that there is evidence that the value of MAVO and HBO changed. The third row tests the hypothesis that the combined educational categories can be represented by the average of the values of the constituent categories, instead of estimating a separate value for each combined category. This row shows that the BIC difference supports constraining the values of the combined levels. The preferred model is thus model 4a.

Model 4a separates the effect of education on the occupational status of the respondent from the scale of education. The effects are shown in Figure 3.3, while the scale is shown in Figure 3.4. The effects can be transformed into standardized effects by multiplying them by 1.62, as the standard deviation of the latent education variable is .310 and the standard deviation of the respondent's occupational status is .191. The standardized effects thus range between approximately .5 for women around 1960 and approximately .6 for men around 2005. These are thus sizeable effects. Figure 3.3 also shows that women gain less occupational status from education than men, while the relative values of the educational categories are the same.

The scale of education is presented in Figure 3.4. The bottom two lines show the scale of education as estimated in model 4a, while the top line shows the *a priori* scale. Comparing the estimated scale with the *a priori* scale from the ISMF shows that

[1] The BIC score is computed as: BIC = -2*ln(likelihood) + ln(N)*k, where N is the sample size and k is the number of degrees of freedom.

Figure 3.3: Effect and the trend in the effect of education on occupational status

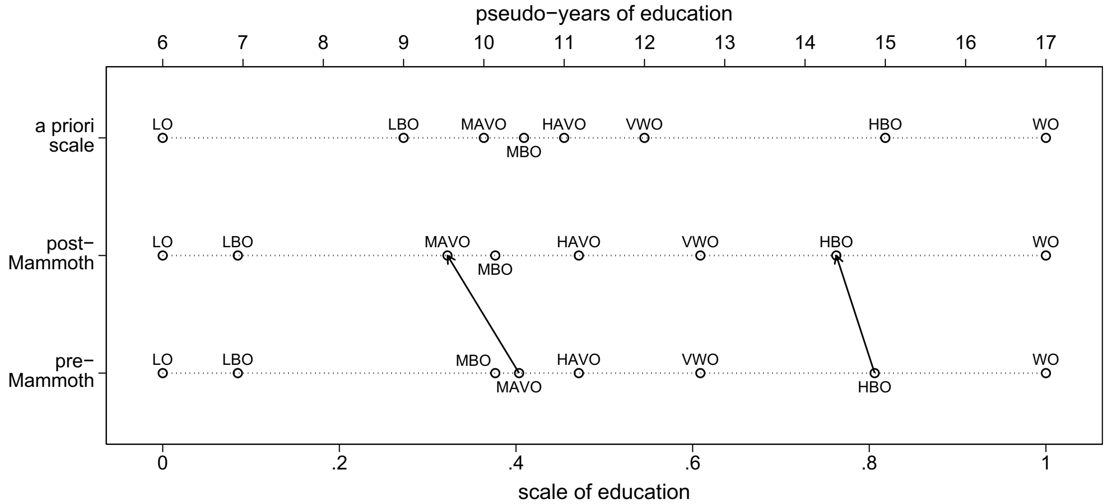


the most striking differences between the two is the value of LBO: LBO is much less valuable than the *a priori* scale suggests. The fact that LBO is the lowest level of secondary education may well result in an extra penalty, explaining why a pseudo-year in LBO is worth less than a pseudo-year in the other forms of secondary education. The value of HAVO and VWO are underrated when using the *a priori* scale of education. This may be explained by fact that some of the respondents with HAVO and VWO as their highest achieved level of education may have started HBO or WO, but never completed it.

Figure 3.4 also shows the comparison between the estimated scale before and after the introduction of the Mammoth Law in 1968. It shows that the value of MAVO decreased after the introduction of the Mammoth Law. Moreover, the rank order changed from a situation where MULO was more valuable than MBO to a situation where MBO was more valuable than MAVO. This is consistent with the transformation from (M)ULO, which was a terminal level in its own right, to MAVO, which is a level preparing for MBO. The decline in the value of HBO may be explained by the fact that the kind of people having access to HBO changed after 1968, as it became accessible through the HAVO.

