European Sociological Review, Vol. 13 No. 1, 1–15

Type of Schooling and Sex Differences in Earnings in the Netherlands

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Though men and women now achieve similar levels of schooling, the types of fields they study still vary widely. Men are overrepresented in technical and economic fields, whereas women are overrepresented in socio-cultural and service fields. In this paper, we examine to what extent the type of field people study affects their earnings, and we try to determine to what extent prevailing differences in type – as opposed to amount – of schooling contribute to the sex difference in earnings. To answer these questions, we estimate standard human capital models of earnings using a large nationally representative sample of higher educated men and women in the Netherlands. We augment previous models by developing a multi-dimensional measure of educational attainment. We subsequently show that male types of training generally have higher earnings returns than female types, that the new schooling measures explain considerably more of the gender gap in earnings than standard measures, and that rates of return to specific types of training have a tendency to differ between men and women.

Type of Schooling and Sex Differences in Earnings in the Netherlands

Although in industrialized countries, schooling is one of the most important determinants of individual differences in earnings, it plays only a minor role in explaining why men earn more than women (Marini, 1989). At first, the limited role of schooling in this regard comes as no surprise, since sex differences in schooling have declined considerably over the past decades. Educational statistics on the Dutch school-leaving population, for example, show that in 1971, 6 per cent of women and 15 per cent of men had received a university or higher vocational degree. Two decades later, the gap had almost disappeared. In 1988, 18 per cent of the women and 22 per cent of the men had received a higher degree (Niphuis-Nell, 1992). Due to this convergence in schooling, one is tempted to conclude that the sources of gender earnings differences among cohorts who are now entering the labour market must lie outside the educational system.

There is a reason, however, to regard this conclusion as premature. A frequent criticism of studies examining the gender gap in earnings is that differences in type of schooling are ignored (Marini, 1989; Daymont and Andrisani, 1984). Analyses of earnings either include a continuous measure of years of completed schooling or a set of dummy variables indicating what level of schooling a person has completed. Using multivariate regression models, authors subsequently examine to what extent gender differences in earnings remain after measures of educational level are taken into account. Similarly, models with and without measures of educational level are compared to assess what part of the gender gap can be attributed to schooling differences. While the caveat that differences in type of schooling might play a role as well is often made, the question of how different types of schooling affect earnings is rarely examined empirically.

Table 1. *Percentage graduating by type and level of schooling and percentage of graduates who are female: the Netherlands, 1991*

	Percentage female		Percentage graduating	
	University	Higher vocational	University	Higher vocational
Applied technical fields and engineering	17.5	15.0	18.6	32.1
Economics, business, and administrative fields	22.1	45.8	12.9	21.0
Natural sciences and mathematics	26.3	—	6.0	—
Law school	49.8	—	14.6	—
Medical sciences, biology, and health service fields	52.6	80.0	11.7	13.7
Arts, languages, and philosophy	63.9	55.8	15.8	9.3
Social sciences and schools of social work	66.9	77.8	14.3	8.4
Education	—	70.9	—	15.6
Service fields, excluding health services	—	—	—	—
Other	—	—	6.1	—
Total	43.3	48.1	100.0	100.0

Source: Central Bureau of Statistics, Annual Educational Statistics 1993.

In this study, we reexamine the link between schooling and earnings by (*a*) analysing how different types of educational attainment affect earnings, and (*b*) by assessing to what extent sex differences in type of schooling contribute to the sex gap in earnings. Our study is motivated by three observations.

First, there are important differences between men and women with respect to type of schooling. Table 1 gives an overview of the degrees issued by institutions of higher education, broken down by sex and type of schooling. Although the numbers of men and women graduating from university and higher vocational school are fairly similar, the type of degrees they receive differ considerably. Men are overrepresented in the fields of economics and administration, technical fields, and – to a lesser extent – medical science. Women are overrepresented in the social sciences, the arts, and the fields relevant to higher service occupations. Since the field of study is an intuitively plausible determinant of earnings, the question arises to what extent prevailing differences in type – in addition to level – of schooling contribute to the sex difference in earnings.

A second reason for looking at type of schooling has to do with a public policy debate about the causes and consequences of gender inequality. In 1987, the Dutch Department of Education began a campaign that aimed to encourage women to choose maths and physics in high school. This campaign was called 'Choose Technical' and was intended to provide women with better opportunities of specializing in technical subjects in university and vocational school. In the same period, the Department of Labour began a campaign, called 'Women Wanted for Men's Work,' which tried to encourage women to choose subjects at college that would give them access to more favourable sectors of the labour market. The ultimate aim of these campaigns was to lower the traditional underrepresentation of women in male fields such as physics, mathematics, and other sciences. The underlying rationale was that among men, these fields generally lead to better labour-market prospects. If women were to enter these fields, so it was believed, they would also end up in higher paying jobs. Although it is too soon to evaluate the success of the campaigns, so far there have only been modest changes in the type of degrees men and women obtain in higher education (SCP, 1994) and women still show less interest in studying technical subjects in high school than men do (Willems and De Grip, 1995).

