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Multilevel Modelling of Refusal and Noncontact in Household Surveys: Evidence from Six UK Government Surveys

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Summary.

In this paper we analyse household unit nonresponse in six major UK government surveys using a multilevel multinomial modelling approach. The models are guided by current conceptual frameworks and theories of survey participation. One key feature of the analysis is the investigation of the extent to which effects of household characteristics are survey specific. The analysis is based on the 2001 UK Census Link Study, a unique data source containing an unusually rich set of auxiliary variables. The study contains the response outcome of six surveys, linked to census data and interviewer observations for both respondents and nonrespondents.

Key Words: multilevel multinomial models, survey unit nonresponse, noncontact, refusal, theories of survey participation, Census Link Study.

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1. Introduction

Nonresponse is a major problem facing researchers in the social and medical sciences and official statistics. Response rates in many surveys have been falling, both in the UK (Martin and Matheson, 1999) and elsewhere (De Heer, 1999; Steeh et al., 2001). In addition to decreasing response rates, there are indications that the type of nonresponse may have changed over time, leading to a possible change in the nature of nonresponse bias (Groves et al., 2002; Groves, 2006). Nonresponse rates and nonresponse bias may both affect the quality of survey data, with potentially serious consequences for data analyses underpinning social science research. For this reason an important goal of survey research is to develop ways to minimise nonresponse, through survey design and data collection methodology, and to reduce the impact of nonresponse bias through modification of data analysis methods. As a key intermediate aim, and of social science interest in itself, it is crucial to gain a better understanding of the nature and predictors of nonresponse.

Current conceptual frameworks for survey participation have identified a number of key factors influencing nonresponse, such as individual and household characteristics, interviewer attributes, the social environment and survey design features. Theories about the effects of individual and household characteristics on survey participation are based on psychological concepts such as social exchange (Goyder, 1987; Dillman, 2000), civic engagement (Brehm, 1993) and social isolation and integration (Goyder, 1987). A more recent theory is the leverage-salience theory (Groves et al., 2000), focusing on the interaction between individual sample member characteristics and survey design features. These theories are concerned with influences on access to the sample unit and cooperation of the sample unit with the survey request, influence of the social context on individual action, interplay of multiple effects on survey participation, and mechanisms by which characteristics of the sample unit affect the performance of the survey design. In face-to-face surveys, it is generally recognised that interviewers have a vital role in contacting sample members and achieving their cooperation, leading to clustering of response behaviour for sample units allocated to the same interviewer.

The aim of this paper is to analyse determinants of household unit nonresponse in face-to-face government surveys, and thus to contribute to a deeper understanding of the process and reasons for nonresponse as a social phenomenon. The models presented here are guided by current conceptual frameworks for survey participation, incorporating the key factors described above. Using a multilevel multinomial logit model, we distinguish between noncontacts and refusals and allow for between-interviewer variation in the probability of each type of nonresponse.

A key strength of our data source is the availability of data from six surveys which vary in their design and subject matter. We are therefore able to test whether the effects of household characteristics on survey participation differ across surveys. This contrasts with most previous research on response that focuses on a single survey with a specific design and survey topic (e.g. O'Muircheartaigh and Campanelli, 1999; Pickery and Loosveldt, 2002 and 2004). When several surveys have been investigated with more detailed information on interviewers, sample unit characteristics tend not to have been taken into account (e.g. Hox and De Leeuw, 2002). The simultaneous analysis of several surveys allows us both to identify general results and to test for variation in response correlates across and within surveys.

Previous empirical research has largely investigated the influences of a small number of factors, primarily using simple methods such as bivariate or logistic regression analyses (e.g. Groves and Couper, 1998). As a result, the effects of multiple influences on survey participation, i.e. how the effect of one factor changes in the presence of another, are not well understood and theoretical frameworks that may suggest multiple influences have not been sufficiently tested in practice (Groves et al., 2000). Recent studies have used multilevel modelling approaches to simultaneously allow for different types of nonresponse and interviewer effects, but are limited with regard to the data available or the methods used. For example, they were based on a relatively small number of interviewers and households with little information on household and interviewer characteristics (Pickery and Loosveldt, 2002; Pickery et al., 2001; O'Muircheartaigh and Campanelli, 1999) and suffered from convergence problems in model estimation (Pickery et al., 2001; O'Muircheartaigh and Campanelli, 1999). The present study aims to address these shortcomings.

