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Recent Trends in Intergenerational Occupational Class Reproduction in the Netherlands 1970–99

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Previous research on intergenerational social mobility among men in the Netherlands has consistently shown that there has been a major trend towards more social fluidity (i.e. less association between origins and destinations) in the second half of the twentieth century. In a first attempt to look at long-term trends, Ganzeboom and De Graaf (1984) matched the 1954 mobility table, constructed by Van Heek and published and documented by Van Tulder (1962), with a table derived from the 1977 Life Situation Survey of Statistics Netherlands. The 1977 table was cast in prestige layers in order to match the format of the earlier published table. Using Hope's (1982) log-linear model (then labelled as the vertical distance model), the young authors found a clear trend, that was expressed in the comparison of a 0.54 versus 0.66 multiplicative coefficient (1.00 being the point of no association). Converted to an annual rate, the speed of change was about −0.95 percent per year. Put in a different way, using linear extrapolation, the Netherlands could be expected to reach perfect mobility by 2023.

The conclusion of *significant change* was not much in line with the 1980s international social mobility literature, the vast majority of which supported the FJH thesis (Featherman et al. 1975) that there are 'no significant differences among industrialised countries'. In order to further scrutinise the finding, the Utrecht Mobility Seminar (a group of stratification researchers then at Utrecht University) brought together and analysed more detailed and voluminous data

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from secondary sources, and matched these with the class measures of social stratification prevailing in the international literature. Ganzeboom et al. (1987) (but see also Luijkx and Ganzeboom 1989 and Luijkx 1994) assembled a set of ten mobility tables for 7,310 men that spanned the 1970–85 period. All these data contained detailed occupation codes and could be matched with the ten-class EGP typology that had been proposed by Erikson et al. (1979). Using this much larger database and more rigorous and controlled harmonisation of data—but using a somewhat smaller time window than the previous analysis—the results were much in line with what was found for the 1954–77 comparison. The scaled association coefficient declined significantly over subsequent surveys, and the trend was even more dramatic, estimated at about −2.2 percent per annum. If linearly extrapolated, Dutch society could be expected to reach the point of perfect mobility by 2014.

Subsequent contributions have widened the time window again. The original data for the 1954 survey are lost, but a dataset collected by Gadourek (1963) in 1958 turned out to be a valuable substitution, and confirmed the earlier conclusion that the Netherlands in the 1950s was less open than in the 1970s (Ganzeboom 1984). Ganzeboom and Luijkx (1995) added data collected before 1970 as well as until 1993 that were cast in prestige and in class categories. Linear extrapolations led them to forecast that perfect mobility would be reached between 2009 and 2019 (cf. Fig. 14.1 that displays the long-term trend in prestige mobility). However, it is only fair to say that Ganzeboom and Luijkx reached more mitigated conclusions on the diagonal parts of their class tables (e.g. they predicted that it would take 400 years before the farm category would become perfectly open), as well as finding (insignificant) traces of curvilinearity in the trends.

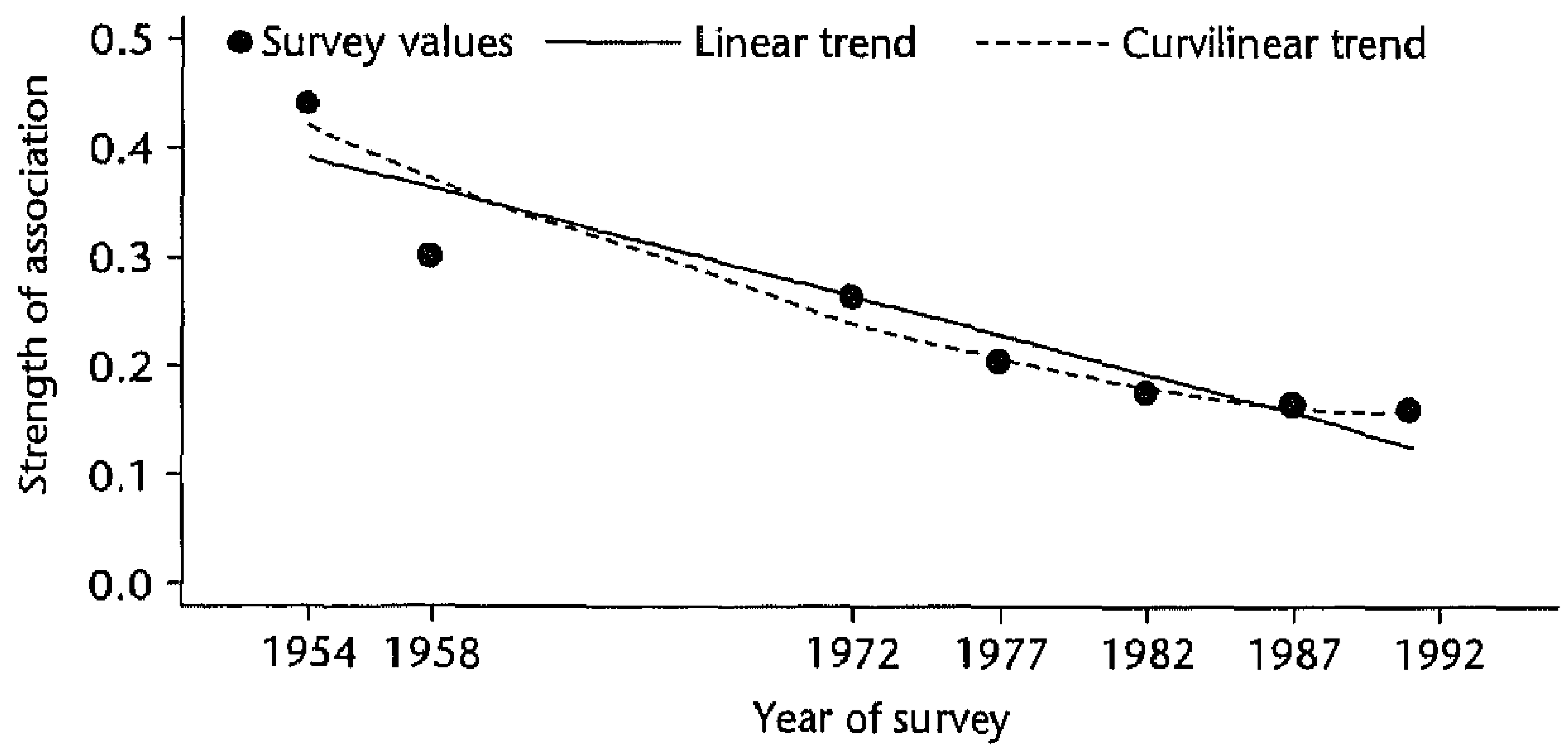

FIG. 14.1. *Long-term trends in intergenerational occupational prestige mobility. Men in the Netherlands 1954–93*

Source: Ganzeboom and Luijkx (1995).

In this chapter, we broaden the scope of these trend analyses in a number of ways. First, by adding a number of recent social mobility files to the existing database, and further expanding the time horizon, we will be able to establish more conclusively how the pattern of social reproduction and mobility in the Netherlands has changed, and in particular to see whether the previously established trends are still continuing or have actually taken different directions by the end of the twentieth century. Secondly, from these files we have available large-scale data on the social mobility of women in the labour force, relative to their father, and can thus answer the question of whether the trends we see for men are paralleled for women in the labour force. These two issues constitute the first part of this chapter. In the second part of this chapter, we accomplish a third aim, by expanding the bivariate social mobility relationship into an elementary three-variable occupational attainment model, with education mediating between father's occupation and respondent's current occupation.

Data

The data sources used in our analysis are listed in Table 14.A1 Altogether they constitute thirty-five samples[1] of men and women of adult age (25–64). Ten of the thirty-five sources are identical to the data used by Ganzeboom et al. (1987) and Luijkx (1994) that established the trend between 1970 and 1985. These sources are marked with an asterisk. However, the counts derived from these sources are not exactly identical to the ones used in the earlier analyses, due to variations in selections and (updated) conversions used. In some of the surveys, questions about occupation have only been asked about current job; in other surveys questions have been included about previous jobs. The analyses in this chapter will be conducted on the group of 'all men', as well as the group of 'women in the labour force'. We selected only those respondents who have a valid code for father's occupation, education, and own occupation. Taken together, we have complete data on 20,769.7 men and 8,897.7 women at our disposal. The number of men in our studies almost triples the number of cases used in our analysis for the period 1970–85.

Note that the analyses for women are restricted to women active in the labour force (i.e. employed or currently seeking work). While for men, we have classified those outside the labour force (primarily due to early retirement and disability) by their previous occupation—if available—for women we used only those with a current occupation or who were unemployed (in which case we used their most recent occupation) and have excluded long-time retirees from the labour market (primarily housewives). It may be important to note

[1] A full description of how the data were harmonised and how weights, selections, and codes need to be interpreted is provided at the first author's website (www.scw.vu.nl/~ganzeboom/ismf) that documents the International Stratification and Mobility File, of which these data are part.

that the participation of women in the labour force has dramatically increased over the period studied[2], from about 25 percent to almost 65 percent most recently. For men, labour force participation is stable at around 75 percent, if not slightly declining. It is to be expected that the dramatic inflow of women will have consequences for the structure of their employment, that is, the distribution of classes. In particular it is to be expected that the expansion of women in the labour force will lead to a stronger representation of classes that were dominated by women to begin with.

The analyses reported in this chapter are conducted on an aggregation of the data over six equally spaced time periods (1970–4, . . . ,1995–9). The virtues of this aggregation are that the results are easier to present and the fit statistics are more robust, as the data are very thinly distributed over the thirty-five tables once they become cross-classified with education.

The occupations in almost all of the data were originally coded to the four-digit Census Classification 1971/1984 (CBS7184) of Statistics Netherlands (Centraal Bureau voor de Statistiek 1971, 1984)[3], which is intimately related to the International Standard Classification of Occupation 1968—ISCO68 (International Labour Office 1969); indeed, the first three digits of these two classifications have a one-to-one mapping. Some of the surveys contain a truncated or aggregated version of these CBS7184-codes, but there are still two or three digits available. Two of the surveys contain a single-digit self-completion code for occupations which is still compatible with the 'EGP classification', which is our final instrument of analysis. Furthermore, the oldest survey used, from 1970, was generated before the Census of 1971 and was coded into the four-digit Census code of 1960 (Centraal Bureau voor de Statistiek 1960). Finally, in one recent survey the occupations are coded by Statistics Netherlands' 1992 SBC (SBC92) classification (Centraal Bureau voor de Statistiek 1992), which is more or less unrelated[4] to the ILO's revision of ISCO in 1988—ISKO88 (International Labour Office 1990).

Using conversion schemes generated by Ganzeboom and Treiman (1996), all the original codes are transferred into the two international standard classifications, ISCO68 and ISKO88. These international codes, together with measures of self-employment and supervision, are then transferred into Erikson and Goldthorpe's (Erikson et al. 1979) tenfold EGP class typology. From the work started by the Utrecht Mobility Seminar and continued by Ganzeboom et al. (1989) and Ganzeboom and Treiman (1996), there are two

[2] The increased participation of women in the labour force largely explains the increased representation of women in the thirty-five surveys, listed in Table 14.A1. However, three studies had lower representation of women due to other features of their design. NET76j and NET87j are restricted to employed women and men (with an overrepresentation of the self-employed), while in NET82u women were undersampled.

[3] The differences between the 1971 and 1984 versions of this classification are very minor and consist of a few additional titles in the 1984 version.

