ON THE COST OF BEING CRUDE: A COMPARISON OF DETAILED AND COARSE OCCUPATIONAL CODING

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ON THE COST OF BEING CRUDE: A COMPARISON OF DETAILED AND COARSE OCCUPATIONAL CODING IN THE ISSP 1987 DATA

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INTRODUCTION

Occupational categories constitute the backbone of sociological research in social stratification. However one conceptualizes occupational status (prestige, class, socio-economic status, cf. Ganzeboom & Treiman 2003), the way in which occupations are initially classified is always a core ingredient of the measurement procedure. Typically, in high quality surveys, information on occupations is recorded in a sequence of open-ended questions. These questions will ask for job title, main duties and activities, employment status and supervising status. Part of this information (usually job title and main activities/duties) is then converted to a detailed occupational classification in post-processing the information. The detailed occupational classifications used are mostly provided by national or international statistical agencies and often distinguish between 500 and 1500 different occupational categories. Coding these categories from the verbatim information is a time-intensive operation that consumes a substantial part of survey budgets.

The basic question of the research reported here is whether this coding operation is worth the trouble. How much do we gain from coding occupations in a detailed classification as opposed to more easy to operate crude procedures? The assumption, of course, that underlies the use of detailed occupational classifications, is that there are sociologically relevant properties of occupations (say educational requirements, earning potentials) that vary among occupations (mostly) at the detailed level. It this is so, using cruder classifications would introduce 'aggregation' bias by obscuring part of that variation and this would result in attenuated associations between occupational variables and their causes and consequences. In the analyses reported below we estimate the degree of attenuation using a standard model of status attainment, in which two occupations occur: father's occupation and respondent's current/last

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occupation.

Some prior experiences have led me to suspect that the degree of attenuation may not be large and may not warrant the costs involved in the implementation of detailed occupational classifications. In an analysis of intergenerational class mobility (Ganzeboom, Luijkx & Treiman, 1989), we used the degree of detail of the underlying occupational codes as a control variable and found that -- all else being equal -- the association between father's occupation and son's occupation tends to be highest in case of moderate crudeness of the occupational data. In another analysis, that reported on validation of the International Socio-Economic Index (ISEI) of occupational status (Ganzeboom, De Graaf & Treiman, 1992), we estimated formal attenuation coefficients for various categorizations of the data in a three variables status attainment model (father's occupation, son's education, son' occupation) and found only moderate attenuation (around .95) for measures with as few as ten or six categories; only for a three category recoding of the data the attenuation was appreciable, although still only .85[2].

There can be three different reasons why previous research has found such minor attenuation effects. A first possibility is that occupations within broad categories do not vary much among one another in sociologically interesting ways. In these cases crude measurement suffices. An alternative possibility is that occupation coding at a detailed level is more prone to measurement error than crude classification. Respondents, interviewers and coders may have a better understanding of an occupation at a crude level than at a detailed level. A third possibility, somewhat related to this second explanation, is that crude classifications -- in particular when used in in-field coding -- pick up variance from other variables and thereby results in stronger associations. For instance, crude occupational schemes are likely to present respondents with clues about skill levels, supervisory status and self-employment, and these sociologically meaningful additions are likely to become part of the criteria that lead the coder, interviewer or interviewee to a decision upon the most plausible category in a precoded response format. We feel that it is particularly worrisome when a person's educational *qualifications* become mixed up with his/her job's educational *requirements* (which is likely to be the case when skill levels are presented), since this confounds measurement with substance in one of the central concerns of social stratification research. If this situation would hold, it is not implausible that crude measures lead to stronger associations in empirical data on father-to-son occupational mobility, as observed in Ganzeboom, Luijkx & Treiman (1989). However, in this case one would expect that the extra strength of the effect disappears, once education is controlled.

[2] The cited attenuation coefficients should be read as the degree to which using a crude measure attenuates covariances/correlations with the occupation variable, relative to a detailed measure.

To investigate these concerns more thoroughly, I compare in the analyses below the structure of status attainment models using detailed classifications and crude classifications. To do so, I take advantage of the fact that there exist a large-scale cross-national dataset that has measured occupations independently in a crude and a detailed way: the International Social Survey Programme 1987 [ISSP87] (ISSP, 1987). While these data are rather old by now, there is no reason to assume that they have become irrelevant to the issues at stake here. To my knowledge, the issue of crude versus detailed occupation coding has not been addressing using this dataset.

Table 1 about here

DATA AND VARIABLES: THE INTERNATIONAL SOCIAL SURVEY PROGRAM 1987

The 1987 issue of the International Social Survey Program (ISSP, 1987), with a module on Social Inequality, included an experiment with a precoded question on occupations, of which details are reproduced here in Table 1. The respondent was asked to choose an appropriate category out of nine, each of which is prompted by a general label and a variable number of typical occupations in the category. In a limited set of countries, this crude question was then followed up with an open question, and the results of these questions were coded in standard occupational classification tools. This crude question was asked for respondent's occupation, father's occupation and respondent's first occupation in all countries, except Hungary[3], but the detailed question in only five countries, and only for father's and respondent's current/last occupation. Since I want to make a comparison between detailed and crude measurement procedure, the analysis will be restricted to the combination of countries and variables for which information was collected independently in both modes. Since there is no detailed information on first occupation in any of the countries, the analyses will concentrate on father's and respondent's current/last occupation. There are five countries in the ISSP87 for which the two sets of information on these two variables were collected: Australia, the USA, Austria, Germany, and Switzerland. In the latter three countries, the detailed occupation codes are provided is the International Standard Classification 1968 [ISCO68], while the Australians and Americans have used national detailed occupations classification (CPS70 and ASCO86, respectively). These two were converted in ISCO68, using previously developed recoding schemes (see ISMF, 2005).

[3] At first impression from the data documentation, it appears as if a similar but different crude question was asked in Hungary, but this turns out not to be the case: the respective variables in Hungary do not contain independent information, but are straight recodes from the questions on detailed occupations.

In all countries an additional question was asked on self-employment of the respondent and his/her father and I decided to combine this information with the crude occupational categories. This is particularly important in the case of professionals, higher administrators, sales workers, and farm workers, since it makes it possible to distinguish self-employed professionals, large business owners, shop owners and farm owners from salaried professionals, managers, sales clerks and agricultural laborers. The two questions in the ISSP87 module thus combine into 2*9=18 separate categories that in practice reduce to 13 categories. Each of these 13 categories was scaled into the International Socio-Economic Index of occupational status ISEI (Ganzeboom, de Graaf & Treiman, 1992), using ISCO68 as a conversion tool (ISMF, 2005). Similarly, the detailed ISCO68 occupation codes were scaled into ISEI. On average, the two parallel ISEI measures correlate between .65 and .75: the correlations are a bit higher for father's occupation than for respondent's occupation. The resulting variables are labeled FISEI and ISEI (father's and respondent's occupation derived from detailed measures), and FASEI and ASEI (derived from the alternative crude measurement), respectively.

The ISSP87 has not only experimented with different procedures for the measurement of occupation, a somewhat related procedure was used for education, that was also measured with two parallel questions, one about the highest grade attained and one about number of years completed. The interpretation of this operation is a bit different than for occupation, since although the highest grade attained question usually implies a less detailed measurement, at the same time it taps distinctions that are locally important. In particular when educational systems are divided in vocational and academic tracks (which is the case in Austria, Germany, and Switzerland), the highest grade attained will tap different and probably more relevant information than the years-of-school completed measure. For the analysis here, the years-of-school measure completed was maintained in its original format. The highest grade completed was rendered in a comparable metric by ranking the different grades according to the years of school completed and express the categories in percentile score. These variables enter the analyses as EDYRS (years of school completed) and EDRANK. On average these are correlated around .80, which implies that they indeed tap somewhat different aspects of the education.

