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Summarising multiple deprivation

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Summarising multiple deprivation

Abstract

Deprivation scales derived from multiple, typically dichotomous, indicators, are increasingly being used to measure households' standards of living, and to complement poverty measures based on low income. We propose a type of multivariate probit model that generalizes the classical measurement model underlying the deprivation scale approach, allowing for heterogeneity and explicitly recognizing the dichotomous nature of the deprivation indicators. The arguments are illustrated with an examination of basic lifestyle deprivation in Britain in the mid-1990s.

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1. Introduction

It is widely agreed nowadays that being poor does not simply mean not having enough money. It means, more generally, a lack of access to resources enabling a minimum style of living and participation in the society within which one belongs. That is, poverty is not only about low income, but also about deprivation. In part, this wider view reflects theoretical concerns that low income provides an ‘indirect’ measure rather than a ‘direct’ measure of poverty, as emphasized by Ringen (1988). In addition, there are more purely empirical concerns about an exclusive focus on low income. The snapshot picture provided by income measures from cross-section surveys may be misleading because, with income-smoothing, current living standards may not reflect current income, and, in any case, there may be substantial measurement errors particularly at the bottom end of the income distribution. A large body of research has pointed out that the people who have a low income are not the same as the population who are most materially-deprived: see inter alia Berthoud et al. (2004), Bradshaw and Finch (2003), Callan et al. (1993), and Perry (2002).

The move away from an exclusive focus on income-based measures has been reflected in policy too. There has been a growing use of deprivation-like indices for social monitoring in Europe (Atkinson et al., 2002). The UK government now includes a wide range of indicators in addition to ‘low income’ in its annual *Opportunity for All* reports monitoring poverty and disadvantage. The Department for Work and Pensions (2003) is to monitor child poverty using a measure of material deprivation alongside two more conventional low-income measures. In Ireland, deprivation indices enter into the official assessments of poverty: they are used alongside low-income measures to summarise ‘consistent poverty’ (Layte et al, 2000).

Against this background, this paper examines some aspects of the methods that underpin summary measures of multiple deprivation. Although we have sympathy with the idea that a snapshot low income measure is an imperfect poverty indicator and with the view that ‘triangulation’ using summary deprivation measures is a useful step forward, at the same time we also believe that there are a number of issues that need to be addressed concerning the construction of a summary deprivation measure from a set of deprivation indicators.¹

The typical summary measure is intended to represent a unidimensional latent scale of ‘deprivation’. We argue that the measurement model assumed to underlie the scale is

¹ For a different approach to these issues, including comparisons with ‘social welfare’ methods of aggregation,

implausible for heterogeneous populations, and propose a model that allows for heterogeneity and which explicitly recognizes the dichotomous nature of the deprivation indicators. The model has the same structure as a multivariate probit regression model with parameter restrictions. Alternatively the model may be interpreted as a means of jointly summarizing the associations between each of the deprivation indicators and household characteristics, without assuming that a latent deprivation scale exists. We explore how our model may be used to summarize deprivation, contrasting its disaggregated approach with the conventional aggregate deprivation scale approach.

The literature relating ‘deprivation’ to multiple deprivation indicators is reviewed in Section 2. The aim is to highlight the key elements of the methods used, drawing attention to the nature of the measurement model describing the relationship between the observed indicators and the latent summary deprivation index that is commonly used in this literature. In Section 3, we set out our extension of the model. The arguments are illustrated in Section 4 with an examination of basic lifestyle deprivation in Britain during the mid-1990s. Section 5 contains a summary and concluding remarks.

2. Multiple deprivation indicators and unidimensional indices of deprivation

There are many ways to define and measure ‘deprivation’, whether overall deprivation or specific dimensions of deprivation, but there are features common to them all:

- *multiple indicators* – the picture of household circumstances is based on multiple indicators of lack or possession of necessities (by contrast, income poverty is summarized using only one indicator);
- *but combined into a summary scale* – lack or possession of each item or activity (usually recorded as a zero or one in the indicator variables) is aggregated into a summary numerical scale (a simple or weighted sum), and households are counted as deprived if their score is greater than some critical number on the scale.

Most derivations of measures of *overall deprivation* are inspired by and derive from Townsend’s (1979) approach to poverty measurement. This was later refined in the Breadline Britain studies (Mack and Lansley 1985; Gordon and Pantazis 1997) and by Gordon et al. (2000). In these studies, the multiple binary indicators refer to whether households lack

see Atkinson (2003).

various items and activities that are perceived as necessities (and their lack is because they cannot afford them rather than because they do not want them.) Examples of the indicators include ‘having heating to warm living areas of the home’, to ‘able to visit friends and family’, and ‘having meat, fish or vegetarian equivalent every other day’. The Policy Studies Institute index of overall ‘hardship’ is similar in structure, except that it uses a prevalence-weighted sum of indicators rather than a simple unweighted sum (Vegeris and McKay 2002; Vegeris and Perry 2003).

Other studies have developed separate measures to summarise each of a number of *separate dimensions of deprivation*. For example, the ESRI Dublin research team have developed scales of basic life-style deprivation, secondary lifestyle deprivation, housing deprivation, and so on: see, for example, Nolan and Whelan (1986a, 1986b), Layte et al. (2001a, b), and Whelan et al. (2001). (They have studied deprivation in Ireland and compared deprivation across EU countries.) A UK application using their methods is Calandrino (2003). The indices of material well-being and of accommodation and housing conditions developed by the Policy Studies Institute also have a close familial resemblance (Vegeris and McKay 2002; Vegeris and Perry 2003). The measure of social exclusion adopted by Burchardt et al. (2002) was differently motivated but was assembled from separate measures of consumption, production, political engagement and social interaction. Although the measures cited each focus on different dimensions of deprivation, they are constructed in the same way as the measures of overall deprivation are: multiple indicators are combined into a single numerical scale.

For the rest of the paper, and to simplify the arguments, we shall assume that one is interested a specific dimension of deprivation.

Suppose that there are K deprivation indicators I_k available for each household in the population, where $k = 1, \dots, K$.² From the multiple indicators, one may construct a summary deprivation index for each household, D , which is the sum of the individual indicators:

$$D = \sum_k I_k. \quad (1)$$

The rationale for using D as a unidimensional scale derives from the underlying measurement model. This model is, however, rarely discussed in the deprivation literature.

² We refer to households as the unit of analysis as the deprivation indicators are typically collected in surveys using questions directed at one person who responds on behalf of the household as a whole. The derivation also assumes that the choice of the indicators to be used has already been resolved. We return to this issue later.