[4] There is no one-to-one mapping between ISKO88 and SBC92, although the principles of revision were quite similar: in both classifications the occupational titles are organised by required skill level, and employment status is no longer taken into account.

separate conversions available to derive the EGP classification: via ISCO68, and via ISKO88 (Ganzeboom and Treiman 2003). The logic used in both conversions is identical. In a first step, each detailed occupation is assigned to an initial EGP category. In a second step, some initial assignments are reallocated by taking into account the information on self-employment and supervising status. The thirty-five datasets vary with respect to the availability and prevalence of self-employment and supervision measures for fathers and respondents. Generally speaking, these indicators are available from two sources: independently asked questions, and information implicit in the occupation codes. It is important to note that both the CBS7184 and ISCO68 reserve separate categories for the self-employed (shop owners, farmers), so that the omission of a separately asked question on self-employment constitutes no great danger to the validity of our measures. The omission of a separate question on supervision constitutes a bigger problem, as some of the distinctions in EGP are critically dependent upon such a measure. If there is no indication of supervision, it is impossible to distinguish between the self-employed with and without employees, and between supervising and skilled manual workers. As eighteen of the thirty-five surveys do not have independent information on supervision for fathers, and two do not have it for respondents, this leaves us with an eightfold version of the EGP classification:

1. Professionals, managers, and large proprietors (I).
2. Associate professionals and managers (II).
3. Routine non-manual workers (IIIab).
4. Small self-employed with and without employees (IVab).
5. Skilled manual workers and manual supervisors (V/VI).
6. Semi- and unskilled manual workers (VIIa).
7. Agricultural workers (VIIb).
8. Self-employed farmers (IVc).

While the two conversions, via ISCO68 and via ISKO88 into EGP, are meant to be identical, the results are not perfectly so. The inconsistencies arise for two reasons:

1. The original classifications in the data do not have one-to-one mappings with ISCO68 and ISKO88, nor is there a one-to-one mapping between the two ISCOs.
2. There are intrinsic differences between the ways in which the two ISCOs are mapped into the EGP classification, mostly due to the different roles employment statuses have in the two classifications.

Note that the combination of these two can work out differently depending upon the nature and distinction of the underlying source code. In our judgment, the ISCO68-to-EGP conversion can be expected to be more valid for separating out the self-employed and agricultural categories (IVab, IVc, VIIb), while ISKO88-to-EGP is definitely stronger in distinguishing between skill levels in both the non-manual and manual categories. By consequence, we derive our final EGP classification by combining the two EGPs using the following rules:

1. Categories 1,2,3,5,6 are taken from the ISKO88-conversion.
2. Categories 4,7,8 are then taken from the ISCO68-conversion.

Note that by applying these *in sequence* the second rule prevails over the first one.

First, we will present descriptive analyses of observed mobility patterns. Subsequently, we will conduct our log-linear analyses of relative mobility patterns.

Descriptive analyses

Table 14.1 displays the marginal distributions for men and women in the labour force over the six periods. We observe familiar differences between

TABLE 14.1. *Class structures for all men and women in the labour force for six five-year periods in the Netherlands (1970–99)*

	Class structure					
	1970–4	1975–9	1980–4	1985–9	1990–4	1995–9
Men						
I	16.2	18.3	16.3	18.5	20.9	24.0
II	14.9	21.9	23.2	24.4	26.1	26.1
III	12.5	8.0	9.8	9.9	9.1	11.9
IVab	9.9	6.6	5.6	5.2	5.0	3.4
V + VI	21.7	24.6	24.5	21.8	21.3	21.1
VIIa	16.5	13.6	15.3	15.9	13.1	10.4
VIIb	2.2	2.2	1.6	1.4	1.3	1.4
IVc	6.1	4.9	3.7	3.0	3.3	1.7
Total	100.0	100.0	100.0	100.0	100.0	100.0
Women						
I	7.1	8.1	5.0	8.1	9.6	11.1
II	21.2	27.1	30.1	30.9	35.2	34.5
III	36.1	40.2	42.3	40.6	36.9	39.7
IVab	11.8	5.8	5.5	5.8	3.8	3.0
V + VI	5.6	4.6	4.9	4.1	3.6	2.7
VIIa	15.4	11.9	10.3	9.3	9.3	7.8
VIIb	0.8	0.7	0.5	0.4	1.1	0.7
IVc	2.0	1.7	1.3	0.8	0.6	0.6
Total	100.0	100.0	100.0	100.0	100.0	100.0

men and women: women are heavily under-represented among the higher managers and professionals and in skilled manual labour, somewhat under-represented in farm occupations, and take relatively large shares of routine non-manual work, semi-, and unskilled manual work, while being about equally represented at the associate managerial and professional level and small self-employed. When we look at the development of the class structure between 1970 and 1999 in Table 14.1, it is striking that there has been a huge increase in both classes I and II. For men both classes developed from about 15 to 25 percent; for women, we see a somewhat differential development for class I and class II. The share of class I increased slowly from about 7 to 11 percent; class II jumped from about 21 to 35 percent. Classes III, V/VI, and VIIb remain stable, whereas there is a marked decrease in the semi- and unskilled manual working class, VIIa, and in the self-employed, IVab, and farmers, class IVc.

Despite the dynamic development in the class structure, there is not much of a development in overall mobility in the Netherlands, but if there is one, it is towards more mobility. Using the eight-category class scheme, it develops from 69.2 to 74.7 percent for men and for women in the labour force from 78.0 to 82.4 percent (Table 14.2).

Analyses of the inflow percentages for the recruitment of men and women into occupational classes, and of the outflow percentages for the distribution of the occupational classes given the origin class, show very few surprises.[5] A somewhat striking feature is the low self-recruitment to self-employed farmers among women (only 62 percent has a farmer father), but this is counterbalanced by the somewhat larger inflow from farm labour origins than among men. Women also have lower self-recruitment than men among the self-employed, but show stronger self-recruitment in the two managerial/professional classes. Overall, one gains the impression that recruitment patterns are somewhat different between genders.

TABLE 14.2. *Percentage mobile for all men and women in the labour force for six five-year periods in the Netherlands (1970–99)*

	Men (%)	Women (%)
1970–4	69.2	78.0
1975–9	72.7	80.5
1980–4	73.8	79.5
1985–9	74.0	80.9
1990–4	74.3	81.7
1995–9	74.7	82.4

[5] Inflow and outflow percentages are presented in Table 14.A2 and 14.A3.

Log-linear models

How then can the association pattern in these cross-classifications be further characterised and what are the historical trends? In order to explore the pattern of association in cross-classified data, it is of some use to compute the full set of contiguous odds ratios in a table:

$$\theta_{ij} = \frac{f_{ij} * f_{(i+1)(j+1)}}{f_{(i+1)j} * f_{i(j+1)}}, \tag{14.1}$$

where θ_{ij} is the odds ratio and f_{ij} represent the four adjacent (observed) frequencies in origin (row) i and destination (column) j.

It is well known that the full set of (in this case forty-nine) contiguous odds ratios constitute a complete account of the association pattern, the so-called saturated model or unconstrained association model. Log-linear models can be interpreted as steps towards constraining the odds ratios in the saturated model to a more parsimonious set in order to find a sociologically more meaningful and statistically more powerful account of the data. There are two directions to constrain the odds ratios. First, we can introduce constraints *between tables* to test for trends (without using within-table constraints). Secondly, we can introduce constraints *within tables*, in order to find a parsimonious and interpretable pattern of social mobility flows. As we will explain further below, combining within-table and between-table constraints potentially generates sociologically meaningful and statistically powerful models of the data.

Between-table constraints

The simplest constraint between tables is the assumption that similar odds ratios are identical between tables:

$$\theta_{ijk} = \theta_{ij(k+1)}, \tag{14.2}$$

where i indices rows, j indices columns, and k indices tables (periods). This model is also known as the Constant Social Fluidity (CnSF) model and constitutes a very broad test to search for trends, as it requires no model of the within-table variation in odds ratios. It uses the full 49 degrees of freedom (in an 8×8 table) to 'model' the odds ratios that constitute the CnSF pattern itself. This may, of course, not be the most parsimonious and statistically powerful account of the data. Moreover, the CnSF model does not provide a meaningful interpretation of the association pattern itself.

Erikson and Goldthorpe (1992) and Xie (1992) have proposed an elaboration of the CnSF model to test for trends, the so-called Unidiff (uniform difference) model or log-multiplicative layer effect model. Unidiff takes an intermediate position between CnSF (same pattern and strength of association in all tables) and the saturated model (different pattern and different strength of association for all tables), by using as a constraint that the set of odds ratios in one table differs from the set of odds ratios in the next table only by a (log-) multiplicative scaling factor:

$$\begin{aligned} \theta_{ijk} &= \theta_{ij}^{\beta_k} \\ \ln \theta_{ijk} &= \beta_k * \ln \theta_{ij}, \end{aligned} \tag{14.3}$$

where $\beta_1 = 1$. In other words, the log odds ratios (θ_{ij}) are equal for each table k except for a multiplicative scaling factor (β_k). While the Unidiff model goes a considerable way in bridging the space between CnSF model and the saturated model, it remains a disadvantage that this model does not lend interpretability to the pattern of odds ratios itself, and still uses a large number of degrees of freedom to model this pattern.

Within-table constraints

In order to look at the association in a more informative way, it is useful to introduce constraints on the pattern of the odds ratios within tables. A class of models that can be used to succinctly summarise the association has been proposed by Goodman (1979*b*): the scaled uniform association models. The starting point of such models can be found in the very restricted uniform association model that assumes all contiguous associations in a table to be identical:

$$\ln \theta_{ij} = \varphi. \tag{14.4}$$

The uniform association model uses a single degree of freedom to characterise all odds ratios in a table, which is a parsimonious but often too restrictive assumption to fit the data. The stringent assumption can be meaningfully relaxed in three ways:

1. By exempting diagonal cells from the association pattern by fitting distinct parameters δ_{ii} to these cells. Such representations are known as quasi uniform association models. Exempting diagonal cells (and separately modelling them) parallels the assumption that staying in one's origin class (i.e. class inheritance) is not necessarily governed by the same contingencies as the pattern of mobility for the mobile.
2. By scaling the distances between the row (μ_i) and column (ν_j) categories:

$$\ln \theta_{ij} = \varphi(\mu_{i+1} - \mu_i)(\nu_{j+1} - \nu_j), \tag{14.5}$$

where μ_i and ν_j are scaling parameters, subject to the constraints of mean 0 and, in this case, variance 8 (the number of origin and destination categories)[6], while φ is the scaled uniform association parameter that describes the association throughout the table, conditional upon the scaling parameters.

3. As a useful special restriction in this model we can introduce equal scalings for rows and columns:

$$\mu_i = \nu_i. \tag{14.6}$$

Taken together, these three specifications constitute the quasi equal scaled uniform association model, or Goodman–Hauser model after its principal inventors (Goodman 1979*b*; Hauser 1984*a*, *b*).

The Goodman–Hauser model is an extremely useful workhorse for comparative mobility analysis, as it combines statistical power and parsimony with a sociologically meaningful representation of the data. Its useful features can be summarised as follows:

1. The parameters of the Goodman–Hauser model have a nice sociological interpretation. The category scalings μ_i and ν_j can be interpreted as measures of the distance between, or similarity among, social categories with respect to mobility chances. If categories are identically scaled ($\mu_1 = \mu_2$), this suggests that they can be regarded as a single social class, but if the scalings are very different, this implies not only that mobility between them is extremely difficult, but also that they have very different mobility exchanges with other classes. We will constrain μ_i and ν_j to be the same for the different period tables.
2. The diagonal density parameters δ_{ii} represent within-class immobility over and above the immobility uniform to all categories. In previous analyses, these patterns have been found to be class-specific. We will model differences over time (δ_{iik}).
3. Finally, the scaled uniform association parameter φ constitutes a single measure of social fluidity and is its most parsimonious representation. We will model the differences over time (φ_k).

The model uses a limited number of degrees of freedom to characterise the pattern of association within tables. In our 8 × 8 tables, the forty-nine elementary odds ratios are summarised by eight scaling parameters (equal for row and columns), one overall scaled uniform association parameter, and eight diagonal cell parameters.

[6] Note that our standardisation constraint differs from the usual convention of fixing the variance in the scalings at 1.0. The particular advantage of our choice is that the scaled uniform association coefficients map into the metric of the Pearson correlation coefficient (−1.00 to 1.00) (Goodman 1981). Goodman shows that if the distribution of counts fits a bivariate normal distribution, the estimated value of φ under this choice of constraint is numerically identical to Pearson's correlation coefficient.