The third status attainment variable is personal earnings, which was originally measured using local currencies and with slightly different prompts. The number of categories varies between 12 and 25. The measures were made cross-nationally comparable by expressing the categories in percentile scores within countries. The resulting variable is labeled INCRANK.

Finally, AGE and sex (FEMALE: women=1, men=0) are used as control variables. The effective samples were restricted to be between 21 and 64 years of age and the data on men and women were pooled on the argument that difference between men and women in distributions can be adequately modeled by using sex as a control variable.

Figure 1 about here

For each of the five countries a nine-variable correlation matrix was derived using pairwise deletion of missing data[4]. In total there are some 5000 cases (as pairwise deletion of missing values has been applied, this varies between relationships) in the analyses. These correlation matrices were analyzed via a structural equation model, estimated in LISREL8 (Jöreskog & Sörbom, 1993), using maximum likelihood fit procedures. This fitted model is displayed in Figure 1. It is almost fully saturated at the structural level, except that I do not assume any direct effect of father's occupation on respondent's income, as well as no association between FEMALE on the one hand and age and father's occupation on the other. The model is estimated in the following versions:

I. A single indicator model, with detailed occupations as measures and the 'best' single indicator for education.
II. A single indicator model, with crude occupations as measured and the 'best' single indicator for education.
III. A model with latent variables for the two occupations and education, with both the detailed and the crude indicator as measures.

Comparison of I and II leads to an assessment whether and to what extent detailed or crude occupation measures lead to higher associations. Given that these are single indicator models, we can use R-squared measures to make the comparison. The comparison is more direct in model III, where the measurement relationships (Lambda's in LISREL) can directly be interpreted as attenuation coefficients, not only relative to one another, but also relative to a true-score model corrected for measurement error. In addition, model III gives an estimate to which extent multiple indicators measurement improves the estimates.

Table 2 about here

Each of the models is estimated for the five countries separately, as well as for all the countries pooled (denoted as XNAT), using the 'invariant' option in Lisrel's multiple group specification. This pooled solution provides a parsimonious insight in the average results, in particular when the between-country differences are not spectacular, as well a useful benchmark for the

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[4] The correlation matrices are available from the author's website: http://home.fsw.vu.nl/hbg.ganzeboom, from which a full version of this paper, including numerical appendices can be downloaded.

country-wise results. The fit statistics are provided in Table 2. The modelling strategy has been that we compare the almost saturated model (a) with a model (b) in which there is no direct effect of father's occupation in earnings. In model (c) I remove in adddition the effect of education on earnings – which leads to an appreciable loss of fit for the single indicator models, but not so much for the multiple indicator models. While none of the estimated models fits the empirical correlation matrices by standard statistical standards, one should take in to account that the analyses deals with more than 5000 cases.

Table 3 about here

RESULTS

Status attainment models

Table 3A gives the structural coefficients for the model b, in which only the detailed occupation codes are used. Table 3B gives estimates for the same model for the crude occupation measures. The models consist of three separate equations that show a familiar pattern to the experienced stratification researcher. The first equation relates education to father's occupation (and sex and age); it suggests that detailed coding is clearly superior to crude coding. On average the effect of father's occupation is attenuated by a factor .91 (.364/. 402). There is also a 4% additional explained variance when one uses the detailed codes to scale father's occupation.

The second equation, for respondent's occupation, shows much less spectacular differences between models. The amount of variance explained is almost the same (.360 versus .359) and there is hardly any difference in the estimated coefficients. Note, however, that the direct effect of father's occupation on respondent's occupation is larger for the crude codes than for the detailed codes. This suggests that the degree of attenuation for father's occupation, as estimated from the first equation, does not apply to the relation between father's occupation and son's occupation. It also suggests that crude measures are slightly more prone to lead the respondent to bias the report on father's occupation towards his/her own occupation.

The coefficients of the third equation, on respondent's earnings, are even more similar between the two coding modes, both with respect to variance explained and the size of the coefficients. On average, the numbers are again slightly in favor of the detailed measure, but this is not the case in all separate countries and the differences are very small. According to both models, earnings are distinctively lower among women and young people (note that there is no control for hours worked in the model) and they are positively affected by both occupation and education. It is of some importance to focus a bit on the net effect of education in income: this effect implies that the higher educated make more money than lower educated *within* jobs of the same level. This net effect of education is routinely observed in income models and may be given different explanations. While it may be true that higher educated are higher remunerated for the same work, because they perform better or because income is awarded for formal credentials, the effect may also occur because of bad measurement of occupation. Using a multiple indicator approach, we will be able to test this latter explanation.

Table 4 about here

Table 4 shows the same status attainment model, but now estimated with a multiple indicator design. By comparing lambda's we can estimate the degree of attenuation directly, relative to the true score. These are spelled out in the measurement part of the model. The model has the advantage of pooling all the evidence into one estimate. The degree of attenuation for crude measurement of father's occupation relative to detailed measurement is found to be .95 (.834/.886), but for respondent it is a meager .99 (.827/.833). This pattern varies a bit between the countries, and in a few instances the estimates even suggest that crude codes are to be preferred over detailed codes. But however one looks at these numbers, the differences between the two modes are very minor. However, the same coefficients can now be compared to unity (1.0), which represents the attenuation relative to the true score. Averaging over coefficients, we can conclude that the attenuation relative to the true score is not so small, but amount to at least 15%. I.e., for each and every correlate of an occupational status, we find at best 85% of the true correlation, if we use either one on the two measures!

Note in passing that the estimated lambdas for education are much closer to unity than those for occupation and almost in balance for three countries. The Australian estimates suggest that years completed is to be preferred over ranked grades, whereas the Austrian case suggests the reverse.

While the analysis of the measurement relationship in Table 4 confirms our conclusions from comparing the single indicator models for the attenuation of crude measures relative to detailed measures (and actually suggest that attenuation is even less spectacular than what these models imply), the spectacular part of the table is part B, on the structural model, as it show how the attenuation relative to the true score affects findings. Crude *or* detailed occupations hardly make a difference, but using *both* does! The effect of father's occupation on education increases by 1.32, the effect of education on occupation by 1.35 and the effect of occupation on income by 1.65. Parallel increases are found for variance explained. Note in particular that in the income equation the effect of education is now estimated to be slightly negative (-.072). Since a negative value is theoretically implausible, I have re-estimated the model without the education effect, which reduced the occupation effect to .434. This still implied a disattenuation relative to the single indicator model of 1.43.

Note also that in the second equation the direct effect of father's occupation on respondent's occupation, relative to the single indicator models, has dropped from .16 to .13. This is an illustration that unreliable measurement attenuates indirect effects more strongly than direct effects. Once a proper measurement model is taken into account, the upward bias in the direct effect disappears. Since the lambda's of the parallel education measures are fairly high, the shift for this is not spectacular, but still in the predicted direction.

All these results are due to the attenuation of the measures relative to the error-corrected true score model, which suggest that for both crude and detailed measurement about 15% attenuation occurs.

Intergenerational mobility tables

The analyses reported above compare the effect of different modes of coding assuming that occupational status is adequately reflected in a (semi-)continuous measure. Much research on occupation, however, uses categorical measures of occupational status. The main argument for preferring categorical representation is the belief that occupational differences result inherently from discrete and multidimensional processes that are best represented by (class) typologies, in which multiple occupational variables are combined. There is in fact ample empirical evidence in favor of this position. In particular in occupational mobility research (in which transitions between two or more occupations are investigated), it has often been shown that the association between variables has properties than cannot be represented by correlation and regression coefficients: multidimensionality and asymmetry. For these types of analyses, various loglinear models have been proposed and used (Hout, 1983).