One characterisation consistent with current practice is a measurement model for each indicator (and person) of the following form:³

$$I_k = \gamma_k + D^* + \varepsilon_k, \text{ for each } k = 1, \dots, K \quad (2)$$

where D^* is the underlying ‘true’ but latent measure of deprivation, γ_k is an item-specific intercept term, ε_k is a measurement error term with zero mean, assumed to be independent of D^* , and the cross-equation error covariances are equal to zero.⁴ Hence, the average of the observed indicators, $(1/K)\sum_k I_k$, is equal to $D^* + (1/K)\sum_k(\gamma_k + \varepsilon_k)$. With sufficiently large K , the sample mean of the equation errors would tend to zero, so that the arithmetic average of the observed indicators for each household equals the household-specific latent deprivation level (plus a constant common across households). The sum of the observed indicators, D , which is what is typically used in practice (rather than the average), preserves the ranking by D^* as well of, course. Given the earlier assumptions, each of the $K(K-1)/2$ unique between-indicator sample covariances $C(I_k, I_j)$, $k \neq j$, provides an estimate of $V(D^*)$.

An important motivation for our analysis is the observation that the measurement model just described assumes *homogeneity*: the same model is assumed to hold for every household in the population. This seems to us implausible in the context of examining deprivation for a society as a whole. Heterogeneity seems much more relevant in the deprivation context than for the samples that psychologists use and the topics that they investigate, e.g. educational test scores among children of a particular age.

One straightforward and familiar means of accounting for heterogeneity would be to assume that the measurement model was the same within each of a number of subgroups of the population, and to analyse each group separately. But this may quickly lead to cell size problems. An alternative means of incorporating heterogeneity, the one that we explore in this paper, is to introduce covariates into the measurement model. Were we to continue to use the measurement model encapsulated in (2) – we propose an alternative model shortly – one way of incorporating heterogeneity would be to suppose that:

$$I_k = \gamma_k + \beta_k'X + D^* + \varepsilon_k, \text{ for each } k = 1, \dots, K \quad (3)$$

³ For authoritative discussions of measurement models in the psychometric literature, see e.g. Lord and Novick (1968) and Nunnally and Bernstein (1994). Although we use (2) to characterise the measurement models used in the deprivation literature, one might argue alternatively that the implicit assumption is that the *total* deprivation score $D = D^* + \eta$, where η is a mean-zero variable uncorrelated with D^* , in which case the expected value of the observed score is equal to the true deprivation level. Given the dichotomous nature of the indicator variables, we prefer the indicator-specific formulation in (2), which we generalise in the next section.

⁴ A household-specific subscript has been omitted to simplify the notation. D^* varies by household but not item, γ_k varies by item but is common across households, and ε_k varies by household and item.

where β_k is a vector of indicator-specific parameters and X is a vector of household-specific characteristics, assumed independent of the ε_k . The questions about deprivation that we use ask respondents about items that they do not want and also cannot afford. The idea expressed in (3) is that there are systematic differences in the propensities to report lack of an item because, even among people with the same latent deprivation D^* , there are heterogeneous views about what they ‘want’, about what they understand by affordability, or about the interpretation of specific questions (e.g. relating to what ‘adequate’ means).

With (3), one has the same measurement model as before, in effect, but the sum of the indicators can be interpreted as a ‘heterogeneity-adjusted’ scale since $(1/K)\sum_k(I_k - \gamma_k - \beta_k'X) = D^*$. (Absolute differences in characteristics correspond to absolute differences in the scale.) If $\beta_k = 0$ for all k , then there is evidence in favour of the measurement model described by (2).

Application of this model is constrained by the fact that, in order to create the heterogeneity-adjusted scale, one needs estimates of the coefficients β_k . A second problem arises because the deprivation indicators, the I_k , are typically *dichotomous indicator variables*. If this is so, the error terms (the ε_k) cannot be continuous normally-distributed variables.

Despite these potential problems, it would be premature to conclude that the heterogeneity-adjusted measurement model has little potential for application. In the next section, we argue that the combination of an observation model with the measurement model set out in (3) yields an approach that can be used to summarise multiple deprivation.

3. A multivariate probit approach

Our first modification to (3) is to suppose that each dichotomous indicator is a realization of an underlying latent variable, with the alternative outcomes in each case depending on whether the corresponding latent variable is above or below a threshold (normalized to zero). That is, we now specify the measurement model for each indicator in terms of a latent variable, I_k^* ,

$$I_k^* = \gamma_k + \beta_k'X + D^* + \varepsilon_k, \text{ for each } k = 1, \dots, K. \quad (4)$$

Both D^* and each ε_k are assumed to be independent normally distributed zero-mean variates, with the ε_k independently distributed across households and items. The composite error terms ($D^* + \varepsilon_k$) are therefore multivariate normally distributed, with each mean equal to zero and

each variance normalized to equal unity.⁵ This measurement model is combined with an observation model specifying the relationship between the observed indicators, the I_k , and their latent counterparts, the I_k^* :

$$I_k = 1 \text{ if } I_k^* > 0 \text{ and } I_k = 0, \text{ otherwise, for each } k = 1, \dots, K. \quad (5)$$

The model characterized by (4) and (5) is a special case of the conventional multivariate probit regression model. It is a special case because the measurement model implies that the cross-indicator error structure takes a special form. If the model is true then, the covariance between any two composite errors – which is the same as the correlation between the errors (by the earlier assumptions) – is equal to the variance of the latent deprivation scale D^* :

$$\rho_{kj} = C(D^* + \varepsilon_k, D^* + \varepsilon_j) = V(D^*), \text{ for all } k \neq j. \quad (6)$$

In the standard multivariate probit model, the ρ_{kj} are not constrained to be equal, which suggests that one might estimate the more general model, and test whether the assumptions implied by the measurement model hold. (There are $K(K-1)/2 - 1$ constraints relative to the general model.)

The proposed model is related to the Rasch model (one-parameter item response model) used in psychometrics. This corresponds to the case when $\beta_k = 0$ for all k , and the error terms ε_k are assumed to be independent logistic variables. (In generalized linear model terminology, the link function is logistic, rather than probit as in (4) and (5).) In the ability testing literature, D^* is a measure of a person's 'ability', and γ_k is a measure of 'item difficulty'. The sum of the observed indicators has been shown to provide a minimal sufficient statistic for D^* in this model (Lord and Novick, 1968, chapter 18). Our model, in which covariates have a direct effect on observed responses, is related to item response models that allow for 'item bias' (otherwise known as 'differential item functioning'). An alternative approach would be to use covariates to introduce heterogeneity into the latent D^* itself, thereby estimating a type of 'multiple indicator multiple cause' (MIMIC) model.⁶ We find it more plausible, however, to think of heterogeneity in measurement, rather than in D^* itself.