Models of trends

Both the Unidiff and the scaled uniform association model can be applied in comparative analysis by introducing between-tables identity, linear, and/or curvilinear restrictions on (parts of) the model. For the Unidiff model, a linear time constraint can be introduced by restricting the scaling factor:

$$\beta_k = 1 + \beta Y, \tag{14.7}$$

where Y is the number of years since 1970: that is, we assume the multiplicative scaling factor β_k develops linearly over time. We can also let β_k develop curvilinearly over time, by using the following constraint:

$$\beta_k = 1 + \beta Y + \gamma Y^2. \tag{14.8}$$

For the scaled association model, our primary tool of analysis will be to let the components of the association pattern φ_k and δ_{iik}vary over time:

$$\begin{aligned} \varphi_k &= \varphi^*(1 + \beta Y) \\ \varphi_k &= \varphi^*(1 + \beta Y + \gamma Y^2) \\ \delta_{iik} &= \delta_{ii}{}^*(1 + \beta Y) \\ \delta_{iik} &= \delta_{ii}{}^*(1 + \beta Y + \gamma Y^2). \end{aligned} \tag{14.9}$$

Regarding the diagonal effects, we assume that the development over time is the same for each diagonal cell i, but that the density per cell i differs.

Fit measures

As our primary measure of goodness-of-fit, we use the conventional log likelihood ratio χ^2 statistic (L^2). We also use the Bayesian information criteria (bic) statistic introduced to the social sciences by Raftery (1986). He argues that comparative mobility studies often have large sample sizes which make it difficult to find models that fit the data according to conventional probability levels. Both L^2 and bic were introduced in Chapter 2.

However, it is important to note that L^2 is sensitive to sparse tables, that is, tables in which many of the observed counts are zero or one. For that reason, we will restrict our interpretation to the *differences* between the statistics, not their absolute value (Wong 2001).

All our models are estimated using LEM (Vermunt 1997). This program provides a versatile tool to model both bivariate and partial association models, and has superseded earlier tools such as GLIM and ASSOC, used by Ganzeboom et al. (1989).

Analyses Part I: bivariate social mobility

Table 14.3 reports on the application of the models introduced above to the six tables for men and for women in the labour force.

Men

Model A in Panel A is that of conditional independence (or perfect mobility), which assumes that all odds ratios are equal to one, and thus that father's and respondent's class are unrelated. This is obviously not the case, given the highly significant L^2 value and the positive bic, which denotes that this model fits worse than the saturated model. Model B, the CnSF model, leaves the odds ratios unconstrained within tables, but constrains them to be equal between tables, and thus provides a (weak) test of the no change in relative mobility hypothesis proposed by Featherman et al. (1975). For men, the CnSF model does not fit the data by conventional test statistics. This confirms earlier findings that there are indeed significant over-time trends. To further test this claim, the CnSF model can be compared to Model C, the uniform difference model, that leaves the odds ratios unrestricted within tables, but scales them by a uniform constant between tables. Relative to common social fluidity, Model C consumes a single degree of freedom for each additional table. Both by conventional L^2 statistics and by bic standards, this model is a significant improvement over the model of no change. However, we can further trim the model by assuming that the between-table differences follow a metric trend: Model D, the linear uniform difference model, restricts the trend parameter to follow a straight line, while Model E, the curvilinear uniform difference model, applies a second-degree polynomial to constrain this parameter. Comparing Models D and E answers the question whether the trend towards more social fluidity has slowed down or has been reversed. Both models are clearly superior to the Unidiff model as well as the common social fluidity model, by L^2 and bic standards, but the linear trend fits marginally better than the curvilinear trend. In conclusion: social fluidity for men in the Netherlands still appears to be developing at a linear pace.

Panel B of Table 14.3 runs through a similar sequence of models, but now using the Goodman–Hauser scaled uniform association model as its way to represent the within-table structure of association. As explained above, scaled uniform association models are more parsimonious than unconstrained association models. This does not pay off for Model F in a better fit in terms of bic and certainly not in terms of L^2. Model F is that of quasi equal scaled uniform association, that is, we assume identical scalings between tables, as well as between rows and columns, but freely varying diagonal parameters δ_{iik}

TABLE 14.3. *Fit statistics for bivariate association models for O (origin class) and D (destination class), men and women in the labour force (ilf), six five-year periods*[a]

Type of model	Men				Women ilf		
	d.f.	L^2	*p*	bic	L^2	*p*	bic
Panel A: unconstrained association models							
A Conditional independence	294	5388.3	.000	2465.6	1271.6	.000	−1401.9
B Common social fluidity	245	340.2	.000	−2095.5	238.7	.601	−1989.2
C Uniform differences	240	274.1	.065	−2111.8	225.1	.747	−1957.4
D Linear uniform differences	244	280.3	.055	−2145.4	226.0	.789	−1992.8
E Curvilinear uniform differences	243	278.0	.061	−2137.7	225.6	.782	−1984.1
Panel B: equal scaled association models							
F Free diagonals	234	534.9	.000	−1791.4	322.6	.000	−1805.3
G Equal Diagonals	274	596.9	.000	−2127.0	358.7	.000	−2133.0
H Unidiffed diagonals	269	587.4	.000	−2086.8	354.1	.000	−2092.0
I Linear association and linear scaled diagonals	277	597.9	.000	−2155.8	356.8	.001	−2162.1
J Linear association and equal diagonals	278	605.0	.000	**−2158.7**	360.6	.001	**−2167.4**
K Curvilinear associations and curvilinear diagonals	275	591.4	.000	−2142.5	355.5	.001	−2145.2
L Curvilinear associations and equal diagonals	277	598.9	.000	−2154.8	359.8	.001	−2159.1
Panel C: unequal scaled association models							
Fa Free diagonals	228	510.5	.000	−1756.1	305.5	.000	−1767.8
Ga Equal diagonals	268	572.5	.000	−2091.7	340.8	.002	−2096.3
Ha Unidiffed diagonals	263	563.3	.000	−2051.3	335.6	.002	−2056.0
Ia Linear associations and linear scaled diagonals	271	574.0	.000	−2120.0	338.2	.003	−2126.1
Ja Linear associations and equal diagonals	272	580.9	.000	−2123.1	342.4	.002	−2131.1
Ka Curvilinear associations and curvilinear diagonals	269	567.5	.000	−2106.7	337.3	.003	−2108.9
La Curvilinear associations and equal diagonals	271	574.7	.000	−2119.4	342.0	.002	−2122.3

[a] Best fitting model according to bic is in boldface.

and strength of association φ_k. The six subsequent Models G through L test whether it is necessary to leave the diagonal parameters free and whether linear and curvilinear constraints to the diagonal parameters and overall association fit better. The best fitting model, by a small margin over the curvilinear trend Model L, is the linear trend Model J, that pools all the between-table differences in a single association parameter that follows a linear trend, while the classes differ only in immobility and scalings that remain constant over time. That is, there is no need, in these data, to postulate that diagonal frequencies (inheritance of class position) develop along different lines than the off-diagonal association.[7]

For reference with the partial analyses in Part II, we have added in Panel C of Table 14.3 the Models Fa–La. In these models the scalings of the categories are allowed to differ between rows and columns, and the association in each table is treated as asymmetric. None of these asymmetric models is superior to its symmetric counterpart, at least not if judged by bic, although by the conventional L^2 comparison the asymmetrical versions are to be preferred.

Women

The parallel analysis for women in the labour force shows very much the same picture as for men, but with some exceptions. First of all, it may be important to note that for the unconstrained association models, all but the conditional independence model fit the data as judged by the nominal L^2 statistic. By this evidence, one could conclude that there are *no* historical trends for women. However, a more powerful test for this conclusion is to be obtained by comparing fit statistics between models, as well as by finding the lowest bic. This exercise points again to Model D: linear uniform differences.

Turning to the scaled association models, again Model J (linear association and equal diagonals) is the best fitting model in terms of bic. We can safely conclude that for women the overall association pattern is developing almost linearly over time, and this happens at the same pace on and off the diagonal.

Time-constant parameters

Figure 14.2(a) displays the estimated time constant scaling parameters for the scaled uniform association Model J. For men and their fathers, we see that they almost perfectly scale the eight occupational classes at equal distance, in the order of the class number (Fig. 14.2(a)). If we would put class IVc between classes V–VI and VIIa, all the scalings would fall almost perfectly on a straight line. The scalings for women and their fathers follow a very similar pattern,

[7] In our earlier analysis of the 1970–85 data (Ganzeboom et al. 1987) we included an independently varying trend parameter for class inheritance, but we do not need it here, at least not by bic standards.

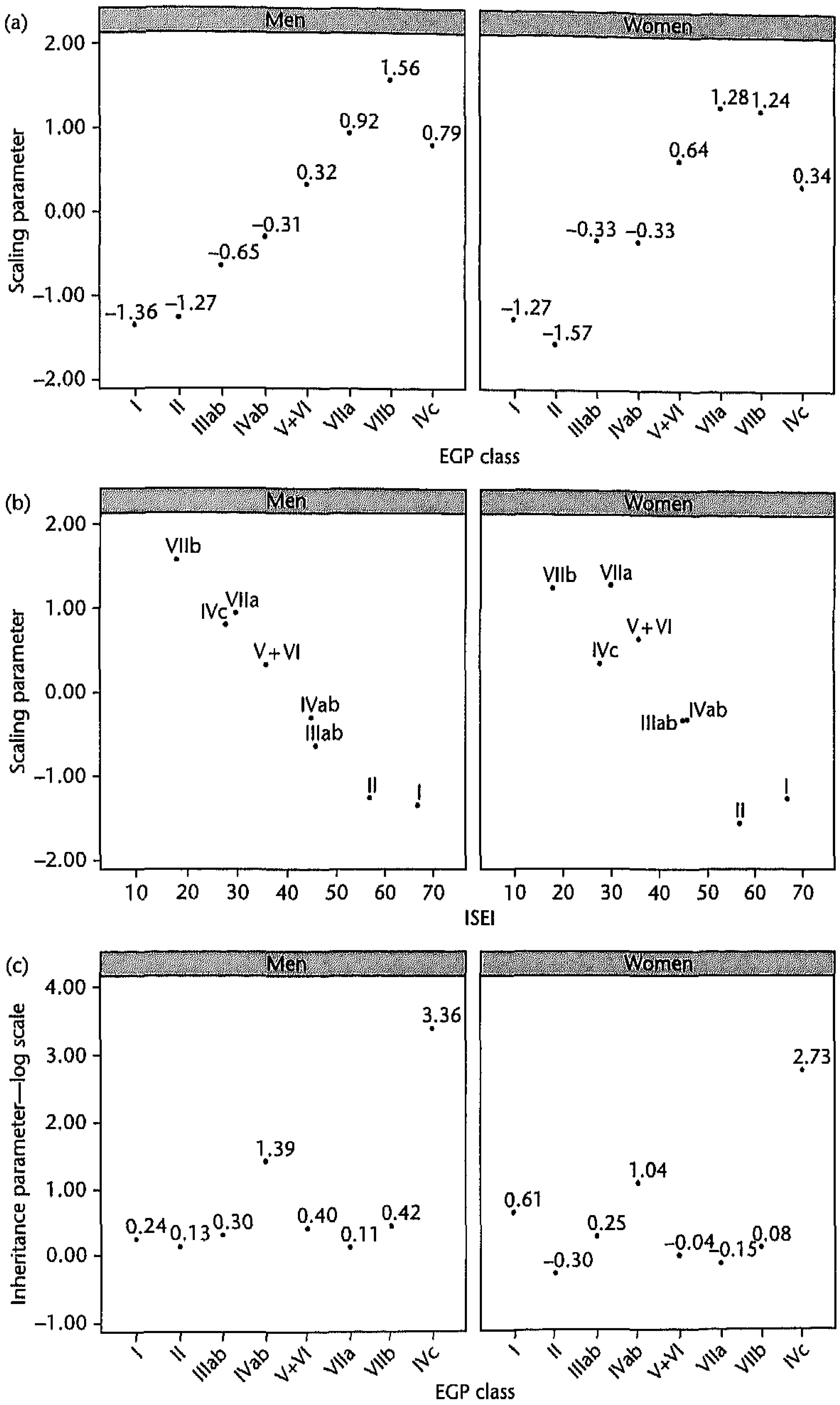

FIG. 14.2. *(a) Estimated scaling parameters for EGP classes (men and women and their fathers separately, against class number). (b) Estimated scaling parameters for EGP classes (men and women and their fathers separately, against ISEI score). (c) Estimated diagonal parameters (men and women separately)*

but have interesting exceptions. For women and their fathers, the positions of the two managerial and professional categories I and II are reversed, and class III (routine non-manual) appears to be scaled lower than among men, while the female self-employed farmers (in fact a rare category) are scaled higher than among men and their fathers. Note that our analysis has been conducted separately for men and women, and that, as a consequence, fathers in the two analyses are differently scaled. While these diversions seem interesting and interpretable, we should not make too much of them, as a pooled analysis (not shown here) suggests that the scalings can be equalised between men and women and their fathers without significant loss of information.

