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Patterns of consent: evidence from a general household survey

Berlin, May 2005

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IMPRESSUM

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Abstract

We analyse consent patterns and consent bias in the context of a large general household survey, the 'Improving survey measurement of income and employment' (ISMIE) survey, also addressing issues that arise when there are multiple consent questions. Using a multivariate probit regression model for four binary outcomes with two incidental truncations, we show that there are biases in consent to data linkage with benefit and tax credit administrative records held by the Department for Work and Pensions, and with wage and employment data held by employers, and also in respondents' willingness and ability to supply their National Insurance Number. The biases differ according to the question considered, however. We also show that modelling consent questions independently rather than jointly may lead to misleading inferences about consent bias. A positive correlation between unobservable individual factors affecting consent to DWP record linkage and consent to employer record linkage is suggestive of a latent individual consent propensity.

Keywords: informed consent, household surveys, consent bias, selection bias, multivariate probit, incidental truncation, data linkage, National Insurance Number

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1 Introduction[1]

Multi-topic general household surveys increasingly seek informed consent from respondents in order to gain additional data, through direct measurements, by collecting bio-medical samples, and by linkages with administrative records. The supplementary data yield substantial research benefits, but the process of seeking informed consent raises a number of issues. The first is that attempts to gain consent – which are likely to bring issues of privacy and confidentiality into the minds of respondents – may lead to higher rates of item non-response and also, in a longitudinal survey, to future sample drop-out. A second issue is whether respondents who provide consent (and for whom the supplementary data are available) are sufficiently representative of the sampled population: do consent procedures introduce a form of selection or 'consent bias', compromising external validity? Analysis of these issues has been largely confined to medical and epidemiological studies; there are few studies of consent patterns in multi-topic or non-health surveys (as we discuss below). But one might expect consent patterns to differ between types of study. For example, a respondent may perceive that health-focused studies are likely to provide greater benefits to him or her personally, by contrast with requests for data linkage for non-health purposes for which the expected benefits to consent are more diffuse.

Multiple consent questions are common nowadays, and this introduces additional issues that have not been analysed before. Some consent and related questions are only asked if some other consents have been given or some other condition has been satisfied, and so analysis of patterns of response to the later questions need to account for potential sample selection biases ('incidental truncations') introduced by differential response to the prior questions. (See Heckman (1976, 1979) for discussion of the general issues.) Moreover, because multiple consent questions are a form of repeated measure, one may examine whether each observed predictor has the same effect on each type of consent, or indeed whether unobserved individual effects influencing consent are correlated and thence suggestive of a latent individual propensity to consent.

[1] This paper derives from a project on 'Improving survey measurement of income and employment' (ISMIE), funded by the ESRC Research Methods Programme (H333250031). We also benefited from ISER's core funding from the ESRC and the University of Essex. We are grateful to our ISER colleagues for assistance in producing the ISMIE dataset, especially Nick Buck, Jon Burton, John Fildes, Heather Laurie, Mike Merrett, and Fran Williams. We are grateful to our colleagues, especially Richard Berthoud and Lucinda Platt, for their comments.

In this paper we provide new analysis of consent patterns and consent bias in the context of a large social survey without a health focus – the 'Improving survey measurement of income and employment' (ISMIE) survey. The issues raised by having multiple consent questions and the complications introduced by question routing are also addressed. To do this, we use novel statistical methods, proposing a multivariate probit model for four binary outcomes with two incidental truncations. Our model could be applied in a number of contexts besides the current one.

We show that there are some consent biases in ISMIE survey respondents' consent to data linkage with benefit and tax credit administrative records held by the Department for Work and Pensions, and with wage and employment data held by employers, and also in respondents' willingness and ability to supply their National Insurance Number (a unique personal identifier) to facilitate the matching with the government agency data. The biases differ according to the question considered, however. We also argue that modelling consent questions independently rather than jointly may lead to misleading inferences about consent bias. Correlations between unobservable individual factors affecting consent to DWP record linkage and consent to employer record linkage provide evidence suggestive of a latent individual consent propensity.

In Section 2, we review existing literature on consent patterns and consent bias. The ISMIE survey and its consent questions are described in Section 3. In Section 4, we set out a multivariate probit model for multiple consent outcomes that accounts for multiple incidental truncations. Results are presented in Section 5. First we document consent patterns for the sample as a whole and for subgroups. We present estimates from our proposed model, and compare them with those derived from independent probit regressions in order to assess the magnitude of potential biases. Our findings are summarised and their implications discussed in Section 6.

2 Previous research on patterns of consent and consent bias

Much of the previous research on patterns of consent has been on epidemiological and other health studies. The major concerns have been that requirements for informed consent may reduce survey response rates (and imply a need to increase sample sizes), and that consent rates may not be uniform among respondents, thereby introducing a form of 'consent bias' into analyses based on the subsample of consenting respondents (Dunn et al. 2004). For example, among the reasons for an unexpectedly low response rate to a large prospective follow-up study of the psychosocial health of the Finnish working-age population in 1998, Korkeila et al. (2001) cited a suspicion of written consent and a connection being made between the individual and the registers mentioned on the consent form. Angus et al. (2003, p. 21) conclude that 'the requirement of a separate, prior consent stage may significantly reduce overall survey response rates and necessitate the use of substantially larger initial samples for population surveys'. In the seven British general population health surveys analyzed by Dunn et al. (2004), consent to follow-up was given by 75%–95% of respondents under age 50 years, with similar rates for consent to review of medical records. Other health studies suggest that it is the timing and method of eliciting consent that matters for response, rather than consent per se: see, for example, Nelson et al. (2002) and Silva et al. (2002).

Consent bias has been reported in a number of recent health studies. (For discussion of various methods to adjust for consent bias, see Smith et al. (2004).) For example, the US study by Jacobsen et al. (1999, p. 330) concluded that 'laws requiring written authorization from patients for research use of medical records can result in substantial biases in etiologic and outcome studies'. Woolf et al. (2000) found in their survey of medical clinic patients, that older patients and those in poorer health were more likely to give permission to be surveyed at home and for their medical records to be reviewed. The authors concluded that '[q]uality and health services research restricted to patients who give consent may misrepresent outcomes for the general population' (2000, p. 1111). The largest epidemiological study, based on seven UK general population health surveys covering some 25,000 respondents (Dunn et al. 2004), stated that '[m]ales, younger people, and subjects reporting the symptom under investigation were more likely to give consent, and these groups may be over-represented in follow-up samples or reviews of medical records' (2004, p. 1087). Differential rates of consent to follow-up for a special survey of sexuality were reported by Dunne et al. (1997), though they also comment that the differences 'should not seriously compromise population estimates' (Dunne et al. 1997, p. 844). Although Dunn et al. (2004) had two consent questions in the majority of their seven studies, they analyzed the responses to each question separately rather than jointly.

Multiple consent questions are now common in multi-topic or non-health studies. For example, the English Longitudinal Survey of Ageing (Marmot et al., 2003) seeks consent in order to collect samples of blood and DNA source material, to record height, weight and grip strength, and to link in information about respondents' National Insurance contributions, benefit, and tax credit records held by government agencies. It also requires consent to link information from hospital episode statistics and from mortality and cancer registration records. The US Health and Retirement Study (Juster and Suzman, 1995) requires consent to collect earnings and benefits data from Social Security Administration files, and health insurance and pension data from respondents' employers. In the UK Millennium Cohort Study (Dex and Joshi, 2004), prior consent is required in order to obtain data from hospital episode statistics and birth registration records, and for the linkages to school records for cohort members and their siblings that are planned for future survey sweeps. The ISMIE survey, analysed in the rest of the paper, is an example of a study without a health focus. Informed consent was used to facilitate linkages with administrative records about benefit and tax credit records held by government agencies, and about earnings and employment data held by employers – the linked records were the basis of a measurement validity study.