Studies of the determinants of nonresponse require information on both respondents and nonrespondents, as well as information on the factors influencing the nonresponse process. However, it is not often possible to link survey data to appropriate sources, such as census returns, administrative registers and interviewer information. The analysis presented in this paper is based on the 2001 UK Census Link Study, a unique data source linking the survey outcome of six major UK government surveys to a rich set of auxiliary variables available for both respondents and nonrespondents, including census data and detailed interviewer information. Although the data have been expensive to collect, they have thus far been analysed only superficially. While researchers have used linked databases of this sort before (Groves and Couper, 1998), this study was designed to eliminate some of the weaknesses of earlier work. The database is considerably richer than other sources. In addition to the usual household information, the study includes individual-level information, interviewer observation data, and unusually detailed information on interviewers and interviewer calling strategies and fieldwork process data.

The remainder of the paper is organised as follows. Section 2 describes the design of the Census Link Study and the analysis sample. The methodology for the analysis is described in Section 3. The results are discussed in Section 4 and concluding remarks are given in Section 5.

2. Rationale and Design of the UK 2001 Census Link Study Database

The UK 2001 Census Link Study database, designed and administered by the UK Office for National Statistics (ONS), contains the response outcome of six major UK government household surveys, linked to 2001 UK census data on a range of household and individual characteristics, interviewer observations about the household, extensive information about the interviewer, and area information (Beerten and Freeth, 2004). All variables are available for both respondents and nonrespondents of the six surveys. The study includes only face-to-face surveys conducted by interviewers. Similar studies have been carried out by ONS in the past - for example the survey outcome for a number of separate surveys was linked to data from the 1991 census - but on a much smaller scale (Foster, 1998).

2.1 The Surveys and Definition of Nonresponse

The six surveys included in this study are: the Expenditure and Food Survey (EFS), the Family Resources Survey (FRS), the General Household Survey (GHS), the Omnibus Survey (OMN), the National Travel Survey (NTS) and the Labour Force Survey (LFS). Further information on the different surveys can be obtained from the ONS website (www.statistics.gov.uk). All surveys are treated as cross-sectional; panel data, such as those collected in the LFS, are not available for this study. The six surveys differ with regards to survey topic and design. Table 1 summarises the main differences in the features of survey design that may influence household response.

[Table 1 about here]

The survey outcome – the dependent variable in our analysis – is an indicator of household participation, distinguishing the two main components of nonresponse: i) *noncontact*, where it has not been possible to contact the eligible household, and ii) *refusal*, where contact has been made but the household refused an interview. This distinction is also made by Groves and Couper (1998) to allow for potential differences in the determinants of each type of nonresponse. Refusal and noncontact are contrasted with cooperation of the household with the survey request, which in this study is defined as a successful contact followed by an interview carried out with *at least one* member of the household. All government surveys considered in the Census Link Study, with the exception of the Omnibus survey, specify that all household members of a certain age take part in the interview, referred to as full cooperation. Failure to obtain information from all household members is classified as partial cooperation. In this paper, focusing on household unit nonresponse only, both fully and partially cooperating households are classified as cooperating households. (The Omnibus survey requires response from only one household member, which we treat as a special case of full household cooperation.)

The six surveys have different refusal and noncontact rates (see Figure 1). The differences in nonresponse rates across surveys may be partly explained by differences in subject matter and design, such as differences in questionnaire length, number of interviewer callbacks, the level of interviewer training and interviewer workload. For example, the higher refusal rates for the EFS might be due in part to the additional requirement of a two-week diary and the low refusal rate for the LFS might be influenced by a short interview and more specialised interviewers. The high rates of noncontact in the Omnibus survey might be attributed in part to a comparatively short fieldwork period and high interviewer workloads (see Table 1).

[Figure 1 about here]

2.2 Information Available for Respondents and Nonrespondents

As discussed in section 1, current conceptual frameworks of survey participation have identified a number of key factors influencing nonresponse. The Census Link Study provides a unique opportunity to study these factors in more detail. The analyses presented in this paper are based on the census and interviewer observation data contained in the linked dataset. Survey records of respondents and nonrespondents were linked to their 2001 UK census record, providing information on households and individuals within households. Interviewer observations on the household were recorded at each visit, even if no contact was made, including characteristics of the accommodation (e.g. whether a house or flat, the presence of security measures such as locked gates or burglar alarms), any information about the household composition, the quality of housing and observations on the surrounding neighbourhood.

