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# Multiple measures of socio-economic position and psychosocial health: proximal and distal measures

Archana Singh-Manoux, Paul Clarke and Michael Marmot

<b>Background</b>	The aim of this paper is to compare three models for exploring the links between different measures of adult socioeconomic position (SEP)—education, occupation, income—and psychosocial health. Model I is a basic univariate regression model with psychosocial health as the outcome and a measure of SEP as the predictor. Model II is a multiple regression model with psychosocial health as the outcome with all three measures of SEP allocated the same temporal position as predictors. Model III treats education, a distal measure of SEP, as antecedent to the proximal measures of SEP in the prediction equations linking SEP to health.
<b>Methods</b>	Participants were drawn from the Whitehall II study, a prospective cohort study of British civil servants. Data analysed here are from Phase 5 (1997–1999) of data collection, 7830 individuals in all. The measures of SEP and psychosocial health were assessed via a self-administered questionnaire.
<b>Results</b>	The three models can lead to completely different conclusions. Model III, our preferred model, shows education to have a stronger indirect effect on psychosocial health when compared to its direct effect. The indirect effect is due to the effect of education on proximal measures of social position, occupation, and income in this case.
<b>Conclusions</b>	Results reported here support the hypothesis that a comparison of the relative importance of the different measures of social position in predicting health is meaningless if the causal relationships among these measures are not accounted for.
<b>Keywords</b>	Socioeconomic position, proximal and distal measures, indirect and direct effects, psychosocial health
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The inverse association between various measures of socio-economic position (SEP) and both mental and physical health is widely recognized. In recent years there have been attempts to compare different indicators of SEP, using multiple regression analysis, in order to identify which has the strongest association with health outcomes.<sup>1–3</sup> A case has been made for occupational position being better than education as a discriminator of socio-economic differentials in health.<sup>1,4</sup> However, other studies have found stronger effects for income,<sup>2,5</sup> or for education.<sup>3</sup> Greater risk of morbidity or mortality in adulthood has principally been related to adult socio-economic circumstances.<sup>6</sup> However, it increasingly appears that ill health in adulthood is linked to an accumulation of risk factors over the course of an individual's life.<sup>7–13</sup> For example,

the risk of respiratory disease in adulthood,<sup>9</sup> or premature death<sup>14</sup> has been found to accumulate over childhood and adolescence.

Multivariate analyses aimed at comparing different indicators of SEP in predicting health have led to inconsistent results. This can be attributed to three reasons:

## Different measures implicate different pathways

Different measures of SEP represent different facets of social position and are differently related to health outcomes.<sup>15</sup> The standard markers of SEP—education, income, and occupation have been found to have stronger or weaker relationships with various risk behaviours,<sup>16</sup> resulting in differential relationship with health outcomes.

## Outcome/disease specificity

Not all ill-health outcomes have the same 'etiologic period'.<sup>17</sup> There is some evidence to suggest that childhood circumstances

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may have closer links with risk of coronary heart disease,<sup>18–20</sup> and not to the same extent with other outcomes like cancer.<sup>14</sup>

**The social gradient is sensitive to the proximal/distal nature of the indicator of socio-economic position employed**

Another explanation for the variable relationship between indicators of SEP and health is likely to be related to the proximal (measure of SEP closer in time to a health outcome) or distal (SEP measure more distant in time from health outcome measure) nature of the particular measure of social position being employed. Proximal measures of social position may discriminate better as they portray the current and accumulated socio-economic circumstances of the individual more accurately.

This third explanation of the variation in the social gradient is the focus of this paper. The idea that there is a valid basis for causal and temporal ordering in the various measures of SEP has been advanced before.<sup>21,22</sup> An analysis of the socio-economic status of individuals at several stages of their lives showed that socio-economic origins have enduring effects on adult mortality through their effect on later socio-economic circumstances such as education, occupation, and financial resources.<sup>23</sup> Distal measures of social position can be seen to affect health directly; and indirectly through their effects on the proximal measures of social position.

This paper considers three different statistical models for analysing the relationship between psychosocial health and three measures of social position: education, occupation, and income. The first model is a simple univariate regression model with one predictor, a measure of SEP, and one health outcome. The second model (Figure 1) is a multiple regression model that ignores temporal relationships between the indicators of SEP. The third model (Figure 2) is derived from the life-course perspective where education is seen to structure occupation and income. In this model education is antecedent to both occupation and income.