A third and more general reason for examining the role of education in more detail lies in the rapid expansion of higher education in the Netherlands. With increasing participation in higher education, the amount of schooling itself will slowly begin to lose salience as a proxy for potential labour-market

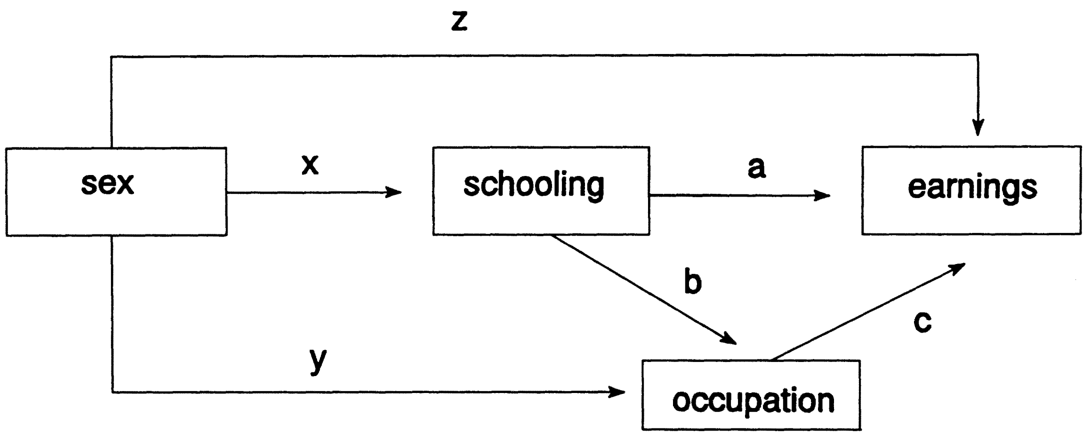

Figure 1. *The earnings attainment model augmented with the variable sex*

productivity. While the type of schooling has always been a consideration for employers in selecting job candidates, there are several reasons to believe that this criterion has become a more important source of information in the last two decades. Because educational expansion has led to a decline in the variance of schooling (SCP, 1994), recent cohorts entering the labour market have become more homogeneous. Since it is unlikely that employers or personnel specialists will treat the better educated cohorts as a homogeneous group, additional criteria may become more important in recruiting and selecting personnel. An efficient match of individual workers to occupational positions requires indicators or screening devices that hold relevant information regarding an individual's productivity. In a highly educated society such as the Netherlands, it may well be that the type of degree people hold becomes an increasingly important screening device in the labour market.

Background and Theory

As in most other modern industrialized countries, there is a significant difference in hourly wages between men and women in the Netherlands. According to the Central Bureau of Statistics, in 1991 women earned 24 per cent less than men (CBS, 1994). Despite rapid changes in women's employment outside the home, as well as increasing levels of education among women, the wage gap has been fairly stable over recent decades (Hooghiemstra and Niphuis-Nell, 1993). Wage differences can be found in all educational groups (Takkenberg and Walschots, 1992), and are particularly large when individuals are approaching midlife (CBS, 1994).

Previous Hypotheses and Findings on Education

Several hypotheses have been suggested to explain sex differences in earnings (Marini, 1989; Siegers, 1981). To review these hypotheses, it is helpful to introduce the standard earnings attainment model, augmented with the variable sex (Figure 1). Several other variables are relevant here as well, such as labour-market experience, household composition, and firm or labour-market characteristics, but for our purposes we limit the theoretical discussion to the three central stratification variables (i.e., education, occupation, and earnings).

The earnings attainment model assumes that schooling has two effects on earnings, a direct and an indirect effect. First, higher education gives access to high status occupations (effect *b*), and high status occupations are paid better (effect *c*). Next to this indirect effect (effect *bc*), there is a direct effect of schooling (effect *a*), which means that when individuals have the same occupation, the better educated will have higher earnings than their less educated colleagues or occupational peers. Most studies generally find evidence of both direct and indirect effects, though the magnitude of the direct effect declines when more detail is used in measuring occupations.

Sex differences in earnings arise in several different ways. The first two are related to the educational system. If women have lower levels of schooling than men (effect *x*), they will have lower earnings due to the effect of education on earnings via occupation (effect *xbc*). Women's lower levels of schooling may also lead to lower earnings because there is a direct effect of schooling on earnings (effect *xa*). In both cases, the ultimate cause of gender inequality lies in the educational system. These two effects are most often considered in the human capital approach. Economists like Oaxaca (1973) and Blinder (1973), for example, have previously argued that due to an educational disadvantage, women enter lower level occupations to begin with, will be less qualified to make promotions within a firm or organization, and will be less successful within a given occupation than men. Labour economists generally focus on education without considering occupation. By excluding occupation, their approach essentially focuses on the combined direct and indirect effects of schooling (i.e., the reduced form effects of schooling).

Women may also have lower earnings because, even when they do have similar levels of schooling, they may have different kinds and levels of occupations than men (effect *yc*). This hypothesis is most frequently adopted by sociologists. England (1984), for example, has argued that men and women with similar qualifications have different earnings because they end up in different sectors of the labour market, different occupations within sectors, or different function levels within occupations. Both supply and demand factors play a role in this hypothesis. Some authors argue that women choose to do different work because they want to have occupations with more flexible working hours and lower monetary penalties for career interruptions (Polacheck, 1981). Others try to find the causes of job segregation in personnel practices, employer discrimination, and legal arrangements (Bielby and Baron, 1986).

Finally, women may have lower earnings because they are paid less even when they have similar levels of schooling and similar kinds of occupations. This is represented in the model by the direct effect of sex (effect *z*). This residual effect is often interpreted as evidence of discrimination, though most authors caution that the magnitude of the residual greatly depends on the way the model is specified (e.g. Treiman and Roos, 1983). The hypothesis of a direct effect has been developed most extensively in the 'comparable worth' perspective (Hartman, Roos, and Treiman, 1985; Baron and Newman, 1990; Kilbourne *et al.*, 1994), in which it is argued that women with similar levels of human capital who do similar work are paid differently.