How adequate are crude occupational classifications in generating discrete occupational measures? It is to be noted beforehand that detailed occupational classifications have the advantage that they can combined in many different typologies, while crude classification leave only few degrees-of-freedom in this respect. However, this is not the issue in this paragraph. Here we assess whether crude and detailed classifications behave differently, when used in constructing a class typology that is consistent with the crude codes.

In order to make comparisons, I combined both detailed and crude occupation with the self-employment code to derive an EGP-class typology with seven categories[5]. By comparing the results from the detailed and crude approach in measurement, we can learn what effects the choice of a crude/detailed coding system has on the results of mobility analyses.

Table 5 about here

Table 5 gives fit statistics and selected parameter estimates for four relevant loglinear models, which compare the tables derived from the two coding modes. Note that the fit statistics here only have descriptive value, since we are not comparing independent samples. Nevertheless, it is immediately apparent from model Ib that notwithstanding their dissimilar marginal distribution the association pattern in the intergenerational mobility table are strikingly similar, as they all approach the number of degrees of freedom. However, the Common Association Model Ib is not a very sharp tool in deciding about differences between tables, since it consumes many degrees-of-freedom to make the comparison. Model Ic uses the uniform association model, extended with generic immobility coefficients to set up a two-degrees-of-freedom comparison (the approach is the same as in Ganzeboom, Luijkx & Treiman, 1989). Model Id conditions the two principal association coefficients, labeled U and IMM, by type of coding. The comparison shows again that there is very little difference between the two ways of recording occupations. This is confirmed again in panel II of the table, where estimates for the parameters in model Id are given. It turns out that these are not only nominally insignificant, but also that the differences between the tables do not amount to much more than a few percentage points. The estimates in panel II also show that there is not a uniform pattern in the association coefficient: in about half the cases the coefficients are in the direction of stronger association for the crude codes, for the other half it is the other way around. This lack of pattern is confirmed by the very small difference in the model for the pooled data that aggregates over these variations among countries. However, is there is any difference, it is that the association is slightly less strong in the data derived from the detailed classification.

These results imply again that for some purposes it makes very little difference whether one starts out from detailed or crude codes. Apart from the differences in marginal distributions, there seems to be even less differences in effect of coding than detected by the procedures that conceptualized occupational status as continuous measures.

CONCLUSIONS AND DISCUSSION

[5] The counts for these mobility tables can also be obtained from the full paper on the website of the author: http://www.fsw.vu.nl/~ganzeboom.

The conclusions from this analysis of the comparison of crude and detailed occupation codes can be formulated as follows:

1. There is very little difference in unreliability (random measurement error) between detailed and crude occupation codes. On average the results from the status attainment models favor the detailed codes by a small margin, but this margin is indeed so small that it seems hard to argue that establishing detailed occupation codes is warranted for this purpose.
2. Crude occupation codes seem to be slightly biased towards immobility, i.e. there appears to be some tendency to put father in the same class as one self. This tendency, again, is very slight.
3. The attenuation effect of single indicator measurement relative to true scores in a multiple indicator measurement is rather dramatic (between .80 and .85) and measuring crude and detailed codes at the same time seems to be a natural way to create a multiple indicator design.

Why is it the case that crude and detailed measurement procedures make so little difference? Can it be the case that a true occupational status score becomes more corrupted, when a less detailed measurement instrument is used? I propose that at least two processes are at work here.

First, deriving detailed occupation codes is a much more complicated procedure than deriving crude codes. Crude codes are basically a self-evaluation by the respondent, who understands best what s/he (or her/his father) is/was doing for a living. Detailed occupation measures, by contrast, require understanding on the part of the interviewer, who records the information, as well as the coder. These two steps of communication take their toll, as any communication leads to misunderstanding. The attenuating effect of these procedures would be testable in a repeated measurement design, in which the same information is recorded independently by different interviewers and coded independently. Unfortunately, such data are not available at this time.

Second, it may be that standard occupational classifications by themselves are less adequate classification tools than their level of detail suggests. It seems plausible that many aspects of occupation determine their educational requirements, their earning potential and their use as resource in social mobility. However, it remains to be seen that those aspects are well covered by the distinctions often made in occupational classification. Previous experiences suggest that there is very little systematic variance with respect to educational requirements and earnings potential in the last two, or even last three digits of ISCO, and it seems likely that the same applies to national classifications. I.e., essentially the same results would arise, if coders / interviewers would have restricted themselves to coding only one or two digits. This does not imply that there is no variation among occupational position in this respect, but only that these are not picked up by the standard classifications.

The way to pick up the importance of the various aspects that are important for the status attainment attributes of someone's occupation is therefore the multiple indicator design, much as we are used to apply it in attitude research. One practical problem with multiple measurements of structural and demographic characteristics may be that good parallel questions are hard to construct. While it is trivial to ask repeated questions on someone's attitude towards abortion, this would be irritating for occupation, education, etc. It strikes me that asking both crude and detailed question in ISSP87 is in fact a natural and acceptable way to circumvent to difficulty. I am currently in the process of collecting and analyzing such data in a national context.

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Table 1: Type of Work Question - ISSP 1987

Here is a list of different types of jobs. Which type did your father have when you were 16 years / [did you have in] the first job you had after you finished your full-time education / [do you have]] in your job now?

01. Professional and technical (for example: doctor, teacher, engineer, artist, accountant)
02. Higher administrator (for example: banker, executive in big business, high government official, union official)
03. Clerical (for example: secretary, clerk, office manager, civil servant, bookkeeper)
04. Sales (for example: sales manager, shop owner, shop assistant, insurance agent, buyer)
05. Service (for example: restaurant owner, police officer, waiter, barber, caretaker)
06. Skilled worker (for example: foreman, motor mechanic, printer, tool and die maker, electrician)
07. Semi-skilled worker (for example: bricklayer, bus driver, tannery worker, carpenter, sheet metal worker, baker)
08. Unskilled worker (for example: labourer, porter, unskilled factory worker)
09. Farm (for example: farmer, farm labourer, tractor driver)

Was your father / were you / are you self-employed, or did he /did you / do you work for someone else?

1.Self-employed, own business or farm
2.Work[ed] for someone else

Table 2: Fit statistics of Lisrel models

	Same pattern		Invariant	
<u>I. Single indicator models, detailed measures</u>				
a. Saturated structural model	10	17	86	277
b. Model (a) - be(6,3)	15	36	87	278
c. Model (b) - be(6,4)	20	136	88	370
<u>II. Single indicator models, crude measures</u>				
a. Saturated structural model	10	17	86	344
b. Model (a) - be(6,3)	15	26	87	345
c. Model (b) - be(6,4)	20	116	88	418
<u>III. Multiple indicator models</u>				
a. Saturated structural model	85	390	197	1560
b. Model (a) - be(6,3)	90	406	198	1567
c. Model (b) - be(6,4)	95	435	199	1577

Table 3: Standardized estimates of an elementary status attainment model with singular indicators for education and occupation

A. Structural coefficients using detailed measures

	AUS	GER	USA	AUT	SWI	XNAT
EDUC (R2)	(.249)	(.218)	(.194)	(.234)	(.197)	(.205)
- FEMALE	-.083	-.057	-.052	-.074	-.133	-.083
- AGE	-.222	-.177	-.131	-.180	-.006	-.142
- FISEI	.335	.408	.386	.413	.424	.402
ISEI (R2)	(.394)	(.414)	(.334)	(.395)	(.328)	(.360)
- FEMALE	.009	.041	.068	.018	.006	.029
- AGE	.203	.138	.148	.100	.099	.136
- FISEI	.095	.156	.128	.251	.117	.149
- EDUC	.570	.578	.532	.496	.511	.537
EARNINGS (R2)	(.464)	(.425)	(.321)	(.362)	(.419)	(.365)
- FEMALE	-.468	-.483	-.355	-.441	-.421	-.435
- AGE	-.034	.240	.233	.026	.189	.143
- EDUC	.207	.054	.157	.159	.094	.138
- ISEI	.194	.341	.293	.282	.349	.290