The linked dataset also contains field process and interviewer calling data - referred to as paradata (Couper, 1998) - as well as detailed information on interviewer characteristics, including interviewing strategies, behaviours and attitudes (Freeth et al., 2002). This more detailed information, however, is not considered in this paper.

The linkage of the different data sources with the response outcome of each survey was carried out by ONS, and the resultant dataset became available for analysis in 2005. The linkage itself raised a number of methodological challenges. Linkage of the survey and census data was based on the address of the household and, if necessary, further identifying information. About 95% of all households were successfully linked to their census record. The linkage of the interviewer observation data and interviewer attitudinal data was based on the interviewer number. All linkage was quality assured by ONS based on the distribution of key variables before and after the linkage. Further details can be found in White et al. (2001), Beerten and Freeth (2004), Freeth (2004), Freeth and Sowman (2003a, 2003b, 2005) and Freeth et al. (2004).

2.3 Analysis Sample and Definition of Explanatory Variables

The analysis sample includes households selected for interview in one of the surveys during May-June 2001, the months immediately following the 2001 Census. The following cases were excluded: all persons under 16 (since only persons 16 and older were eligible to take part in the surveys); sample units that were unable to respond due to language comprehension difficulties; individuals and households that were imputed in the 2001 census (because only basic area information was available for these cases); vacant homes; households that had moved between the census and the survey date (to avoid, for example, a mis-match between interviewer observations and census data); mode switches, where after failing to receive a face-to-face interview a telephone interview was attempted; and re-issues, cases where one interviewer failed to get a positive outcome from a sample unit and subsequently the sample unit was re-issued to another interviewer to attempt conversion. The analysis sample includes all households for which the survey outcome could be linked successfully to census information and interviewer observation data and for which the interviewer could be identified. The analysis file contains 18,530 households and 565 interviewers. The number of households sampled in each of the six surveys is 3683 for the EFS, 2219 for the FRS, 3415 for the GHS, 3318 for the Omnibus, 2642 for the NTS and 3253 for the LFS.

The explanatory variables of interest in this paper are household characteristics from the census, and interviewer observations on the household and the area in which it is situated. Table 2 shows the coding and percentage distributions over cases within each of the three types of response status of all explanatory variables included in the final models. (Details of model selection are given in Section 4.)

[Table 2 about here]

Since household unit nonresponse is the dependent variable of interest, individual-level information for the household reference person (HRP) is used to obtain household-level variables, an approach that has been used elsewhere (e.g. Groves and Couper, 1998). The HRP is defined as the person who is the main owner, renter or in some other way responsible for the accommodation, and who has the highest income (and in some circumstances who has the highest income and is oldest) (Walker et al., 2002). The rationale for this definition is that the main householder is the person who exerts the most influence on the household's living patterns and circumstances. Taking characteristics of the HRP is a way of selecting one person in the household to represent the household as a whole. For example, if the HRP is unemployed this implies that the whole household is affected by low or no income. The HRP is identified in the census data but may not be the person who first interacted with the interviewer (which cannot be identified in the dataset). An alternative way of defining household-level measures, which would avoid discarding information from other household members, would be to calculate within-household averages of the variables of interest. However, this approach is infeasible for the categorical variables considered here.

Some of the variables were subject to item nonresponse and there is therefore missing data for some of the explanatory variables included in the final models. In some cases it was possible to impute the missing items by using other information available for the household or interviewer (e.g. in some cases where census information was incomplete, interviewer observations could be used). Nevertheless some missing data remained and, rather than dropping sample units with incomplete data from the analysis, we created an extra 'missing' category for those variables subject to item-nonresponse. In the majority of cases, however, the proportion missing was very small.