Empirically, all the above hypotheses have received some support. Although the sources of pay differences continue to be debated, in the Netherlands there seems to be consensus that the largest part of the gap in earnings can be attributed to the fact that men and women with similar educational qualifications have different kinds of occupations (Schippers and Siegers, 1986, 1988). In other words, it is believed that the direct effect of sex on occupation (controlling for education), combined with the effect of occupation on earnings, is the most significant cause of gender differences in wages (effect *yc*). Most studies consequently examine the causes and consequences of occupational or job segregation between men and women. In the Netherlands, these studies focus on a variety of demand-side factors, such as employer preferences (Oosterhuis and Glebbeek, 1988), job-rating systems (Remery and Van Doorne-Huiskes, 1992), internal labour markets (De Gijsel *et al.*, 1991), and firm characteristics (Bosch, 1992).

While we acknowledge the role of occupation in the development of earnings inequality, we also believe that the effects of education warrant further investigation. If men and women differ in type of schooling (effect *x*), and if type of schooling affects earnings, the possibility arises that part of the sex effect still runs through education. This effect may either be direct, indirect through occupation, or both. All three scenarios, however, involve educational differences. In our analyses, we develop alternative measures of schooling to re-examine the issue of whether the gender gap in earnings can be explained by educational differences. Our primary focus is on the reduced form effect of schooling (effect *xa* and effect *xbc* combined), though we also provide analyses estimating the direct effects of schooling.

An Alternative Conceptualization of Schooling

Our conceptualization of educational attainment follows the standard human capital approach to earnings (Becker, 1964; Mincer, 1974). In this perspective, human capital is defined as the skills that increase an individual's marginal productivity in the labour market. People invest in their productive capacities to maximize lifetime income. These investments bear a considerable cost in the form of tuition and foregone earnings. People invest in human capital as long as the expected wage benefits exceed the costs of investment. In its original formulation, Becker (1964) considered on-the-job training, formal schooling, health, and information as the prime examples of human capital. For on-the-job training, he further made a distinction between general and specific human capital. General human capital includes skills that can be applied in several different firms; specific human capital is accumulated in a single firm and cannot be used elsewhere. Since the skills learned in school can be used in a range of labour-market sectors and occupations, Becker regarded formal schooling as a form of general human capital.

Empirical research has followed this line of reasoning by treating formal schooling as a one-dimensional concept, where duration or length of schooling is the one and only discriminating characteristic. In practice, this means that years of schooling and labour-market experience are used as key indicators of human capital. Studies subsequently estimate subgroup differences in earnings or wages while controlling for years of schooling or compare the rate of return to years of schooling across subgroups. In industrialized countries, the income returns to an additional year of schooling vary from 4 per cent to 9 per cent, depending on how income is measured and on how the model is specified (Rosenfeld and Kalleberg, 1990; Treiman and Roos, 1983). Recent analyses of hourly wages in the Netherlands indicate that the return to schooling is between 5 and 6 per cent for both men and women (Schippers and Siegers, 1988).

We argue that, in addition to length of schooling, a distinction can be made between types of schooling. More specifically, we extend Becker's distinction between general and specific on-the-job training to formal schooling. General schooling takes place in the early years of a person's life and focuses on the accumulation of general knowledge such as history, foreign languages, literature, and geography on the one hand, and basic skills such as reading and arithmetic on the other. These forms of human capital can either not be applied directly to specific functions in the labour market (e.g. geography), or are equally useful in a wide variety of occupations (e.g. reading skills). Most importantly, they prepare a person for specialized training later in life. Specialized training, in contrast, is oriented towards the accumulation of skills that are most useful in certain jobs or in certain sectors of the labour market. Perhaps the most obvious example is vocational school (e.g. law school prepares for practising law), but in the Netherlands, university training focuses on specific occupational skills as well. Most Dutch undergraduates study a single subject for the entire duration of study, in contrast to the United States, for example, where undergraduates generally choose a variety of courses.

Although many types of specialized training exist, we believe that four main categories can be distinguished: technical training, economic-administrative training, socio-cultural training, and training for the caring professions. Technical training can be defined as training oriented towards the accumulation of knowledge about the functioning of complex objects and corresponding skills to operate them. The prime examples here are engineering and physical sciences. In economic-administrative training, people learn about the functioning and management of business, organization, and trade. Business schools and university departments of economics are the most obvious examples, but several others exist as well, such as higher economic-administrative schools (HEAO) and public administration science. Socio-cultural training can be defined as training oriented towards the accumulation of knowledge about symbolic meanings, cultural codes, and the functioning of human society in general. Prime examples are arts, languages, and social sciences. Training for the caring professions, finally, includes a variety of schools that prepare students for service occupations which involve a considerable amount of social interaction, such as social work, teaching, and nursing.

The above dimensions are ideal types. In practice, each vocational school or course of college study offers a mix of training. Law school, for example, is partly oriented towards economic-administrative training, but also focuses on socio-cultural aspects. Medical school, to give another example, is mostly technical, but involves social and caring skills as well. A given college course or vocational school can be regarded as offering a certain amount of training on each dimension. In principle, the amount of training in a given dimension can be measured by the length of time students spend on training in this area (e.g. the number and duration of courses).

Because they prepare students for different kinds of work, it can be expected that the different types of training yield different rates of return with respect to earnings. We have to keep in mind, though, that the actual occupational destinations of students in a certain field may vary. An engineering major, for example, may end up in a high-status technical job, but he or she may also enter higher management positions later in his or her career. A graduate in one of the social sciences may end up being a college teacher, in which case he or she earns less than the engineering graduate, but he or she may also make a career in the higher levels of the government bureaucracy. The different types of courses are intended to offer training for certain sectors of the labour market; where students in fact end up is an empirical question. In this study, we begin to answer this question by examining the effects of type of schooling on individual differences in hourly earnings. In a later study, we intend to analyse longitudinal data in order to examine the effect of type of schooling on occupational careers.