The numerical values of the *a priori* scale and the estimated scale are presented in

Figure 3.4: Scale of education



the first two columns of Table 3.6. In the third column, the estimated scale is rescaled such that the metric resembles pseudo-years of education (LO is fixed at 6 and WO is fixed at 17). In the final column, this scale has been stylized by rounding to the nearest half-year. This stylized scale will result in a variable with a metric that is as easy to interpret as the *a priori* scale, but more closely represents education as a resource for attaining occupational status.

Table 3.6: The *a priori* and the estimated scale of education

level	*a priori* scale	estimated scale	rescaled	stylized scale
LO	6	0	6.00	6.0
LBO	9	.085	6.94	7.0
MAVO[a]	10	.404	10.44	10.5
MAVO[b]	10	.324	9.55	9.5
MBO	10.5	.377	10.14	10.0
HAVO	11	.471	11.18	11.0
VWO	12	.609	12.70	12.5
HBO[a]	15	.806	14.87	15.0
HBO[b]	15	.763	14.39	14.5
WO	17	1	17.00	17.0

[a] Before the Mammoth Law: ULO and MULO for MAVO and HTS for HBO

[b] After the Mammoth Law

3.7 Conclusion

This chapter started with the questions concerning which values best represent each level of education in the Netherlands, and how these values have changed over time. Two mechanisms are proposed through which the scale of education could change over time. The first mechanism is educational reform, which can mean that an educational category before and after a reform should be treated as two different categories. In this chapter the focus is on one particular educational reform: the Mammoth Law implemented in 1968. The second mechanism concerns the changes in the supply of highly schooled labor relative to the demand for highly schooled labor. If supply increased (decreased) faster than the demand, then the value of the educational categories is likely to decrease (increase). However, this will only influence the scale of education if the change in value of some categories is stronger than the change in value of other categories, since the scale of education measures only the relative distances between the categories.

In order to study these two issues, a scale of education is estimated such that it is optimal for predicting occupational status, using a model proposed by Yamaguchi (2002), and implemented in the statistical package Stata (StataCorp, 2007) as the `propcnsreg` module (Buis, 2007a) that is documented in Technical Materials I. This model estimates both the effect of education and the scale of education. The model resulted in a scale of education that is summarized in Figure 3.4. This estimated scale was compared with an often-used *a priori* scale as found in the International Stratification and Mobility File (Ganzeboom and Treiman, 2009). The major deviation from the *a priori* scale is that the *a priori* scale overrates the value of LBO, which means that respondents with LBO had on average lower status occupations than was predicted using the *a priori* scale. In order to facilitate the use of this scale in other analyses a stylized version of this scale using the metric of pseudo-years of education was presented in Table 3.6.

Using this model, it was not possible to reject the hypothesis that the introduction of the Mammoth Law in 1968 has not influenced the value of the educational categories for all but two educational categories: MAVO and HBO. The change in the value of MAVO was expected as this level changed from a level that prepared for the labor market to a level that prepared for a subsequent level of education (MBO). A possible reason for the change in the value in HBO could be due to the fact that it became accessible via HAVO. The hypothesis that changes in the supply and demand for highly-educated labor has not led to changes in the relative values of the educational categories could not be rejected. So, the relative distances between the categories remained mostly constant, even though the effect of education on occupational status increased over time.

One way in which the scale could be improved is to use additional indicators like a higher income, and access to more desirable social networks, or one could scale education by how much individuals or families have invested in order to attain a level of education. This would lead to a number of different scales of education. These different scales could be used to create a more comprehensive scale of education by constraining them to be equal. Moreover, by testing whether these scales can be combined into a single scale, one can test the hypothesis that the value of education is a one-dimensional concept rather than a multi-dimensional one. Moreover it may be useful to estimate a scale with higher level of detail, in particular distinguishing between completed and attended educational categories. In the current context this may be most useful for estimating the values of higher general secondary education (HAVO) and pre-university education (VWO). It is likely that a large proportion of respondents that report these categories as their highest achieved level of education have also had some years of higher professional education (HBO) or university, but did not finish these categories. This would lead to an overestimation of the value of HAVO and VWO, as the benefit these respondents received from attending university or HBO is incorrectly assigned to the HAVO or VWO categories. Furthermore, distinguishing between various degrees of incomplete primary education could prove useful when one wants to create a scale that can be used in countries where — or in historical periods when — incomplete primary education is prevalent.