3. Methodology

3.1 Specification of the Multilevel Multinomial Model

A multilevel multinomial model is used to explore the effects of household characteristics on household nonresponse, distinguishing refusal and noncontact. A multilevel model allows for correlation in nonresponse probabilities for households allocated to the same interviewer. Failure to account for clustering by interviewer leads to underestimated standard errors and therefore incorrect inferences. A multilevel multinomial modelling approach was also adopted by O'Muircheartaigh and Campanelli (1999). The advantage of using a multinomial model, rather than fitting separate binary logistic models for each type of nonresponse, is that the effects of household characteristics on the probability of refusal and noncontact may be evaluated simultaneously and tested for equivalence. Furthermore, we can allow and test for correlation between the unobserved interviewer influences on the different types of nonresponse. We denote by y_{ij} the outcome for household i of interviewer j which is coded

$$y_{ij} = \begin{cases} 0 & \text{cooperation} \\ 1 & \text{refusal} \\ 2 & \text{noncontact.} \end{cases}$$

The response probabilities are denoted by $\pi_{ij}^{(s)} = \Pr(y_{ij} = s)$, $s = 0, 1, 2$. Taking cooperation (full or partial) as the reference category, the multilevel multinomial model can be written

$$\log\left(\frac{\pi_{ij}^{(s)}}{\pi_{ij}^{(0)}}\right) = \boldsymbol{\beta}^{(s)^T} \mathbf{x}_{ij}^{(s)} + u_j^{(s)}, \quad s = 1, 2 \qquad (1)$$

where $\mathbf{x}_{ij}^{(s)}$ is a vector of household and interviewer level covariates and cross-level interactions, $\boldsymbol{\beta}^{(s)}$ is a vector of coefficients, and $u_j^{(s)}$ is a random effect representing unobserved interviewer characteristics.

Model (1) consists of two simultaneous equations. The first equation ($s = 1$) models the log of the ratio of the probability of refusal to that of cooperation as a function of covariate and interviewer effects, and the second ($s = 2$) models the log of the ratio of the probability of noncontact to that of cooperation. The above specification allows for a different set of covariates to be included in the refusal and noncontact equations. This is important because previous studies have found that the refusal and noncontact processes are quite different (Groves and Couper, 1998), although in practise there may be some overlap in their predictors. For covariates included in both equations, their effects may differ for the two types of nonresponse and it may be of interest to test whether a given characteristic has the same effect on both refusal and noncontact rates.

The interviewer random effects are also outcome-specific but are assumed to follow a bivariate normal distribution, i.e. $\mathbf{u}_j = (u_j^{(1)}, u_j^{(2)}) \sim N(\mathbf{0}, \mathbf{\Omega})$ where

$$\mathbf{\Omega} = \begin{pmatrix} \sigma^{2(1)} & \\ \sigma^{(12)} & \sigma^{2(2)} \end{pmatrix}.$$

The variance parameters $\sigma^{2(1)}$ and $\sigma^{2(2)}$ are respectively the residual between-interviewer variances in the log-odds of refusal versus cooperation, and the log-odds of noncontact versus cooperation. The parameter $\sigma^{(12)}$ is the covariance between the unobserved interviewer influences on the probabilities of household refusal and noncontact. A positive residual covariance would be expected if interviewers who have low (high) noncontact rates tend also to be good (weak) at securing a household's participation. Equation (1) is commonly referred to as a random intercept model because the effect of interviewer j is to change the log-odds of refusal or noncontact versus cooperation by an amount $u_j^{(s)}$, regardless of the values of the covariates $\mathbf{x}_{ij}^{(s)}$. In a more general random coefficients model, the effects of elements of $\mathbf{x}_{ij}^{(s)}$ may vary across interviewers.

It should be noted that none of the six surveys in the Census Link Study employed an interpenetrated sampling scheme where interviewers are allocated at random to households. It is therefore not possible to separate interviewer effects from primary sample unit (PSU) effects. O'Muircheartaigh and Campanelli (1999) analysed data from an interpenetrated sample experiment, in which addresses were allocated at random to interviewers within pools of PSUs, and used a cross-classified multilevel model to disentangle interviewer and PSU effects on nonresponse.

The multilevel multinomial model is estimated using Markov chain Monte Carlo (MCMC) methods as implemented in the MLwiN software (Browne, 2004). Noninformative priors were assumed for all parameters. We present results from 80,000 chains with a burn-in of 5000, using approximate quasi-likelihood estimates (Goldstein, 2003, pp. 112-113) as starting values for the sampling.