Analysis of consent rates and consent bias is rare in multi-topic surveys, however. Gustmann and Steinmeier (1999), Haider and Solon (1999), and Olson (1999) considered how successful the Health and Retirement Study (HRS) has been in matching Social Security administrative records to respondents. (Linkage was conditional on consent and provision of a Social Security Number to facilitate matching.) The overall linkage rate was 75%, with some variations by sex, ethnic group, and household net worth, for example. These were viewed as 'not huge', however, and Haider and Solon concluded that the sample with linked earnings data was 'reasonably representative' (1999, p. 6). However, as Olson (1999) makes clear, the absence of an HRS matched record could arise for several reasons in addition to respondent refusal to provide consent: consent forms that were not personally signed could not be used, some forms arrived too late to be used, and some respondents were unable to provide Social Security Numbers (SSNs). In sum, there appears to have been no analysis of patterns of consent to

SSA record linkage per se, nor analysis of respondents' supply of SSNs. And, as far as we know, there has been no analysis of these questions jointly with other HRS consent questions, for example those concerning linkages to Medicare records.

There have been several US experimental studies concerned with, first, assessing respondents' understanding of consent questions and the risks that they perceived to be associated with them and, second, examining the impact of respondents' concerns about privacy and confidentiality on survey response rates and consent propensities (see the surveys by Singer 1993, 2003). Singer et al. (2003) showed that greater concerns about privacy and confidentiality were associated with lower participation rates in the decennial Census, according to three measures of participation. Guarino et al. (2001) found that requests for SSNs were associated with a small but significant decline in mail response to Census 2000 and a higher probability of a returned form being incomplete. Singer's (2003) experimental study based on the Survey of Consumer Attitudes showed that the greater the concern about willingness-to-participate questions, the lower the probability of survey participation. And, among those who said that they would be willing to participate, those who perceived the studies as more threatening were less likely to sign a consent form. Issues of incidental truncation arising from the focus on those willing to participate were not addressed.

3 The ISMIE survey and the consent questions

The household survey data in our study were derived from the ISMIE survey, a follow-up to the 2001 wave of the BHPS-ECHP panel. (For full details, see Jäckle et al. 2004.) The BHPS-ECHP panel was derived from a random sample of private households, the UK component of the European Community Household Panel Survey (ECHP-UK). This began in 1994, with annual interviews thereafter. Following the major reorganisation in ECHP design in the mid-1990s, a sub-sample was drawn from the ECHP-UK and surveyed jointly with the primary samples of the British Household Panel Survey (BHPS) from 1997 onwards. Households were eligible for selection if all adult members had been interviewed in the previous wave, and one of the following applied: (a) the household reference person was unemployed currently or in the last year; (b) the household reference person was receiving lone parent benefit; (c) the housing was rented; or (d) means-tested benefits were received. These criteria were intended to provide an over-representation of 'low income' households, though the realised sample contained a notable number of households with middle-range income and some with high incomes.

Funding for the BHPS-ECHP subsample expired in 2001. This provided an opportunity to interview respondents once more for purely methodological purposes: an experimental study comparing the effects of dependent and independent interviewing and a validation study based on comparisons of linked survey responses and administrative records, with record linkage conditional on consent (as described shortly). Funding for the additional interview round and the research was secured through the ESRC Research Methods Programme, and ISMIE fieldwork took place in spring 2003.

Interviews were sought with all BHPS-ECHP panel members who had responded in survey year 2001, i.e. 1,167 individuals aged 16+ in 785 households. Eligible movers were followed to their new address. The achieved sample with complete interviews was 1,033 adults, i.e. 89% of the eligible sample. The ISMIE questionnaire was the same as that given to the main BHPS sample in Autumn 2002, except that some short modules were added for the purposes of the methodological work, and some others (e.g. about health) were excluded in order to minimize total respondent burden and to economise on survey costs. Computer-assisted personal interviewing (CAPI) was used.

The ISMIE survey has several advantages for the topics addressed in this paper. The sample size is relatively large, and compares favourably with the experimental studies by Singer (2003) and Singer et al. (2003). The questionnaire covers many topics and provides a large amount of information about respondents and, moreover, the longitudinal nature of the study means that information from previous interview waves can also be utilised. Having multiple consent questions – strictly speaking, two consent questions and a NINO-supply question – means that we can examine whether each process is determined in the same way, and whether there is evidence of a latent consent propensity.

Although the ISMIE survey does not provide a representative cross-section sample of the UK population – because of non-random response to the original 1994 ECHP-UK survey, the sample selection in 1997, and because of potentially non-random sample drop-out – it includes individuals from a wide range of population subgroups. (Information about sample composition is provided in the next section.) In particular, the sample is not restricted to low-income households, partly because the 1997 BHPS-ECHP sample was selected using proxy measures of low income rather than direct measures of income itself, and because of income mobility between 1997 and 2003. Our analysis does not use weights or other methods to take account of differential sample inclusion probabilities. Our results therefore refer to a particular sample, but we believe that that sample is sufficiently broad to be generally informative about the issues under discussion.

The two consent questions and the National Insurance number (NINO) question were asked at the end of the ISMIE individual interview. (The CAPI script is reproduced in the Appendix.) After the interviewer had read a preamble stating that additional analysis was being undertaken this year especially to assess the quality of data collected in the survey, all respondents were asked whether they were happy to give us permission to link their answers with the administrative records held by the Department for Work and Pensions (DWP) and Inland Revenue about their benefits and tax credits, but not about their income tax. (The information is held in files at the Information and Analysis Directorate of the DWP. There are records for each person who is currently receiving, or has received, any one of 15 benefits. These include Child Benefit, Housing Benefit, Working Families Tax Credit, several types of disability benefit, Income Support, Job Seeker's Allowance and the state retirement pension.) If respondents answered that they didn't know whether to give consent, or queried why the information was required, the interviewer provided more information, and then repeated the consent question. Everyone who gave consent was then asked to tell the interviewer their NINO, with respondents being asked to consult a payslip or other records such as a pension or benefit book or NINO card. Respondents who gave oral consent also signed a form confirming consent.

Finally, all individuals who had worked in the previous week for an employer (i.e. excluding the self-employed) were told that another part of the research checking the accuracy of the data collected involved contacting employers for some details about the 'current job, pay, and conditions'. These respondents were then asked whether they would give us permission to contact their current employer. Individuals who gave oral consent also signed a form confirming consent, and employer contact details were collected from them.

Of the 1,033 ISMIE respondents, 799 (77.4%) gave permission to match their benefits and tax credit data with records held by the DWP (hereafter 'DWP consent'). Of the 799 consenting respondents, 708 (88.6%) were willing and able to supply their NINO. Of these, 477 (67.4%) derived the NINO from a payslip or other document like a pension payment book. A further 218 (30.8%) did not consult records but were certain that the number given was correct. These responses provide positive support for the accuracy of the data provided. (See Jenkins et al. 2004 for further analysis of the accuracy of the NINOs supplied.) By way of comparison, note that Brudvig's (2003) experimental study based on the US Census 2000 showed that Social Security Numbers were accurate if they were reported, with an estimated validation rate of some 95%. Brudvig did not examine the determinants of willingness and ability to provide a Social Security Number per se (and the fraction that provided a SSN was not reported), but this was cited explicitly as a useful topic for future research (2003, p. 1).