The ordering of the classes for men is a familiar one, as it is almost perfectly linear with the socio-economic status of the respective occupations. Figure 14.2(b) plots the estimated scaling parameters against the average International Socio-Economic Index (ISEI) of occupational status of the EGP categories (Ganzeboom et al. 1992). ISEI and the scaling are almost perfectly colinear. For women, the interpretation is more complicated, as class II is scaled slightly higher than class I. Given that the estimated scalings derive primarily from the off-diagonal association, we can conclude that women's recruitment into class II and outflow from class II is more related to father's status than that in class I.

Figure 14.2(c) plots another time constant part of the scaled uniform association Model J, the diagonal or immobility parameters, as they differ between the eight classes. We see a familiar pattern for both men and women: direct immobility is particularly prevalent among self-employed farmers (IVc) and other small self-employed (IVab)—but distinctively less than among farmers. For men, the least immobile category is that of semi- and unskilled workers (VIIa). This pattern is in line with earlier findings, both in the Netherlands and elsewhere (Ganzeboom et al. 1987, 1989). The immobility coefficients are generally lower for women than for men, in particular in classes with strong inheritance (IVab and IVc). However, there is one exception to this rule, as higher professional and managerial status (class I) appears to be more inheritable from fathers to daughters than from fathers to sons. Note, however, that, as Fig. 14.2(a) showed, class I among women is actually scaled lower than class II, and has fewer female incumbents to begin with: we should not over-interpret this finding.

Trend parameters

Finally, we can turn towards the interpretation of the trend parameters in the models. What do they show about historical developments in social mobility patterns?

Figure 14.3(a) plots the values of the estimated Unidiff coefficients for men and women in the unconstrained model, taken from Model C, together with

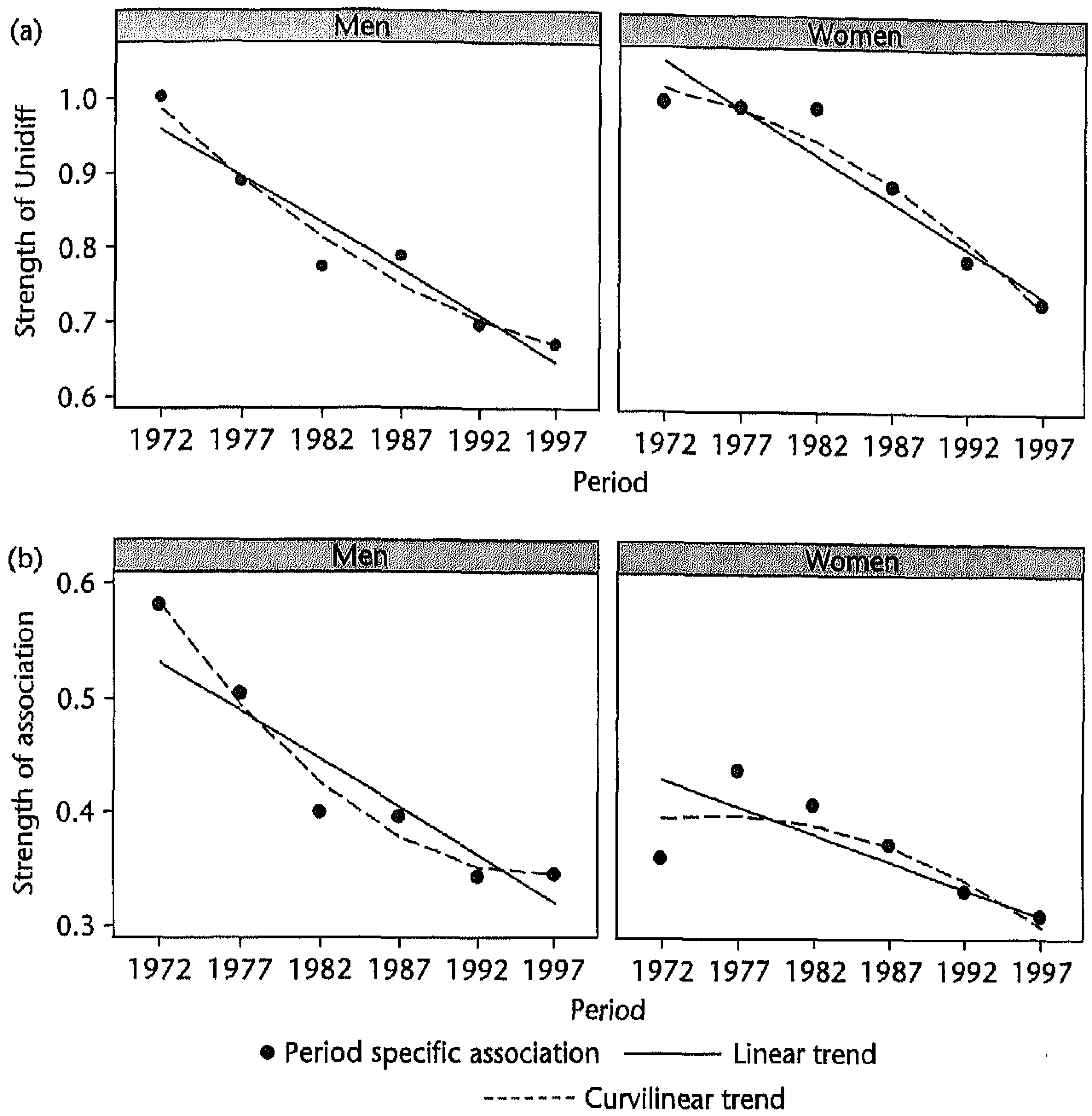

FIG. 14.3. *(a) Trends in Unidiff for bivariate origin–destination (men and women separately). (b) Trends in scaled uniform association for bivariate origin–destination (men and women separately)*

the linear and curvilinear trends estimated in Models D and E. We see a clear downward trend in the data, both for men and for women. The linear trend line implies that the Unidiff between the tables (for both men and women) went down by about 30 percent in twenty-five years (from mid-first to mid-last period), an almost 1.2 percent decline per year. This would confirm earlier conclusions (for men) that the mobility regime of the Netherlands will reach perfect openness before the middle of the twenty-first century.

A somewhat different picture emerges when we look at the trends in the estimated scaled uniform association model (Fig. 14.3(b)). Taken as a linear trend—for men—there is an even more dramatic decline of intergenerational reproduction—about 1.6 percent per year—but there is also some evidence of curvilinearity, and the downward trend seems to have slowed since 1985, the last year of observation in most of our previously published analyses. The estimated polynomial is essentially flat around 1999. If this is the true model, we can expect no further decline in the future and the Netherlands will never see the dawn of perfect mobility!

The trends for women in Fig. 14.3(b) are similar, but less steep—about 1.1 percent per year—and with somewhat more variation around the curve. For women, there is a non-significant and very slight curvilinear trend in the observations for the scaled association models, but it suggests an acceleration of the trend.

Analyses Part II: ascription and achievement in occupational attainment

Having established a definitive trend towards less social reproduction in the Netherlands between 1970 and 1999, we can now begin to disentangle the intergenerational occupational association. In line with the traditional status attainment model, pioneered by Blau and Duncan (1967), it is useful to think of the occupational mobility relationship as being composed of two pathways (cf. Fig. 14.4):

1. Fathers transfer their occupational status to their children via education. Social background influences educational attainment, and educational attainment to a large extent determines occupational outcomes.
2. Fathers also transfer their occupational status position directly to their children, partly by the immediate transfer of proprietorship and other employment statuses, and partly by providing their sons with occupational aspirations, access to employment via networks, etc.

The simple decomposition of occupational mobility into a direct and an indirect pathway leads to an important consequence for expectations about historical trends in intergenerational occupational mobility. Under the general expectation of increasing achievement and decreasing ascription—as derived from standard modernisation theory (Blau and Duncan 1967;

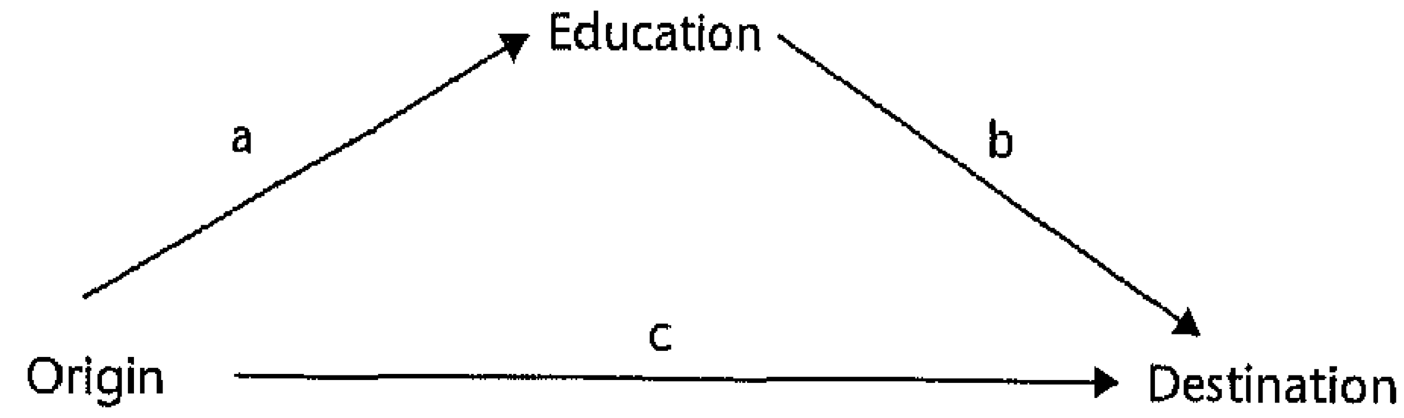

FIG. 14.4. *Basic status attainment model*

Treiman 1970)—*no definitive prediction can be derived on the total relationship* (Boudon 1974*b*). For reasons of declining ascription, we would expect relations (a) and (c) to be going down in strength, but by the spread of achievement values and meritocratic selection in the labour market, relationship (b) will become stronger. The result for the total effect (a × b + c) is undetermined if we cannot further quantify our expectations. In other words: a decline in the direct effect of father's status on educational outcomes and occupational results may be counterbalanced by an increasing association between education and occupational outcomes. For this reason alone, studying the trends in the separate components of the intergenerational occupational reproduction pattern is theoretically more conclusive than studying the total relationship—as we did in the first part of this chapter. In our context, where we obviously find that the trend towards more social mobility is stronger than the trend towards less social mobility, the same issue arises, but now on the partial relationships. When controlling for the education– occupation relationship, the two remaining indicators should be purer measures of intergenerational social mobility, and show stronger trends than the total relationship in the bivariate data.

The analysis of direct and indirect effects in intergenerational occupational reproduction has traditionally been conducted with a status attainment model that expresses standardised effects in an ordinary least squares multiple linear regression framework (Blau and Duncan 1967). Such indirect effect models lead to an easily comprehensible quantification of the intergenerational occupational transfer process, and allow for the study of trends in the parameters. The classical status attainment model can only be calculated at the cost of some simplifying assumptions. A major assumption is that patterns of socio-economic reproduction can be adequately measured or summarised by continuous variables, and that correlation and regression coefficients are sufficient representations of these associations. The intergenerational occupational mobility literature of the past twenty-five years has conclusively established that this is *not* the case: occupations and (to a lesser extent) educational levels cannot be measured sufficiently by a single continuous status measure only, and their associations cannot be adequately summarised in a single correlation or covariance. On the contrary, research in this field has amply illustrated the discrete and multidimensional nature of these status positions. In the tradition of log-linear models, pioneered by Hauser (1978) and Goldthorpe (1980), it has in particular been shown: (1) that associations between father's and son's occupation, and between education and occupation, need to be modelled in a multi-parameter representation; and (2) that these parameters may show diverging trends when compared across countries or across time. Furthermore, this research literature has reached some consensus on adopting the EGP class categories as its international standard of measuring occupational status.