Analyses

We analyse the 1991 *Aanvullend Voorzieningengebruik Onderzoek* (AVO). The AVO is a large, nationally representative sample of households from the Dutch population and was originally designed for examining income differences and the use of government services and subsidies. In every household all members over the age of 16 were interviewed. The question on type of schooling was asked of respondents with a middle vocational degree, a higher vocational degree, or a university degree. Because the technical fields of study in middle vocational schools are difficult to compare with the technical fields in higher education – learning to do carpentry and learning physics are hardly comparable – we only focus on the effects of schooling in the higher educated segment of the population (i.e. those with higher vocational and university training). Another reason for this limitation is that middle vocational schools do not offer training in the socio-cultural, legal, and medical fields. We limit the sample to men and women with a paid job between 18 and 65 years of age.[1] In total, we have 835 men and 421 women with valid data on all variables in the analysis.

Measures

Our measure of schooling combines two elements of education: the type of degree obtained and the length of schooling it requires to obtain the degree. To measure length of schooling, we focus on formal duration rather than on the actual number of years a person has spent in school. While there is considerable variation in the time people spend in college, people who take longer to graduate in principle accumulate the same skills and follow the same courses. For all different higher educational degrees we calculated how many generalized years of schooling are needed and how many specialized years of schooling. To attend higher vocational training in the Netherlands (HBO) a person needs 11 years of general schooling; to attend university (WO) a person needs 12 years. Higher vocational training takes on average 4 years of specialized training. University takes an average of 6 years, with the exception of medical school, which takes 8 years (including internships). We adjusted the length of specialized schooling for persons who had both vocational and university training to 6 years, since the highest level of schooling obtained is most relevant in the labour market. In these cases, we also used the type of schooling for the highest degree obtained (i.e., university training).[2]

To develop measures of specialized schooling, we partition the number of years of specialized training into four components: technical, economic-administrative, socio-cultural, and caring. A few examples will illustrate how we constructed our measures. Physical science focuses on technical training only,

Table 2. *Means and standard deviations (in parentheses) of all variables used in the analysis*

Independent variable	Women	Men	Difference[a]
Logarithm of hourly earnings	3.063	3.444	10.09**
	(0.523)	(0.694)	
Tenure (in decades)	0.556	0.898	7.52**
	(0.600)	(0.854)	
Tenure squared	0.669	1.536	6.57**
	(1.391)	(2.585)	
Experience with previous employers	0.756	0.788	0.79
(in decades)	(0.715)	(0.691)	
Experience squared	1.081	1.098	0.16
	(1.817)	(1.867)	
Married/cohabiting (0/1)	0.621	0.735	4.33**
	(0.486)	(0.442)	
Children at home (0/1)	0.445	0.533	3.08**
	(0.497)	(0.499)	
Total years of schooling	15.014	14.987	−0.21
	(1.986)	(2.334)	
General years of schooling	11.030	10.884	−1.75
	(1.287)	(1.521)	
Specialized years of schooling	3.974	4.089	1.40
	(1.312)	(1.500)	
Years of econ.-admin. schooling	0.480	0.727	3.40**
	(1.135)	(1.319)	
Years of technical schooling	0.994	1.540	5.00**
	(1.608)	(2.021)	
Years of socio-cultural schooling	1.023	0.802	−2.61**
	(1.438)	(1.489)	
Years of training for caring professions	1.476	1.021	−6.52**
	(1.199)	(1.217)	

[a]Based on t-test for continuous variables (two-tailed) and χ^2-test for dichotomous variables.
$*P<0.05$ $**P<0.01$.

which means that we assign 6 years of technical schooling, and 0 years of socio-cultural, economic-administrative, and caring schooling. A health vocational degree, on the other hand, is a mixed form. It is largely aimed at caring, but it is partly technical as well. Obtaining this degree takes four years, and we subsequently assign 0.7×4 years $= 2.8$ years of caring schooling and 0.3×4 years $= 1.2$ years of technical schooling. Medical school, in contrast is more technical in nature; for this educational type we assign 0.8×8 years $= 6.4$ years of technical schooling and 0.2×8 years $= 1.6$ years of schooling for caring professions. In other words, for each type of schooling, we decide a priori which part is technical, which part economic-administrative, which part socio-cultural, and which part is caring. These parts add up to 1, and we subsequently multiply each part by the length of time it takes to obtain the degree. The partitions we chose, listed in Appendix A, are based on our knowledge of the educational system in the Netherlands. Although they could be improved in subsequent research by using the judgement of educational experts and personnel specialists, we would like to emphasize that our way of distinguishing types of schooling is fairly robust with respect to small changes in the four components.

In Table 2, we present the means and standard deviations for the different schooling components. We also present tests indicating whether sex differences are statistically significant. According to our measures, men and women have more or less the same number of years of general and specialized schooling. This comes as no surprise, since all the members of our sample belong to the higher educated segment of the labour market. Looking subsequently at the different types of schooling, we observe that women spend more time in training for socio-cultural and caring professions than men, whereas men spend more time in training for economic-administrative and technical fields than women. Because these differences are statistically significant, our approach captures the major differences in type of schooling, as revealed by national educational statistics (Table 1), quite well.

To estimate the reduced form effects of schooling, we control for several other independent variables which are often used in analyses of the earnings gap: tenure (i.e., experience with the current employer), tenure squared, experience with previous employers, experience squared, whether the respondent is married or cohabiting, and whether the respondent has young children living at home. Experience with previous employers is approximated in the conventional way (age − years of schooling − 6 − years with current employer).[3] The means, presented in Table 2, show that employed women have fewer years of experience with their current employer, are less likely to be married, and less often have young children at home.

