

Intra-generational mobility and social distance: Work history analysis and occupational structure

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Patterns of intra-generational job transitions can be treated as indicators of social distance, whereby occupational units between which transitions are more frequent may be considered ‘closer’ to each other. Statistical models can be used to assign scores to occupational units which anticipate those distances. Early results suggest that a single dimensional hierarchy of scores, approximating differences in ‘generalised advantage’, best represents the structure of career transitions in Britain.

- Weber: *social class*: ‘the totality of those class situations within which individual and generational mobility is easy and typical’
social status: social interaction - marriage, friendship, common lifestyle
- Questions: (1) What kind of structure underlies each of these processes?
(2) How do the structures compare?
- Class or status groupings? Continua?
- Evidence that friendship, marriage and inter-generational mobility structures are very similar
- Also that a continuous hierarchy predominates over groups and boundaries

- Intra-generational mobility (careers, work-lives)
 - Double aspect of structure and individual movement
 - Pattern of individual movements demonstrates the existence/nature of a structure
 - Structure is reproduced through individual movements
 - Coherent means of describing occupational careers
- Compare examples taken from Cambridge Family History Study (using CAMSIS scores based on occupations at marriage of grooms, their fathers and fathers-in-law)

- Social distance and social space
 - Starting point is a cross-tabulation: e.g. respondents by friends, husbands by wives, fathers by children, jobs by succeeding jobs
 - Detailed job categories: information not lost by initial aggregation
 - Cells with higher relative frequencies indicate social closeness/similarity of row and column categories; conversely, lower relative frequencies indicate greater social distance/difference
 - Various techniques are now available for attempting to establish how much of the information on pair-wise similarity/difference can be accommodated in a simple space
- Scores from location on first, major dimension

- Preliminary work only on modern datasets
 - Intra-generational patterns may be more likely to display class boundaries
 - Education and qualifications largely fixed
 - Sectoral constraints
- If the intra-generational structure is markedly different, then scores based on it should be used to map individual work lives
- If very similar, then more easily-obtained, representative scores can be used

- **Resources** : Work history surveys, **BHPS** and **FWLS** (latter includes ethnic minority ‘boost’)
- Combined record, all start to end job transitions:

Features of the derived dataset: ‘Consecutive transitions’	
Number of respondents (males)	9675
Number of job-to-job transitions	40256
Number of non-diagonal transitions	28746
Transitions not treated as “pseudo-diagonals”	39190
	D.o.b :
Average respondent age per record	1948
“Soc-by-status” categories :	407
407={5 Empst * 371 SOC} - sparse	

Extensions :

- Other comparable datasets, both UK & abroad
- Account for other population groups / subgroups (gender, regional, ethnic, ..)
- Inclusion of non-employment positions
- Inclusion of duration / stability weighting
- Inclusion of all intra-career permutations

CAMSIS models for association between units:

			Ending Job Units			
			1	2	..	407
Occ Units ↓ →			750	700	..	100
Derived scores ↓ →						
Starting Job Units	1	720	30	15	..	0
	2	725	13	170	..	1

	407	110	0	2	..	80

- **Correspondence Analysis** for dimension scores
- **Goodman's RC-II** association models, row and column scores
- **Constraints / comparisons** in RC-II models

$$\hat{m}_{ij} = \hat{a}_i \hat{b}_j \exp(\hat{\tau}[\hat{x}_i \hat{y}_j])$$

$$= \hat{a}_i \hat{b}_j \hat{L}_{k(i,j)} \sum_1^{M1} \exp(\phi^m X_i^m Y_j^m) \sum_1^{M2} \exp(\hat{\zeta}^m [\theta_i^m \theta_j^m]) \underline{G}(\kappa_{(i,j)})$$

Latter allows to compare multiple models by :

- (multiple) dimension structures
- model grouping constraints
- fit statistics
- 'pseudo-diagonal' effects

Initial models' broadly coherent first dimension:

Selected rankings of soc-by-status titles (CA model, starting occupations)		
Top 10 titles (1-10)	Middle 10 titles (197-206)	Bottom 10 titles (398-407)
<u>M</u> Chartered & cert. accountants	<u>E</u> Postal workers, mail sorters	<u>Se0</u> Bricklayers, masons
<u>M</u> Software engineers	<u>E</u> Inspectors, testers (metal & electrical)	<u>E</u> Bricklayers, masons
<u>M</u> Medical practitioners	<u>M</u> Other craft & rel. occupa n.e.c.	<u>E</u> Preparatory fibre processors
<u>E</u> Software engineers	<u>M</u> Plant & machine operatives n.e.c.	<u>E</u> Carpenters and joiners
<u>E</u> Chartered & cert. accountants	<u>E</u> Precis. instrument makers & repairers	<u>E</u> Spinners, doublers, twisters
<u>E</u> Treasurers & co. financial managers	<u>E</u> Hairdressers, barbers	<u>E</u> Other textiles operatives
<u>Su</u> Computer analyst /progr.s	<u>E</u> Hospital porters	<u>E</u> Cabinet makers
<u>M</u> Treasurers & co financial managers	<u>Se0</u> Painters & decorators	<u>E</u> Plasterers
<u>E</u> Other Medical Professional	<u>E</u> Electrical engineer, not profess.	<u>Se0</u> Carpenters & joiners
<u>E</u> Architects	<u>Se</u> All others in misc. occupations n.e.c.	<u>E</u> Steel erectors