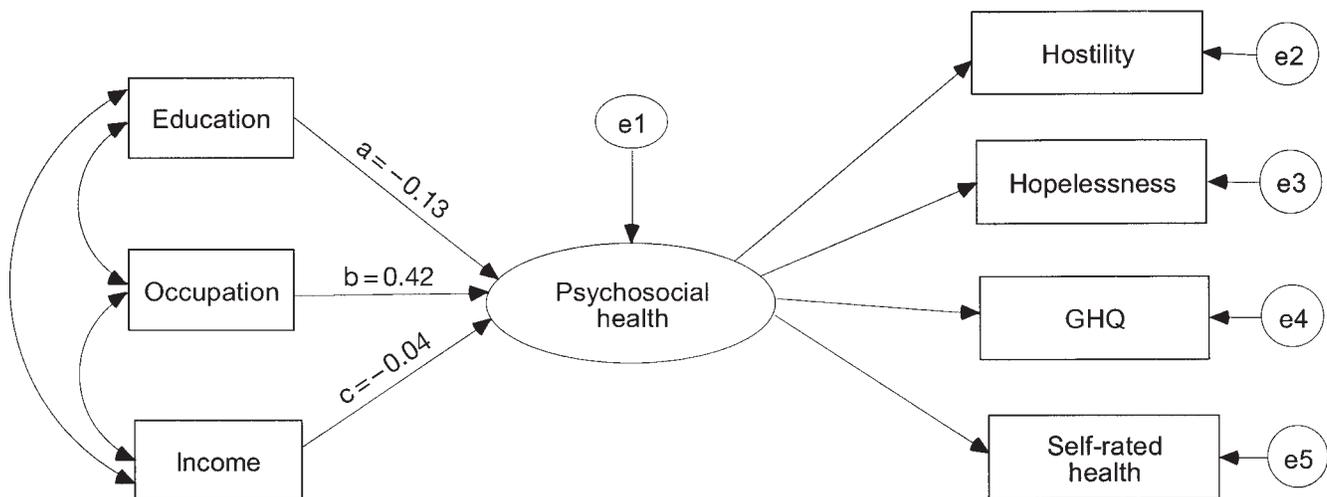
We hypothesize that the third model will permit a better understanding of the effects of education, a distal measure of SEP here, as it will allow us to explore both the direct and indirect effects of education on psychosocial health. The distal quality attributed to education in relation to occupation and income is based on the assumption that most individuals attain their educational qualifications before being employed or having an income. Therefore, the proximal or distal quality of a measure of SEP depends on its temporal place in the life course. All three models will be explored separately in men and women as there is extensive research evidence showing gender-specific relationships between measures of SEP and health.<sup>24–27</sup>

**Participants and Methods**

**Participants**

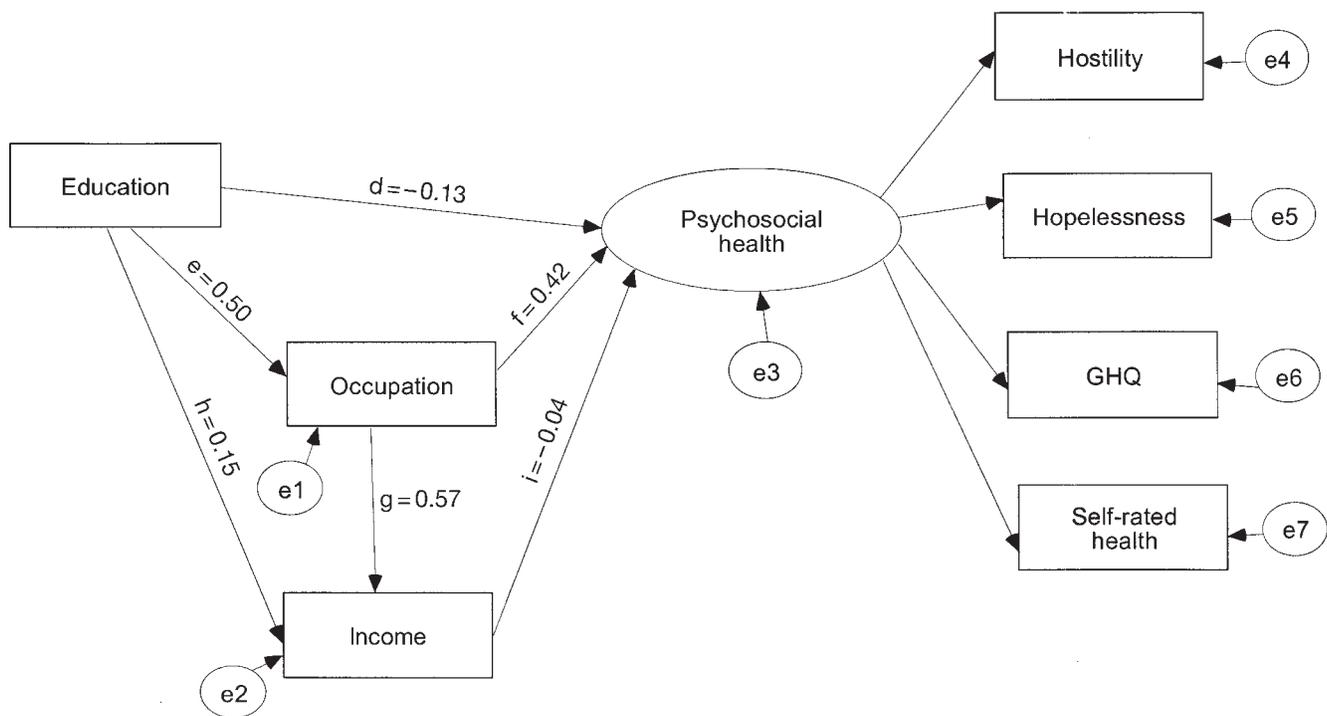
The target population for the Whitehall II study was all the London-based office staff, aged 35–55, working in 20 Civil Service departments.<sup>28</sup> With a response rate of 73%, the final cohort consisted of 10 308 participants (6895 men and 3413 women) at the first phase of data collection between 1985 and 1988. The screening at baseline (Phase I) involved a clinical examination, and a self-administered questionnaire containing sections on demographic characteristics, health, lifestyle factors, work characteristics, social support, and life events. Since baseline screening five further data collection rounds have been completed. Successive phases alternate between collecting data by self-administered questionnaire only and collecting data via a clinical screening in addition to questionnaire completion. The most recent phase of data collection (Phase VI) was completed between 2000–2001.