Predicted probabilities of cooperation, refusal and noncontact can be calculated to aid model interpretation. A reorganisation of equation (1) gives

$$\pi_{ij}^{(s)} = \frac{\exp(\boldsymbol{\beta}^{(s)^T}\mathbf{x}_{ij}^{(s)} + u_j^{(s)})}{1 + \sum_{r=1}^{2}\exp(\boldsymbol{\beta}^{(r)^T}\mathbf{x}_{ij}^{(r)} + u_j^{(r)})}, \quad s = 1,2$$

$$\pi_{ij}^{(0)} = 1 - \pi_{ij}^{(1)} - \pi_{ij}^{(2)} \tag{2}$$

The magnitude of the effect of a covariate $x_k^{(s)}$ can be assessed by calculating predicted probabilities for a range of values of $x_k^{(s)}$, holding constant the values of all other elements of $\mathbf{x}^{(s)}$. The mean predicted probabilities $\boldsymbol{\pi}^* = (\pi^{(0)^*}, \pi^{(1)^*}, \pi^{(2)^*})$ for a set of covariate values $\mathbf{x}^{(s)} = \mathbf{x}^{(s)^*}$ $(s = 1,2)$ can be obtained via a simulation approach which involves generating random effect values from the estimated distribution. The simulation method is described by Rasbash et al. (2005) in the context of calculating the variance partition coefficient for a two-level binary logit model; details of the procedure for a multilevel multinomial model are given in the Appendix of this paper. Simulating from across the random effect distribution yields predicted probabilities that have a population average interpretation, i.e. probabilities that are averaged across unobserved interviewer characteristics. In this paper predicted probabilities are calculated by varying the values of one variable (or two in the case of an interaction effect) at a time, holding all other covariates at their sample mean value. In the case of a categorical variable, the dummy variable associated with a particular category takes on the value of the sample proportion in that category instead of the usual 0 or 1 value.

3.2 Modelling Strategy

We consider three specifications of the multilevel multinomial model for survey participation. All models include dummy variables for survey to control for design differences among the six surveys. The 'null' model (Model 0) allows only for survey differences. This model is then extended to include interviewer random effects (Model 1). Finally, we introduce household-level variables, which include individual characteristics of the household representative, household characteristics, information about the area in which the household is located and interviewer observations about the household (Model 2). Two-way interactions between household variables and the survey indicators are tested to determine whether the effects of household characteristics are the same across surveys.

We compare Models 1 and 2 to examine the extent to which any between-interviewer variation in survey participation rates can be explained by differences in the characteristics of households allocated to interviewers. Adjusting for household and area characteristics may reduce the between-interviewer variance if households with a low propensity of cooperation are clustered within interviewer assignments. For example, interviewers allocated to London households may have a low participation rate that is due to location rather than interviewer characteristics.

The selection of variables for inclusion in Model 2 was guided by preliminary simple logistic regression analyses and substantive theory. Specifically, we test the theories of survey participation outlined in Section 1. Variables that were not statistically significant at the 5% level, and did not interact significantly with other variables, were removed from the models. Joint (Wald) tests were carried out to test the significance of categorical variables with more than two categories. Due to the availability of a large number of potential predictors, testing of variables and interaction terms was primarily guided by theories of nonresponse and interpretation. Rather than testing all possible interactions we have restricted our investigations to terms of scientific interest as informed by nonresponse theories.

4. Results

4.1 Interviewer Random Effects

Table 3 shows estimates of the random effects covariance matrix and the deviance information criterion (DIC) statistic, a Bayesian analogue of the likelihood-based Aikake information criterion which balances model fit and model complexity (Spiegelhalter et al. 2002). A comparison of the DIC for Model 0 (including only survey effects and no interviewer random effects) and for the same model with interviewer effects (Model 1) suggests between-interviewer variation in nonresponse rates. (The difference in DIC is 25281-24971 = 310 for three additional parameters.) The significant, positive random effect correlation suggests that interviewers with low (high) refusal rates tend also to have low (high) noncontact rates, a finding which is consistent with previous research (O'Muircheartaigh and Campanelli, 1999). The addition of household-level variables (Model 2) leads to a large reduction in the DIC and a moderate reduction in the interviewer-level variances and covariance.