To sum up so far, we have proposed a model for summarizing multiple deprivation indicators, one that allows for heterogeneity in the measurement model and that recognizes

⁵ If we were able to observe the continuous latent variable, the normalization would not be required. With only discrete realizations observed, there is not enough information to estimate separate variances. Observe too that the intercept term in each equation is not statistically identified: because the threshold defining the relationship between the I_k and I_k^* cannot be observed.

⁶ On these various models, see e.g. Skrondal and Rabe-Hesketh (2004).

the dichotomous nature of the indices. The cost of the greater generality relative to the conventional model is that an index equal to the sum of the observed deprivation indicators no longer has the neat interpretation in terms of the latent deprivation dimension (D^*). We referred earlier to the idea of a ‘heterogeneity-adjusted’ deprivation scale. If the general model holds, then this is now defined by $(1/K)\sum_k(I_k^* - \gamma_k - \beta_k'X)$. Although fitting of the multivariate probit model provides estimates of the β_k , the scale itself cannot be calculated because the I_k^* are latent, not observed.⁷

The general model's contributions

Although the general model does not lead directly to an additive deprivation scale, it makes two contributions. The first is that it serves to remind readers of the strong assumptions that are typically made in deprivation research. We have not seen these discussed in the deprivation context before. Discussion has focused on the choice of indicators per se, rather than on the methods used to summarise the information encapsulated in them.

Second, more substantively, the multivariate probit model can provide estimates relevant to summarising deprivation, notably estimates of the predicted probability of each combination of observed deprivation indicators. This is particularly important because deprivation analysts mostly use a deprivation scale as a straightforward means to determine who it is that is deprived to a greater or a lesser degree.

If there are two indicators available ($K = 2$), for example, then one can use our model to generate predictions of each of following joint probabilities for each household: $\Pr(I_1 = 1, I_2 = 1)$, $\Pr(I_1 = 0, I_2 = 1)$, $\Pr(I_1 = 1, I_2 = 0)$, and $\Pr(I_1 = 0, I_2 = 0)$. (One could also calculate the predicted marginal probabilities, or conditional probabilities.) And from these joint probabilities, one can also generate estimates of the probabilities of having a deprivation score (the sum of the I_k ; $I_1 + I_2$ in this example) equal to zero, one, or two. With more than two indicators available, there are more probabilities, of course, but the principle is the same: one can generate predicted joint probabilities, and thence probabilities of having particular deprivation score values. In fact, many of the probabilities are not likely to be of interest, as researchers most commonly choose a deprivation score cut-off and examine the

⁷ See also the previous footnote on the identifiability of the intercept term in each equation. D^* may be derived in a number of other variants of the item response model, e.g. using empirical Bayes methods: the model assumptions provide the identifying restrictions. See e.g. Skrondal and Rabe-Hesketh (2004).

characteristics of those with a deprivation score above the cut-off. By analogy, one may use the multivariate probit model to calculate every sample member's probability of having a deprivation score greater than the chosen threshold. And then one may examine who it is that has the highest and lowest probabilities: given the model assumptions, higher values of D^* translate directly into higher predicted probabilities.⁸

An alternative interpretation of the model

Although, so far, we have interpreted our multivariate probit model in terms of an underlying latent deprivation scale, one does not have to do this. That is, one could treat the model simply as a statistical description of the association between deprivation indicator outcomes and personal characteristics, and use it to generate predicted probabilities of particular deprivation score values, and so on, as above. That is, it can also be interpreted as a model of the 'determinants' of each of the deprivation indicators, by contrast with models of the determinants of overall deprivation scale (cf., inter alia, Layte et al. 2001).

There are some attractions to this alternative interpretation, as it avoids supposing that there is a *latent deprivation scale* and instead focuses on *observed indicators*. We make this argument motivated by the observation that the primary use of summary deprivation indices has been to identify the people who are most deprived, and the implicit or explicit argument made is that this group should be prioritised for extra help in the form of higher social benefits, labour market training, or some other assistance. We believe that the formulation, implementation, and evaluation of policies to reduce deprivation are problematic if the social problem to be targeted ('deprivation') is a latent construct. By contrast, the individual indicators refer to concrete items and activities, whose meaning is much more transparent. Although we use latent variables in our model, they refer to underlying propensities to have a *specific* item or engage in a particular activity, and we need make no appeal to a scale that *aggregates* across indicators.

It is easier to formulate measures to ensure households have, say, 'heating to warm living areas of the home' or 'a damp-free home' than to develop measures that reduce 'housing deprivation', for example. This question about the use of latent constructs would be

⁸ Our emphasis on predicted probabilities derived from a regression model for the individual deprivation indicators bears similarities to the work of Desai and Shah (1988). The key difference is that they estimated a number of univariate logit models (one per indicator), rather than estimating the models jointly as we do. As we have emphasised, a key feature of the joint estimation is that the correlations between model errors have a substantive interpretation given the measurement model typically assumed.

less of an issue if households' lack or possession of each item or activity underpinning a deprivation index were equally responsive to variations in income (say), or other factors such as labour market attachment. There is little evidence available about this (but see Desai and Shah, 1988), though our modelling framework provides a means to check it.

In the next section, we shall illustrate our arguments using data about basic life-style deprivation in Britain.

4. Empirical illustration: basic life-style deprivation in Britain

Data

We used data from wave 6 (survey year 1996) of the British Household Panel Survey. The advantages of the BHPS data are that they are based on a large national population sample and (from this wave onwards) contain a battery of questions about deprivation in addition to more conventional indicators of household living standards such as income.⁹ We focus on 'basic life style' deprivation, summarized using seven binary indicator variables. The first six variables summarize responses to questions put to the household reference person asking whether he or she would like to be able to *PHRASE* but must do without *PHRASE* because they cannot afford it, where *PHRASE* refers to:¹⁰

- Keep your home adequately warm (1.9 percent)
- Pay for a week's annual holiday away from home (20.1 percent)
- Replace worn out furniture (13.4 percent)
- Buy new, rather than second hand, clothes (5.3 percent)
- Eat meat, chicken, fish every second day (3.1 percent)
- Have friends or family for a drink or meal at least once a month (6.5 percent)

Each variable was scored one if there was an enforced lack of the relevant item or activity and zero otherwise; the percentage in parentheses is the fraction of the sample with an enforced lack. The seventh binary indicator variable summarized difficulties in meeting housing costs: i.e. whether the responding household

⁹ See <http://www.iser.essex.ac.uk/bhps> for full BHPS documentation.