Our dependent variable is the natural logarithm of hourly earnings. As is common in other studies, we do not have direct reports of hourly earnings but rely on monthly reports of earnings from labour or self-employment. To calculate hourly earnings, we use reports of the number of hours worked according to the respondent's employment contract. Because the self-employed do not have employment contracts we used the number of hours worked in a 'typical' week for this group. We also estimated models excluding the self-employed, but arrived at identical results. Most respondents report earnings after taxes. Since men and women are sometimes taxed differently in the Netherlands, largely because the tax system includes adjustments for living arrangements, we calculated earnings before taxes (gross incomes), using a commonly applied gross−net program developed by Grift and Van Basten (1994).

Models and Analytical Strategy

Our analytical strategy is to estimate a set of nested regression models using the log of hourly earnings as a dependent variable. If W_i is an individual's hourly earnings and S_i is the respondent's sex ($S_i = 1$ for women, $S_i = 0$ for men), our baseline model can be defined as follows,

$$\ln W_i = \alpha + \beta S_i + \epsilon_i \qquad (A)$$

Model A simply estimates total relative earnings differences between men and women. The estimated sex difference equals $\exp(\beta)$. Expressed in percentages, the female earnings disadvantage amounts to $100^*[1 - \exp(\beta)]$.

In Model B, we add the vector of earnings determinants discussed before (X_i), with the exception of schooling variables.

$$\ln W_i = \alpha + \beta S_i + \Sigma_j \gamma_j X_{ij} + \epsilon_i \qquad (B)$$

In this model, $\exp(\beta)$ is the relative earnings difference after taking into account sex differences in the other independent variables. If the effect of sex declines from Model A to Model B, it may be concluded that part of the sex difference in earnings can be attributed to sex differences in the means of the standard earnings determinants. More specifically, the relative decline in $100^*[1 - \exp(\beta)]$ is the percentage of the female earnings disadvantage that can be attributed to the female disadvantage in experience, tenure, and the other standard earnings determinants.[4]

In Model C, we add educational attainment, measured in years of schooling YRS_i. This model closely approximates the standard practice in human capital studies of earnings.

$$\ln W_i = [B] + \delta YRS_i + \epsilon_i \qquad (C)$$

In this model, δ is the conventional estimate of earnings returns to schooling. Expressed in percentages, the estimated rate of return to an additional year of schooling is $100 \times \delta$.

Subsequently, in Model D, we partition years of schooling into two components: years of schooling preparing for university or vocational school, which we call general schooling (YRS_i^g), and years of vocational school or university study, which we call specialized schooling (YRS_i^v). In this model, δ^g is the estimated rate of return to general schooling while δ^s is the estimated rate of return to specialized schooling. Since $YRS_i = YRS_i^g + YRS_i^s$, the difference in fit between Models C and D tests whether $\delta^s = \delta^g = \delta$.

$$\ln W_i = [B] + \delta^g YRS_i^g + \delta^s YRS_i^s + \epsilon_i \qquad (D)$$

In Model E, we partition total years of specialized schooling into the four different types of schooling: years of economic-administrative schooling (YRS_i^{se}), years of technical schooling (YRS_i^{st}), years of socio-cultural schooling (YRS_i^{ss}), and years of training for the caring professions (YRS_i^{sc}).

$$\begin{aligned}\ln W_i =& [B] + \delta^g YRS_i^g + \delta^{se} YRS_i^{se} + \delta^{st} YRS_i^{st} \\ &+ \delta^{ss} YRS_i^{ss} + \delta^{sc} YRS_i^{sc} + \epsilon_i\end{aligned} \qquad (E)$$

By comparing the fit of Models D and E we can test whether the different types of training have differential effects on earnings. Or, to put it more formally, because $YRS_i^s = YRS_i^{se} + YRS_i^{st} + YRS_i^{ss} + YRS_i^{sc}$, Model D assumes that $\delta_i^{se} = \delta_i^{st} = \delta_i^{ss} = \delta_i^{sc} = \delta^s$, whereas Model E allows these effects to differ.

In the models discussed so far, only standard earnings determinants are used as control variables. Because no information on job characteristics is included, Models C, D, and E essentially estimate the reduced form effects of schooling, that is, the direct effect of schooling together with the indirect effect of schooling through occupation. To assess whether the different types of schooling also have direct effects on earnings, we include a number of dummy variables for occupation and industry in Model F. For occupation we consider five dummy variables (Occ_{ik}): managerial, administrative, commercial, service, and manual occupations (professional occupations are the reference category). For industry we use six dummy variables (Sec_{il}): construction, trade, transport, banking and commerce, services, and agriculture (manufacturing is the reference category).[5]

$$\ln W_i = [E] + \Sigma_k \eta_k Occ_{ik} + \Sigma_l \eta_l \mathrm{Sec}_{il} + \epsilon_i \qquad (F)$$

Explaining the Earnings Gap

Summary statistics of Models A through F are presented in Table 3. Regression coefficients are presented in Table 4. For each model, we present the (adjusted) R^2, the degrees of freedom, the change in fit (according to an F-test), and the effect of sex on earnings. We compare our models in two different ways. First, we compare the overall fit of the models. This comparison allows us to examine if schooling variables help explain individual differences in earnings. Second, we compare the effect of sex across models. This comparison allows us to examine if schooling variables help explain differences in earnings between men and women.