The data for these analyses are drawn from Phase V of the Whitehall II study, data for which was collected between 1997–1999. Response at Phase V was 76% (7830 participants) of those who participated at baseline screening, 12 years previously. In addition to those who failed to respond to invitations to



**Figure 1** Direct effects of education, income, and occupation on psychosocial health (Model II), path coefficients shown for men in the Figure

Notes: a, b, and c are standardized regression coefficients reflecting the effect of education, occupation, and income on psychosocial health. 'e' terms (1 to 5) represent the error terms associated with endogenous variables in the model.



**Figure 2** Direct and indirect effects of education, income, and occupation on psychosocial health (Model III), path coefficients shown for men in the Figure

Notes: d, e, f, g, h and i are standardized regression coefficients reflecting the effects (direct and indirect) of education, occupation, and income on psychosocial health.

'e' terms (1 to 7) represent error associated with endogenous variables in the model.

participate, non-responders included participants who had died or those who could not be traced. The loss to follow-up is not influenced by age ( $P = 0.65$ ) or sex ( $P = 0.51$ ) but is influenced by employment grade ( $P < 0.001$ ), with the attrition rate being significantly higher in the lower grades.

### Measures

All measures used in this study were drawn from the questionnaire administered at Phase 5 of data collection.

#### Education

Education was measured as the highest level of education achieved, with the respondent choosing one of the 11 categories in the questionnaire. This was regrouped into five standard hierarchic levels: (1) no formal education; (2) lower secondary education; (3) higher secondary education; (4) university degree; and (5) higher university degree.

#### Occupation

Occupational position was assessed via civil service employment grade. The 12 non-industrial grade levels were regrouped to lead to 6 employment grades.

#### Income

Respondents were asked to pick a category that corresponded most closely with their annual personal income ('amount received annually from salary or wages, or pensions, benefits and allowances before deduction of tax'). There were eight categories in all ranging from '<£9999' to '>£70 000'. For the purposes of analysis the two highest and the two lowest personal income categories

were collapsed to leave six categories. These categories are as follows, 1  $\geq$  £50 000; 2 = £35 000–£49 999; 3 = £25 000–£34 999; 4 = £20 000–£24 999; 5 = £15 000–£19 999; and 6  $\leq$  £14 999.

#### Psychosocial health

Psychosocial health was conceptualized as a latent variable measured via four indicators. These were: *Hostility*, measured using 23 items (Cronbach's alpha = 0.82) from the Cook-Medley hostility scale.<sup>29</sup> *Hopelessness*, measured using six items adapted from Beck's Hopelessness scale.<sup>30</sup> These six items (Cronbach's alpha = 0.80) were measured on five-point scales. *General Health Questionnaire* (GHQ) is a 30-item screening questionnaire for minor psychiatric disorder suitable for use in the general population samples.<sup>31</sup> The GHQ items were scored on four-point Likert scales (0–3) in order to assign each individual a score reflecting the degree of intensity of psychological distress reported by the individual. *Self-rated health* was assessed on a five-point scale via the following question: 'In general, would you say your health is excellent/very good/good/fair/poor'. High scores on all four indicators imply poor psychosocial health.

#### Modelling and statistical methods

The first step in our analysis consisted of setting up a measurement model for the elaboration of the latent health construct. This involved specifying the indicators of the latent construct, psychosocial health in this case, and assessing its reliability. Specification of the measurement model resembles confirmatory factor analysis in that the indicators used to define the latent

construct are theoretically driven. Psychosocial health has been assessed via four observed variables: hostility, hopelessness, GHQ, and self-rated health. The appropriateness of the measurement model involves examination of the statistical significance of each factor loading and calculation of the composite reliability. Composite reliability is a measure of the internal consistency of the indicators, depicting the extent to which they indicate the common latent construct.<sup>32</sup> Composite reliability of around 0.70 is seen to be an acceptable level.<sup>32</sup>

Once the psychosocial health measure was established the effects of SEP on health were estimated using Models I, II, and III. All three models treat the different indicators of SEP as continuous variables so the interpretation of the regression coefficients in all three models is similar. Model I is a univariate regression model; three such models are specified, each with psychosocial health as a dependent variable and a measure of SEP as the independent variable. Model II is a multiple linear regression model with the three measures of SEP as independent variables. A path diagram for Model II is depicted in Figure 1. All observed variables in the figures are denoted by rectangular boxes and unobserved variables in ovals. The unobserved variables are latent constructs and error terms. Error terms are associated with all endogenous variables and represent measurement error along with effects of variables not measured in the study. Correlations between variables are denoted by double-headed arrows and causal paths by single-headed arrows. Model II (Figure 1) compares the relative importance of the three measures of SEP in predicting psychosocial health. Paths *a*, *b*, and *c*, denoted by single headed arrows, link all three measures of social position to psychosocial health. These paths estimate the effect of a measure of social position on psychosocial health while adjusting for the effects of the other measures of SEP.