¹⁰ More complete details of the derivation of the indicator variables are provided in the Appendix.

- had any difficulties paying for their accommodation in the last twelve months (6.9 percent)

Those reporting payment problems scored one on this variable; otherwise it was zero.

These variables are representative of those used in the literature. They are a subset of those used by Townsend (1979) and the later Breadline Britain studies. They were introduced to the BHPS when that survey was used to contribute data to the UK component of the European Community Household Panel (ECHP) – the same variables were available on a harmonized basis for all countries in the survey. The list corresponds closely to those used to summarize basic life-style deprivation in the many ECHP-based studies of deprivation by the research team from ESRI Dublin: see inter alia Layte et al. (2001), and Whelan et al. (2001). The indicators overlap with the ten indicators proposed for measurement of adult material deprivation by the UK Department for Work and Pensions (2003).

Summary statistics

There were 4,859 households with non-missing information on all seven indicators from an overall sample of 5,064 households. Sixty-nine percent experienced no deprivation according to any of the seven indicators, 15 percent were deprived of two items, and 8 percent of two items, 4.4 percent of four items, and 2.8 percent were deprived of 4–7 items. (Only one household was deprived on all seven items.) Thus, the key distinction appears to be between households with no deprivation according to any indicators, and those household deprived of at least one item (31 percent of the sample). We focus on this distinction in what follows.

The ‘reliability’ of the deprivation scale formed by summing the scores on each deprivation indicator is usually assessed with reference to estimates of the Cronbach alpha statistic, α . Given the classical measurement model set out in (2), α is the square of the correlation between the scale D and the latent factor D^* ; it summarizes the extent to which the multiple indicators comprising a summative scale are consistent with each other, in the correlation sense. (See Nunnally and Bernstein 1994 for further discussion.) If each I_k is statistically independent of each of the other indicators, then $\alpha = 0$. At the other extreme, if all the I_k are perfectly correlated with each other (equal), then $\alpha = 1$.

Our estimate of α for the sample as a whole is 0.653 (see Table 1), which is typical for data such as these, and within the bounds of what is usually considered to be acceptable (though lower than the 0.81 reported by Whelan et al. 2001). The remainder of Table 1 shows

estimates of α calculated separately for 12 subgroups of households, where the groups are defined in terms of the age of the household reference person, marital status, the presence of one or more dependent children, and of at least one full-time worker (working 30+ hours per week). These variables characterize substantively important heterogeneity, but without the subgroup numbers becoming too small. There is a large range in estimates of α , ranging from 0.756 (non-elderly childless single adult householders not in full-time work) to 0.492 ('other' households, a diverse residual category). One interpretation of these results might be that different collections of indicators should be used to construct deprivation scales for different sorts of households – but this would conflict with the standard approach using all the indicators for all households. An alternative interpretation, and the one we would emphasize, is that the subgroup differences in α are suggestive of the relevance of heterogeneity. Let us therefore turn to our model with heterogeneity.

<Table 1 near here>

Multivariate probit model estimates

The choice of the variables to characterize heterogeneity is clearly an important one in the application of our model. We distinguish households in terms of the sex and age of the household reference person, the number of adults and number of children in the household, and whether or not there is at least one full-time worker. Our aim here is to differentiate between types of household, rather than to characterize the 'determinants' of deprivation in a more causal sense (though a version of the model could also be used to do this). Cf. Layte et al. (2001) who explicitly consider 'determinants', and report OLS regressions of overall deprivation scale values on measures of household composition, and the household head's sex, age, marital status, education, social class, and employment 'precarity', and log equivalent household income.¹¹ By not including income as a regressor, we also differ from the Breadline Britain studies. Gordon et al. (2000), for example, included household income in their deprivation scale regressions arguing, in effect, that a statistically significant negative association would be indicative of the conceptual validity of their deprivation scale. Our view is that deprivation and low income are different poverty concepts and therefore it is inappropriate to use the latter to validate the former.

¹¹ Desai and Shah (1988) report independent logit regressions for each of eight separate deprivation indicators on measures of household type (14 categories), region, income, wealth, and the household head's education level, health, and whether born in the UK.

The estimated coefficients of the model are shown in Table 2, and the estimated cross-equation correlations are shown in Table 3.¹² The coefficients show the relationship between each regressor and the latent variable I_k^* : cf. (4). The association with age was specified using a linear spline in order to allow for a non-linear relationship. The estimates show that heterogeneity is relevant: for every deprivation indicator there are many coefficient estimates that are statistically significant. Moreover, at first glance, each of the regressors appears to have a similar effect on each of the latent deprivation propensities. This was examined formally using Wald tests of the hypothesis that the coefficients on a given variable in each equation are equal. The final column of Table 1 shows the p -values for these tests. It turns out that the null hypothesis of equality is strongly rejected only for the full-time worker regressor, with a p -value of 0.00 (though the relevant coefficient is negative in every equation). For every other regressor, the null hypothesis cannot be rejected at the 5% level or greater. The joint hypothesis that each set of coefficients is equal is strongly rejected, however (p -value = 0.00).

Each of the cross-equation correlations is positive, as expected, and statistically significant (Table 2). They range widely in value, however, from a minimum of 0.268 (housing, warmth) to a maximum of 0.631 (visitors, meat), which is inconsistent with the restricted measurement model. Recall from (6) that this model implies that each of the correlations is an estimate of $V(D^*)$. We re-estimated the model imposing the equal-correlation constraint, deriving an estimate of $\rho = 0.505$ (t -ratio = 33.66). A likelihood ratio test of this model versus the more general model with unrestricted correlations yielded a test statistic of 125.3, implying strong rejection of the restriction of equal correlations.

<Table 2 and Table 3 near here>

Implications of the model estimates

We argued earlier that model estimates could be used to summarize the probabilities of different combinations of deprivation indicator outcomes, and we now illustrate this, focusing on the probabilities of being deprived according to one or more deprivation indicators. Observe that, in general, the direction of the effect on this probability of a change in a particular explanatory variable cannot be read directly from Table 2: in principle, a regressor may have different effects in different equations, and these various effects on the joint

¹² All estimates and predictions were derived using Stata programs written by the authors that are freely

probability may offset each other. This is less of an issue in our case, however, because of the similarity of corresponding coefficients across equations (see above).