Model A only includes the sex variable. The effect of sex in this model is -0.396, which means that on average, women have 32.7 per cent lower hourly earnings than men (i.e. $100 \times [1 - \exp(-0.396)]$). Model B, which also includes standard earnings determinants, gives a better fit than Model A. The change in F is statistically significant at the 5 per cent level. When comparing the effect of sex across models, we notice that the earnings disadvantage of women declines with 11.8 per cent (from 32.7 to 20.9 per cent). Hence, in relative terms, sex differences with respect to the standard earnings determinants explain 36 per cent of the observed female earnings disadvantage (i.e. $[32.7 - 20.9]/32.7$). The results of these calculations are presented in the last two columns of Table 3.

Model C includes the conventional measure of schooling, i.e., level of completed schooling, scaled in years. Not surprisingly, Model C has a better fit than Model B; this simply indicates that the schooling variable has a statistically significant effect on earnings. In addition, we observe that the relative earnings difference between men and women decreases from $20.9 - 20.5$ per cent. Hence, sex differences in years of schooling make virtually no contribution to the female disadvantage in earnings (i.e. [20.9–20.5]/32.7 or 1 per cent). Model D, which distinguishes general and specialized years of schooling, also yields a better fit, showing that general and specialized schooling give different returns. In contrast to our previous model, however, the distinction between generalized and specialized schooling does not explain much of the female earnings disadvantage.

Model E introduces the four different types of specialized training to the equation. Table 3 shows that this model has a better fit than Model D, which means that we can reject the hypothesis that the

Table 3. *Comparison of models for earnings*

Model	R^2 (adj.)	Df	Change in F	Effect of sex	% Disadvantage	% Explained by schooling[a]
A: Baseline model	0.079	1255	—	−0.396	32.7	—
B: Model A+standard wage determinants	0.327	1249	78.23**	−0.235	20.9	—
C: Model B+years of schooling	0.367	1248	79.56**	−0.229	20.5	1.2
D: Model B+general and specialized schooling	0.375	1247	16.82**	−0.224	20.1	2.5
E: Model B + general schooling+4 types of schooling	0.382	1244	5.77**	−0.195	17.7	9.8
F: Model E+occupation and industry	0.409	1231	5.42**	−0.171	15.7	—

[a]Percentage explained by schooling.
$*P<0.05$ $**P<0.01$

different types of training offer the same rates of return. When focusing on sex differences, we notice that the relative earnings disadvantage declines to 17.7 per cent. Hence, when both level and type of schooling are considered, about 10 per cent of the female earnings disadvantage can be attributed to schooling differences between men and women (i.e. [20.9 − 17.7]/32.7). While this is not a large amount, it is substantially larger than what years of schooling alone could explain (1 per cent).

We continue with Model E – our best model so far – and add dummy variables for occupation and sector. When comparing the change in F, we see that Model F has a better fit than model E. The effect of sex is −0.171, which means that the relative earnings disadvantage of women decreases from 17.7 per cent in Model E to 15.7 per cent in Model F. Hence, given the effects of standard earnings determinants and our extended set of schooling variables, occupation and sector explain another 6 per cent of the earnings gap (i.e. [17.7 − 15.7]/32.7).

Before discussing the effects of schooling, we summarize our decomposition. The total female disadvantage is 32.7 per cent. Of this gap, 36 per cent can be attributed to the fact that women have less experience, 10 per cent can be attributed to the fact that men and women have different levels and types of schooling (given differences in experience and tenure), and 6 per cent can be attributed to the fact that men and women are working in different groups of industries and occupations (given differences in experience and schooling). In total, these variables explain 52 per cent of the relative sex gap in earnings.

The Effects of Schooling

The estimated regression coefficients are presented in Table 4. Since we are mainly interested in the effects of schooling, we abstain from discussing Model A and B and shift our attention to Model C. In the standard human capital model (Model C), we find that the effect of education is 0.061, showing that each year of schooling is associated with a 6 per cent increase in earnings. This return to schooling corresponds well with findings from earlier analyses in the Netherlands using different data (Schippers and Siegers, 1988). Model D shows that the returns to schooling are higher for specialized training (10 per cent) than for general training (3 per cent). We have to keep in mind, however, that our sample is limited to the more highly educated workforce. Hence, differences in general schooling are smaller than they would be in a sample of the population at large.

When focusing on different types of specialized training (Model E), we observe that all types have positive effects. The strengths of these effects, however, differ in a systematic fashion. A comparison of the coefficients shows that economic-administrative

Table 4. *Coefficients for regression of the logarithm of hourly earnings on selected independent variables*

Independent variable	Model A	B	C	D	E	F
Woman (0/1)	−0.396**	−0.235**	−0.229**	−0.224**	−0.195**	−0.171**
	(0.038)	(0.033)	(0.032)	(0.032)	(0.033)	(0.033)
Tenure (in decades)		0.441**	0.456**	0.433**	0.459**	0.421**
		(0.056)	(0.055)	(0.055)	(0.055)	(0.055)
Tenure squared		−0.033	−0.032	−0.028	−0.035**	−0.026
		(0.019)	(0.019)	(0.019)	(0.018)	(0.018)
Experience with previous employers (decades)		0.331**	0.339**	0.324**	0.343**	0.310**
		(0.63)	(0.61)	(0.061)	(0.060)	(0.060)
Experience squared		−0.031	−0.022	−0.019	−0.025	−0.025
		(0.024)	(0.23)	(0.023)	(0.023)	(0.022)
Married/cohabiting (0/1)		0.303**	0.290**	0.279**	0.281**	0.254**
		(0.035)	(0.034)	(0.034)	(0.034)	(0.034)
Children at home (0/1)		−0.054	−0.039	−0.039	−0.036	−0.021
		(0.034)	(0.033)	(0.032)	(0.032)	(0.032)
Years of total schooling			0.061**			
			(0.007)			
Years of general schooling				0.025*	0.018	0.014
				(0.011)	(0.012)	(0.012)
Years of specialized schooling				0.095**		
				(0.011)		
Years of econ.-admin. schooling					0.129**	0.116**
					(0.015)	(0.015)
Years of technical schooling					0.095**	0.081**
					(0.012)	(0.012)
Years of socio-cultural schooling					0.087**	0.080**
					(0.014)	(0.014)
Years of training for caring professions					0.066**	0.057**
					(0.016)	(0.017)
Occupation						—[a]
Industry						—[b]
Intercept	3.458**	2.688**	1.738**	2.024**	1.908**	2.403**
	(0.022)	(0.046)	(0.116)	(0.134)	(0.172)	(0.148)