Education is added as a dimension in our analysis in four distinct categories that have a clear hierarchical order and are sufficient to represent the major differences in credentials that have been produced by the Dutch educational system over the past century:

(1) primary education until age twelve (LO);
(2) lower secondary education and lower vocational training, ages 13–15/16 (MAVO, LBO, VBO);
(3) higher secondary education, including the middle level of vocational training, ages 13–17/19 (HAVO, VWO, MBO); and
(4) tertiary education, ages 18–23 (HBO, WO).

We describe and use a set of partial association models that estimate trends and association patterns for the elementary status attainment model, consisting of the relationship between origin O (father's occupational class), E (respondent's education), and D (respondent's occupational class). In fact, we are analysing an $8*4*8*6$ four-dimensional table, and generalise the Unidiff and Scaled Association models to a partial association context. Using a 'modified path analysis' (Goodman 1973), we estimate parameters for three relationships, using a simultaneous model:

$$O \rightarrow E \quad \text{(a)}$$
$$E \rightarrow D \mid O \quad \text{(b)}$$
$$O \rightarrow D \mid E \quad \text{(c)}$$

The causal order dictates that that the $O \rightarrow E$ relationship is modelled without conditioning on the third variable, while the other two relationships are modelled within categories of the third variable.

The approach we take here is similar in its aims incorporating log-linear constraints in a conditional multinomial logistic regression (CMLR) model, as applied by Hendrickx and Ganzeboom (1998) and Dessens et al. (2003) (cf. Breen (1994) for another application to social mobility data). However, while the CMLR methodology allows us to estimate or apply scalings on the social classes, as well as to exempt diagonal densities, it does not look at the origin, education, and destinations (*OED*) distribution as a simultaneous distribution that is modelled using a system of partial associations. In this respect, our current approach is very congruent with Blau and Duncan's use of causal models, in which a system of simultaneously estimated linear equations is used to model a correlation (or covariance) matrix. Also, estimating partial association models in LEM (Vermunt 1997) is much easier to accomplish than the complicated models proposed in the CMLR literature. However, as far as the $ED \mid O$ and $OD \mid E$ relationships are concerned, the estimated parameters are identical.

Apart from answering the old questions on pattern and trend in intergenerational status transfer, partial association models allow us to answer new questions about social mobility that cannot be answered by classical status attainment models, or by bivariate log-linear models. The set of old questions includes those on trends in the partial associations, parallel to those we would ask in the traditional status attainment model. These questions are now answered using a more detailed and better fitting model of these associations. Another set of old questions concerns the pattern of social mobility, that are now answered for all relationships in the *OED* distribution, but this time in a partial framework. The new questions ask how different components of these partial associations react to changing historical circumstances. More specifically, we can observe how diagonal and off-diagonal parts of the association develop differentially, for men and women separately.

Partial uniform difference models

Panel A of Table 14.4 reports on uniform difference partial association models for the three-variable data, cross-classified by period. These models leave the set of elementary partial odds ratios unconstrained, but estimate the historical trends by constraining the differences between the six periods. Model A0 is the common social fluidity model: each of the three partial associations (*OE*, *ED* | *O*, and *OD* | *E*) is constant for all six periods. This model does not fit for men in terms of L^2, but does fit for women. However, a quick scan of Table 14.4 leads to the conclusion that all models fit for women and none for men (according to the L^2 criterion). For that reason, we will rely mainly on the bic measure to reach conclusions.

In Model A1, each of the three partial associations (*OE*, *ED* | *O*, and *OD* | *E*) is 'Unidiffed' over period; in other words, the historical differences in association patterns are unconstrained. Model A1 serves as a baseline. However, note that in terms of bic, this benchmark fits worse than the common social fluidity Model A0. The subsequent Models A1a–A1c constrain one of the partial relationships to develop linearly over time. Each of these models fits the data better than the unconstrained model for men and for women, except for Model A1c for men. For men, Model A1d with all partial relationships developing linearly fits best. Subsequently, Models A1e–A1g test specifically whether any of these trends can actually be constrained to be historically constant. This is not the case, as is shown by the comparison of the fit statistics to that of Model A1.

Figure 14.5(a)–(c)displays the association coefficients estimated in Model A1, together with the best-fitting linear trend Model A1d and the curvilinear trend Model A1h. In these figures, the first observation (1970–4) serves as the point of reference, and, using the linear trend line, we can find the proportional change over the twenty-five-year time window. As we can see, trends towards more fluidity are found in all three partial relationships for both men and women. However, the trend is strongest in the direct *OD* relationship,

TABLE 14.4. *Fit statistics for partial association models for O (origin class), D (destination class), and E (education), men and women in the labour force (ilf)*[a]

Type of Model	Men				Women ilf		
	d.f.	L^2	p	bic	L^2	p	bic
Panel A: Unidiff models							
A0 Common social fluidity	1337	1746.5	.000	−11544.9	1239.2	.973	−10918.9
A1 Unidiffed common social fluidity	1322	1610.8	.000	−11531.5	1200.6	.992	−10821.1
A1a Linear *OE*; unidiffed *ED* | *O* and *OD* | *E*	1326	1622.7	.000	−11559.4	1203.3	.993	−10854.8
A1b Linear *OD* | *E*; unidiffed *OE* and *ED* | *O*	1326	1614.9	.000	−11567.2	1202.5	.993	−10855.5
A1c Linear *ED* | *O*; unidiffed *OE* and *OD* | *E*	1326	1651.8	.000	−11530.3	1215.1	.986	−10843.0
A1d Linear *OE*, *ED* | *O* and *OD* | *E*	1334	1669.0	.000	−11592.6	1219.4	.989	−10911.4
A1e Constant *OE*; unidiffed *OD*|*O* and *ED* | *O*	1327	1645.2	.000	−11546.8	1207.5	.991	−10859.6
A1f Constant *OD* | *E*; unidiffed *OE* and *ED* | *O*	1327	1648.7	.000	−11543.3	1209.0	.991	−10858.1
A1g Constant *ED* | *O*; unidiffed *OE* and *OD* | *E*	1327	1669.1	.000	−11523.0	1222.8	.981	−10844.3
A1h Curvilinear *OE*, *ED* | *O* and *OD* | *E*	1331	1642.9	.000	−11588.9	1207.9	.993	−10895.6
Panel B: scaled association models—scalings							
B1 All unequal scores—free diagonals	1334	1936.5	.000	−11325.1	1307.5	>.500	−10823.3
B1a Equal *E*-scores	1336	1981.5	.000	−11300.0	1337.2	.486	−10811.8
B1b Equal O-scores	1340	2043.1	.000	−11278.1	1343.5	.468	−10841.9
B1c Equal *D*-scores	1340	2039.5	.000	−11281.7	1341.2	.485	−10844.1
B1d Equal O–D scores	1346	2145.1	.000	−11235.8	1399.2	.153	−10840.7
B1e Equal O–*D* scores; equal *E* scores	1348	2192.6	.000	−11208.2	1410.7	.115	−10847.4
Panel C: scaled association models—trends with equal scalings							
C0 Linear associations—free diagonals	1360	2243.8	.000	−11276.3	1428.7	.095	−10938.6
C1 Curvilinear associations—free diagonals	1357	2220.4	.000	−11269.9	1416.6	.127	−10923.3
C2 Curvilinear associations—unidiffed diagonals	1392	2272.2	.000	−11566.0	1439.3	.184	−11218.9
C3 Curvilinear associations—curvilinear diagonals	1395	2275.1	.000	−11593.0	1439.8	.197	−11245.7
C4 Curvilinear associations—linear diagonals	1396	2275.5	.000	−11602.5	1439.8	.203	−11254.8
C5 Curvilinear associations—fixed diagonals	1397	2280.9	.000	−11607.1	1443.2	.190	−11260.5
C6 Linear associations—fixed diagonals	1400	2306.9	.000	−11610.8	1455.3	.148	**−11275.7**
C7 Free associations—fixed diagonals	1396	2251.2	.000	**−11626.8**	1437.2	.216	−11257.4

[a] Best fitting model according to bic is in boldface.

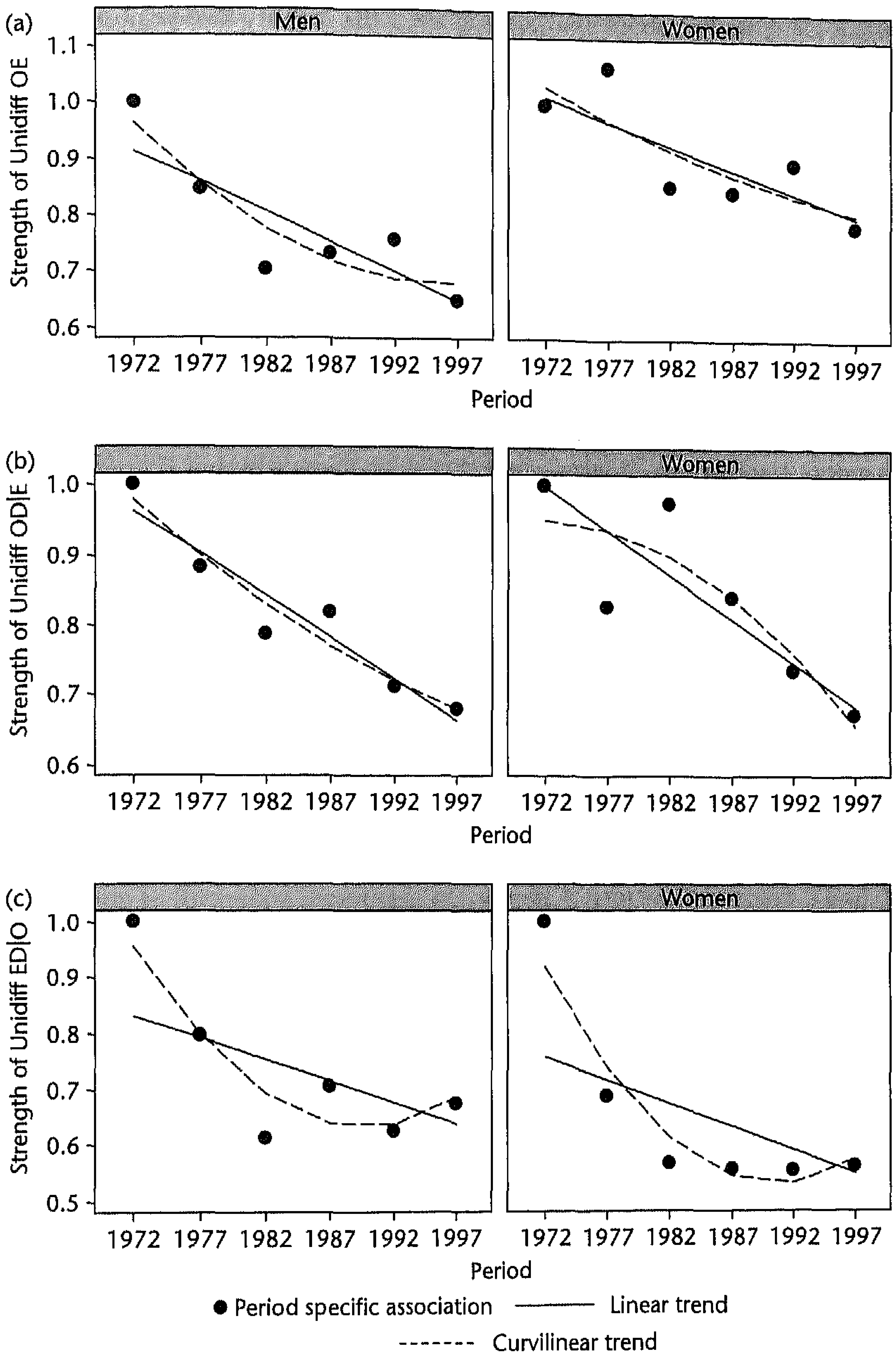

FIG. 14.5. *(a) Trends in Unidiff OE (men and women separately). (b) Trends in Unidiff OD | E (men and women separately). (c) Trends in Unidiff ED | O (men and women separately)*

which declines by about 30 percent over the twenty-five-year period for both men and women, while the other two relationships go down by about 20–25 percent. The downward trend is also strong in the *OE* relationship, which is in line (in fact a recalculation) of results from earlier research with some of the same data (De Graaf and Ganzeboom 1990). Finally, the trend in the partial *ED* relationship appears to be statistically different from zero, and negative. If interpreted to be of substantial importance, it implies that educational credentials have become *less* important over time, which is in contradiction to the ascription/achievement trend hypothesis.