B. Structural coefficients using crude measures

	AUS	GER	USA	AUT	SWI	XNAT
EDUC (R2)	(.184)	(.195)	(.216)	(.205)	(.143)	(.178)
- FEMALE	-.083	-.035	-.056	-.050	-.109	-.070
- AGE	-.222	-.189	-.124	-.188	.043	-.136
- FASEI	.335	.378	.415	.378	.366	.373
ASEI (R2)	(.387)	(.334)	(.373)	(.438)	(.344)	(.363)
- FEMALE	.077	-.090	.138	.002	-.063	.011
- AGE	.172	.118	.130	.047	.063	.106
- FASEI	.158	.196	.115	.232	.136	.167
- EDUC	.571	.476	.562	.543	.512	.531
EARNINGS (R2)	(.382)	(.420)	(.293)	(.341)	(.422)	(.359)
- FEMALE	-.486	-.442	-.365	-.432	-.404	-.433
- AGE	.030	.232	.246	.042	.190	.146
- EDUC	.165	.025	.195	.170	.075	.122
- ASEI	.254	.367	.218	.251	.366	.297

AUS: Australia, GER: Germany (West), USA: United States, AUT: Austria, SWI: Switzerland, XNAT: Cross-national (pooled).

Table 4: Standardized estimates of an elementary status attainment model with multiple indicators for education and occupation

	AUS	GER	USA	AUT	SWI	XNAT
I. Measurement models						
FISEI						
--> detailed	.886	.886	.886	.886	.886	.885
--> crude	.826	.798	.911	.790	.858	.835
EDUC						
--> years	.907	.907	.907	.907	.907	.901
--> rank	.819	.914	.883	.989	.905	.899
ISEI						
--> detailed	.836	.836	.836	.836	.836	.835
--> crude	.872	.737	.862	.863	.822	.829
II. Structural model						
EDUC (R2)	(.246)	(.341)	(.282)	(.398)	(.308)	(.298)
- FEMALE	-.082	-.052	-.057	-.072	-.136	-.090
- AGE	-.244	-.183	-.084	-.192	.041	-.124
- FISEI	.469	.505	.542	.458	.534	.503
ISEI (R2)	(.551)	(.631)	(.611)	(.624)	(.589)	(.591)
- FEMALE	.042	.006	.127	.025	-.005	.038
- AGE	.220	.207	.171	.152	.094	.165
- FISEI	.196	.091	.122	.161	.056	.136
- EDUC	.554	.835	.664	.846	.766	.710
EARNINGS (R2)	(.413)	(.457)	(.354)	(.368)	(.481)	(.404)
- FEMALE	-.491	-.469	-.393	-.441	-.406	-.439
- AGE	-.023	.229	.205	.013	.175	.120
- EDUC	0	0	0	0	0	0
- ISEI	.434	.395	.465	.390	.478	.434

AUS: Australia, GER: Germany (West), USA: United States, AUT: Austria, SWI: Switzerland, XNAT: Cross-national (pooled).

Table 5: Fit statistics and estimated association coefficients for intergenerational occupational mobility, using detailed and crude coding procedures.

I. Fit statistics (LR2)

	ndf	AUT	GER	USA	AUT	SWI	XNAT
a. Independence (O*T,D*T)	72	374	380	300	506	245	1809
b. Common association (a+O*D)	36	27	26	29	27	32	379
c. Two common components (a + DIA + U + INH)	64	76	74	91	80	70	423
d. Two components (c + (U+INH)*T)	62	71	71	89	79	71	418

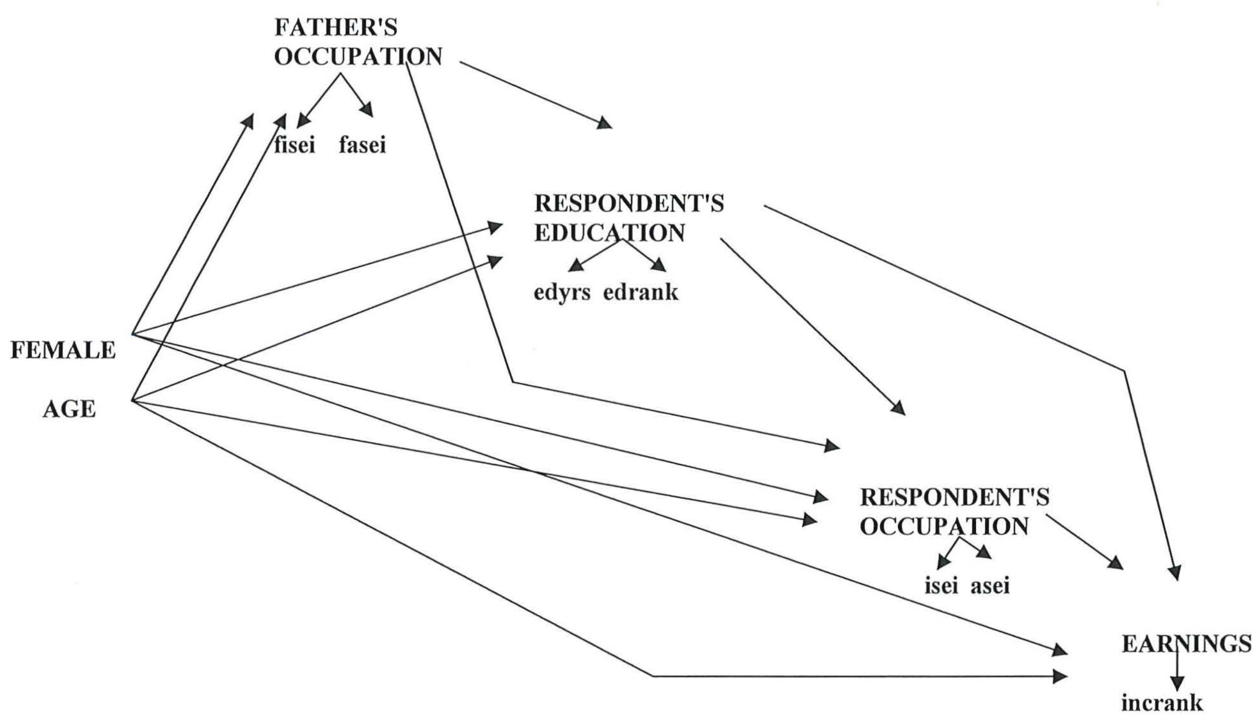
II. Parameters model I.d

		AUT	GER	USA	AUT	SWI	XNAT
U		.065	.123	.065	.106	.067	.097
U*T		-.005	.005	-.004	-.010	-.008	-.004
INH		dia	dia	dia	dia	dia	dia
INH*T		-.089	-.118	-.078	.048	.009	-.049

Notes:
O: Origin. D: Destination. T: Type of coding: (1) detailed (0) crude. IMM: class immobility coefficients. U: uniform association coefficient. INH: uniform inheritance coefficient. Dia: class-specific inheritance coefficients. Ndf Degrees-of-freedom. Note that the comparisons are not on independent samples and that the entries only have descriptive value.

AUS: Australia, GER: Germany (West), USA: United States, AUT: Austria, SWI: Switzerland, XNAT: Cross-national (pooled).