Of the 1,033 ISMIE respondents, 434 (42.0%) were in employment and therefore were asked for consent to contact their employer for record linkage purposes (hereafter 'employer consent'). Among the subgroup asked the question, 254 respondents (58.5%) gave consent, and all bar one provided employer contact details.

In sum, there were two consent questions (about DWP and employer record linkage) plus a NINO supply question, and two of these questions were asked only of a subset of respondents. This design raises questions of whether there is consent bias (whether consent propensities differ systematically among respondents), whether the nature of any bias differs according to the question asked, what the impact is of the incidental truncations arising from the question routing, and whether the information from multiple consent questions yields additional information about respondents. The next section proposes a statistical model to address these questions.

4 A statistical model of patterns of consent

4.1 Model specification

There are four binary outcomes – DWP record linkage consent, NINO supply, whether employee, and employer record linkage consent – that we propose modelling jointly. For each individual, we suppose that there is a continuous latent propensity determining each outcome, with the value of each observed outcome depending on whether the latent propensity is above or below a critical threshold (normalised at zero). Whether the NINO supply and employer record linkage consent outcomes are observed at all depends on the DWP consent and employment outcomes, respectively. Each individual's latent propensity is assumed to be characterised by a linear function of observable predictors plus an orthogonal white-noise error term summarising unobservable individual factors. No restrictions are placed on the cross-equation correlations of the error terms.

The model specification is shown in detail in Table 1, equations (1)–(5). We propose a four-variate probit regression model with two outcomes incidentally truncated. It is an extension of the bivariate probit model with sample selection proposed by Van de Ven and Van Praag (1981).

Consistent with the literature reviewed in Section 2, we define consent bias to occur if there is a systematic association between respondent characteristics and consent, specifically if there are elements of each β, γ, or θ that differ significantly from zero. We can also examine whether the same characteristics affect each outcome similarly. (The vectors summarising predictors $\boldsymbol{W_i}$, $\boldsymbol{X_i}$, and $\boldsymbol{Z_i}$, have many common elements: see below.) We are also interested in the magnitudes of any consent biases, and examine these later with analysis of how predicted consent probabilities vary with differences in characteristics. The estimates of ρ_{bn} and ρ_{em} are informative about the relevance of incidental truncation: it is ignorable only if both are zero. Finally, if having controlled for differences in observed characteristics, the estimate of ρ_{bm} is significantly positive, then arguably there is evidence of a general latent consent propensity.

Table 1
Statistical model of patterns of consent

Eqn.	Outcome	Latent propensities	Observed binary outcomes
For each respondent $i = 1, \ldots, N$:			
(1)	DWP record linkage consent	$B_i^* = \boldsymbol{W_i}'\boldsymbol{\beta} + b_i$	$B_i = I(B_i^* > 0)$
(2)	NINO supply	$N_i^* = \boldsymbol{X_i}'\boldsymbol{\gamma} + n_i$	$N_i = I(N_i^* > 0)$ if $B_i = 1$, else unobserved
(3)	Employee	$E_i^* = \boldsymbol{Y_i}'\boldsymbol{\delta} + e_i$	$E_i = I(E_i^* > 0)$
(4)	Employer record linkage consent	$M_i^* = \boldsymbol{Z_i}'\boldsymbol{\theta} + m_i$	$M_i = I(M_i^* > 0)$ if $E_i = 1$, else unobserved
(5)	Error terms	$(b_i, n_i, e_i, m_i) \sim N_4(\mathbf{0}, \Omega)$, where Ω is a symmetric matrix with typical element $\rho_{rs} = \rho_{sr}$ for $r, s \in \{b, n, e, m\}$ and $r \neq s$, and $\rho_{rr} = 1$, for all r. The errors in each equation are assumed to be orthogonal to the predictors.	

Notes. $I(.)$ is the indicator function equal to one if its argument is true, and zero if false. $N_4(.)$ is the four-variate normal distribution function.

A sufficient condition for identification of model parameters, given unconstrained cross-equation correlations, is a set of exclusion restrictions. We require that there are variables affecting DWP consent and employment propensities that have no direct effect on NINO supply and employer consent propensities, i.e. variables entering the $\boldsymbol{W_i}$ and $\boldsymbol{Y_i}$ vectors but not $\boldsymbol{X_i}$ and $\boldsymbol{Z_i}$, respectively. (The variables are discussed below.) Since the model is identified by the non-linearities in functional form, the over-identification restrictions concerning the exclusion of the instruments (and hence their validity) can be tested. An alternative sufficient identification condition would be to constrain the cross-equation correlations to zero from the outset, in which case each of the four equations could be estimated using a univariate probit regression model – the single-equation approach adopted in earlier research on patterns of consent (see Section 2). We argue below that this restricted model can be rejected in favour of the model shown in Table 1, and we use comparisons of estimates and predicted probabilities from the two models to illustrate how the different models lead to different conclusions about patterns of consent.

4.2 The sample likelihood and the partial likelihood estimator

In the survey data, each individual may fall into one of four regimes, where the regimes correspond to the cells of cross-tabulation of the binary outcomes for DWP consent (B_i) and employment (E_i). If we drop the individual-specific subscript i for clarity's sake, define a set of index variables $k_T = 2T - 1$ for $T \in \{B, N, E, M\}$, and represent the q-variate standard normal distribution function by $\Phi_q(.)$, then the likelihood for an individual with $B = 0$ and $E = 0$ (regime 1; N and M unobserved) is

$$\mathcal{L}_1 = \Phi_2(k_B \boldsymbol{W}'\boldsymbol{\beta}, k_E \boldsymbol{Y}'\boldsymbol{\delta}; k_B k_E \rho_{be}). \tag{6}$$

If, instead, $B = 0$ and $E = 1$ (regime 2; $M = 0$ or 1, N unobserved), the likelihood is

$$\mathcal{L}_2 = \Phi_3(k_B \boldsymbol{W}'\boldsymbol{\beta}, k_E \boldsymbol{Y}'\boldsymbol{\delta}, k_M \boldsymbol{Z}'\boldsymbol{\theta}; k_B k_M \rho_{bm}, k_E k_M \rho_{em}, k_B k_E \rho_{be}). \tag{7}$$

If $B = 1$ and $E = 0$ (regime 3; $N = 0$ or 1, M unobserved), the likelihood is

$$\mathcal{L}_3 = \Phi_3(k_B \boldsymbol{W}'\boldsymbol{\beta}, k_N \boldsymbol{X}'\boldsymbol{\gamma}, k_E \boldsymbol{Y}'\boldsymbol{\delta}; k_B k_N \rho_{bn}, k_N k_E \rho_{ne}, k_B k_E \rho_{be}) \tag{8}$$

and if $B = 1$ and $E = 1$ (regime 4; all outcomes observed), the likelihood is

$$\begin{aligned}\mathcal{L}_4 = \Phi_4(&k_B \boldsymbol{W}'\boldsymbol{\beta}, k_N \boldsymbol{X}'\boldsymbol{\gamma}, k_E \boldsymbol{Y}'\boldsymbol{\delta}, k_M \boldsymbol{Z}'\boldsymbol{\theta};\\ &k_B k_N \rho_{bn}, k_B k_E \rho_{be}, k_B k_M \rho_{bm}, k_N k_M \rho_{nm}, k_N k_E \rho_{ne}, k_E k_M \rho_{em}).\end{aligned} \tag{9}$$