To help gauge the differences in deprivation probabilities across households of different types that are implied by the model estimates, consider first a reference household type defined as a single male householder aged 20, with no children and not in full-time work. For this case, our model predicts a probability of being deprived on 1+ indicators of 42.9 percent. If, instead, the householder was a woman rather than a man, the predicted probability is 52.5 percent. The presence of dependent children appears to have a substantial effect, but the presence of additional adults does not. If there were two children present rather than none, other things being equal, the predicted probability is 56.2 percent, but if there two adults rather than one, the prediction is 42.5 percent (which is virtually the same as for the reference household type). The predicted probability falls with age, broadly speaking, and is markedly smaller for households in which the head is of pension age. For example, if the reference householder were 30 years old instead of 20, the predicted probability is 26.0 percent. For those aged 40, 50, 60, and 70, the corresponding predictions are 22.5 percent, 28.6 percent, 16.0 percent, and 8.8 percent respectively.¹³ The probability of being deprived according to one or more indicators is much lower for households with a full-time worker: if the reference householder were in full-time work, other things equal, the predicted probability would fall to 15.9 percent.

We now illustrate how the model estimates may be used to address the issues that have been of perennial interest in the deprivation literature, *viz* the relationship between deprivation and income, in particular the extent to which the most deprived are also those who have low income, and identifying who are the most deprived.

The relationship between deprivation and income is illustrated by Figure 1. This is a scatterplot of the estimated probability for each household of being deprived of at least one item against income (where income is household annual income adjusted for size and composition using the modified OECD equivalence scale). The superimposed line is a local polynomial smooth of the probabilities over the income range. The figure indicates that, on average, probabilities decline with income, especially in the lower income ranges. (The

available. See Cappellari and Jenkins (2003) for details.

¹³ The substantially lower probabilities of being deprived on 1+ indicators for elderly households raises some questions about the suitability of the underlying questions for identifying the people who are most deprived in an objective sense. It may be that many elderly household reference persons said that they did not want the relevant item or activity. Their own assessment may differ from society's collective views about what really counts as deprivation. For more on this, see McKay (2004). Also see Halleröd (1994), who proposed weighting deprivation items differently for different groups.

bumps on the right hand side of the picture can be discounted because of the small numbers.) For reference, note that a low income cut-off of 60 percent of median income corresponds to an income value of £4,363, shown as a vertical line in the figure. Notwithstanding this relationship on average, it is also clear that there is substantial variation in deprivation probabilities at each level of income, especially in the lower ranges. Put another way, the overlap between the membership of low income population and of the group predicted to be deprived is not perfect – as has been emphasized in earlier literature (see the Introduction).

To indicate that the application of our approach is not limited to one type of predicted deprivation probability, we also show the analogous figure referring to the probability of being deprived on all seven indicators. See Figure 2. The predicted probabilities are of course much lower on average than in Figure 1, but there is the same negative relationship between the deprivation probability and income on average, and also a large variation about the average at each level of income.

<Figure 1 and Figure 2 near here>

The composition of the ‘worst off’ group is summarized using three measures in Table 4. Column (a) defines the worst off to be those households with an income below a low income cut-off set equal to 60 percent of the median; column (b) refers to households with a predicted probability of being deprived of at least one item that is greater than 0.5; and column (c) refers to households observed to be lacking at least one item. For each of these measures, the table shows the breakdown by household type, using the same twelve group categorization as was employed in Table 1.

There are clear differences between the results based on the low income measure and those based on the deprivation measures. When the former is used, just under 36 percent of the ‘worst off’ households are made up of households with a reference person of pension age, twice the fraction apparent when the deprivation measures are used. This subgroup’s share of the ‘worst off’ population is 18.4 percent for the measure based on the predicted probability, and 18.9 percent for the measure based on the deprivation count. According to the low income measure, only 6.6 percent of the worst off are non-elderly couple households with children with at least one full-time worker, whereas according to the predicted probability measure, the share accounted for by this group is a massive 30.4 percent. According to the deprivation count it is 24.8 percent. In short, elderly households are notably prevalent among the worst off if the low income measure is used but, if the deprivation measures are used, it is non-elderly couples who form a relatively high share of the worst off. Observe that subgroup

shares for the two deprivation measures are quite similar, which is another way of saying that our model fits the observed data well.

The differences between the income and deprivation measures in highlighting who is worst off is underlined further by examination of how the risks of being in the worst off group vary by household type. See Table 5. Column (a) shows the subgroup risks using a low income measure; column (b) shows average predicted probabilities of being deprived of at least one item by subgroup; and column (c) shows the subgroup risks of having an observed deprivation count of one or more. Observe that the estimates for all households taken together are similar in all three cases, around three in ten. Again, however, there are large differences across the household types – a contrast between the low income measure on the one hand, and the deprivation measures on the other hand. As in Table 4, there are marked differences between the results for elderly and non-elderly households. For example, the risk of having a low income is 61 percent for elderly single men and 70 percent for elderly single women, but the corresponding average predicted probabilities and subgroup risks of a non-zero deprivation score are both much smaller, some 21 percent and 28 percent respectively. Among non-elderly households, the risk for households with at least one person in full-time work of being among the worst off is relatively low according to the low income measure, but relatively high according to the other two measures. For example, the risk of a low income is only 6.4 percent for working couple households with children, but the average predicted probability of being deprived of at least one item is 28.6 percent.

5. Summary and conclusions

It is widely agreed that snapshot measures of low income are imperfect indicators of poverty status, and that there are advantages to looking at low income status in combination with some measure(s) of material deprivation. In this paper we have argued, however, that there are issues regarding the methodological foundations of the deprivation indices that need to be addressed. We were motivated by the desire to incorporate heterogeneity into the underlying measurement model, and also by discomfort with basing analysis on the assumption of a latent scale of deprivation. This has led us to propose a multivariate probit regression approach to the summary of multiple deprivation indicators. This approach can incorporate heterogeneity, and is based on the observed disaggregated data with no necessary reference to

an overall latent index of deprivation (though, as we have shown, it may also be interpreted thus).

The paper illustrates a trade-off in deprivation analysis possibilities between weak measurement assumptions and ease of application. On the one hand, there is the simple measurement model that is typically assumed (implicitly). Its strong assumptions provide underpinning for an aggregate index that is easy to calculate and straightforward to use in analysis. It is therefore unsurprising that it has been widely used. On the other hand, if one embraces a more general and arguably more realistic measurement model, then it is correspondingly less straightforward to summarize multiple deprivation – though it can be done, as we have demonstrated. One can use the model to examine the probabilities of different combinations of deprivation indicator scores. We have also demonstrated how our disaggregate deprivation measure can be used to identify the worst off using predicted probabilities, and to illustrate an imperfect overlap between this group and the group identified using a low income measure – as has been done previously using the conventional deprivation scale approach.