Model III is depicted in Figure 2. It reflects temporal ordering among the different measures of SEP. Education is the distal measure of SEP, while occupation and income are proximal measures of SEP. Therefore, education is theorized to have both a direct effect (path *d*, denoted by single headed arrow between education and psychosocial health) and indirect effect on psychosocial health. The indirect effect of education on psychosocial health involves three pathways: the first is path *ef*, the second is path *egi*, and the third is path *hi* (Figure 2).

Structural equation models<sup>33</sup> (SEM) were used to fit all three models, with a measurement model used to elaborate the latent psychosocial health construct. It was convenient to fit all three models using a SEM software package, but equally Models I and II could have been fitted using a standard regression package with the latent health outcome calculated separately. Indeed, the health outcome could be a manifest variable, in which case the measurement model would be unnecessary. It should therefore be emphasized that the focus here is on using SEM to model the temporal ordering between the three measures of SEP and psychosocial health in Model III, and not specifying the measurement model for psychosocial health.

The indirect effects of a variable are mediated through intervening variables.<sup>34</sup> To assess model fit, root mean square error of approximation (RMSEA) and comparative fit index (CFI) were used.<sup>33,35</sup> An RMSEA value of below 0.05 and a CFI value close to 1 indicates a good fitting model. The analyses were carried out using AMOS version 4.01.<sup>36</sup> The AMOS program

allows maximum likelihood estimation based on incomplete data, known as full-information maximum likelihood (FIML). This approach is based on the direct maximization of the likelihood of all observed data, not just from cases with complete data. Full-information maximum likelihood is preferable to estimation based on complete data (the listwise deletion approach) as FIML estimates will show less bias and be more reliable than the listwise deletion approach even when data deviate from missing at random and are non-ignorable.<sup>37</sup> The results were checked using asymptotically distribution free methods (as some of the data are not normally distributed) and similar results to FIML were found. Bollen's incremental fit-index values were also examined as these are least biased due to non-normality of variables and they were all above 0.99.

## Results

Table 1 shows the breakdown of the sample by measures of SEP used in this study. Initial examination of the data consisted of an examination of the bivariate relationships between the three measures of SEP and the four indicators of psychosocial health used in this paper (Table 1). High scores on all four measures of psychosocial health represented poorer well-being. As expected, there was an inverse association between SEP and indicators of psychosocial health. This implies that irrespective of the measure of SEP used, low social position was associated with higher levels of hostility, hopelessness, and poorer self-rated health. The test for trend shown in Table 1 was done using a one-way ANOVA. Minor psychiatric disorder as assessed by the GHQ showed a significant inverse relationship only with the measure of occupational position.

The measurement model was specified separately for men and women. Among men the factor loadings of the different indicators on psychosocial health were as follows: hostility: 0.51 ( $P < 0.001$ ), hopelessness: 0.75 ( $P < 0.001$ ), GHQ: 0.67 ( $P < 0.001$ ), self-rated health: 0.45 ( $P < 0.001$ ). The factor loadings in women were hostility: 0.51 ( $P < 0.001$ ), hopelessness: 0.75 ( $P < 0.001$ ), GHQ: 0.68 ( $P < 0.001$ ), self-rated health: 0.42 ( $P < 0.001$ ). All four indicator variables had significant loadings on psychosocial health among both men and women. The composite reliability of the latent construct psychosocial health was 0.69 in both men and women, implying that the four observed variables reliably measure the latent construct psychosocial health.

The results reported in Table 1 are further explored using three separate univariate regressions with the latent construct psychosocial health as the outcome (Table 2, Model I). In these analyses all three measures of SEP were used, individually and one at a time, to predict psychosocial health. All measures of social position have a significant effect on the outcome measure. Furthermore, all regression coefficients were positive indicating the high scores on the measures of social position (implying lower social position) are associated with high score on psychosocial health (implying poorer health). Results for all three models explored in this study are reported using standardized regression coefficients. These coefficients are calculated from standardized data and reflect the impact on the outcome variable of a change of one standard deviation in the predictor variables. For example, according to Model I (Table 2, Model I), an increase of one standard deviation in occupational position