Scaled partial association models

Uniform difference models are adequate to explore and to test general trends in partial associations. However, while they do show whether there are trends or not, and specify the direction of such trends, uniform difference models leave the patterns of partial associations themselves undisclosed. We now know that the strength of association in $OD \mid E$ declines, but we do not know what this association looks like. In order to find a more informative model of the underlying structure, we adapt Goodman's (1979*b*) scaled association model RCII to partial associations. Each of the partial associations can now be characterised by a similar set of parameters as in part I of the analysis in this chapter:

$\left.\begin{matrix} \mu'_i, \nu'_j, \xi'_k \\ \mu''_i, \nu''_j, \xi''_k \end{matrix}\right\}$ the scalings of the origin, destination, and education categories

$\delta_{ii.l}$ the diagonal effects

$\varphi'_l, \varphi''_l, \varphi'''_l$ the scaled partial association parameters.

By implication, each variable will have two sets of scalings, depending upon the partial relationship in which it occurs. We can conceive of the two scalings of father's occupation (μ'_i, μ''_i) as the optimal scalings to predict educational attainment and to predict the direct transfer of occupational status. The two scalings of education (ξ'_k, ξ''_k) reflect the optimal scaling of education as, respectively, a destination (reward), and as an origin (resource). Finally, the two scalings of class destination (ν'_j, ν''_j) represent the optimal orderings of respondents' occupations as derived from, respectively, educational resources and father's status.

In order to reach a simple representation of the partial scaled association model, it is necessary to constrain the parameters. There are many ways to do this, and each represents substantive hypotheses about the properties of status distributions and transfer of status positions in the Netherlands in this period, and probably status attainment structures more generally. The most obvious constraints are:

1. The two scalings of E are equal to one another ($\xi_k' = \xi_k''$), representing the hypothesis that what people strive for in educational attainment is identical to what education brings them as a resource in the occupational attainment process.
2. The two scalings of O are equal to one another ($\mu_i' = \mu_i''$); that is, fathers are identically ordered with respect to their capabilities to promote the educational and the occupational opportunities of their children.
3. The two scalings of D are equal to one another ($\nu_j' = \nu_j''$), representing the assumption that occupational destinations are identically ordered when either education or father's occupational status is the resource of relevance.
4. The scalings of O and D are equal ($\mu_i' = \mu_i'' = \nu_i' = \nu_i''$).

To us, assumption (1) appears to be the most likely one among these four to hold. Clearly, education can at some level be conceptualised as a single hierarchy that at the same time is a reward and a resource. Assumptions (2) and (3) are much less plausible. On the one hand, it may very well be that fathers with different statuses have different strategies to promote their children's careers (via education and in the labour market), and that access to occupations depends upon whether one's resources derive from one's father directly, or from educational attainment. On the other hand, assumptions (2) and (3) would be in line with one of the major conclusions of stratification research (Inkeles and Rossi 1956; Treiman 1977; Hout 2003), that occupational status is fairly stable across time and space. This is of course also the justification to formulate hypothesis (4), which, if true, implies that (2) and (3) are also true.

For each of the three partial associations, we can potentially define a set of diagonal coefficients (δ). However, for the *OE* and *ED* relationships, these coefficients would have a complicated interpretation, specifying a special affinity between educational and occupational class categories. As the data are not constructed that way, it is rather hard to interpret what this would mean. By contrast, diagonal coefficients are easily conceptualised in the partial $OD \mid E$ relationship, even more so than in the bivariate *OD* relationship. Moreover, a plausible assumption is that the *OD* partial association is primarily composed of direct transfer of occupation, as measured by the diagonal densities, and that the off-diagonal association is weak or non-existent. This is the implication of Yamaguchi's (1983) early argument about the role of specific and generalised resources in occupational mobility. As a consequence, we restrict the use of diagonal parameters to the $OD \mid E$ relationship.

Panel B of Table 14.4 lists the models to test these assumptions about the structure of the parameters, while for the time being leaving the historical trends unconstrained. Model B1 is again the benchmark model, similar in conception to Model A1, but this time using scaled association models to account for the partial associations. As we have observed for the bivariate case in the previous section, scaled association models fit the data less well than the uniform difference models—this seems to be the cost we pay for modelling the association in a more informative way.

Model B1a constrains the educational scalings to be equal. Model B1b constrains the two scalings of father's occupation to be equal, Model B1c the two scalings of respondent's occupation, Model B1d constrains all occupational scalings for fathers and sons to be identical, and, finally, Model B1e constrains both the educational scalings and the occupational scalings to be equal. The hypotheses of constant scalings are more or less confirmed by the data for women, but need to be rejected for men. In other words, the classical hypothesis of historical constancy in occupational hierarchies is not confirmed. It holds best for educational categories.

Figure 14.6(a)–(c) plots, one against the other, the various pairs of scalings of the origin, education, and destination categories found in the baseline Model B1. We can note that even if the differences for men are statistically significant by any sensible test, the correlation between the scalings is still quite close. This is particularly so for the education scalings, that—despite their statistical deviation from it—appear to be essentially identical. This is less the case for the occupation scalings, which is somewhat erratic for women, but rather regular for men. For men, we can see that the major asymmetry in the scalings occurs for the farmer categories (IVc and VIIb). The substantive interpretation of these asymmetries is that the class origins of those who take up farming (other than by continuing father's farm status) is much higher than the destination classes for those sons who have left farming occupations. This asymmetry is a general feature of social mobility patterns and has been reported elsewhere for bivariate analyses as well (Ganzeboom et al. 1989: 50, n. 15) elsewhere, although we did not detect it in part I of the analysis here.

While the farm asymmetry is an interpretable feature of the data, there are other asymmetries in the scalings—in particular for women and their fathers—that cannot be interpreted in the scope of the current contribution. Most of these are marginal and do not imply a different ordering of the classes on the mobility dimension. We have therefore chosen to disregard the evidence of asymmetry for the time being and continue with symmetrically specified models, that is, we constrain all occupational (origin and destination) scalings, as well as the education scalings, to be equal between tables.

Panel C of Table 14.4 presents scaled association models with trends, in a similar fashion as trends are presented for the Unidiff models in Panel A. While we observe much higher fit statistics than for the unconstrained

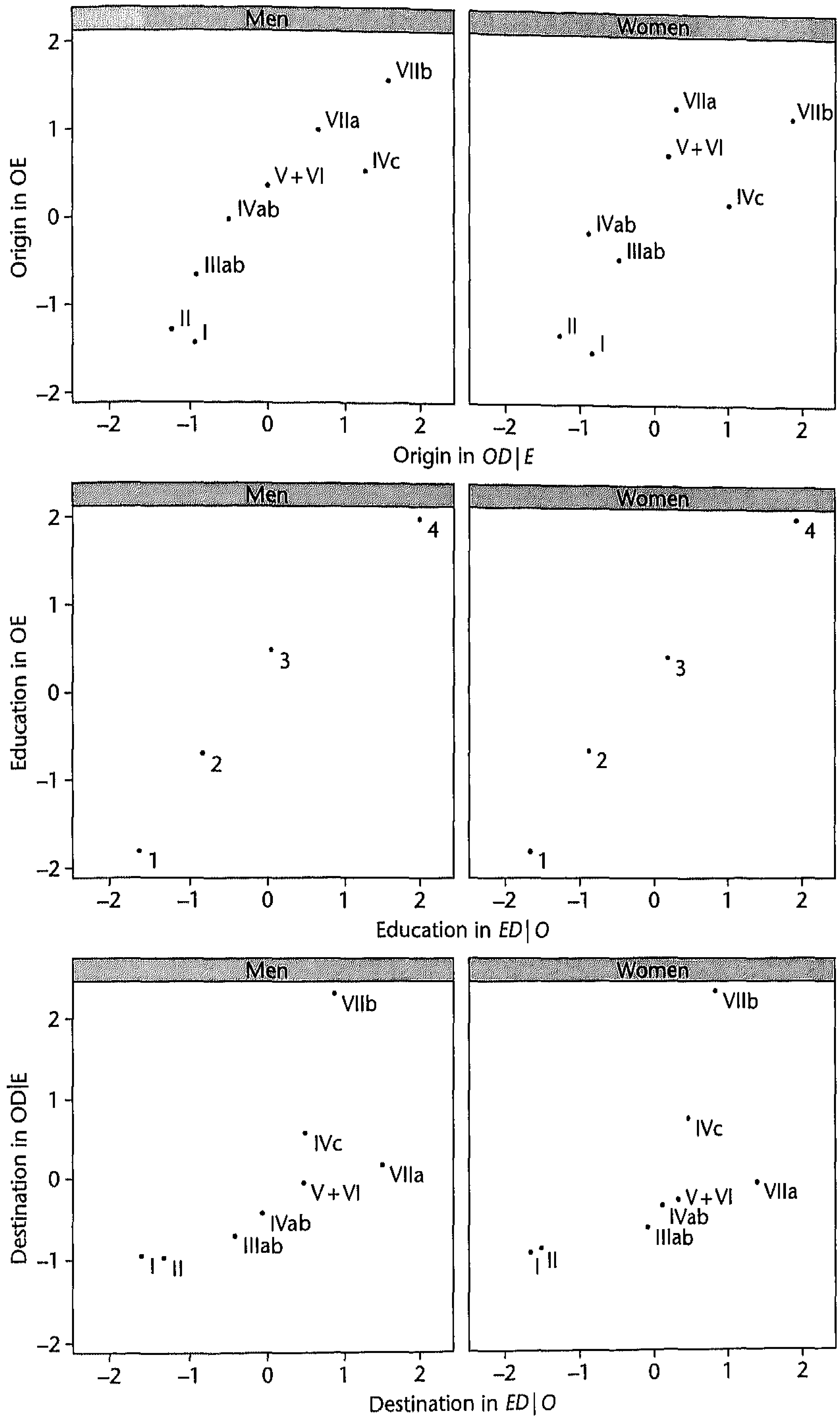

FIG. 14.6. *(a) Origin scalings in OE and OD | E relation (men and women separately). (b) Education scalings in OE and ED | O relation (men and women separately). (c) Destination scalings in OD | E and ED | O relation (men and women separately).*