The contribution to the overall sample log-likelihood for any given individual is therefore

$$\log \mathcal{L} = (1 - B)(1 - E) \log \mathcal{L}_1 + (1 - B)E \log \mathcal{L}_2 + B(1 - E) \log \mathcal{L}_3 + BE \log \mathcal{L}_4. \tag{10}$$

The 1,033 individuals in our sample data came from 715 households (454 single-respondent households; 261 multiple-respondent households). This clustering means that the standard i.i.d. assumption underlying the maximum likelihood principle is implausible. Rather than explicitly modelling within-household consent patterns, which would have added a layer of complexity beyond the scope of this paper, we maximised (10) to derive consistent parameter estimates, and derived standard errors using a robust variance (sandwich) estimator with households as clusters. This is what Wooldridge (2002, Chapter 13) refers to as a partial likelihood estimator. Hypothesis testing can no longer be based on likelihood ratio tests; we use Wald tests instead.

We evaluated multivariate standard normal distribution functions using simulation methods based on the GHK simulator (Gourieroux and Monfort, 1996, 93–107) with 250 random draws. For maximization, we used a combination of the modified Newton-Raphson and Davidon-Fletcher-Powell routines implemented in Stata's *ml* command, together with its *cluster* option to derive the robust variance estimator (StataCorp, 2003).

4.3 The choice of predictors

The set of predictors of DWP consent, NINO supply, and employer consent – the elements of $\boldsymbol{W}_i$, $\boldsymbol{X}_i$, and $\boldsymbol{Z}_i$ – included controls for the respondent's sex, age (summarised using a linear spline with knots at 25, 40, 50, and 60), household composition (six household types), and geographical location (whether living in London and the South-East).

In addition we used predictors summarising differences in respondents' willingness and ability to provide consent. Our choice of variables was influenced by literature on consent and on survey non-response more generally. (See e.g. Groves et al. (1992), and Esser (1993) on rational choice theory and Tourangeau et al. (2000) on cognitive approaches. Schräpler (2003) provides a useful review.) We seek a measure of differences between respondents at each stage of the response process: understanding the particular question asked, processing and retrieving the information required to answer the question, and responding to the interviewer. Differences in cognitive and other (e.g. physical) factors may have effects at each stage. Particularly relevant for consent questions are perceptions of risk (Singer 2003). Administrative record linkage involves access by third parties to intimate personal information, potentially raising issues in respondents' minds about invasion of privacy and risk of disclosure to unauthorized persons. Respondents differ in the extent to which they perceive these issues and in how they react to them. Respondents may be more likely to consent if they recognize a social benefit arising from the questions (the consent questions' preamble drew attention to the importance of data quality for policy users of the data), and if they have developed rapport and trust with interviewers.

The ISMIE survey contains a relatively rich set of variables related to these issues that we were able to use, also exploiting the longitudinal nature of the survey. There are measures of the respondent's educational qualifications and of their household income. For example, one might suppose that educated individuals are more likely to perceive the social benefits of consent and so have higher consent rates. One might expect consent propensities to decline with income, given the commonly expressed view that income information is particularly sensitive. We have measures of whether the respondent has any self-assessed health problems

(14 types relating to sight, hearing, skin conditions, chest/breathing, stomach/digestion, diabetes, anxiety and depression etc., alcohol or drugs, epilepsy, migraine, cancer, stroke, other), and whether there were any interviewer-assessed problems affecting the interview (any one of six types: eyesight, hearing, reading, English, language, and interpretation).

We expect respondents with partial response in previous interviews – specifically those with any item non-response to income questions – to be less likely to give consent. We also used length of the previous interview as a predictor: controlling for interview problems, we supposed that having a long interview reflected greater rapport with the interviewers or survey process, and hence increased propensity to consent or to supply a NINO. (It is sometimes argued that a change in interviewer between waves of a longitudinal survey disturbs respondents' rapport with the survey. In our preliminary modelling, this variable was never a statistically significant predictor, and so was dropped.)

DWP consent and NINO supply rates were expected to differ between respondents who had been in receipt of means-tested benefits or tax credits and those who had not. For example, non-recipients may feel that there is no point in providing consent if they believe that there are no records about them to link with.

All the predictors cited in the last two paragraphs were measured at the Autumn 2001 interview prior to the ISMIE interview. This reduces the risk of endogeneity problems. For example, we wish to avoid any possibility that lack of consent led interviewers to be more likely to report problems with the interview or that the process of gaining consent led to longer interviews. (As it happens, use of contemporaneous measures led to similar results.)

Another predictor of consent propensities and NINO supply was the dependent interviewing experimental group to which the respondent belonged. The ISMIE research programme includes analysis of the effects on survey measures of income and employment of proactive and reactive dependent interviewing (DI) techniques by contrast with conventional independent interviewing methods. (See Lynn et al. 2004 for details.) With proactive DI, information from previous interview waves is fed forward to remind the respondent of previous responses and, with reactive DI, clarification about inconsistencies between current and previous reports is sought. Questions are asked afresh each wave with independent interviewing. Respondents were allocated randomly to the three experimental groups (each forms one third of the sample). If respondents interpret reactive DI as raising doubts about the quality of their responses, thereby disturbing interview rapport, consent propensities may be reduced. Proactive DI might reduce consent propensities if the feeding-forward of past information makes the request for additional information via record linkage appear of less importance, or if the request raises perceptions of potential loss of privacy and disclosure in future.

All the predictors discussed so far were included in $\boldsymbol{W_i}$, $\boldsymbol{X_i}$, and $\boldsymbol{Z_i}$, with the exception of previous receipt of means-tested benefits which was assumed not to affect employer consent propensities. For identification of the NINO supply propensity equation, we also included in the DWP consent equation a binary indicator of whether the respondent was a recipient of Income Support (IS) at the ISMIE interview but not at the previous interview. (IS is the main safety-net social assistance benefit in Britain.) Our argument is that the process of making an IS claim raises respondent awareness of the Department for Work and Pensions and its work – the DWP is the government department most closely associated with benefits policy – and therefore affects propensities to consent to linkage with DWP records. On the other hand, NINO supply propensities are unlikely to be affected because NINOs are required for many purposes besides making a benefit claim. (Preliminary analysis indicated that moves into receipt of other benefits did not have effects similar to that of moves into IS.)

The variables used to predict employment propensities were commonly used ones: sex, household composition, age, educational qualifications and health problems. For identification of the employer consent equation, we also included a measure of local labour market slackness in the employment equation: the ratio of the unemployment stock to the vacancies stock in the respondent's travel-to-work area at the previous interview.

5 Analysis of patterns of consent

5.1 Patterns of consent

Patterns of response to each outcome variable are shown in Table 2 for the sample as a whole (row 1) and broken down by respondent characteristics (the remaining rows). The statistics in parentheses are *p*-values from a Pearson test of independence in a two-way table. Table 2 suggests that DWP consent rates were significantly lower among respondents who were aged 40–49 years, or single householders, or who had relatively short previous interviews or problems with that interview. This is *prima facie* evidence of consent bias. Among those who gave DWP consent, there appears to be little significant cross-sample variation in propensities to supply a NINO, with the exception that rates are noticeably lower among those subject to proactive dependent interviewing, or living in travel-to-work areas with the largest unemployment/vacancy ratios. There was also little cross-sample variation in employer consent rates among those respondents who were employed, with the exception that the consent rate was markedly lower among respondents with item non-response to income questions at the previous interview.