What we have not addressed in this paper is the choice of deprivation indicators, and this is a major topic in itself. (See e.g. MacKay and Collard's (2004) analysis and development of a set of deprivation indicators to be implemented in the UK Family Resources Survey.) We have simply taken these as given, as our goal was to focus on a rather different issue – how to summarize the information encapsulated in a set of indicators. Our predilection is to avoid methods assuming a latent scale. To us, poverty measurement needs to be based on transparent measures, and latent scales are not transparent by their very nature; nor are the statistical models used in their construction. By contrast, the multivariate probit methods proposed in this paper avoid assumptions about a latent deprivation scale (though they can be related to one, if desired), but one can summarize deprivation nonetheless, focusing on the separate deprivation indicators. We suggest that the methods proposed are worthy of further investigation.

References

Atkinson, A.B. 'Multidimensional deprivation: contrasting social welfare and counting approaches', *Journal of Economic Inequality*, 1, 51–65.

- Atkinson, A.B., Cantillon, B., Marlier, E., and Nolan, B. (2002), *Social Indicators. The EU and Social Exclusion*, Oxford University Press, Oxford.
- Berthoud, R., Bryan, M. and Bardasi, E. (2004), *The Relationship between Income and Material Deprivation over Time*, DWP Research Report, forthcoming.
- Bradshaw, J. and Finch, N. (2003) 'Overlaps in dimensions of poverty', *Journal of Social Policy*, 32, 513–525.
- Burchardt, T., Le Grand, J., and Piachaud, D. (2002), 'Degrees of exclusion: developing a dynamic multidimensional measure'. In: Hills J, Le Grand J, and Piachaud D (eds.) *Understanding Social Exclusion*, Oxford University Press, Oxford.
- Calandrino, M. (2003), 'Low-income and deprivation in British families', Working Paper Number 10, Department for Work and Pensions, London. <http://www.dwp.gov.uk/asd/asd5/WP10.pdf>
- Callan, T. Nolan, B., and Whelan, C.T. (1993), 'Resources, deprivation, and the measurement of poverty', *Journal of Social Policy*, 22, 141–172.
- Cappellari, L. and Jenkins, S.P. (2003), 'Multivariate probit regression using simulated maximum likelihood', *The Stata Journal*, 3, 278–294.
- Department for Work and Pensions (2003), *Measuring Child Poverty*, Department for Work and Pensions, London
- Desai, M. and Shah, A. (1988), 'An econometric approach to the measurement of poverty', *Oxford Economic Papers* 40: 505–522.
- Gordon, D. and Pantazis, C. (1997), *Breadline Britain in the 1990s*, Ashgate, Aldershot.
- Gordon, D., Adeleman, L., Ashworth, K., Bradshaw, J., Levitas, R., Middleton, S., Pantazis, C., Patsios, D., Payne, S., Townsend, P., and Williams, J. (2000), *Poverty and Social Exclusion in Britain*, Joseph Rowntree Foundation, York.
- Halleröd, B. (1994), 'A new approach to the direct consensual measure of poverty', Social Policy Research Centre Discussion Paper No 50 (October), University of New South Wales, Sydney. <http://www.sprc.unsw.edu.au/dp/dp050.pdf>
- Layte, R., Nolan, B., Whelan, C. (2000), 'Targeting poverty: lessons from monitoring Ireland's national Anti-Poverty Strategy', *Journal of Social Policy* 29: 553–575.
- Layte, R., Maître, B., Nolan, B. and Whelan, C.T. (2001), 'Explaining levels of deprivation in the European Union', *Acta Sociologica*, 44, 105–122.
- Lord, F.M. and Novick, M.R. (1968), *Statistical Theories of Mental Test Scores*, Addison-Wesley, Reading MA.
- Mack, J. and Lansley, S. (1985), *Poor Britain*, George Allen & Unwin, London.

- McKay, S. (2004), 'Poverty or preference? What do "consensual deprivation indicators" really measure?', *Fiscal Studies*, forthcoming.
- McKay, S. and Collard, S. (2004), 'Developing deprivation questions for the Family Resources Survey', IAD Research Division Working Paper No. 13, Department for Work and Pensions, London. <http://www.dwp.gov.uk/asd/asd5/wp2004.asp>
- Nolan, B. and Whelan, C. (1996a), 'Measuring poverty using income and deprivation indicators: alternative approaches', *Journal of European Social Policy* 6: 225–240.
- Nolan, B. and Whelan, C. (1996b), *Resources, Deprivation and Poverty*, Clarendon Press, Oxford.
- Nunnally, J.C. and Bernstein, I.H. (1994). *Psychometric Theory*, third edition, McGraw-Hill, New York.
- Perry, B. (2002), 'The mismatch between income measures and direct outcome measures of poverty', *Social Policy Journal of New Zealand*, 19, 101–127.
- Ringen, S. (1988), 'Direct and indirect measures of poverty', *Journal of Social Policy*, 17, 351–365.
- Skrondal, A. and Rabe-Hesketh, S. (2004), *Generalized Latent Variable Modeling: Multilevel, Longitudinal, and Structural Equation Models*, CRC Press, Boca Raton FL.
- Townsend, P. (1979), *Poverty in the United Kingdom*, Harmondsworth, Penguin.
- Vegeris, S. and McKay, S. (2002), *Low/Moderate-income Families in Britain: Changes in Living Standards*, DWP Research Report No. 164, Corporate Document Services, Leeds.
- Vegeris, S. and Perry, J. (2003), *Families and Children Study 2001: Report on Living Standards and the Children*, DWP Research Report No. 190, Corporate Document Services, Leeds.
- Whelan, C., Layte, R., Maître, B., and Nolan, B. (2001), 'Income, deprivation and economic strain: an analysis of the European Community Household Panel', *European Sociological Review* 17: 357–472.