**Table 1** Means of psychosocial health indicators<sup>a</sup> for categories of socio-economic position measures

		f (%)	Hostility		Hopelessness		GHQ <sup>b</sup>		Self-rated health		
			Male M (SD)	Female M (SD)							
<b>Education</b>	<b>high</b>	1	13.7%	5.57 (4.03)	5.28 (3.89)	7.43 (3.27)	7.23 (2.98)	24.35 (10.33)	23.42 (9.49)	2.60 (0.89)	2.28 (0.84)
		2	21.9%	6.09 (4.29)	5.60 (4.29)	7.89 (3.50)	7.62 (3.22)	24.60 (10.43)	23.90 (10.10)	2.55 (0.89)	2.50 (0.89)
		3	26.7%	6.07 (4.37)	6.04 (4.27)	7.54 (3.42)	7.84 (3.42)	23.53 (10.66)	24.32 (11.09)	2.52 (0.90)	2.51 (0.88)
		4	26.7%	6.29 (4.52)	6.13 (4.35)	7.76 (3.41)	7.94 (3.56)	23.48 (10.63)	24.23 (10.28)	2.59 (0.87)	2.58 (0.88)
		<b>low</b>	5	11.0%	6.56 (4.41)	6.89 (4.44)	8.52 (3.80)	8.05 (3.65)	25.00 (11.27)	23.77 (10.35)	2.73 (0.89)
<i>Test for Linearity</i>			<i>P</i> < 0.0005	<i>P</i> < 0.0005	<i>P</i> = 0.001	<i>P</i> = 0.001	<i>P</i> = 0.49	<i>P</i> = 0.43	<i>P</i> = 0.02	<i>P</i> < 0.0005	
<b>Occupation</b>	<b>high</b>	1	20.1%	4.92 (3.72)	4.88 (3.78)	6.74 (2.99)	6.93 (3.07)	22.30 (9.35)	22.67 (9.20)	2.36 (0.85)	2.31 (0.88)
		2	21.4%	5.59 (3.92)	5.54 (3.97)	7.25 (3.07)	7.44 (3.15)	23.51 (9.86)	23.55 (10.68)	2.47 (0.84)	2.44 (0.86)
		3	13.6%	5.79 (4.13)	6.04 (4.09)	7.65 (3.31)	7.81 (3.14)	24.12 (11.16)	23.92 (10.06)	2.54 (0.87)	2.49 (0.85)
		4	16.5%	6.34 (4.17)	6.03 (4.28)	7.89 (3.42)	7.86 (3.41)	24.12 (11.16)	24.54 (10.15)	2.67 (0.86)	2.57 (0.86)
		5	13.6%	7.44 (4.89)	6.92 (4.65)	8.97 (3.99)	8.44 (3.52)	26.44 (12.97)	24.95 (10.96)	2.79 (0.96)	2.61 (0.88)
<b>low</b>	6	14.8%	8.04 (5.24)	7.35 (4.90)	9.33 (3.88)	8.83 (3.91)	26.10 (11.13)	25.53 (11.58)	2.92 (0.90)	2.86 (0.92)	
<i>Test for Linearity</i>			<i>P</i> < 0.0005								
<b>Income</b>	<b>high</b>	1	9.4%	5.16 (3.67)	5.11 (4.03)	6.89 (3.02)	7.08 (3.10)	24.31 (9.76)	23.18 (9.15)	2.42 (0.86)	2.32 (0.83)
		2	15.2%	5.47 (3.79)	5.76 (3.99)	7.29 (2.99)	7.48 (3.24)	24.20 (9.83)	24.76 (10.45)	2.48 (0.85)	2.44 (0.91)
		2	16.6%	5.62 (4.09)	5.71 (4.02)	7.45 (3.46)	8.00 (3.36)	24.07 (10.76)	24.48 (10.47)	2.55 (0.86)	2.45 (0.86)
		4	14.3%	5.95 (4.33)	5.72 (4.39)	7.70 (3.52)	7.46 (3.22)	23.98 (11.18)	24.51 (11.02)	2.53 (0.87)	2.54 (0.88)
		5	14.5%	6.58 (4.71)	6.21 (4.49)	8.19 (3.53)	8.10 (3.65)	24.21 (11.27)	23.23 (10.53)	2.58 (0.89)	2.62 (0.85)
<b>low</b>	6	30.0%	7.01 (4.75)	6.61 (4.51)	8.37 (3.73)	8.06 (3.49)	24.32 (11.04)	23.74 (10.28)	2.76 (0.93)	2.65 (0.92)	
<i>Test for Linearity</i>			<i>P</i> < 0.0005	<i>P</i> < 0.0005	<i>P</i> < 0.0005	<i>P</i> < 0.0005	<i>P</i> = 0.79	<i>P</i> = 0.46	<i>P</i> < 0.0005	<i>P</i> < 0.0005	

<sup>a</sup> High scores on all indicators denotes poor psychosocial health.

<sup>b</sup> General Health Questionnaire.

**Table 2** Effects (standardized regression coefficients) of indicators of socio-economic position<sup>a</sup> on psychosocial health<sup>b</sup>

<b>Sex</b>	<b>Indicator of socio-economic position</b>	<b>Model I</b>	<b>Model II</b>	<b>Model III</b>	
		Univariate effect	Direct effect	Direct effect	Indirect effect
M	Education	0.05 ( <i>P</i> = 0.01)	-0.13 ( <i>P</i> < 0.001)	-0.13 ( <i>P</i> < 0.001)	0.19 ( <i>P</i> < 0.001)
	Occupation	0.33 ( <i>P</i> < 0.001)	0.42 ( <i>P</i> < 0.001)	0.42 ( <i>P</i> < 0.001)	-0.02 ( <i>P</i> = 0.10)
	Income	0.17 ( <i>P</i> < 0.001)	-0.04 ( <i>P</i> = 0.10)	-0.04 ( <i>P</i> = 0.10)	NA
F	Education	0.10 ( <i>P</i> < 0.001)	-0.05 ( <i>P</i> = 0.12)	-0.05 ( <i>P</i> = 0.12)	0.16 ( <i>P</i> < 0.001)
	Occupation	0.25 ( <i>P</i> < 0.001)	0.36 ( <i>P</i> < 0.001)	0.36 ( <i>P</i> < 0.001)	-0.07 ( <i>P</i> < 0.001)
	Income	0.10 ( <i>P</i> < 0.001)	-0.12 ( <i>P</i> < 0.001)	-0.12 ( <i>P</i> < 0.001)	NA

<sup>a</sup> High scores on all measures of social position denote low social position.