Table 2
Patterns of consent, by ISMIE respondent characteristics

Percentages (p-values)

Characteristic	Category	DWP consent	NINO supply (given DWP consent)	Employee	Employer consent (given employee)
All respondents		77.4	88.6	42.0	58.5
Sex	Male	77.4	89.5	40.4	60.3
	Female	77.2	87.4	44.3	56.3
		(0.842)	*(0.327)*	*(0.179)*	*(0.375)*
Age (years)	16–24	78.7	88.7	62.5	50.6
	25–39	77.6	91.8	65.2	59.5
	40–49	71.4	85.5	59.2	65.0
	50–59	75.8	91.4	46.4	56.3
	60+	80.3	86.4	5.5	61.1
		(0.023)	*(0.306)*	*(0.000)*	*(0.408)*
Household composition	Single	70.4	86.5	15.4	41.0
	Couple, no kids	83.4	91.3	36.0	59.6
	Couple & kids	78.6	87.0	60.4	59.0
	Lone parent	74.3	96.2	54.0	61.0
	Other	86.7	88.5	40.0	83.3
		(0.023)	*(0.570)*	*(0.000)*	*(0.140)*
Educational qualifications:	No	77.2	87.7	32.9	54.9
A-level(s) or higher[§]	Yes	77.8	90.3	60.1	62.5
		(0.827)	*(0.263)*	*(0.000)*	*(0.106)*

to be continued

Percentages (p-values)

Characteristic	Category	DWP consent	NINO supply (given DWP consent)	Em-ployee	Employer consent (given employee)
Household income (quartile group)§	Lowest	73.0	90.0	8.5	45.5
	2nd	80.2	87.4	30.2	56.4
	3rd	78.3	91.1	57.8	59.1
	Highest	77.9	86.1	71.7	60.5
		(0.373)	*(0.456)*	*(0.000)*	*(0.633)*
Lived in London or South-East§	No	76.3	89.3	41.3	58.4
	Yes	81.5	86.2	44.6	58.6
		(0.157)	*(0.289)*	*(0.426)*	*(0.973)*
Had health problem(s)§	No	75.3	92.1	61.4	53.8
	Yes	78.2	87.2	34.0	62.1
		(0.317)	*(0.058)*	*(0.000)*	*(0.089)*
Length of interview (quartile group)§	Shortest	70.7	89.4	30.1	51.3
	2nd	83.0	89.1	42.6	62.8
	3rd	79.2	87.4	47.2	56.8
	Longest	76.6	88.6	48.8	61.0
		(0.013)	*(0.932)*	*(0.001)*	*(0.425)*
Problems with interview§	No	78.7	88.6	43.8	58.5
	Yes	55.5	88.2	13.1	62.5
		(0.0002)	*(0.944)*	*(0.000)*	*(0.818)*
Income item non-response§	No	77.9	88.4	48.3	60.3
	Yes	75.4	89.3	20.8	44.9
		(0.440)	*(0.745*	*(0.000)*	*(0.043)*
Type of interviewing	Independent	75.3	92.0	42.5	64.2
	Proactive DI	77.1	84.8	43.7	52.4
	Reactive DI	79.7	89.1	39.8	59.1
		(0.396)	*(0.029)*	*(0.562)*	*(0.111)*
Received means-tested benefits§	No	75.6	88.3	53.6	57.9
	Yes	80.2	89.1	23.6	60.6
		(0.096)	*(0.745)*	*(0.000)*	*(0.645)*
Moved into IS receipt	No	77.0	88.6	43.8	58.4
	Yes	86.4	89.5	2.3	–
		(0.143)	*(0.865)*	*(0.000)*	*(0.401)*
Unemployment/vacancy ratio in travel-to-work area (quartile group)§	Lowest	79.5	85.0	49.8	60.5
	2nd	80.6	90.0	38.8	65.1
	3rd	79.1	95.4	42.5	53.6
	Highest	72.9	83.4	36.7	53.4
		(0.267)	*(0.003)*	*(0.042)*	*(0.360)*
N		1033	799	1033	434

Notes. §: Measured at the interview prior to the ISMIE one. Statistics in parentheses are *p*-values from a design-based Pearson test of independence in a two-way table, adjusting for repeated observations within households.

There is also indicative evidence that consent proclivities are correlated. Among those who provided employer consent, 90.0% provided DWP consent and supplied a NINO. Among employees who gave DWP consent, 63.7% supplied a NINO and gave employer consent; among non-employees who gave DWP consent, 88% provided a NINO.

These summaries are suggestive but cannot be conclusive. Many respondent characteristics are correlated, and one cannot discern the separate impact of each one holding others constant. Moreover, the breakdowns do not provide good estimates of correlations in unobserved consent propensities or, more generally, take into account potential biases due to incidental truncation. To address these issues, we turn to the estimates of our multivariate probit regression model.

5.2 Multivariate probit regression model estimates

Wald tests of instrument validity indicate that our model is identified. A sufficient condition for identification is rejection of the null hypothesis that the relevant coefficient is equal to zero in the case where instruments were included in an equation, and non-rejection of the null in the equation from which the instruments were excluded. Respondents moving into IS receipt were more likely to give consent to DWP record linkage ($\chi^2(1) = 8.50$, $p = 0.004$) and the slacker the labour market in which respondents lived, the less likely they were to be an employee ($\chi^2(1) = 7.25$, $p = 0.007$). In addition, from estimates of an augmented version of the model (results not shown), we could reject the inclusion of move-into-IS-receipt from the NINO supply equation ($\chi^2(1) = 0.06$, $p = 0.810$) and of the unemployment/vacancy ratio from the employer record linkage equation ($\chi^2(1) = 1.17$, $p = 0.280$), or reject their joint inclusion ($\chi^2(2) = 1.23$, $p = 0.539$).

We assess the existence and magnitude of consent biases through analysis of the variation of predicted probabilities of consent outcomes with variations in respondent characteristics. Specifically, we summarise our model estimates in terms of the marginal effects associated with each regressor. Each marginal effect (ME) in the DWP consent equation, for example, shows how the probability of DWP consent changes given a one unit change in the associated regressor (a change from zero to one for binary indicator variables), calculated at the sample values of the predictors in that equation. For the NINO supply equation, the MEs refer to the probability of NINO supply conditional on DWP consent, and for the employer consent equation, they refer to the probability of employer consent conditional on employment. For both conditional probabilities, the probability of the conditioning event is held constant at the value predicted for a person with the sample mean values of the characteristics. (One has to take account of the fact that a marginal change in a predictor may change the probability of the conditioning event as well as the outcome event – the relevant equations have common predictors. The ME calculation method is described in more detail by Cappellari and Jenkins (2004, p. 604) and Stewart and Swaffield (1998, p. 39).)

Our use of the probability metric to assess consent bias differs from that of other researchers. Most have estimated logistic regression models and considered the variation in odds ratios associated with changing values of a particular categorical variable. (See e.g. Dunn et al. (2004) and Woolf et al. (2000).) We believe that examination of variations in probabilities rather than odds ratios is preferable because the probability metric is more intuitive and easily understood. It also allows us to straightforwardly examine the effects of changes in the values of continuous variables as well as categorical ones, and we can derive the probabilities from our multi-equation model.