Note: Estimated standard errors in parentheses; $N = 1256$.
$^{*}P < 0.05$ $^{**}P < 0.01$ (two-tailed tests).
[a]Coefficients for occupation dummies are 0.163** (managers), −0.114** (administrative jobs), −0.205* (commercial jobs), −0.217** (service jobs), −0.190* (manual workers); professionals are the reference category.
[b]Coefficients for industry dummies are −0.083 (construction), −0.195* (trade), −0.189* (transport), −0.097 (bank/commerce), −0.182** (services), −0.545** (farm). Manufacturing is the reference category.

training yields the highest benefits in terms of earnings (13 per cent). The benefits of technical schooling and socio-cultural schooling are 10 per cent and 9 per cent respectively, while training for the caring professions gives the smallest increase in earnings (7 per cent). When we focus on the effects of the different types of schooling in Model F, which includes control variables for occupation, we notice that the effects decrease.[6] Hence, part of the schooling effect is indirect, via occupation. The order of the magnitude of the effects stays the same, however, indicating that the different types of training also yield different direct returns.

Table 5. *Coefficients for regression of the logarithm of hourly earnings for men and women separately*

Independent variable	Women	Men
Tenure	0.521**	0.487**
	(0.107)	(0.066)
Tenure squared	−0.114*	−0.037
	(0.045)	(0.021)
Experience with previous employers	0.438**	0.384**
	(0.097)	(0.076)
Experience squared	−0.104**	−0.022
	(0.040)	(0.027)
Married/cohabiting (0/1)	0.039	0.397**
	(0.048)	(0.045)
Children at home (0/1)	−0.123*	0.009
	(0.051)	(0.041)
Year of general schooling	0.022	0.020
	(0.020)	(0.014)
Years of economic-administrative schooling	0.141**	0.125**
	(0.024)	(0.0.18
Years of technical schooling	0.088**	0.099**
	(0.019)	(0.014)
Years of socio-cultural schooling	0.118**	0.083**
	(0.022)	(0.017)
Years of training for caring professionals	0.097**	0.059**
	(0.024)	(0.020)
Intercept	1.992**	1.908**
	(0.235)	(0.172)
Number of respondents	421	835

Note: Estimated standard errors in parentheses.
$^*P < 0.05$ $^{**}P < 0.01$ (two-tailed tests)

Given our finding that traditionally male types of schooling yield higher returns than other forms of schooling, the question arises whether this is solely due to the differential distribution of men and women over the four types of schooling. It is also possible that the different types of training yield different returns for men and women. For example, the rate of return to a typically male field such as technical training could be lower for women than for men. Similarly, the rate of return to a field not dominated by males, such as socio-cultural training, could be higher for women. In other words, is the relative magnitude of the returns to the different types of schooling different for women than for men? To answer this question, we estimate our regression models for men and women separately (using interaction effects). We use Model E for this exercise, since we are interested in the total effects of the different types of training. Adding interaction effects of the schooling variables and sex leads to a rather modest improvement in fit. The change in F is 1.6 with a *P*-value of 0.18.[7] Hence, we should be cautious in interpreting the results (presented in Table 5).

To assess the gain of investing in one type of schooling rather than another, we compare the four coefficients for each sex separately.[8] We therefore set the rate of return to socio-cultural training to 100 for men and women separately and subsequently calculate how much more (or less) a year of investment in the other types of training yields. This comparison shows that to the average man, investing in technical training is worth 19 per cent more than investing in socio-cultural training (i.e. 0.099/0.083). To the average woman, the relative gain from technical training is 25 per cent lower (i.e. 0.088/0.118). Similar results apply to economic-administrative training. To the average man, investing in economic training is worth 51 per cent more than investing in socio-cultural training. To the average woman, it is worth 19 per cent more. Although we repeat that differences are modest from a statistical point of view, these findings may well point towards a 'chilling effect.' The 'chilling effect' hypothesis was suggested by Daymont and Andrisani (1984), who argued that the underrepresentation of women in male-dominated fields of study is partly due to the fact that the benefits of such investments are meagre for women.

To conclude our discussion, we present the effects of the other independent variables. For both men and women, each year of experience with the present employer yields a 5 per cent increase in earnings. As expected, returns for work with previous employers are somewhat lower. In addition, for women there is a negative coefficient on tenure squared and experience squared, indicating that earnings begin to increase at a slower rate the more tenure and experience women accumulate (the point at which earnings begin to decline with experience is 21 years). For men, we do not observe such a pattern; the squared terms are not statistically significant. Consistent with a host of earlier studies, we find that married men have higher hourly earnings than other men.

For women, there is no earnings premium for being married, but neither is there a penalty. Having young children at home decreases earnings by 12 per cent for women, and there is no effect for men.