Figure 1: The elementary status attainment model



Appendix 1: Correlation matrices analyzed in LISREL analyses

COUNTRY: 1 AUSTRALIA

	FEMALE	AGE	FISEI	FASEI	EDYRS	EDRANK	ISEI	ASEI	INCRANK
Mean	1.51058	39.97602	40.44930	39.29655	11.21086	5.07616	47.10141	47.30804	4.90371
Std Dev	.50006	11.97737	16.04875	14.74175	2.74302	2.59767	15.68878	14.16571	2.86757
Cases	1418	1418	1282	1305	1399	1418	1203	1107	1267
FEMALE	1.00000								
AGE	-.01115	1.00000							
FISEI	-.01735	-.10268	1.00000						
FASEI	-.04153	-.10166	.72065	1.00000					
EDYRS	-.09427	-.25534	.40196	.36064	1.00000				
EDRANK	-.12720	-.17278	.36026	.32916	.93690	1.00000			
ISEI	-.04904	.04735	.30346	.30143	.55595	.50705	1.00000		
ASEI	.01461	.00907	.34709	.34361	.57714	.55250	.65491	1.00000	
INCRANK	-.49741	-.00438	.16262	.16948	.34929	.35074	.33263	.34206	1.00000

COUNTRY: 2 WEST GERMANY

Mean	1.55545	41.70301	39.24683	41.83477	10.03834	5.02632	44.52925	44.62032	5.13696
Std Dev	.49715	12.73842	14.45497	12.01097	2.72677	2.69232	13.81421	10.73270	2.95857
Cases	1064	1064	709	926	965	1064	718	935	606
FEMALE	1.00000								
AGE	-.00037	1.00000							
FISEI	.01539	-.11365	1.00000						
FASEI	.00080	-.10479	.73470	1.00000					
EDYRS	-.05071	-.22390	.42745	.36922	1.00000				
EDRANK	-.03483	-.22813	.46887	.39788	.78987	1.00000			
ISEI	.01377	-.00938	.38803	.37376	.61203	.61368	1.00000		
ASEI	-.10677	-.01086	.32447	.37290	.53980	.53064	.68137	1.00000	
INCRANK	-.48101	.22451	.08678	.08506	.23367	.17218	.36534	.41891	1.00000

COUNTRY: 4 USA

Mean	1.56879	39.31617	42.07390	39.28610	12.95165	5.33979	46.42246	45.64404	4.98441
Std Dev	.49545	11.80623	17.21066	15.34400	2.95628	2.70701	16.26818	13.95998	2.92443
Cases	1243	1243	1042	1108	1241	1239	1193	1149	962

FEMALE	1.00000								
AGE	.00461	1.00000							
FISEI	-.02283	-.25024	1.00000						
FASEI	-.01036	-.24898	.74534	1.00000					
EDYRS	-.06106	-.22787	.41999	.44633	1.00000				
EDRANK	-.05471	-.18581	.39231	.42025	.87134	1.00000			
ISEI	.03312	-.00475	.31305	.28301	.54818	.54636	1.00000		
ASEI	.10280	-.02580	.31481	.33233	.57577	.58076	.64779	1.00000	
INCRANK	-.35311	.19378	.17415	.13254	.28566	.28335	.36589	.28512	1.00000

COUNTRY: 5 AUSTRIA

Mean	1.54627	42.10154	36.79185	37.08921	9.76556	5.23938	41.63401	41.11949	4.99124
Std Dev	.49817	13.26383	13.29401	12.46519	2.63910	2.64514	14.22216	12.45527	3.03458
Cases	778	778	687	695	755	777	694	703	571

FEMALE	1.00000								
AGE	.07574	1.00000							
FISEI	.02567	-.16698	1.00000						
FASEI	-.03339	-.16597	.77298	1.00000					
EDYRS	-.08248	-.30629	.49229	.40338	1.00000				
EDRANK	-.07701	-.25480	.44175	.41094	.69547	1.00000			
ISEI	-.00612	-.06713	.45366	.38040	.50198	.57964	1.00000		
ASEI	-.04452	-.12975	.46663	.44756	.51823	.62660	.77321	1.00000	
INCRANK	-.45248	-.06695	.13899	.14199	.17169	.34957	.37512	.37096	1.00000

COUNTRY: 11 SWITZERLAND

Mean	1.3829	39.9753	43.1892	42.0604	10.8005	4.8847	49.9172	49.1694	5.1544
Std Dev	.4864	11.5041	16.5058	13.3785	3.4848	2.9040	15.2784	12.1972	2.8701
Cases	799	812	745	745	762	798	737	767	712

FEMALE	1.00000								
AGE	-.08427	1.00000							
FISEI	.04723	-.10951	1.00000						
FASEI	.05528	-.12820	.71942	1.00000					
EDYRS	-.11205	-.04121	.41815	.40225	1.00000				
EDRANK	-.09202	.00511	.37823	.35486	.75369	1.00000			
ISEI	-.05388	.06465	.32012	.29841	.55507	.56714	1.00000		
ASEI	-.10827	.05311	.29060	.30602	.52446	.56647	.68407	1.00000	
INCRANK	-.46606	.24330	.15011	.08339	.32713	.32047	.43612	.46205	1.00000

Appendix 2: Intergenerational occupational mobility patterns using detailed and crude classifications.

CODE Value = 1 Detailed
COUNTRIES: All (XNAT)

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FEGP (Row Pct / Col Pct)	Service Class 1	Low NonManual 2	Small Selfemploy 3	Skilled Worker 4	Semi-Unskilled W 5	Farm Labor 6	Farmer 7	Row Total
1	57.0	21.2	5.8	6.8	7.8	.4	.9	896
Service Class	37.5	21.2	22.2	9.6	11.8	9.1	6.3	23.0
2	46.5	28.0	2.9	14.4	7.4	.8		243
Low NonManual	8.3	7.6	3.0	5.5	3.0	4.5		6.2
3	33.4	24.6	14.3	14.0	12.5	.6	.6	329
Small Selfemploy	8.1	9.0	20.1	7.3	6.9	4.5	1.6	8.5
4	29.1	24.9	4.9	22.8	16.9	.6	.9	1080
Skilled Worker	23.1	30.0	22.6	38.8	30.6	13.6	7.9	27.7
5	25.6	24.3	5.4	20.3	22.3	1.1	1.0	700
Semi-Unskilled W	13.1	19.0	16.2	22.4	26.3	18.2	5.5	18.0
6	10.6	20.2	6.7	24.0	28.8	6.7	2.9	104
Farm Labor	.8	2.3	3.0	3.9	5.1	15.9	2.4	2.7
7	23.0	18.1	5.6	14.6	18.0	2.8	18.0	540
Farmer	9.1	10.9	12.8	12.5	16.3	34.1	76.4	13.9
Column	1362	897	234	634	594	44	127	3892
Total	35.0	23.0	6.0	16.3	15.3	1.1	3.3	100.0

Pearson's R	.33573	.01524	22.22952	.00000 *4
Spearman Correlation	.31972	.01518	21.04556	.00000 *4

CODE Value = 2 Crude
COUNTRIES: All (XNAT)