Estimated MEs are reported in Table 3, with the coefficient estimates underlying them reported in Appendix Table 1. For each equation of the model, Table 3 also reports a baseline predicted probability, calculated by setting the values of predictors equal to sample means. This provides a reference point for assessing whether the MEs are large or small.

The estimates indicate that there are systematic and statistically significant associations between respondent characteristics and consent outcomes, i.e. there is consent bias. Moreover the nature of the biases depends on the question asked.

Table 3

Estimated marginal effects: DWP consent, NINO supply, employment, and employer consent (four-variate probit regression model accounting for incidental truncations)

	Pr(DWP consent)			Pr(NINO supply |DWP consent)			Pr(Employee)			Pr(Employer consent |Employee)		
	Marginal Effect	(SE)		Marginal Effect	(SE)		Marginal Effect	(SE)		Marginal Effect	(SE)	
Predicted probability (at means)	*0.7913*			*0.9019*			*0.2611*			*0.6602*		
Respondent's sex is male	0.0092	(0.0232)		–0.0282	(0.0215)		0.0360	(0.0314)		–0.0827	(0.0658)	
Age (linear spline)												
16–24	0.0141	(0.0100)		0.0083	(0.0093)		0.0078	(0.0102)		0.0118	(0.0224)	
25–39	–0.0116	(0.0053)	***	–0.0001	(0.0042)		0.0004	(0.0050)		0.0026	(0.0108)	
40–49	0.0047	(0.0066)		–0.0020	(0.0046)		–0.0126	(0.0066)	*	–0.0050	(0.0157)	
50–59	0.0079	(0.0066)		0.0031	(0.0057)		–0.0137	(0.0082)	*	0.0167	(0.0206)	
60+	0.0048	(0.0029)	*	–0.0051	(0.0023)	***	–0.0518	(0.0076)	***	0.0066	(0.0466)	
Household type (ref: single)												
Couple, no children	0.1459	(0.0345)	***	0.0447	(0.0366)					0.1704	(0.1311)	
Couple with child(ren)	0.1341	(0.0420)	***	–0.0056	(0.0460)					0.2113	(0.1518)	
Lone parent	0.0822	(0.0427)	*	0.0214	(0.0409)					0.2311	(0.1267)	*
Other	0.1709	(0.0373)	***	0.0725	(0.0422)	*				0.3084	(0.1228)	***
No. adults in household							0.0278	(0.0163)	*			
No. children in household							–0.0466	(0.0155)	***			
Lived in London or South East§	0.0575	(0.0326)	*	–0.0201	(0.0272)		0.0087	(0.0421)		–0.0797	(0.0910)	
Education ≥ A-level(s) §	–0.0048	(0.0298)		0.0235	(0.0226)		0.1089	(0.0360)	***	–0.0140	(0.0794)	
Had health problems§	0.0241	(0.0324)		–0.0546	(0.0228)	***	–0.0821	(0.0361)	***	0.1478	(0.0769)	*
Log(household income)§	0.0322	(0.0252)		–0.0022	(0.0231)					0.0469	(0.0693)	
Received means-tested benefit(s)§	0.0790	(0.0293)	***	–0.0042	(0.0271)							
Length of interview (hours) §	0.1213	(0.0734)	*	–0.0488	(0.0322)					0.1691	(0.1348)	
Problems with interview§	–0.2922	(0.0810)	***	0.0319	(0.0437)					–0.0489	(0.2060)	
Income item non-response§	–0.0170	(0.0355)		0.0352	(0.0222)					–0.2584	(0.1166)	***
Proactive dependent interviewing	0.0101	(0.0309)		–0.0716	(0.0313)	***				–0.1219	(0.0851)	
Reactive dependent interviewing	0.0357	(0.0325)		–0.0367	(0.0278)					–0.06	(0.0843)	
Moved into IS receipt	0.1437	(0.0343)	***									
Local unemployment/vacancy ratio§							–0.3576	(0.0565)	***			
ρ_{bn}	–0.1222	(0.3843)										
ρ_{be}	0.0594	(0.0702)										
ρ_{bm}	0.6777	(0.1146)	***									
ρ_{ne}	0.0858	(0.0896)										
ρ_{nm}	–0.0555	(0.1719)										
ρ_{em}	–0.5379	(0.2658)	**									
Log partial likelihood	–1,489.2											
N	1027											

Notes. §: Measured at previous interview. *: $0.05 \le p < 0.10$. **: $0.01 \le p < 0.05$. ***: $p < 0.01$. Simulated maximum likelihood estimation, GHK simulator, 250 draws. Robust standard errors in parentheses, adjusting for multiple observations within households. Marginal effect shows change in probability given one unit change in regressor (from 0 to 1 for binary indicators). Marginal effects and predicted probabilities evaluated at the sample means of the regressors. Estimated coefficients are shown in Appendix Table 1.

Consider the effects of differences in age, for example. The relationship between age and probability of DWP consent is broadly V-shaped (after a slight rise between the ages of 16 and 25), and the effects are relatively large. For example, the DWP consent probability declines by more than one percentage point per year between the ages of 25 and 39, other things being equal, or 15 percentage points over the interval compared to a baseline average probability of 0.79. In contrast, the probability of NINO supply varies hardly at all with age, apart from a small decline for those aged 60+. And there is no statistically significant relationship with employer record linkage consent propensities.

Household composition is strongly associated with DWP consent rates, less strongly associated with employer consent rates, and not significantly associated at all with the NINO supply rate. For both consent questions, it is single respondents who have the lowest consent probabilities and 'other' households who have the largest consent probabilities. However for DWP consent, lone parents have a lower consent propensity than respondents in a couple, whereas for employer consent, it is the reverse. The MEs in the DWP consent and employer consent equations are all substantial, being at least eight percentage points in the former case, and at least 16 percentage points in the latter case.

Respondents who had had health problems are less likely to supply a NINO but more likely to grant employer consent, and there was no association with DWP consent propensities. Respondents assessed as having problems with the previous interview were very much less likely to provide DWP consent (the ME is a massive 29 percentage points), but those who had established greater rapport (as measured by the length of the previous interview) were more likely to consent. Neither factor had an impact on NINO supply or employer consent propensities, however. On the other hand, respondents with past item non-response on income were much less likely to provide employer consent (the marginal effect is a 25 percentage point reduction), but this characteristic did not affect NINO supply or DWP consent propensities. NINO supply propensities, and those propensities only, were lower for respondents with responses to income and employment questions from the previous interview fed back to them (the proactive dependent interviewing experimental group). We cannot distinguish whether the effect arises because feeding forward makes the request for additional information via record linkage appear of less importance, or because the request raises perceptions of potential loss of privacy and disclosure in future.

Having educational qualifications to A-level standard, sex, and living in London or the South-East are not significantly associated with either of the two consents or NINO supply. Household income per se is not either, but there is an association with income and DWP consent propensities revealed through another variable. Respondents who previously received means-tested benefits (and therefore had low income by definition) have consent rates about 8 percentage points higher.

Estimates for the employment equation are consistent with others in the labour supply literature. (Comparisons of fit with various specifications led us to summarize household composition in this equation in terms of the number of adults and number of children.) The chances of being an employee are relatively flat up to age 40, decline over the following two decades, and then fall precipitately after age 60. Respondents with educational qualifications to A-level standard, and those without health problems, are more likely to be employees. The more children in the household, the lower are employment probabilities. Perhaps surprisingly, the probability of employment does not differ between the sexes.