Appendix

The deprivation indicator questions are derived from six BHPS questions about participation and activities and one about housing arrears. The six first six questions are of the following form: Here is a list of things which people might have or do. Please look at this card and tell me which things you (and your household) have or do? *PHRASE*. (Response codes are: yes, no, missing, not applicable, telephone interview, don't know.) For those who answered 'no' to the first question, there is a follow-up question of the form: 'Would you like to be able to *PHRASE*, but must do without because you cannot afford it?' (Response codes are the same as for the first question. The 'not applicable' code includes those who said 'yes' to the first question.) The *PHRASE* is changed for each question. The full wording of the phrases is:

- Keep your home adequately warm.
- Pay for a week's annual holiday away from home.
- Replace worn out furniture.
- Buy new, rather than second hand, clothes.
- Eat meat, chicken, fish every second day.
- Have friends or family for a drink or meal at least once a month.

We defined households to be deprived according to each indicator if the response was no to the first question, and yes to the second. The seventh indicator, concerning problems with paying housing costs, was derived from the question asking 'Many people these days are finding it difficult to keep up with their housing payments. In the last twelve months would you say you have had any difficulties paying for your accommodation?' (Those who answered yes were counted as deprived. (Individuals receiving 100% rent rebates were counted as not deprived.)

Table 1
The ‘reliability’ of a basic lifestyle deprivation scale:
Cronbach alpha estimates for all households, and by household type

Household type	α	SE*	N^\dagger
All households	0.653	(0.012)	4,859
<i>Elderly (household reference person of pension age)</i>			
Single man	0.683	(0.076)	151
Single woman	0.653	(0.039)	505
Couple	0.620	(0.031)	499
<i>Non-elderly</i>			
Single, kids, full-time worker	0.704	(0.035)	198
Single, kids, no full-time worker	0.500	(0.036)	244
Single, no kids, full-time worker	0.633	(0.055)	349
Single, no kids, no full-time worker	0.756	(0.028)	224
Couple, kids, at least one full-time worker	0.563	(0.027)	1,323
Couple, kids, no full-time worker	0.657	(0.042)	159
Couple, no kids, at least one full-time worker	0.552	(0.045)	726
Couple, no kids, no full-time worker	0.544	(0.044)	149
<i>Other</i>	0.492	(0.078)	163

Notes. The calculations assume the measurement model shown in (2). Summary index equals sum of scores on the seven binary deprivation indicators discussed in the text. *: bootstrap standard error (99 replications). Sample is all households with no missing information on any one of the seven deprivation indicators. †: number of households in subgroup. Subgroup membership could not be determined for 169 households (missing data).

Table 2
Indicators of basic life-style deprivation: multivariate probit estimates

Regressor	Dependent variables							Tests of equal coefficients: <i>p</i> -values*
	Warm (1)	Holiday (2)	Furniture (3)	Clothing (4)	Meat etc (5)	Visitors (6)	Housing (7)	
Household reference person is female	0.167 [1.77]	0.208 [4.59]	0.206 [4.21]	0.172 [2.65]	0.041 [0.54]	0.187 [3.09]	0.162 [2.73]	0.56
Age < 30†	-0.033 [1.44]	-0.037 [2.99]	-0.031 [2.28]	-0.017 [0.97]	-0.073 [4.04]	-0.003 [0.19]	-0.033 [2.19]	0.06
Age 30–39	-0.006 [0.28]	-0.020 [1.95]	-0.001 [0.06]	-0.013 [0.89]	0.016 [0.94]	0.028 [2.06]	0.000 [0.03]	0.05
Age 40–49	0.016 [0.70]	0.017 [1.52]	0.013 [1.06]	0.041 [2.62]	0.002 [0.13]	0.003 [0.22]	0.008 [0.59]	0.49
Age 50–59	-0.014 [0.63]	-0.038 [3.50]	-0.026 [2.24]	-0.030 [2.05]	-0.016 [0.89]	-0.029 [2.06]	-0.035 [2.41]	0.90
Age 60+	-0.033 [2.71]	-0.027 [5.14]	-0.014 [2.65]	-0.027 [3.70]	-0.038 [3.69]	-0.030 [4.05]	-0.025 [3.17]	0.20
No. children	0.066 [1.34]	0.143 [5.60]	0.137 [5.05]	0.165 [4.81]	0.078 [1.93]	0.183 [5.88]	0.111 [3.60]	0.13
No. adults	0.082 [1.66]	-0.009 [0.34]	-0.050 [1.65]	-0.039 [0.99]	-0.093 [2.02]	-0.056 [1.44]	0.024 [0.70]	0.06
1+ full-time worker(s)	-0.649 [6.01]	-0.719 [12.6]	-0.520 [8.56]	-0.724 [9.43]	-0.558 [6.37]	-0.600 [8.27]	-0.387 [5.37]	0.00
Intercept	-0.989 [1.67]	0.755 [2.29]	0.068 [0.19]	-0.784 [1.68]	0.694 [1.49]	-1.225 [2.57]	-0.337 [0.84]	
Log-likelihood	-7112.94							

Notes. Dependent variables defined in text. Simulated maximum likelihood estimates, GHK simulator, 50 draws. $N = 4680$ households. *: Null hypothesis is that the coefficient on the variable of interest is equal in each of the seven equations; *p*-value based on Wald test. †: the effect of age was specified using a linear spline. $|t$ -ratio/ shown in brackets.

Table 3
Estimated cross-equation correlations

Equations	ρ_{kj}	t-ratio/
Holiday, warmth	0.359	[7.14]
Furniture, warmth	0.431	[9.14]
Clothing, warmth	0.427	[8.09]
Meat, warmth	0.442	[7.58]
Visitors, warmth	0.356	[6.49]
Housing, warmth	0.268	[4.62]
Furniture, holiday	0.615	[27.79]
Clothing, holiday	0.531	[16.48]
Meat, holiday	0.531	[13.66]
Visitors, holiday	0.557	[18.95]
Housing, holiday	0.400	[12.04]
Clothing, furniture	0.624	[21.64]
Meat, furniture	0.500	[12.87]
Visitors, furniture	0.548	[18.13]
Housing, furniture	0.437	[13.18]
Meat, clothing	0.571	[14.01]
Visitors, clothing	0.536	[14.99]
Housing, clothing	0.358	[8.65]
Visitors, meat	0.631	[17.68]
Housing, meat	0.294	[6.02]
Housing, visitors	0.391	[10.02]

Notes. See Table 2 for multivariate probit coefficient estimates.