EGP Page 1 of 1

FEGP (Row Pct / Col Pct)	Service Class 1	Low NonManual 2	Small Selfemploy 3	Skilled Worker 4	Semi-Unskilled W 5	Farm Labor 6	Farmer 7	Row Total
1 Service Class	50.1	29.6	5.9	8.4	5.3	.3	.4	786
	30.0	18.4	14.3	10.6	7.0	4.8	2.4	18.3
2 Low NonManual	39.9	38.8	7.4	9.0	4.4	.5		569
	17.3	17.4	13.1	8.2	4.2	7.1		13.3
3 Small Selfemploy	28.7	30.9	18.7	9.8	10.3	.5	1.2	418
	9.1	10.2	24.3	6.6	7.2	4.8	3.9	9.7
4 Skilled Worker	24.9	32.2	4.7	23.3	13.6	.6	.6	977
	18.5	24.9	14.3	36.7	22.3	14.3	4.7	22.8
5 Semi-Unskilled W	21.8	26.4	6.5	16.4	27.0	.6	1.4	899
	14.9	18.7	18.1	23.6	40.7	11.9	10.2	21.0
6 Farm Labor	21.4	18.8	9.1	12.3	29.2	5.2	3.9	154
	2.5	2.3	4.4	3.1	7.5	19.0	4.7	3.6
7 Farmer	20.9	21.1	7.6	14.3	13.5	3.3	19.3	488
	7.8	8.1	11.5	11.3	11.1	38.1	74.0	11.4
Column Total	1315	1267	321	622	597	42	127	4291
	30.6	29.5	7.5	14.5	13.9	1.0	3.0	100.0

Pearson's R	.35009	.01423	24.47679	.00000 *4
Spearman Correlation	.32367	.01439	22.40293	.00000 *4

CODE Value = 1 Detailed

COUNTRY Value = AUS

EGP

FEGP	Row Pct / Col Pct	Service Class 1	Low NonManual 2	Small Selfemploy 3	Skilled Worker 4	Semi-Unskilled W 5	Farm Lab or 6	Farmer 7	Row Total
1		53.2	24.9	6.1	5.1	8.2	.7	1.7	293
Service Class		38.0	25.7	22.2	11.0	17.3	11.8	16.7	26.7
2		48.0	33.3	1.3	10.7	6.7			75
Low NonManual		8.8	8.8	1.2	5.9	3.6			6.8
3		34.4	28.2	13.0	13.7	8.4	1.5	.8	131
Small Selfemploy		10.9	13.0	21.0	13.2	7.9	11.8	3.3	11.9
4		32.6	25.1	6.7	18.4	15.1	1.3	.8	239
Skilled Worker		19.0	21.1	19.8	32.4	25.9	17.6	6.7	21.8
5		28.9	26.4	8.6	15.2	18.8	1.5	.5	197
Semi-Unskilled W		13.9	18.3	21.0	22.1	26.6	17.6	3.3	17.9
6		13.8	24.1	6.9	24.1	20.7	6.9	3.4	29
Farm Labor		1.0	2.5	2.5	5.1	4.3	11.8	3.3	2.6
7		26.1	22.4	7.5	10.4	14.9	3.7	14.9	134
Farmer		8.5	10.6	12.3	10.3	14.4	29.4	66.7	12.2
Column		411	284	81	136	139	17	30	1098
Total		37.4	25.9	7.4	12.4	12.7	1.5	2.7	100.0

Pearson's R	.27920	.03040	9.62584	.00000 *4
Spearman Correlation	.26690	.02922	9.16848	.00000 *4

CODE Value = 2 Crude

COUNTRY Value = AUS

EGP

FEGP	Row Pct / Col Pct	Service Class 1	Low NonManual 2	Small Selfemploy 3	Skilled Worker 4	Semi-Unskilled W 5	Farm Labor 6	Farmer 7	Row Total
1 Service Class	Row Pct	55.8	25.2	4.4	6.6	6.2	.9	.9	226
	Col Pct	33.8	19.5	9.9	11.9	9.5	28.6	5.4	20.9
2 Low NonManual	Row Pct	42.4	37.6	5.6	9.6	4.8			125
	Col Pct	14.2	16.1	6.9	9.5	4.1			11.5
3 Small Selfemploy	Row Pct	30.4	26.4	20.9	10.8	7.4	.7	3.4	148
	Col Pct	12.1	13.4	30.7	12.7	7.5	14.3	13.5	13.7
4 Skilled Worker	Row Pct	31.0	31.0	6.5	19.0	11.3	.6	.6	168
	Col Pct	13.9	17.8	10.9	25.4	12.9	14.3	2.7	15.5
5 Semi-Unskilled W	Row Pct	25.2	22.1	10.1	14.7	25.6	.4	1.9	258
	Col Pct	17.4	19.5	25.7	30.2	44.9	14.3	13.5	23.8
6 Farm Labor	Row Pct	21.1	28.9	5.3	5.3	28.9	2.6	7.9	38
	Col Pct	2.1	3.8	2.0	1.6	7.5	14.3	8.1	3.5
7 Farmer	Row Pct	20.0	24.2	11.7	9.2	16.7	.8	17.5	120
	Col Pct	6.4	9.9	13.9	8.7	13.6	14.3	56.8	11.1
Column Total		373	292	101	126	147	7	37	1083
		34.4	27.0	9.3	11.6	13.6	.6	3.4	100.0

Pearson's R	.32842	.02881	11.43202	.00000 *4
Spearman Correlation	.31978	.02852	11.09666	.00000 *4

CODE Value = 1 Detailed
COUNTRY Value = AUT

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FEGP	Row Pct / Col Pct	Service Class 1	Low NonManual 2	Small Selfemploy 3	Skilled Worker 4	Semi-Unskilled W 5	Farm Labor 6	Farmer 7	Row Total
1 Service Class	Row Pct	55.8	20.8	5.2	9.1	6.5		2.6	77
	Col Pct	33.3	10.7	18.2	6.0	4.0		3.4	12.6
2 Low NonManual	Row Pct	21.6	45.9	2.7	27.0		2.7		37
	Col Pct	6.2	11.3	4.5	8.5		8.3		6.0
3 Small Selfemploy	Row Pct	17.3	25.0	19.2	23.1	15.4			52
	Col Pct	7.0	8.7	45.5	10.3	6.4			8.5
4 Skilled Worker	Row Pct	20.1	29.1	1.7	24.0	21.8	.6	2.8	179
	Col Pct	27.9	34.7	13.6	36.8	31.2	8.3	8.6	29.2
5 Semi-Unskilled W	Row Pct	16.9	26.2	.8	19.2	32.3	1.5	3.1	130
	Col Pct	17.1	22.7	4.5	21.4	33.6	16.7	6.9	21.2
6 Farm Labor	Row Pct		14.3		21.4	35.7	21.4	7.1	14
	Col Pct		1.3		2.6	4.0	25.0	1.7	2.3
7 Farmer	Row Pct	8.9	12.9	2.4	13.7	21.0	4.0	37.1	124
	Col Pct	8.5	10.7	13.6	14.5	20.8	41.7	79.3	20.2
Column Total		129	150	22	117	125	12	58	613
		21.0	24.5	3.6	19.1	20.4	2.0	9.5	100.0

Pearson's R	.45703	.03453	12.70101	.00000 *4
Spearman Correlation	.43409	.03586	11.91086	.00000 *4

CODE Value = 2 Crude
COUNTRY Value = AUT

FEGP / EGP (Row Pct / Col Pct)	Service Class 1	Low NonManual 2	Small Selfemploy 3	Skilled Worker 4	Semi-Unskilled W 5	Farm Labor 6	Farmer 7	Row Total
1	44.6	32.4	2.7	10.8	9.5			74
Service Class	26.0	12.4	8.0	9.2	5.6			11.7
2	39.1	43.5	5.8	7.2	2.9	1.4		69
Low NonManual	21.3	15.5	16.0	5.7	1.6	7.1		11.0
3	25.0	26.9	19.2	17.3	11.5			52
Small Selfemploy	10.2	7.2	40.0	10.3	4.8			8.3
4	16.1	35.6	1.3	22.1	20.8	1.3	2.7	149
Skilled Worker	18.9	27.3	8.0	37.9	24.6	14.3	7.0	23.7
5	13.6	32.1	2.1	13.6	33.6	.7	4.3	140
Semi-Unskilled W	15.0	23.2	12.0	21.8	37.3	7.1	10.5	22.2
6	14.3	23.8	4.8	9.5	28.6	9.5	9.5	21
Farm Labor	2.4	2.6	4.0	2.3	4.8	14.3	3.5	3.3
7	6.4	18.4	2.4	8.8	21.6	6.4	36.0	125
Farmer	6.3	11.9	12.0	12.6	21.4	57.1	78.9	19.8
Column Total	127	194	25	87	126	14	57	630
	20.2	30.8	4.0	13.8	20.0	2.2	9.0	100.0