The estimates of cross-equation correlations in individual error terms (the ρ) are shown at the bottom of Table 3. There is evidence of a latent general individual propensity to consent since, controlling for observed characteristics, individuals who are more likely to consent to DWP record linkage are also more likely to consent to employer record linkage: the estimate of ρ_{bm} is 0.678 and is precisely estimated. Unobservable individual factors influencing NINO supply propensities are uncorrelated with unobservable individual factors influencing consent propensities: although the estimates of ρ_{bn} *and* ρ_{nm} are negative, both have large standard errors. Put another way, there is no evidence that incidental truncation of the NINO supply equation is an important issue. On the other hand, there is evidence that incidental truncation matters for estimation of employer consent propensities. Individuals who are more likely to be employees, other things being equal, are less likely to provide employer consent: the estimate of ρ_{em} is around –0.538 and precisely estimated.

The pattern of estimated correlations led us to estimate a series of nested models in which a number of correlations were constrained to equal zero. A Wald test of the hypothesis $\rho_{bn} = \rho_{be} = \rho_{ne} = \rho_{nm} = 0$ had a $\chi^2(3)$ test statistic of 0.570, $p = 0.904$. The model with these restrictions imposed had a partial likelihood value of –1490.0, and the estimate of ρ_{bm} was 0.697 (s.e. 0.098), and the estimate of ρ_{em} was –0.565 (s.e. 0.236). Coefficient estimates (and their precision) were almost identical to those for the general model. The full set of estimates is not reported for brevity's sake.

The conventional approach of modelling each consent equation independently is equivalent to constraining all the cross-equation error terms to be zero. A Wald test indicated rejection of these constraints ($\chi^2(5) = 182.7$, $p < 0.0001$). Although the independent probits version of the model was rejected, the estimates from it are of interest nonetheless because they can be used to investigate the implications of ignoring incidental truncation and cross-equation error correlation more generally. If there were no incidental truncation, the independent probit estimates would be consistent but not efficient; with incidental truncation, estimates are inconsistent as well. Estimates derived using four independent probit regressions are reported in Appendix Table 2. When estimates of coefficients and of their precision are compared with their general model counterparts (shown in Appendix Table 1), there appear to be close similarities. Does this mean that ignoring incidental truncation, and cross-equation correlations more generally, has no substantive practical consequences?

5.3 Comparisons of predicted probabilities

To answer this question, we compared estimates of predicted probabilities for a range of (hypothetical) individuals with different characteristics. (The calculations also enable us to comment further on the magnitude of consent biases: see below). The predictions are summarized in Table 4, with the numbers in the columns headed 'Joint' derived from the four-variate joint model and the numbers in the columns headed 'Indep.' derived from independent probit regression models. The top panel of Table 4 indicates how the probabilities vary with age, the middle and bottom panels indicate how they vary with household composition and a range of other characteristics (holding age constant).

The two modelling approaches produce very similar predictions for the probability of DWP consent and the probability of NINO supply conditional on DWP consent: corresponding estimates are mostly within one or two percentage points of each other. These results are not surprising given that the estimate of ρ_{bn} was insignificantly different from zero.

Table 4
Predicted probabilities: joint and independent models

Case number and characteristics	Pr(DWP consent)		Pr(NINO supply |DWP consent)		Pr(employer consent |employee)	
	Joint	Indep.	Joint	Indep.	Joint	Indep.
Single, no children, and:*						
1. Age = 20	0.568	0.571	0.935	0.944	0.300	0.331
2. Age = 25	0.662	0.636	0.962	0.966	0.472	0.415
3. Age = 30	0.585	0.568	0.960	0.966	0.505	0.430
4. Age = 35	0.505	0.497	0.959	0.965	0.539	0.446
5. Age = 40	0.425	0.427	0.957	0.964	0.571	0.461
6. Age = 45	0.457	0.463	0.953	0.959	0.464	0.439
7. Age = 50	0.490	0.499	0.948	0.953	0.348	0.417
8. Age = 55	0.545	0.551	0.957	0.960	0.505	0.441
9. Age = 60	0.598	0.602	0.966	0.966	0.660	0.466
10. Age = 65	0.630	0.634	0.953	0.955	0.477	0.384
11. Age = 70	0.661	0.665	0.937	0.941	0.254	0.307
Aged 20 and:*						
1. Single	0.568	0.571	0.935	0.944	0.300	0.331
12. Couple, no children	0.774	0.771	0.966	0.971	0.526	0.486
13. Couple, 1 child	0.749	0.751	0.935	0.941	0.524	0.493
14. Couple, 2 children	0.749	0.751	0.935	0.941	0.488	0.493
15. Lone parent, 1 child	0.687	0.686	0.952	0.958	0.560	0.518
16. Other (3 adults)	0.859	0.813	0.986	0.958	0.826	0.742
Aged 20, couple and 1 child:						
13. Base case	0.749	0.751	0.935	0.941	0.524	0.493
As case 13, except:						
17. Had health problems	0.775	0.778	0.879	0.890	0.626	0.565
18. Had A-levels	0.744	0.743	0.950	0.954	0.559	0.544
19. Income at lower quartile	0.729	0.727	0.950	0.955	0.474	0.463
19. Income at upper quartile	0.764	0.767	0.921	0.928	0.559	0.514
21. Interview problems	0.438	0.444	0.952	0.959	0.470	0.615
22. Had income item non-response	0.730	0.713	0.958	0.955	0.263	0.337
23. Interview duration at lower quartile	0.736	0.737	0.938	0.943	0.505	0.481
23. Interview duration at upper quartile	0.767	0.768	0.930	0.937	0.549	0.509
25. Proactive dependent inter-viewing	0.761	0.766	0.872	0.876	0.389	0.392
26. Received means-tested benefits	0.830	0.841	0.933	0.939	0.524	0.493

Notes. Predicted probabilities and standard errors (in parentheses) derived from model estimates reported in Appendix Tables 1 ('Joint') and 2 ('Indep.'). *: And female, lived outside London & South-East, no A-levels, no health problems, median income, not receiving means-tested benefits, no new IS claim, median interview duration, no interview problems, no income item non-response, independent interviewing, median local unemployment/vacancy ratio.

For the predicted probabilities of employer consent conditional on employment, more substantial differences are apparent. For example, at ages 25–40 and 50–70, the predicted probability from the four-variate probit model is more than five percentage points higher than that from the independent probit model. This result should be assessed with caution given the relatively large standard errors associated with the underlying coefficients (see Table 3 or Appendix Table 1). Differences between models persist, however, when one focuses on statistically significant predictors. For example, the predicted conditional probability of employer consent is around 0.83 for a 20 year old respondent living with two other adults according to the general model (case 16) but almost ten percentage points lower, 0.74, according to the independent probit regression. A 20 year old single person with past income item non-response has a predicted conditional employer consent probability of 0.26 according to the general model (case 22), but some eight percentage points higher according to the independent probit regression.

These relatively large differences suggest that estimates based on independent probit regressions can lead to misleading estimates in comparison with a more general model that accounts for incidental truncation.

5.4 More on the magnitude of consent biases

The predicted probabilities also provide an additional perspective on the magnitude of consent biases, complementing that provided by the marginal effects. We focus on the estimates derived from the general model and variations associated with statistically significant predictors. Look again at Table 3 (columns headed 'Joint').