Table 4
The composition of the ‘worst off’ group: three measures compared

Household type	<i>Column percentages</i>		
	Households with low income (a)	Households with Pr(deprived of 1+ items) > 0.5 (b)	Households deprived of 1+ items (c)
<i>Elderly (household reference person of pension age)</i>			
Single man	7.32	1.23	2.55
Single woman	27.75	11.69	10.07
Couple	11.61	5.50	6.28
<i>Non-elderly</i>			
Single, kids, full-time worker	1.73	4.06	5.04
Single, kids, no full-time worker	13.88	9.43	10.63
Single, no kids, full-time worker	2.26	4.39	5.85
Single, no kids, no full-time worker	12.52	9.60	8.77
Couple, kids, at least one full-time worker	6.64	30.39	24.81
Couple, kids, no full-time worker	7.92	7.01	7.09
Couple, no kids, at least one full-time worker	1.36	6.03	10.26
Couple, no kids, no full-time worker	3.77	6.07	3.42
<i>Other</i>	3.24	4.59	5.22
Total	100.00	100.00	100.00
<i>N (households)</i>	<i>1356</i>	<i>2408</i>	<i>1608</i>

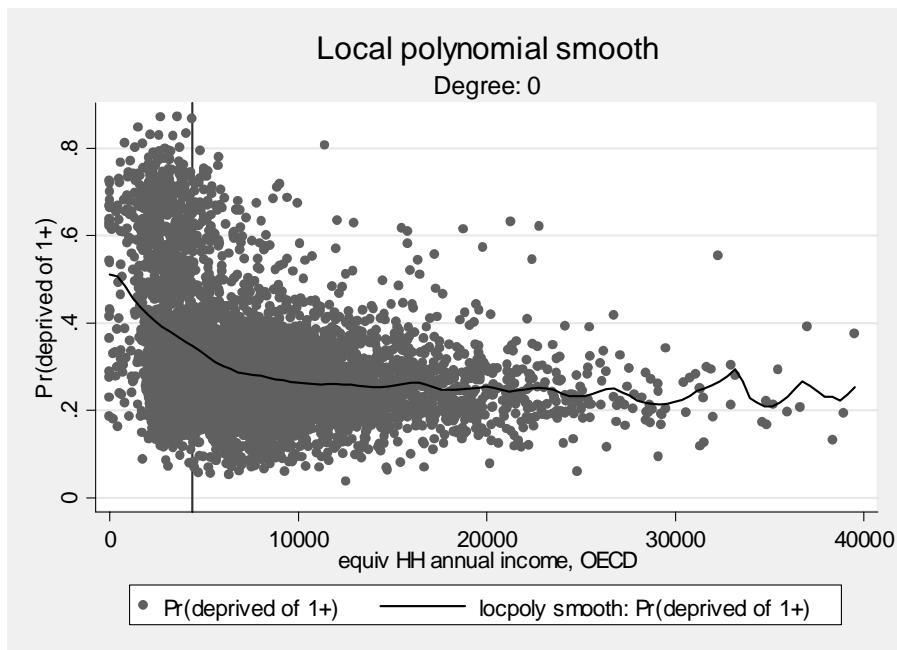
Notes. (a) Low income means having an income less than 60% of median income, where income is annual household gross income equivalised using the modified OECD scale. (b) Probabilities calculated from model estimates shown in Tables 1 and 2. (c) Sample count.

Table 5
Subgroup risks of being in the ‘worst off’ group: three measures compared

Household type	<i>Percentages</i>		
	Proportion with low income (a)	Average Pr(deprived of 1+ items) (b)	Proportion deprived of at least one item (c)
<i>Elderly (household reference person of pension age)</i>			
Single man	61.01	20.85	21.85
Single woman	70.10	28.56	28.12
Couple	30.20	22.60	18.04
<i>Non-elderly</i>			
Single, kids, full-time worker	11.44	26.11	39.39
Single, kids, no full-time worker	73.60	59.78	67.62
Single, no kids, full-time worker	8.33	24.55	23.78
Single, no kids, no full-time worker	70.64	52.47	58.04
Couple, kids, at least one full-time worker	6.41	28.57	26.38
Couple, kids, no full-time worker	61.05	61.26	63.52
Couple, no kids, at least one full-time worker	2.41	22.72	19.97
Couple, no kids, no full-time worker	33.33	41.24	36.24
<i>Other</i>	23.50	35.28	39.26
All	27.26	30.94	30.58

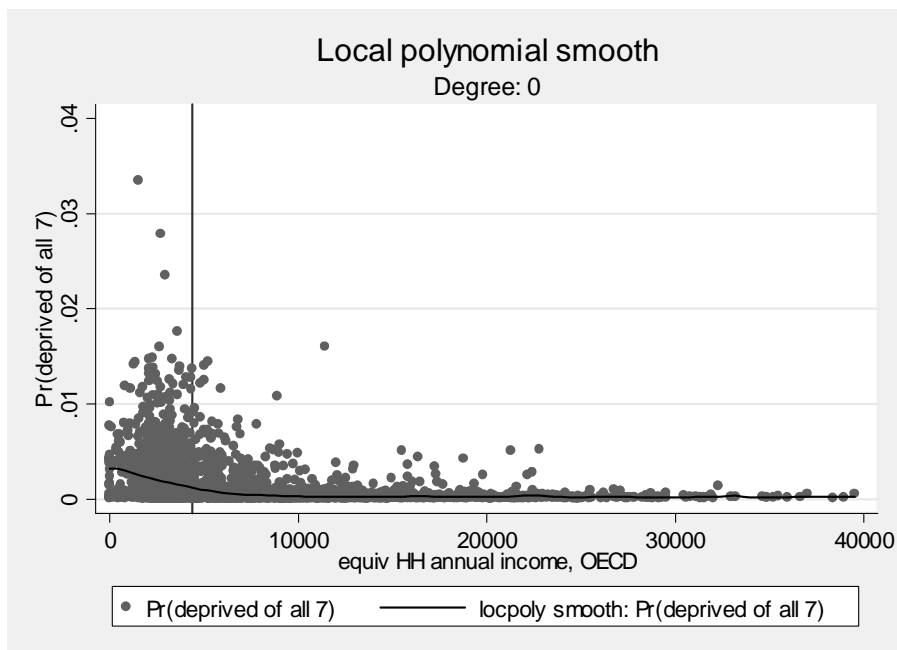
Notes. As for Table 4.

Figure 1
The relationship between the probability of being deprived of at least one item and income



Notes: Probabilities predicted from model estimates shown in Tables 1 and 2. Line drawn on scatterplot is a local polynomial smooth of degree zero (i.e. local mean smoothing), with kernel half-width = 750. Graph drawn for incomes less than £40,000 only. Low income cut-off equal to 60% of median income is shown as a vertical line.

Figure 2
The relationship between the probability of being deprived on all seven items and income



Notes: As for Figure 1.