Conclusion

Although men and women now complete similar levels of schooling, the type of fields they study vary widely. Men are overrepresented in technical and economic-administrative fields, women are overrepresented in socio-cultural and caring fields. Our analyses show that these types of schooling have significantly different effects on earnings. These differences closely follow the male–female distinction: male-dominated fields generally have higher rates of return than female-dominated fields. Together, these findings suggest that part of the female earnings disadvantage can be attributed to sex differences in type of schooling. Empirically, we show that when considering sex differences in level and type of schooling simultaneously, about 10 per cent of the female earnings disadvantage can be attributed to women's disadvantage with respect to level and type of schooling. Finally, we find evidence – although it is weak – that male-dominated fields such as technical training yield higher returns to men than to women, whereas female-dominated fields such as socio-cultural training yield higher returns to women than to men. Larger data-sets are needed to examine this issue conclusively.

In sum, we believe that contemporary schooling differences between Dutch men and women play a non-trivial role in the earnings process. Though the 10 per cent we find is not large, it is not unimportant, and it is clearly higher than what is found when using a one-dimensional conceptualization of formal schooling – the standard practice in previous analyses of earnings. Several authors have concluded previously that the sources of contemporary earnings differences between men and women must be sought outside the educational system. Our findings indicate that this conclusion may be unwarranted. Our conclusion corresponds with an earlier analysis of American data by Daymont and Andrisani (1984). In a longitudinal analysis of American college graduates, Daymont and Andrisani show that 29 to 42 per cent of the earnings gap can be explained by sex differences in the type of subject studied at college. Consistent with our findings, they also show that women are paid less for male-dominated specialisms than are men.

In future work, analyses of levels and types of schooling can also be applied to occupational differences. Since sex segregation in the higher educational system closely matches the pattern of sex segregation in the labour market, it is to be expected that a significant part of occupational differences between men and women can be explained by differences in the way men and women invest in their human capital. Next to such a supply-side approach, we also need to consider the extent to which men and women with similar kinds of specialized training end up in similar kinds of jobs and similar types of occupations. Perhaps the relatively lower effects of technical schooling among women can be explained by the fact that these types of investment do not give them easy access to the better-paying sectors of the labour market. To examine the impact of schooling on occupational careers, the distinction between levels and types of schooling can be applied to the occupational domain as well. After all, the most frequently used occupational scales, such as prestige or SEI, are one-dimensional, and hence do not distinguish between type and level of occupational status. Recently developed scales of cultural and economic occupational status would be a valuable tool in making such distinctions (De Graaf and Kalmijn, 1995) and would allow us to examine both schooling and occupation from a multi-dimensional perspective.

Notes

1. Several authors in the past have argued that estimates of the effects of schooling on earnings for women are biased. Not all women work, and if women who work are a selected sample with respect to earning ability, selection bias may arise. While the reasoning is plausible, previous analyses have shown that the magnitude of this bias is small (e.g. Kilbourne *et al.*, 1994; Wellington, 1994). In addition, the estimated magnitude of the bias greatly depends on how well one is able to model the decision to participate in the labour market. Given the limited amount of information on

demographic and work histories in our data, we believe a correction for selection bias will be of little value.

2. Combining higher vocational training with a few years of college is currently not uncommon, but the question of whether and how such detours through the educational system affect earnings would require a separate study.
3. Experience and tenure are scaled in decades.
4. Our procedure resembles the standard regression decomposition technique commonly used in analyses of wage differences between subgroups. More specifically, in a regression decomposition, authors typically calculate what part of the sex gap can be attributed to differences in means and what part can be attributed to differences in regression coefficients (Oaxaca, 1973; Blinder, 1973). The part attributed to differences in means can be calculated using the coefficients in the equation for males or the coefficients in the equation for females. These calculations provide a range of possible values. Our procedure essentially comes down to weighting the difference in means by the coefficients for the total equation. Since these coefficients will be a weighted average of the male and female coefficients, our estimates will be somewhere in between the possible range of values in a standard regression decomposition. We do not consider the other part of the decomposition (i.e. the difference which can be attributed to sex differences in coefficients), since this part of the decomposition depends on the scale of the independent variable. Since the scale is not fixed in advance, this part of the decomposition is arbitrary (Jones, 1983).
5. We would like to point out that the direct effect of schooling, that is, the effect of schooling after taking into account job characteristics, greatly depends on the level of detail used in the job measures. The more detail used, the lower the direct effect will be. The combined direct and indirect effect will stay the same, however. Hence, we have more confidence in the earlier models than in the later model.
6. For presentational purposes, coefficients for occupation and industry dummies are reported in the footnote to Table 4.
7. The improvement in fit is calculated by adding interactions of sex and schooling to a model which consists of model E plus interactions of sex and the standard earnings determinants.
8. When comparing a given coefficient between men and women, we notice that the effects of specialized training appear to be somewhat stronger for women than for men.

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Acknowledgement

We thank the ICS Data Archive for making available the data on which the analyses in this paper are based.

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Manuscript received: November 1994

Appendix A. *Partition of types of schooling into the four components of specialized training*

Type of schooling	Specialized training			
	Technical	Economic	Socio-cultural	Caring
Agricultural colleges	0 .8	0.2	0	0
Agricultural university	0.6	0.3	0.1	0
Technical colleges	1.0	0	0	0.0
Physical sciences	1.0	0	0	0.0
Health-care colleges	0.3	0	0	0.7
Medical school	0.8	0	0	0.2
Economic colleges	0.2	0.7	0	0.1
Economic university degree	0.2	0.7	0	0.1
Law colleges	0	0.5	0	0.5
Law university degree	0	0.7	0.0	0.3
Teacher training colleges	0	0.0	0.5	0.5
Art Schools	0	0.0	1.0	0
Arts and humanities degrees	0	0	1.0	0
Schools of social work	0	0	0.2	0.8
Social and cultural sciences	0.1	0	0.7	0.2
Police and military academy	0.4	0.2	0	0.4