Appendix: Description of data sources

Table 3.7: Merged educational categories and the sizes of the the pre- and post-Mammoth cohorts in Dutch surveys that were post-harmonized in the International Stratification and Mobility File (Ganzeboom and Treiman, 2009)

survey number	survey code[a]	year	cohorts	N pre-Mammoth	N post-Mammoth	merged categories
1	net58	1958	1891–1933	902	0	
2	net67	1967	1896–1942	1,144	0	(LBO MAVO) (HAVO VWO MBO) (HBO WO)
3	net67t	1967	1927–1942			(HAVO VWO) (HBO WO)
4	net70	1970	1891–1945	1,334	0	(LBO MAVO) (HAVO VWO)
5	net71c	1971	1898–1944	1,130	0	(LBO MBO) (HAVO VWO) (HBO WO)
6	net71	1971	1891–1946	1,282	0	(LBO MAVO) (HAVO VWO)
7	net74p	1974	1891–1949	730	0	(HAVO VWO)
8	net76j	1976	1900–1951	669	0	(HAVO VWO)
9	net77	1977	1891–1952	2,659	0	(MAVO MBO) (HAVO VWO)
10	net77e	1977	1891–1952	1,195	0	(HAVO VWO)
11	net79p	1979	1891–1954	1,119	0	
12	net81e	1981	1891–1956	1,518	0	(HAVO VWO)
13	net82e	1982	1891–1957	1,041	0	(HAVO VWO)
14	net82n	1982	1917–1957	1,931	0	
15	net82u	1982	1917–1957	637	0	
16	net85o	1985	1904–1960	3,080	260	(HAVO VWO)
17	net86e	1986	1893–1961	994	110	(HAVO VWO)
18	net86l	1986	1907–1961	2,327	313	(MAVO HAVO) (VWO MBO) (HBO WO)
19	net87i	1987	1907–1962	961	156	(HAVO VWO)
20	net87j	1987	1897–1962	530	72	(HAVO VWO)
21	net87s	1987	1915–1962	620	96	(HAVO VWO)
22	net88o	1988	1912–1963	3,073	654	(HAVO VWO)
23	net90	1990	1920–1965	1,345	425	(HAVO VWO)

Continued on next page

Table 3.7 – continued from previous page

survey number	survey code[a]	year	cohorts	N pre-Mammoth	N post-Mammoth	merged categories
24	net90o	1990	1913–1965	2,704	834	(HAVO VWO)
25	net91j	1991	1909–1966	1,055	404	(LBO MAVO) (HAVO VWO)
26	net92f	1992	1915–1968	1,169	457	
27	net92o	1992	1911–1967	2,793	992	(HAVO VWO)
28	net92t	1992	1903–1967	1,749	790	(HAVO VWO)
29	net94e	1994	1905–1969	776	480	(LBO MAVO) (HAVO VWO MBO)
30	net94h	1994	1913–1969	479	389	
31	net94o	1994	1911–1969	2,687	1,194	(HAVO VWO)
32	net95h	1995	1916–1970	1,096	724	
33	net95s	1995	1925–1970	1,002	595	
34	net95y	1995	1944–1970	39	983	
35	net96	1996	1909–1971	340	247	
36	net96c	1996	1901–1971	794	576	
37	net96o	1996	1911–1971	2,456	1,474	(HAVO VWO)
38	net96y	1996	1962–1971	0	288	
39	net98	1998	1902–1973	364	323	
40	net98e	1998	1908–1973	822	672	
41	net98f	1998	1915–1973	865	891	
42	net98o	1998	1911–1973	2,364	1,885	(HAVO VWO)
43	net99	1999	1906–1974	956	926	
44	net99a	1999	1904–1974	4,274	3,712	
45	net99i	1999	1916–1974	562	570	
46	net00f	2000	1916–1975	678	648	
47	net00s	2000	1930–1975	442	393	
48	net02e	2002	1907–1978	805	901	
49	net03f	2003	1924–1978	741	1,089	
50	net03n	2003	1923–1979	2,753	3,579	
51	net04e	2004	1910–1980	619	728	
52	net04i	2005	1912–1980	612	766	
53	net06e	2006	1912–1981	501	808	
54	net06i	2006	1907–1981	572	891	

[a] Codes refer to the data references