Pearson's R	.48308	.03164	13.82620	.00000 *4
Spearman Correlation	.46346	.03377	13.10697	.00000 *4

CODE Value = 1 Detailed
COUNTRY Value = GER

FEGP (Row Pct / Col Pct)	EGP: Service Class 1	Low NonManual 2	Small Selfemploy 3	Skilled Worker 4	Semi-Unskilled W 5	Farm Labor 6	Farmer 7	Row Total
1	54.7	25.0	4.7	10.9	4.7			64
Service Class	30.7	14.5	12.5	4.6	4.1			13.1
2	35.3	29.4	5.9	17.6	11.8			17
Low NonManual	5.3	4.5	4.2	2.0	2.7			3.5
3	36.2	13.8	19.0	17.2	13.8			58
Small Selfemploy	18.4	7.3	45.8	6.5	10.8			11.9
4	15.7	25.4	2.2	43.2	13.5			185
Skilled Worker	25.4	42.7	16.7	52.3	33.8			37.8
5	16.7	24.0	1.0	31.3	24.0	3.1		96
Semi-Unskilled W	14.0	20.9	4.2	19.6	31.1	42.9		19.6
6		25.0	5.0	35.0	25.0	5.0	5.0	20
Farm Labor		4.5	4.2	4.6	6.8	14.3	14.3	4.1
7	14.3	12.2	6.1	32.7	16.3	6.1	12.2	49
Farmer	6.1	5.5	12.5	10.5	10.8	42.9	85.7	10.0
Column	114	110	24	153	74	7	7	489
Total	23.3	22.5	4.9	31.3	15.1	1.4	1.4	100.0

Pearson's R	.37202	.04128	8.84461	.00000 *4
Spearman Correlation	.35070	.04246	8.26411	.00000 *4

CODE Value = 2 Crude

COUNTRY Value = GER

EGP

FEGP (Row Pct / Col Pct)		Service Class 1	Low NonManual 2	Small Selfemploy 3	Skilled Worker 4	Semi-Unskilled W 5	Farm Labor 6	Farmer 7	Row Total
1 Service Class	Row Pct	41.7	40.0	2.6	10.4	5.2			115
	Col Pct	28.1	14.9	8.8	7.1	5.3			14.2
2 Low NonManual	Row Pct	25.0	58.6	3.4	8.6	4.3			116
	Col Pct	17.0	22.0	11.8	5.9	4.4			14.4
3 Small Selfemploy	Row Pct	19.0	46.4	15.5	10.7	8.3			84
	Col Pct	9.4	12.6	38.2	5.3	6.1			10.4
4 Skilled Worker	Row Pct	18.1	35.4	2.4	32.6	11.5			288
	Col Pct	30.4	33.0	20.6	55.3	28.9			35.6
5 Semi-Unskilled W	Row Pct	14.0	26.5	1.5	18.4	39.0	.7		136
	Col Pct	11.1	11.7	5.9	14.7	46.5	25.0		16.8
6 Farm Labor	Row Pct		21.4	21.4	21.4	28.6	7.1		14
	Col Pct		1.0	8.8	1.8	3.5	25.0		1.7
7 Farmer	Row Pct	12.7	27.3	3.6	30.9	10.9	3.6	10.9	55
	Col Pct	4.1	4.9	5.9	10.0	5.3	50.0	100.0	6.8
Column Total		171	309	34	170	114	4	6	808
		21.2	38.2	4.2	21.0	14.1	.5	.7	100.0

Pearson's R	.36668	.03224	11.18936	.00000 *4
Spearman Correlation	.35922	.03222	10.92774	.00000 *4

CODE Value = 1 Detailed
COUNTRY Value = SWI

EGP

FEGP (Row Pct / Col Pct)	Service Class 1	Low NonManual 2	Small Selfemploy 3	Skilled Worker 4	Semi-Unskilled W 5	Farm Labor 6	Farmer 7	Row Total
1	62.0	19.0	7.0	7.0	4.5	.5		200
Service Class	41.1	26.0	23.0	15.4	14.8	25.0		29.2
2	55.9	18.6	3.4	13.6	6.8	1.7		59
Low NonManual	10.9	7.5	3.3	8.8	6.6	25.0		8.6
3	53.8	23.1	7.7	7.7	7.7			13
Small Selfemploy	2.3	2.1	1.6	1.1	1.6			1.9
4	34.0	26.7	10.2	15.0	13.1	.5	.5	206
Skilled Worker	23.2	37.7	34.4	34.1	44.3	25.0	5.3	30.1
5	38.1	17.1	12.4	21.9	8.6		1.9	105
Semi-Unskilled W	13.2	12.3	21.3	25.3	14.8		10.5	15.4
6	22.2	33.3	11.1	22.2	11.1			9
Farm Labor	.7	2.1	1.6	2.2	1.6			1.3
7	28.3	19.6	9.8	13.0	10.9	1.1	17.4	92
Farmer	8.6	12.3	14.8	13.2	16.4	25.0	84.2	13.5
Column	302	146	61	91	61	4	19	684
Total	44.2	21.3	8.9	13.3	8.9	.6	2.8	100.0

Pearson's R	.31316	.03642	8.61148	.00000 *4
Spearman Correlation	.28944	.03623	7.89670	.00000 *4

CODE Value = 2 Crude
COUNTRY Value = SWI

EGP

FEGP	Row Pct / Col Pct	Service Class 1	Low NonManual 2	Small Selfemploy 3	Skilled Worker 4	Semi-Unskilled W 5	Farm Labor 6	Farmer 7	Row Total
1 Service Class	Row Pct	50.6	28.5	12.7	7.0	1.3			158
	Col Pct	28.8	21.4	23.8	13.1	5.7			22.1
2 Low NonManual	Row Pct	45.4	29.4	13.5	9.2	1.2	1.2		163
	Col Pct	26.6	22.9	26.2	17.9	5.7	33.3		22.8
3 Small Selfemploy	Row Pct	30.8	61.5	7.7					13
	Col Pct	1.4	3.8	1.2					1.8
4 Skilled Worker	Row Pct	31.5	33.9	9.1	13.9	10.3	.6	.6	165
	Col Pct	18.7	26.7	17.9	27.4	48.6	16.7	5.3	23.0
5 Semi-Unskilled W	Row Pct	26.4	34.0	13.2	17.9	6.6	.9	.9	106
	Col Pct	10.1	17.1	16.7	22.6	20.0	16.7	5.3	14.8
6 Farm Labor	Row Pct	50.0	7.1	14.3	7.1	7.1	7.1	7.1	14
	Col Pct	2.5	.5	2.4	1.2	2.9	16.7	5.3	2.0
7 Farmer	Row Pct	34.0	16.5	10.3	15.5	6.2	1.0	16.5	97
	Col Pct	11.9	7.6	11.9	17.9	17.1	16.7	84.2	13.5
Column Total		278	210	84	84	35	6	19	716
		38.8	29.3	11.7	11.7	4.9	.8	2.7	100.0