Variations in characteristics are associated with large differences in predicted probabilities. For example, the probability of DWP consent is about 0.43 at age 40 for a single childless woman (case 5) but some 50% higher, 0.66, if she were aged 70 instead (case 11). A woman aged 20 has a predicted probability of 0.57 if she is single, but 0.77 if she is part of a childless couple, and even higher, 0.86, if she is a member of a three-adult childless household (cf. cases 2, 12, and 16). Among the other cases, two stand out. First, among 20 year old women with a partner and one child, those with no previous interview problems have a predicted DWP consent probability of 0.75 compared to a predicted probability of only 0.43 if there had been problems (cf. cases 13 and 21). Second, the predicted probability is notably higher for those who previously received means-tested benefits: 0.83 compared to 0.75 (cf. cases 21 and 13). In the other cases (17–20, 22–25) the variation from the baseline predicted probability is small.

Belonging to a childless multi-adult household is associated with a five percentage point smaller probability of NINO supply conditional on DWP consent (cf. cases 16 and 1). For a 20 year old married women with one child, those who had health problems have a conditional probability of NINO supply some five percentage points lower than those without health problems, other things being equal. And having been subject to proactive dependent interviewing rather than independent interviewing is associated with a decline in the predicted probability of about the same amount.

There are some relatively large consent biases in employer consent conditional on employment. Compare, for example, a probability of 0.30 for a 20 year single person living alone and a probability of 0.83 for a 20 year old living in a three-adult childless household, other things being equal (cf. cases 1 and 16). Among married 20 year olds with one child, those with previous income item non-response have a predicted conditional employer consent probability of 0.26 which is almost half the corresponding probability for a woman with income item non-response (cf. cases 13 and 22).

Overall, these estimates suggest that consent biases can be large, though their nature depends on the outcome considered. For example, consent biases in conditional NINO probabilities are generally smaller than consent biases in DWP consent probabilities. The characteristics associated with bias vary with outcome too, with the exception of household type which is associated with relatively large biases in each case.

6 Summary and conclusions

This paper has analysed patterns of consent and consent bias in the context of a large general household survey; most previous studies have focused on consent bias in the context of surveys focusing on health. We have drawn attention to the potential issues that are raised by multiple consent questions and the complications introduced by question routing; previous research has considered consent questions separately rather than jointly. To address these issues, we proposed a multivariate probit model that controls for incidental truncations.

We have shown that there are consent biases in survey respondents' consent to data linkage with benefit and tax credit administrative records held by the Department for Work and Pensions, consent to linkage with wage and employment records held by employers, and also in respondents' willingness and ability to supply their NINO. This means that samples of consenting respondents may not be representative of the population being studied – the conclusion from several studies of consent bias in health surveys also applies in general household surveys. For example samples based on respondents who provide DWP linkage consent are likely to under-represent middle-aged individuals, single householders, and over-represent people on low income (those who have received means-tested benefits). However our results also underline that the nature of consent bias differs according to the question considered. For example, samples based on respondents who provide employer consent under-represent individuals prone to income item non-response. (They made up about one tenth of the employees in the ISMIE survey data.)

We have also argued that modelling consent questions independently rather than jointly may lead to misleading inferences: single equation models do not take account of incidental truncation. In the ISMIE survey, this form of sample selection bias affected the estimation of employer consent propensities but not NINO supply propensities. Multiple equation models can also reveal more than single equation models. Correlations between unobservable individual factors affecting consent to DWP record linkage and consent to employer record linkage provide evidence suggestive of a latent individual consent propensity. Because many surveys include multiple consent questions, with some questions directed only to subsamples of respondents, our methods should have general application.

Our results also highlight how survey researchers might take steps to reduce consent biases in future. We have shown how propensities to provide consent are associated with clearly observable characteristics such as household type. And, in the context of a longitudinal survey, we have seen how information about the previous interview is informative about consent responses in the current interview. For example respondents with problems at the previous interview were very unlikely to provide consent to DWP record linkage. This sort of information could be used to identify respondents with low consent propensities, and develop modified consent question modules for this group. This could be thought of as an extension of the idea of ‘tailoring’ the request for survey participation to the circumstances and concerns of sample members (Groves et al. 1992; Morton-Williams 1993).

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Appendix:

Computer-Assisted Personal Interview script for ISMIE Survey consent and NINO questions

Data Linkage with the DWP

F53_intro

This is a special year for the survey as we have gained funding to carry out additional analysis to assess the quality of the data we collect on the survey. This work is especially important as data from the survey are used by many policy makers and government departments. So it is important that we can say with certainty that the data we provide is accurate and giving the correct information.

To ensure that our records are complete and accurate, we would like to use information held by the Department for Work and Pensions and Inland Revenue about your benefits and tax credits (but NOT about your income tax).

F53

Are you happy to give us your permission to link your answers with the administrative records held by these government departments?

Yes	GO TO E137
No	GO TO F55
Don't know/respondent queries why	GO TO F53_Prompt

F53_Prompt

IF ASKS 'WHY'

"Researchers want to check accuracy and completeness of the survey answers about benefits and tax credits"

IF ASKS ABOUT THE CONSEQUENCES OF SAYING 'YES'

"Like everything else you have told us, this information will be completely confidential and will be used solely for research purposes. No information that can identify you will be made available to the Department for Work and Pensions, the Inland Revenue, or anyone else outside the research team. Taking part in this study will not affect your benefit or tax credit entitlements or dealings with any Government Departments now or in the future".

IF ASKS HOW THE LINK WILL BE DONE

"To link the information from the Department for Work and Pensions and Inland Revenue with your answers, we shall pass them your name, address, sex and age. These personal details will be removed as soon as the information has been linked".

GO TO F54

F54 Are you happy to give us your permission to link your answers with the administrative records held by these government departments?

YES	GO TO E137
NO	GO TO F55
DK/Can't say	GO TO F55

National Insurance Number

E137 To help us make this link to the administrative data, can you tell me your National Insurance number please?

ASK RESPONDENT TO CONSULT A PAYSLIP OR OTHER RECORDS SUCH AS A PENSION OR BENEFIT BOOK OR NATIONAL INSURANCE NUMBER CARD

IF RESPONDENT ASKS 'WHY DO YOU WANT THIS?' RESPOND…

"This is just to ensure our records are accurate."

IF RESPONDENT QUERIES 'WHY?' AGAIN RESPOND…

"This will be used for research purposes when checking the data and will not be released to anyone outside the research team"

IF RESPONDENT IS STILL UNWILLING TO PROVIDE THE INFORMATION CODE 'REFUSED' BELOW

ENTER NUMBER:		GO TO E138
Don't Know	GO TO F55	
Refused	GO TO F55	

E138 INTERVIEWER CODE FOR ALL CASES WHERE A NUMBER GIVEN

1 NI number taken from payslip or other document

2 NI number remembered and respondent certain correct
3 NI number remembered but respondent not certain

Employers details

ASK IF EMPLOYEE ONLY

F55 Another part of the work on checking the accuracy of the data we collect involves contacting your current employer for some details about your current job, pay and conditions.

Would you give us your permission to contact your employer?

Yes GO TO F55_Details
No GO TO F55_W11

F55_Details WRITE IN

Contact name
Employer/Firm name
Address details:
Number and street
Town
County
Postcode
Telephone number inc. STD code

GO TO F55_W11

Note. Respondents who provided verbal consent were also asked to signed a form confirming the consent, with separate signature for each of the DWP and employer linkage questions.