<sup>b</sup> High score on psychosocial latent construct denotes poorer health.

in men (indicating lower SEP) increases 0.33 standard deviation in psychosocial health (indicating poorer health). The advantage of standardized regression coefficient is that it eliminates the problem of dealing with different units of measurement, allowing assessment of the relative importance of predictor variables to be made.

Model II (Figure 1) is essentially a multiple regression of health on the three SEP measures, allowing estimation of the effect of each measure of SEP on psychosocial health while controlling for the effects of the other two measures. Model III (Figure 2) is an SEM model allowing estimation of both direct and indirect effects of education, a distal measure of SEP in this analysis. The purpose of the analysis is not to compare Models II and III in terms of how well they fit the data, rather it is to demonstrate how treating a distal predictor as a proximal predictor can give misleading results. In fact, both these models fit the data equally

well; for example the combined fit for men and women is:  $\chi^2 = 514.96$ , d.f. = 22, MSEA = 0.047, CFI = 0.995. This is because they are equivalent models,<sup>38</sup> the difference being that Models II and III provide alternative ways of looking at the data.

As is clear from Figure 1, Model II treats the three measures of SEP as being situated at the same point in temporal space. It allowed us to examine the direct effects of each measure of social position on psychosocial health. In men, the direct effect is significant for education and occupation but not for income. The negative coefficient (Table 2) for education indicates that a low score of education (implying higher education) is associated with a high score on psychosocial health (implying poorer health). The positive direct effect of occupation on psychosocial health implies that higher score on occupation (implying lower position) is associated with high score on psychosocial health (implying poorer health). The results obtained here (for both

education and income) are different from the univariate model, essentially because the effect of each indicator of SEP on health in Model II is analysed while controlling for the effects of the other two measures.

For women, the direct effects of SEP on psychosocial health (Table 2) are significant for occupation and income. A high score on occupation (implying lower SEP) is related to a higher score on psychosocial health (implying poorer health), whereas a low score on income (implying higher income) is associated with a high score on psychosocial health (implying poorer health). The size of the direct effect of the three measures of SEP used on psychosocial health is strongest for occupation, in both men and women.

As depicted in Figure 2, Model III takes into account hypothesized temporal relationship between the measures of SEP. Education was seen to have direct effect *d* on psychosocial health and indirect effects *ef*, *egi*, and *hi* on psychosocial health. From Table 2, it can be seen that the direct effects of all three measures of SEP remained the same in Model III. The difference between Model II and III is that the latter permits the estimation of indirect effect. The indirect effect of education in men was calculated as following: path *ef* ( $0.50 \times 0.42 = 0.21$ ) + path *egi* ( $0.50 \times 0.57 = -0.04$ ) + path *hi* ( $0.15 \times -0.04 = -0.01$ ); leading to a total indirect effect of 0.19 (Table 2). The indirect effect implies that a higher score on education (implying lower level of education) is associated with a higher score on psychosocial health (implying poorer health). The same pattern of results holds for the indirect effects of education on psychosocial health in women.

In our conceptualization of the direct and indirect effects model, occupation was allowed to have an effect on personal income (Figure 2). Therefore, occupation had a direct effect *f* and an indirect effect *gi* on psychosocial health. Income was hypothesized only to have a direct effect on psychosocial health. The indirect effect associated with education was relatively large for both men and women. Occupation was the strongest predictor of psychosocial health in both men and women, poorer occupational position was associated with poor psychosocial health. High personal income was not found to be protective of psychosocial health in this sample.

## Discussion

This paper set out to show that distal measures of SEP affect health both directly and indirectly, and that ignoring the indirect effects will produce misleading conclusions concerning the importance of measures of SEP to health. The indirect effect of distal measures of SEP is mediated by the effect of distal measures of SEP on the proximal measures. In other words, education influences health outcomes both directly; and indirectly through its effect on occupation and income. Here we have illustrated this using psychosocial health but conclusions drawn here potentially apply to any other health outcome.

The direct effect of education was assessed by adjusting for the effects of occupation and income (Figure 1) in multiple regression analysis (Model II). This is standard practice in analysis where the aim is to identify 'independent' effects of predictors, measures of SEP in this case. The direct effect of education suggests that high educational achievement is predictive of poorer psychosocial health. However, this conclusion, based on

multiple regression where the temporal aspect of different measures of SEP is ignored, is correct but misleading. From Table 2, the direct effect of education on psychosocial health for men is  $-0.13$ . This is not erroneous; it is plausible to believe that the better-educated have poorer psychosocial health than those less educated given that they have achieved the same income and occupational status. However, the indirect effect of education on psychosocial health is positive, 0.19 (from Table 2). We would suggest that this is a better indication of the effect of education on psychosocial health through the life course. In fact, this was seen in the simple analysis provided by Model I, with the effect of education on psychosocial health estimated without adjusting for the effects of the proximal measures of SEP (occupation and income, in this paper).