Pearson's R	.29443	.03684	8.23234	.00000 *4
Spearman Correlation	.23255	.03695	6.38905	.00000 *4

CODE Value = 1 Detailed
COUNTRY Value = USA

EGP

FEGP	Row Pct / Col Pct	Service Class 1	Low NonManual 2	Small Selfemploy 3	Skilled Worker 4	Semi-Unskilled W 5	Farm Labor 6	Farmer 7	Row Total
1 Service Class	Row Pct	58.4	17.9	5.0	6.9	11.1	.4	.4	262
	Col Pct	37.7	22.7	28.3	13.1	14.9	25.0	7.7	26.0
2 Low NonManual	Row Pct	54.5	18.2	3.6	10.9	12.7			55
	Col Pct	7.4	4.8	4.3	4.4	3.6			5.5
3 Small Selfemploy	Row Pct	37.3	26.7	10.7	6.7	17.3		1.3	75
	Col Pct	6.9	9.7	17.4	3.6	6.7		7.7	7.4
4 Skilled Worker	Row Pct	37.3	20.3	3.3	17.7	20.3	.4	.7	271
	Col Pct	24.9	26.6	19.6	35.0	28.2	25.0	15.4	26.9
5 Semi-Unskilled W	Row Pct	25.6	25.0	3.5	19.8	26.2			172
	Col Pct	10.8	20.8	13.0	24.8	23.1			17.1
6 Farm Labor	Row Pct	15.6	12.5	9.4	18.8	40.6	3.1		32
	Col Pct	1.2	1.9	6.5	4.4	6.7	25.0		3.2
7 Farmer	Row Pct	31.9	19.9	3.5	14.2	23.4	.7	6.4	141
	Col Pct	11.1	13.5	10.9	14.6	16.9	25.0	69.2	14.0
Column Total		406	207	46	137	195	4	13	1008
		40.3	20.5	4.6	13.6	19.3	.4	1.3	100.0

Pearson's R	.25684	.03037	8.42910	.00000 *4
Spearman Correlation	.26153	.03016	8.59426	.00000 *4

CODE Value = 2 Crude

COUNTRY Value = USA

FEGP (Row Pct / Col Pct) \ EGP	Service Class 1	Low NonManual 2	Small Selfemploy 3	Skilled Worker 4	Semi-Unskilled W 5	Farm Labor 6	Farmer 7	Row Total
1 Service Class	50.2	28.6	5.2	9.4	6.1		.5	213
	29.2	23.3	14.3	12.9	7.4		12.5	20.2
2 Low NonManual	45.8	29.2	5.2	9.4	10.4			96
	12.0	10.7	6.5	5.8	5.7			9.1
3 Small Selfemploy	34.7	24.0	19.0	5.8	15.7	.8		121
	11.5	11.1	29.9	4.5	10.9	9.1		11.5
4 Skilled Worker	30.4	25.1	5.3	22.2	15.9	1.0		207
	17.2	19.8	14.3	29.7	18.9	18.2		19.6
5 Semi-Unskilled W	25.1	24.3	5.0	17.8	27.0	.4	.4	259
	17.8	24.0	16.9	29.7	40.0	9.1	12.5	24.6
6 Farm Labor	22.4	13.4	9.0	16.4	34.3	4.5		67
	4.1	3.4	7.8	7.1	13.1	27.3		6.4
7 Farmer	33.0	22.0	8.8	17.6	7.7	4.4	6.6	91
	8.2	7.6	10.4	10.3	4.0	36.4	75.0	8.6
Column Total	366	262	77	155	175	11	8	1054
	34.7	24.9	7.3	14.7	16.6	1.0	.8	100.0

Pearson's R	.25994	.02902	8.73102	.00000 *4
Spearman Correlation	.25115	.02935	8.41550	.00000 *4

Appendix 3: Marginal distributions of father's and respondent's occupations, using detailed and crude classdications

a. Fathers occupation

CODE Value = 1 Detailed

FEGP (Col Pct)	COUNTRY AUS	AUT	GER	SWI	USA	Row Total
1 Service Class	26.7	12.6	13.1	29.2	26.0	896 23.0
2 Low NonManual	6.8	6.0	3.5	8.6	5.5	243 6.2
3 Small Selfemploy	11.9	8.5	11.9	1.9	7.4	329 8.5
4 Skilled Worker	21.8	29.2	37.8	30.1	26.9	1080 27.7
5 Semi-Unskilled W	17.9	21.2	19.6	15.4	17.1	700 18.0
6 Farm Labor	2.6	2.3	4.1	1.3	3.2	104 2.7
7 Farmer	12.2	20.2	10.0	13.5	14.0	540 13.9
Column Total	1098 28.2	613 15.8	489 12.6	684 17.6	1008 25.9	3892 100.0

Chi-Square	Value	DF
Pearson	220.75868	24
Likelihood Ratio	241.35894	24

CODE Value = 2 Crude

FEGP (Col Pct)	COUNTRY AUS	AUT	GER	SWI	USA	Row Total
1 Service Class	20.9	11.7	14.2	22.1	20.2	786 18.3
2 Low NonManual	11.5	11.0	14.4	22.8	9.1	569 13.3
3 Small Selfemploy	13.7	8.3	10.4	1.8	11.5	418 9.7
4 Skilled Worker	15.5	23.7	35.6	23.0	19.6	977 22.8
5 Semi-Unskilled W	23.8	22.2	16.8	14.8	24.6	899 21.0
6 Farm Labor	3.5	3.3	1.7	2.0	6.4	154 3.6
7 Farmer	11.1	19.8	6.8	13.5	8.6	488 11.4
Column Total	1083 25.2	630 14.7	808 18.8	716 16.7	1054 24.6	4291 100.0

Chi-Square	Value	DF
Pearson	389.83464	24
Likelihood Ratio	397.39217	24

b. Respondent's occupation

CODE Value = 1 Detailed

EGP (Col Pct)	AUS	AUT	GER	SWI	USA	Row Total
1 Service Class	37.4	21.0	23.3	44.2	40.3	1362 35.0
2 Low NonManual	25.9	24.5	22.5	21.3	20.5	897 23.0
3 Small Selfemploy	7.4	3.6	4.9	8.9	4.6	234 6.0
4 Skilled Worker	12.4	19.1	31.3	13.3	13.6	634 16.3
5 Semi-Unskilled W	12.7	20.4	15.1	8.9	19.3	594 15.3
6 Farm Labor	1.5	2.0	1.4	.6	.4	44 1.1
7 Farmer	2.7	9.5	1.4	2.8	1.3	127 3.3
Column Total	1098 28.2	613 15.8	489 12.6	684 17.6	1008 25.9	3892 100.0

Chi-Square	Value	DF
Pearson	347.52865	24
Likelihood Ratio	323.96517	24

CODE Value = 2 Crude

EGP (Col Pct)	AUS	AUT	GER	SWI	USA	Row Total
1 Service Class	34.4	20.2	21.2	38.8	34.7	1315 30.6
2 Low NonManual	27.0	30.8	38.2	29.3	24.9	1267 29.5
3 Small Selfemploy	9.3	4.0	4.2	11.7	7.3	321 7.5
4 Skilled Worker	11.6	13.8	21.0	11.7	14.7	622 14.5
5 Semi-Unskilled W	13.6	20.0	14.1	4.9	16.6	597 13.9
6 Farm Labor	.6	2.2	.5	.8	1.0	42 1.0
7 Farmer	3.4	9.0	.7	2.7	.8	127 3.0
Column Total	1083 25.2	630 14.7	808 18.8	716 16.7	1054 24.6	4291 100.0

Chi-Square	Value	DF
Pearson	370.46048	24
Likelihood Ratio	367.40572	24