Employment Status : Se{0}: Self-Employed {no employees}; M: Manager; Su: Supervisor; E : Employee

- Careerist credentialised cf intelligensia?
- Some low crafts / building jobs (may be some PSD's)
- Other evidence that declining sector = disadv.
- First dimension *less* clearly separable

BHPS W9 Cambridge scale v's

Job transitions score



**Job-transitions scales' predictive validity
(Employed males BHPS W9)**

	<u>Positive Correl R</u>		<u>Associations Eta-2</u>	
	CAMSIS	Wkly pay (ln)	Educ, Deg/Dip	Tory vote
CA O	0.89	0.38	0.18	0.01
CA D	0.89	0.38	0.18	0.01
RC1.1 O	0.89	0.37	0.18	0.01
RC2.4 O	0.89	0.33	0.18	0.01
RC3.1 O=D	0.86	0.35	0.18	0.01

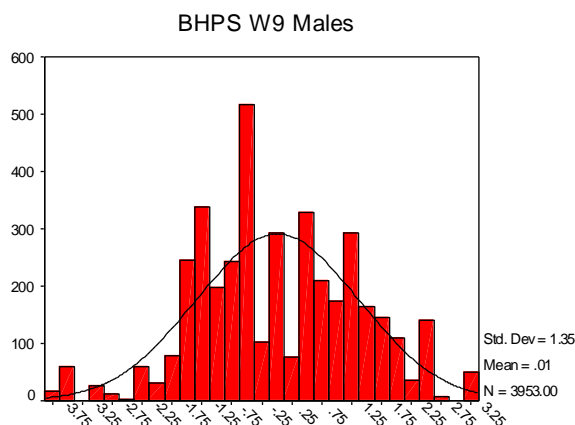
[O: Origin; D: Destination]

Others :

CAMSIS	-	0.37	0.18	0.02
Cambridge	0.90	0.36	0.19	0.01
Hope-Gld.	0.80	0.50	0.17	0.01

N ≈ 4000 in all cases

Job Transitions RC3.1 Starting Scores



Clustering into Categories : Eta-Squared BHPS Wave 7 (1997)

	CA	RC3	CAMSIS	H-G	Inc.
Schema (# categories):					
Educ. (4)	0.27	0.25	0.29	0.24	0.11
SEG (19)	0.78	0.74	0.80	0.82	0.32
HG gps (36)	0.79	0.79	0.81	1.00	0.35
EGP (11)	0.80	0.76	0.81	0.83	0.29
Wright (12)	0.63	0.57	0.60	0.69	0.27
Savage (4)	0.57	0.50	0.54	0.62	0.20
Martin (3)	0.60	0.54	0.58	0.65	0.21
SOC Maj (9)	0.77	0.73	0.79	0.75	0.25
Elias (4)	0.51	0.45	0.53	0.66	0.25
MAN (2)	0.65	0.66	0.70	0.53	0.10
RGSC (7)	0.77	0.73	0.80	0.79	0.25

- Job transition scales are not more clustered into any of these schema, than other scales

RC models allow comparison of model variations through aggregate fit statistics:

Equality of start and end scores?			
	Log-like	Df and Npar	BIC
1.1 One dim., start end scores unequal	-416468	163992 1656	-1604057
3.1 One dim., start = end scores	-417150	164802 846	-1611282
			N=40256

⇒ Equality more efficient; difference more interesting

Value of number of categories : categorical schema nested in general soc-by-status model?			
<i>(One dim., start & end scores unequal)</i>	Log-like	Df ; Npar	BIC 1
1.1 407 soc-by-status	-416468	163992 1656	-1604057
1.2 11 Goldth. classes	-466551	165607 41	-1521016
1.3 36 H-G unit groups	-459862	165511 137	-1533375
1.4 5 Status values	-477507	165631 17	-1499358
1.5 9 Major groups	-466959	165615 33	-1520283
			N=40256

⇒ Don't favour categorical schema for job-transitions

Conclusions

- Initial patterns: 1 dimensional hierarchy
- Slight differences from social interaction scale scores
- Fuller account of data structures may yield different dimension structures, eg :
 - Non-employment types
 - segmentation / regional differences
 - duration weighting
 - population subgroups
 - Other UK data sources / X-national
 - Pseudo-diagonals;