Different indicators of SEP—parental social class, educational, occupational position, income, etc.—are routinely compared for their effects on ill health and mortality. These comparisons ignore the fact that different measures of SEP are linked to different phases of the life course, and that they are also associated with each other. Taking into account the links between different measures of SEP changes the conclusions drawn from comparative analyses. The results reported here show different signs for direct and indirect effects, with the direct effects model (Model II) not showing higher educational level to be predictive of good psychosocial health. It is only when the indirect effects of education are considered, does the relationship between education and psychosocial health become clear.

The existence of socio-economic inequality in health is readily accepted. However, the causal pathways linking SEP to poor health are only beginning to be explored. It is likely that education informs lifestyles and attitudes towards and knowledge of health behaviours. Similarly, occupational position is likely to be important due to the effects of the work environment, both physical and psychological, on health. Income has theoretically been linked to the material deprivation pathway, the lack of income preventing basic needs from being met. In fact, theorists propose a wider effect of education on health. Ross and Wu<sup>22</sup> have advanced three possible pathways between education and health:

### *Work and economic conditions*

Higher education leads to better jobs, lower unemployment and thus better work conditions.

### *Social-psychological resources*

Higher education arms individuals with a sense of personal control, also allowing them to establish better social support.

### *Health lifestyle*

Individuals who have a better education have a healthier lifestyle—they exercise more, drink moderately and smoke less.

It is likely that the recent trend in social inequalities research to compare the various indicators of SEP is driven by a need to understand varying results. American studies have traditionally used education to measure SEP,<sup>39</sup> while the British studies have used occupational position.<sup>28</sup> The use of education has been championed on the grounds that it is less liable to reverse causation, is stable over the life course, and can be applied to those outside work.<sup>40</sup> The disadvantage with education is that it does not capture the changes in adult socio-economic circumstances or accumulated SEP.

In this paper we have chosen to ignore childhood socio-economic circumstances for the sake of simplicity. Early childhood circumstances are likely to influence adult health through both direct and indirect effects. The direct effects may involve susceptibility to disease through biological mechanisms or through the socialization of unhealthy behavioural practices or psychological response strategies. The indirect effects are likely to be mediated by adult SEP achieved by individuals. There is some evidence to suggest that childhood socio-economic circumstance shows an independent effect on both adult health and on health related behaviour.<sup>40</sup>

The results presented here attempt to show that when different measures of SEP are being compared for their effect on health, the interrelationships between them should be accounted for. Conclusions drawn from studies where the various indicators of SEP are allocated the same temporal space will almost certainly be misleading. We have used a simple example to show that proximal and distal measures of SEP operate differently due to the interrelationship among them. These associations among the various measures of SEP will be critically important in models where pathways linking SEP to health along with possible confounders are explicated.

Conclusions similar to the ones drawn in this paper were recently published by Weitkunat and Wildner.<sup>41</sup> In their paper, unequal proximity of different variables is considered in relation to predicting health. Psychological factors are hypothesized as being more distal than biological factors and it is hypothesized that assigning them equal proximity will produce misleading results. The authors used a simulation study to show that multiple regression analysis can give misleading results when analysing 'sequentially caused relationships' because it treats a 'distant causal factor' as being equally distant to the outcome as a 'proximal causal factor'. The authors used this artificial example to show that pathway analysis is correctly able to identify the true causal sequence. The variables we examined were all measures of adult SEP, and we have shown that 'unequal proximity' is an issue even when predictor variables are similar in nature. In our paper, proximity is considered in terms of temporal place of a measure of SEP in relation to a health outcome. However, the analogy with Weitkunat and Wildner is clear, offering support for our conclusions.

A recent paper by Didelez and colleagues<sup>42</sup> also focuses on the necessity of choosing appropriate statistical models as being key to obtaining valid and meaningful results in epidemiological studies. The limitations of restricting analyses to regression models is discussed, with the authors emphasizing the need for quantitative data analyses to reflect advances in conceptual and theoretical models. Didelez *et al.*<sup>42</sup> discuss the relationship between research and theory concluding that '... oscillation, refinement, and replication is fundamental to providing the rationale for inclusion and modelling of variables'.