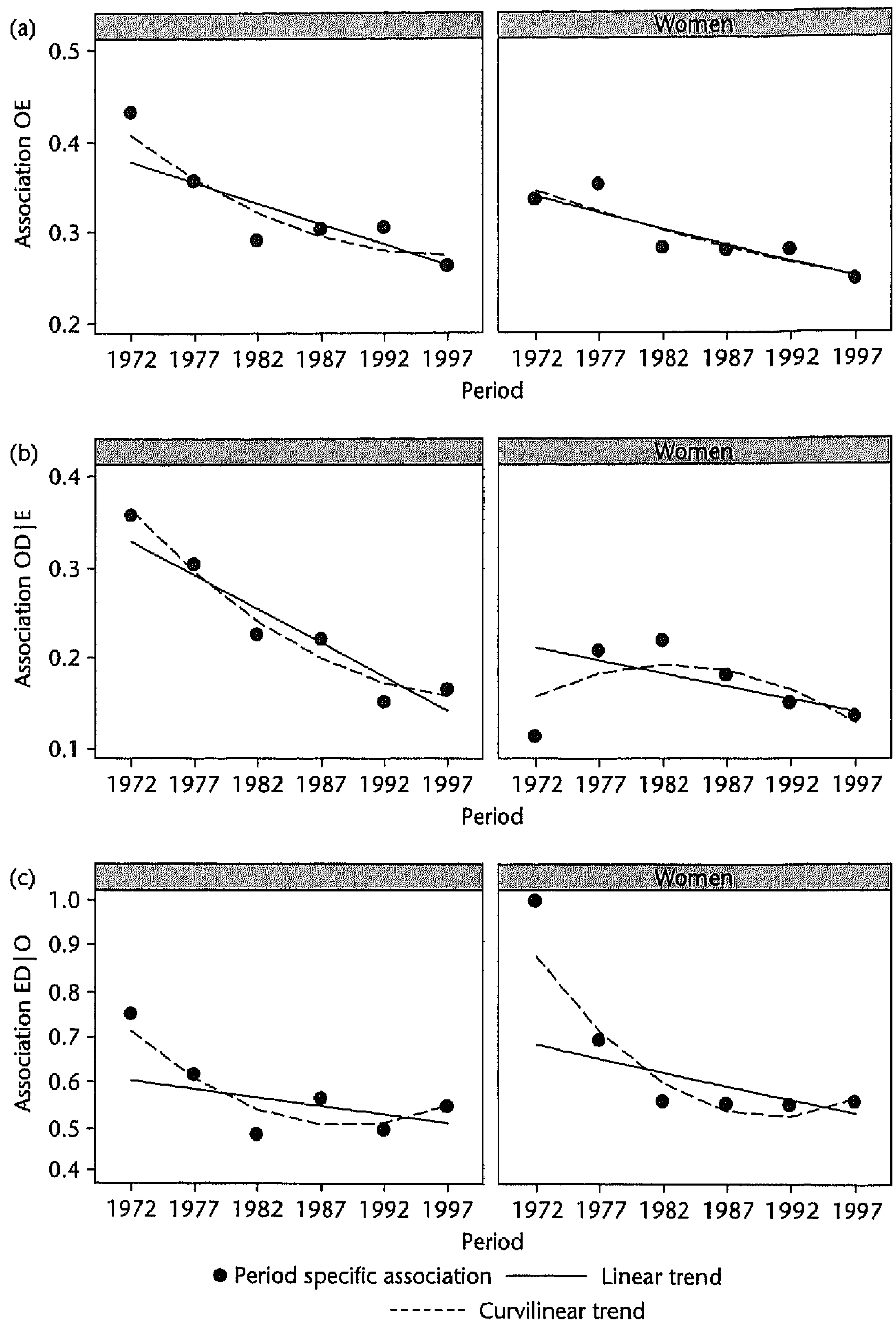

FIG. 14.7. *(a) Trends in OE uniform association (men and women separately). (b) Trends in OD | E uniform association (men and women separately). (c) Trends in ED | O uniform association (men and women separately).*

models, we find essentially the same pattern of results as in Panel A. The *ED* | *O* partial association can be regarded as being approximately stable over the six periods (except for 1970–4), while both *OD* | *E* and *OE* change significantly in a downward direction over time. However, in the *OD* relationships, there are now two parameters to capture the change, being the general diagonal association (inheritance of social class position) and the residual off-diagonal association. The important finding for this association is that all the historical change is concentrated in the off-diagonal part: for the diagonal densities the hypothesis of no change can be upheld.

Figure 14.7(a)–(c) displays the pattern of partial association coefficients found in Models C7, C6, and C5; these are the coefficients found in the separate tables and the linear and curvilinear trends implied by the model. The trends—for men—are more differentiated than they were for the uniform difference models. Most strikingly, we see that the major decline of intergeneration occupational class reproduction occurs in the direct effect (*OD* | *E*), but outside the diagonal (−2.3 percent on an annual basis for men and −1.3 percent for women). By contrast, the diagonal densities in this relationship can be constrained to be historically constant. Also, the densities for the diagonal parameters resemble very much the bivariate ones (see Fig. 14.8(a) and (b)). Remember, the direct effect concerns intergenerational status transfer outside the educational channel: it is how fathers and offspring relate, once the indirect effect via education has been taken into account. As it turns out, this effect is a mixture of two components that behave differently in the historical context. The first component consists of the cases in which the children are found in the same occupational class as their father; there are no historical changes in this component. The second component is how fathers help their children to obtain a job once the child has left the father's occupational class; it turns out that these transfers have almost vanished over the period of observation.

A second important finding from the scaled association model is that now the *ED* | *O* effect is somewhat closer to historical constancy than in the uniform difference models. While the downward trend of −0.6 percent for men and −0.9 percent for women on an annual basis is still statistically significant, it is the component of the model that develops least strongly over time. In general, for women, the trends revealed by the scaled association models are very similar to those for men, but less pronounced.

Conclusions and discussion

How has the pattern of intergenerational occupational class mobility and class reproduction in the Netherlands changed over the last thirty years? Using data from thirty-five surveys that cover the 1970–99 period, and taking

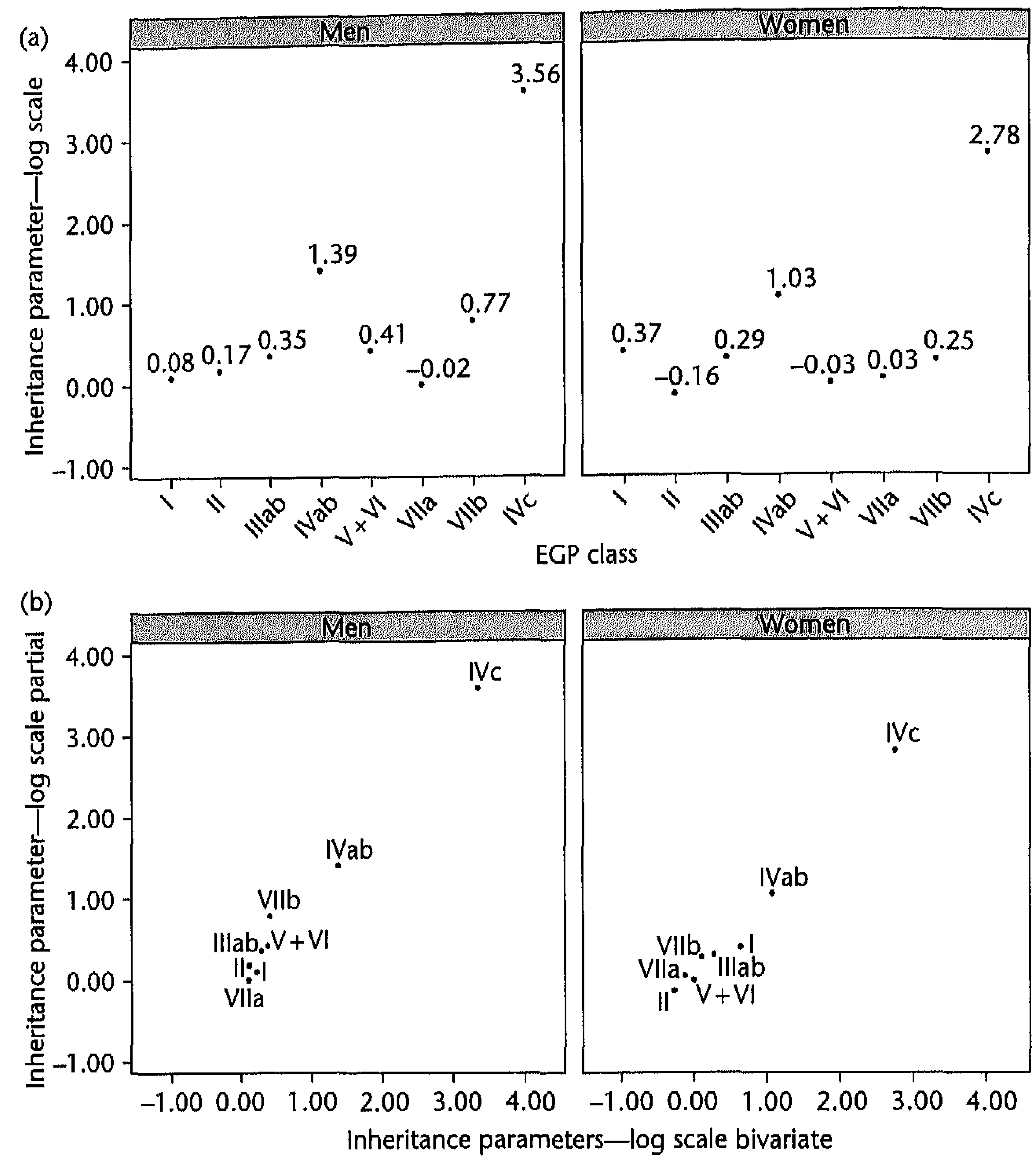

FIG. 14.8. *(a) Estimated diagonal parameters (partial) (men and women separately). (b) Estimated diagonal parameters (partial versus bivariate) (men and women separately).*

evidence from both unconstrained and constrained (scaled) association models, we are able to establish the following conclusions about bivariate intergenerational mobility patterns:

1. There is a clear downward trend in total social reproduction. The trend is stronger for men than for women. The annual decrease in scaled uniform association for men is estimated at −1.6 percent, for women only at −1.1 percent. However, women started at a lower level than men and by

the end of our time window (1999) social fluidity among men and women was about the same.

2. Somewhat against our expectations—derived from our previous assessment of trends using data up to 1992—we find no significant evidence that the historical trends towards more social fluidity are actually declining in pace. Although it remains to be seen in the long run whether our current extrapolations pan out, the evidence up to 1999 is still consistent with a stationary trend, which leads us to forecast that perfect social fluidity will be reached in the foreseeable future. Of course, we are well aware that such extrapolations are unjustified, and have no firm theoretical foundation.
3. Our conclusions on historical trends hold for both analytical models we use, the unconstrained uniform difference model and the constrained Goodman–Hauser scaled association model. The unconstrained model adds no other detail to our conclusion, but the scaled association model does. The scaling parameters of this model show a familiar gradient between the eight occupational classes: they closely resemble their socio-economic status. Densities on the diagonal of the intergenerational occupational mobility table are differentiated by class, with a familiar pattern: very high reproduction of farm occupation and high reproduction among the self-employed, while reproduction is particularly low among low status classes. Furthermore, with respect to trends, the results for the Goodman–Hauser scaled association model show that the between-table differences can be summarised adequately in one single coefficient and no distinct trends exist for the diagonal of the tables; this is similar to how we model trends in unconstrained association models.

The most important conclusion here is, of course, on the trend in social reproduction itself: it is clearly downward, with little sign of slowing down.

In the second part of the analysis, we applied partial association models to the relationships between the three variables of the elementary status attainment model. The conclusions can be summarised as follows:

1. When conceived as partial associations, the pattern of social mobility/social reproduction shows significant asymmetries between occupations as resources and occupations as rewards. At the same time we find different scalings for fathers, daughters, and sons. We have chosen to disregard these asymmetries in the analysis here, but they appear to be interesting for future analysis.
2. Otherwise, the partial scaled association analysis for the pattern of association does not reveal substantive differences from the bivariate analysis. The scalings of the occupational classes and the diagonal densities are virtually identical to the bivariate case.

3. The general trend towards more social fluidity is also replicated in the partial analysis. The trends towards more openness do not only apply to the ascriptive parts of the status attainment patterns (fathers promoting their children's educational and occupational outcomes directly), but also to the achievement part (the partial association between education and occupation), which is in contradiction with common theories on the model.
4. In the scaled association model, we find evidence of somewhat diverging trends between the different components of intergenerational status transfer, as well as between men and women. For men, the direct intergenerational transfer of occupational class, as measured by the diagonal densities, is stronger than for women and historically stable; by contrast, there is a steep decline in the association between fathers and sons as far as the off-diagonal partial association is concerned. Father's class has become much less important for son's destination, once the latter has left the father's class. This pattern of historical changes also applies to women, but it is less pronounced.

The most important conclusion here is that the trend towards more social fluidity occurs in all partial relationships, including the one in which it was not expected: the *ED* | *O* relationship. This result was also found for France, Great Britain, and Sweden (see chapter 15).

To explain the finding of decreasing social reproduction, it appears to us of foremost importance to point out that it is consistent both with previous findings on the Netherlands and with received theories of social mobility. The downward trends we observe are predominantly what various forms of modernisation theory predict, and is also in line with what earlier research has concluded about the Netherlands. The explanatory question might thus be better formulated as why, if so, there are no such trends in other countries? There are different ways to answer this question, but an obvious one is to point to the importance of the multitude of data points we use, the long-term perspective we take, and the strict harmonisation of the data we applied, as a possible explanation for 'Dutch exceptionalism'. Note too that in an earlier contribution (Ganzeboom et al. 1989) we also found a massive rejection of CnSF, not only by showing systematic between-country differences, but also systematic trends towards more social fluidity. We anticipate that our 1989 conclusions will prove to hold true for the 1970s to 1990s comparison in this book, as long as a sufficient amount of comparative data points and comparatively sensitive statistical tests are used.