There are some important areas of further work that need to be addressed before causal interpretations can be made. The data reported here are cross-sectional and these models need to be replicated with longitudinal data before firm conclusions about the causal effect of each variable on health can be drawn. Also, other health outcomes need to be analysed in order to examine the direct and indirect effects of proximal and distal measures on different health outcomes. Despite these shortcomings, this paper offers an example of the way in which specific

theoretical relationships between variables can be examined. It should also be noted that SEM is obviously not being advocated as a panacea, but only as one of the ways in which theoretically driven analyses can be specified. We have discussed recent papers that have used other techniques that address the need for a close relationship between theory and analysis: path analysis,<sup>41</sup> and graphical chain models.<sup>42</sup>

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## Commentary: Structural equation modelling in epidemiology: some problems and prospects

Geoff Der

In their editorial on a life course approach to chronic disease epidemiology Ben-Shlomo and Kuh predict that 'techniques ... currently under-utilized in conventional epidemiological

analyses, for example structural equation modelling, path analysis, G-estimation and multi-level modelling, will become more widespread'.<sup>1</sup> In this issue, Singh-Manoux and colleagues<sup>2</sup> present a structural equation model which offers a simple and appealing solution to a type of problem that will be familiar to epidemiologists. The problem, in their example, is that the unconditional effect of education on health is positive,

as expected, but when conditioned on, or adjusted for, occupational grade and income, the direction of the effect is reversed.

Situations like this are common where predictors are correlated and typically involve imprecise estimates, due to large standard errors, or unstable estimates that are sensitive to changes in relatively few data points. The problems are more severe the greater the degree of association among the predictors with the most severe form occurring when there is a perfect linear relationship between them. The term 'collinearity', strictly speaking, refers to this extreme case, although its usage has now been extended to cover less than perfect association. In observational research, true collinearity is very rare and apparent examples are much more likely to be due to model misspecification.

Perhaps by analogy with true collinearity, 'collinearity' in the looser sense is often treated as a technical problem and one to be overcome by technical means, for example: variable selection, principal component scores, or techniques like ridge regression. However, it can also be viewed as an issue of interpretation. Singh-Manoux and colleagues take this line describing the negative conditional effect of education as 'misleading' although not 'erroneous' and they add 'it is plausible to believe that the better educated have poorer psychosocial health than those less educated *given that* they have achieved the same income and occupational status'. With correlated predictors, it is the subjects who do not conform to the pattern that provide information about the conditional effects and, for highly correlated predictors, these may be few in number and heterogeneous. In such cases it can be useful to ask 'who are these people and why are they exceptional?' and even to examine the data for possible answers. Substantial measurement error may be one answer.

In contrast to the technical remedies for collinearity, the solution proposed by Singh-Manoux and colleagues imposes a temporal ordering on the predictors, which yields more plausible results.

For those inclined towards a life course approach this may be particularly appealing. Theoretically important variables are retained rather than being dropped or rendered less interpretable as principal component scores and they are ordered, or structured, to represent a theoretically based model. Add to these advantages the prospect that regression dilution can be reduced by employing latent variables, and the use of full information maximum likelihood to reduce the impact of missing values, and structural equation models (SEM) begin to seem attractive indeed.

Why then are they still under-utilized in epidemiology? Unfamiliar terminology and methods? The fact that some (LISREL) models appear to be formulated entirely in Greek? Or the dozens of vicariously related fit statistics? More probably it is because the most popular SEM programs (LISREL, EQS and AMOS) lack many of the basic features available in general or generalized linear models.

Structural equation models, in common with many other multivariate techniques, assume that all the variables employed are continuously and normally distributed. Adhering strictly to this assumption would severely restrict their use and exclude some of the control variables routinely included in models for other health outcomes, e.g. sex, social class, and smoking. The paper by Singh-Manoux *et al.* typifies the more pragmatic use of

SEM. None of their predictors are continuous and 'some of the data are not normally distributed' so that the results are checked using distribution free methods. The one dichotomous variable, sex, is handled partly by separate analysis and partly by multi-group analysis: a technique whereby the separate covariance matrices for subgroups are analysed jointly and subgroup differences are modelled by imposing or relaxing across group constraints. However, multi-group analysis is usually confined to a single variable. It is not uncommon to see published models that simply include dichotomous variables, like sex, as if they were continuous normal covariates, with or without the usual advice to treat the results with caution (How much caution?). What would a newcomer make of a method whose practitioners frequently flout its basic assumptions? What if they were also told that there is debate about how to include interactions and non-linear relationships into such models?<sup>3</sup>

Then there is the problem of equivalent models. In the paper, models II and III are equivalent—that is, they both fit the data equally well. But model III is not the only other model equivalent to model II. Take Figure 2, for example: the three boxes for the predictors of health could be re-labelled with any of the five other permutations of 'Education', 'Occupation' and 'Income' and still yield equivalent models. Choosing the most plausible model makes sense, but care must be taken to avoid circular reasoning.

Having said all that, SEM is a developing area and methods which remove some of the limitations are percolating through to mainstream packages. At the same time, there are new programs, such as *Mx*<sup>4</sup> and *Mplus*,<sup>5</sup> which are much more flexible, both in the range of data types that can be accommodated and the models that can be fitted.

Structural equation models can be thought of as combining path analysis with latent variables. Singh-Manoux and colleagues emphasize the advantages of the path analysis aspect but the incorporation of latent variables is at least as important. Indeed, Muthén<sup>6</sup> argues that the notion of latent variables, when expanded to include latent categorical variables, subsumes a wide range of statistical concepts and their associated methods of analysis. These include random effects, multilevel models, growth curve models, latent class analysis, and cluster analysis. His general latent variable modelling framework may already contain most of the tools needed for a life course approach and surely that *is* an appealing prospect.

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