Secondly, we need to address the unexpected finding that the *ED* | *O* association is also declining over the period of observation: why did education become less important for recruitment on the labour market (as did father's occupation)? Why would this be so? An obvious explanation would be that the claim of increasing meritocratic selection is too broad to explain developments within industrial and post-industrial countries like the Netherlands between 1970 and 1999. It has been argued that the way in which educational differentials operate as a device of selection depends to a large extent on the dispersion of the educational distribution (Rijken 1998). If the higher and lower educated are widely dispersed in terms of qualifications and competences, it is easier for employers to select on education, than if the higher and lower educated overlap in competences. It has been an important feature of the Dutch educational system—also compared to developments elsewhere—that educational dispersion indeed has decreased (Ganzeboom and Treiman 1993; Rijken 1998), due to an effective increase in the minimum school-leaving age and rather strict control over the length of higher education (four years). As a consequence of the policies educational credentials must have lost some of their discriminatory power. Some theorists (Bourdieu 1984 [1979]) have speculated that in such circumstances family background regains importance as a selection device. Our findings show that this has not been the case.

Finally, there remains the question of whether our extrapolations towards reaching perfect mobility will hold true. Will the intergenerational association reach a natural minimum, or will developments in Dutch society countervail the existing trend? The question of a 'natural minimum' falls outside the scope of this chapter. However, some evidence relevant to that issue can be found in cross-national comparative research. While we believe that the Netherlands have moved from a comparatively closed society in the 1950s towards a relatively open one around 2000, we do not anticipate that the Dutch have reached the pinnacle of social fluidity yet. We believe that proper comparisons with some of the traditional immigration societies (Israel, Australia, New Zealand), as well as with some of the Nordic welfare states, would show the Netherlands to be at best a runner up in the league of nations. Thus we expect that there is still room to move. It seems more plausible to us that conditions of changing social inequality may slow the pace of meritocratisation. There is evidence that the Dutch have shared in the global upward trend towards more income inequality, with rising poverty rates and an increase in unemployment and self-employment. There is also evidence that the Dutch higher education system has become less accessible to children of low and middle income groups, with stronger exclusionary effects of economic resources (Janssen and Ultee 1994). In sum, we feel that periodical future research is called for, to establish conclusively whether the trend towards more social fluidity remains. However, up to the most recent point of observation covered by our current time window (1999), we have found no convincing evidence of a reversal of trend.

Appendix

TABLE 14.A1. *Data sources for men and women in the labour force in the Netherlands 1970–99*

Nr AKRO	Abbreviated study title	Occupation code	No. of digits	No. of men	No. of women	Response rates
1 net70*	National Election Study 1970–73	cbs60	4	747.0	148.0	74
2 net71*	Parliamentary Election Study 1971	cbs7184	4	687.7	116.6	76
3 net74p*	Political Action Survey I 1974	isco68	3	348.0	109.0	67
4 net76j*	Justice of Income Survey 1976	cbs7184	4	512.3	85.6	69
5 net77*	CBS Life Situation Survey 1977	cbs7184	4	1,290.0	310.0	70
6 net77e*	Parliamentary Election Study 1977	cbs7184	4	509.0	95.0	64
7 net79p*	Political Action Survey II 1979	cbs7184	4	579.0	191.0	65
8 net81e	Parliamentary Election Study 1981	cbs7184	4	631.0	238.0	83
9 net82e	Parliamentary Election Study 1982	cbs7184	4	484.0	163.0	74
10 net82n*	National Labour Market Survey 1982	F: cbs71	2	847.0	325.0	n.a.
11 net82u*	National Prestige and Mobility Survey 1982	cbs7184	4	405.0	68.0	60
12 net85o*	Strategic Labour Market Survey 1985	cbs7184	4	967.1	363.8	41
13 net86e	Parliamentary Election Study 1986	cbs7184	4	492.0	202.0	83
14 net86l	CBS Life Situation Survey 1986	cbs84a	2	971.0	323.5	57
15 net87i	Cultural Changes [ISSP] 1987	cbs7184	4	519.0	175.0	82
16 net87j	Justice of Income Survey 1987	cbs7184	4	296.0	125.0	60
17 net87s	Primary and Social Relationships 1987	cbs7184	4	320.0	152.0	78
18 net88o	Strategic Labour Market Survey 1988	cbs7184	4	379.6	191.0	n.a.
19 net90o	Strategic Labour Market Survey 1990	cbs7184	4	430.3	214.1	n.a.

20 net90s	Social and Cultural Trends 1990	cbs7184	4	896.0	400.0	48
21 net91j	Justice of Income Survey 1991 [ISJP]	isco68	3	395.0	134.0	n.a.
22 net92f	Family Survey I 1992–93	cbs7184	4	754.4	346.8	43
23 net92o	Strategic Labour Market Survey 1992	cbs7184	4	441.7	251.4	n.a.
24 net94e	Parliamentary Election Survey 1994	cbs7184	2	520.9	172.9	52
25 net94h	Households in the Netherlands pilot 1994	cbs7184	4	425.1	260.3	58
26 net94o	Strategic Labour Market Survey 1994	cbs7184	4	380.9	236.0	n.a.
27 net95h	Households in the Netherlands 1995	cbs7184	4	850.0	503.0	40
28 net96	Social Inequality in the Netherlands 1996	cbs7184	4	285.0	204.7	36
29 net96c	National Crime Study 1996	c	1	409.0	263.0	37
30 net96o	Strategic Labour Market Survey 1996	cbs7184	4	586.3	389.2	n.a.
31 net98	Social and Economic Attitudes 1998	cbs7184	4	313.6	187.8	31
32 net98e	Parliamentary Election Study 1998	sbc92	5	491.4	341.2	50
33 net98f	Netherlands Family Survey II 1998	cbs7184	4	871.0	517.0	48
34 net98o	Strategic Labour Market Survey 1998	cbs7184	4	936.9	667.7	n.a.
35 net99	Use of Information Technology 1999	c	1	797.4	427.0	43
	Total			20,769.7	8,897.7	

Notes: cbs60, Dutch Census Classification 1960; cbs7184, Dutch four-digit Census Classification 1971/1984 (default); cbs84a, Aggregated version of cbs7184; sbc92, CBS Standard Occupational Classification 1992; isco68, Internal Standard Classification of Occupations 1968; F, Fathers only; c, Single digit class categories compatible with EGP-classification.

See also: www.scw.vu.nl/~ganzeboom/ismf

* 'Original ten'.

TABLE 14.A2. *Number of cases, outflow, and inflow percentages for men 1970–99*

Origin		Destination								
		I	II	III	IVab	V + VI	VIIa	VIIb	IVc	Total
I	*N*	853.1	768.4	230.8	114.7	255.6	151.0	13.0	6.9	2,393.4
	Outflow	35.6	32.1	9.6	4.8	10.7	6.3	0.5	0.3	100.0
	Inflow	20.6	15.5	10.9	10.4	5.5	5.4	4.0	1.0	11.5
II	*N*	714.6	935.6	239.3	66.7	333.9	130.3	8.2	11.7	2,440.2
	Outflow	29.3	38.3	9.8	2.7	13.7	5.3	0.3	0.5	100.0
	Inflow	17.2	18.9	11.3	6.0	7.2	4.6	2.5	1.7	11.8
III	*N*	388.8	536.2	246.9	59.4	267.7	129.6	7.8	9.1	1,645.6
	Outflow	23.6	32.6	15.0	3.6	16.3	7.9	0.5	0.6	100.0
	Inflow	9.4	10.8	11.6	5.4	5.8	4.6	2.4	1.3	7.9
IVab	*N*	554.7	633.0	315.8	426.2	443.1	296.3	23.2	24.2	2,716.5
	Outflow	20.4	23.3	11.6	15.7	16.3	10.9	0.9	0.9	100.0
	Inflow	13.4	12.8	14.9	38.6	9.6	10.6	7.2	3.5	13.1
V + VI	*N*	777.2	1048.6	515.8	165.2	1546.1	704.1	38.8	19.3	4,815.1
	Outflow	16.1	21.8	10.7	3.4	32.1	14.6	0.8	0.4	100.0
	Inflow	18.8	21.1	24.3	15.0	33.5	25.1	11.9	2.8	23.2
VIIa	*N*	470.1	560.7	366.5	131.2	1114.6	845.4	59.7	24.2	3,572.4
	Outflow	13.2	15.7	10.3	3.7	31.2	23.7	1.7	0.7	100.0
	Inflow	11.3	11.3	17.3	11.9	24.2	30.1	18.4	3.5	17.2
VIIb	*N*	78.1	104.7	56.3	27.7	253.4	202.5	53.0	27.7	803.4
	Outflow	9.7	13.0	7.0	3.5	31.5	25.2	6.6	3.5	100.0
	Inflow	1.9	2.1	2.7	2.5	5.5	7.2	16.3	4.0	3.9
IVc	*N*	309.1	372.0	153.2	113.1	396.4	349.9	121.2	568.1	2,383.0
	Outflow	13.0	15.6	6.4	4.8	16.6	14.7	5.1	23.8	100.0
	Inflow	7.5	7.5	7.2	10.2	8.6	12.5	37.3	82.2	11.5
Total	*N*	4,145.7	4,959.1	2,124.6	1,104.3	4,610.9	2,809.1	324.9	691.1	20,769.7
		20.0	3.9	10.2	5.3	22.2	13.5	1.6	3.3	100.0
		100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

TABLE 14.A3. *Number of cases, outflow, and inflow percentages for women in the labour force 1970–99*

Origin		Destination								
		I	II	III	IVab	V + VI	VIIa	VIIb	IVc	Total
I	*N*	232.6	571.4	419.0	41.2	36.1	46.9	2.2	1.3	1,350.7
	Outflow	17.2	42.3	31.0	3.1	2.7	3.5	0.2	0.1	100.0
	Inflow	28.1	19.7	12.0	10.4	11.2	5.7	3.4	1.8	15.2
II	*N*	173.8	586.7	492.6	33.4	33.0	42.0	3.3	2.5	1,367.4
	Outflow	12.7	42.9	36.0	2.4	2.4	3.1	0.2	0.2	100.0
	Inflow	21.0	20.3	14.1	8.4	10.3	5.1	5.3	3.4	15.4
III	*N*	66.0	270.9	362.2	26.9	20.3	50.4	2.0	0.7	799.5
	Outflow	8.3	33.9	45.3	3.4	2.5	6.3	0.3	0.1	100.0
	Inflow	8.0	9.4	10.4	6.8	6.3	6.1	3.3	1.0	9.0
IVab	*N*	94.7	386.4	406.7	110.8	24.4	71.4	2.0	4.1	1,100.4
	Outflow	8.6	35.1	37.0	10.1	2.2	6.5	0.2	0.4	100.0
	Inflow	11.4	13.4	11.6	27.9	7.6	8.7	3.2	5.6	12.4
V + VI	*N*	130.1	523.9	867.8	66.8	91.1	281.3	10.6	4.2	1,975.8
	Outflow	6.6	26.5	43.9	3.4	4.6	14.2	0.5	0.2	100.0
	Inflow	15.7	18.1	24.8	16.8	28.3	34.2	16.9	5.8	22.2
VIIa	*N*	70.3	274.2	599.5	65.4	75.6	223.1	8.1	8.8	1,325.1
	Outflow	5.3	20.7	45.2	4.9	5.7	16.8	0.6	0.7	100.0
	Inflow	8.5	9.5	17.1	16.5	23.5	27.1	13.0	12.1	14.9
VIIb	*N*	8.6	38.0	90.2	10.2	9.6	36.8	3.0	5.6	202.0
	Outflow	4.3	18.8	44.6	5.1	4.8	18.2	1.5	2.8	100.0
	Inflow	1.0	1.3	2.6	2.6	3.0	4.5	4.8	7.7	2.3
IVc	*N*	52.9	242.4	259.5	42.1	31.9	70.8	31.6	45.6	776.7
	Outflow	6.8	31.2	33.4	5.4	4.1	9.1	4.1	5.9	100.0
	Inflow	6.4	8.4	7.4	10.6	9.9	8.6	50.2	62.6	8.7
Total	*N*	828.9	2,894.0	3,497.4	396.9	322.1	822.8	62.9	72.8	8,897.7
		9.3	32.5	39.3	4.5	3.6	9.3	0.7	0.8	100.0
		100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0