[Table 3 about here]

4.2 Interpretation of Household Characteristics

We now turn to the interpretation of the final model (Model 2). Table 4 presents the estimated coefficients of the household variables and interactions. The missing value categories included in the model have been suppressed from Table 4 to save space. With the exception of the variables 'Highest qualification' and 'Economic activity' the proportions missing are very small (see Table 2), and none of the coefficients for the missing value categories were statistically significant. The selected model includes interaction effects between survey and several household-level variables. To aid interpretation of these survey-specific effects, predicted probabilities of noncontact and refusal have been computed for each cell of the two-way interaction, with all other covariates in Model 2 held constant at their sample means (Table 5).

[Table 4 and 5 about here]

Factors influencing the probability of contact

We might expect noncontact to depend primarily on household characteristics (such as the presence of physical impediments), lifestyle characteristics (such as proxies of time spent at home), and interviewer strategies for contacting sample members. The results show that the probability of contact is higher, for example, among households living in a house rather than a flat (consistent across all surveys - see Table 5) and for couple households as opposed to single-person households (with particularly low noncontact rates for the GHS, NTS, EFS and LFS and comparatively high rates for the Omnibus - see Table 5). Previous research has identified interviewer observations on the presence of physical barriers, such as intercom systems, as important predictors of the probability of noncontact (Groves and Couper, 1998). We find, however, that the effects of these variables are not statistically significant after controlling for other factors, such as type of accommodation. Interviewer observations on the condition of the house and the safety of the area have a significant effect on making contact even after controlling for other variables, with higher noncontact rates for houses in a poor condition and houses in areas where the interviewer would feel unsafe walking after dark. Although indicators of geographical location (dummies for rural and London residence) are significant predictors of noncontact in simple models with survey dummies as the only additional variables, their effects are not significant in the final model (Table 4); part of their effect can be explained by variables such as accommodation type. Some survey-specific geographical effects have been found, however, with a particularly low noncontact rate in London areas for the FRS and comparatively high rates for the EFS and Omnibus (see Table 5).

Indicators of single-person households, and the presence of dependent children, pensioners, carers or employed adults, may be regarded as proxies for the time spent at home as well as lifestyle. Apart from presence of carers, these variables were found to be significant predictors of noncontact. In line with previous research (Groves and Couper, 1998), we find that households with children and pensioners are more likely to be contacted, whereas single households and households with an adult in employment are less likely to be found at home. Multiple-occupancy households in the UK show higher contact rates than single-person households (consistent across all surveys) but lower rates than couple households (apart from in the GHS and LFS - see Table 5). This may reflect the fact that multiple-occupancy households often consist of a number of students or young professionals whose lifestyles are closer to those of single-person households than of families but, because there are more independent individuals in the household, it is more likely that at least one person will be found at home.

Factors influencing the probability of survey participation

Our choice of variables for consideration as predictors of survey participation was guided by the findings of previous studies and, in particular, socio-psychological concepts and theories proposed in the survey research literature. In our discussion of the results from the final statistical model, we suggest which theories a particular finding might support. We note however that, in common with much of the earlier research, there are imperfect matches between the theoretical constructs and the auxiliary data available and the mapping of characteristics at the household or interviewer level to one or more of such concepts is difficult. The analysis also focuses on the identification of the response behaviour of different subgroups within the population.

We find a lower rate of survey participation among households in which the household reference person (HRP) is poorly qualified or unemployed (see Tables 4 and 5). Moreover, there is evidence that a sample person is less likely to cooperate if their house is judged by the interviewer to be in a worse condition than others in the same area or if the house is in an area in which the interviewer would feel unsafe after dark. This may indicate lower participation rates among disadvantaged groups as was also hypothesised by Groves and Couper (1998). In this context, the economic status of the HRP appears to be a useful indicator of the status of the household as a whole because the HRP usually has main (financial) responsibility for the household. For example, if the HRP is unemployed this would imply that the whole household is affected by low or no income. Education of the reference person as an indicator of household socioeconomic status (SES) has also been used by Groves and Couper (1998, Ch. 5.3).

According to the theory of social exchange (Goyder, 1987; Groves et al., 1992; Dillman, 2000) individuals who believe they have received few or poor services from government and those feeling disadvantaged may be least obligated to respond to a government request. Variables used to investigate the social exchange theory in previous research relate to SES, for example occupation, education and income. Most of the survey research literature argues that the process of social exchange should imply a curvilinear relationship between cooperation and SES with both low and high SES groups being less likely to participate than average: low SES groups because they connect the survey request with a previous unsatisfactory relationship with government and feelings of being disadvantaged, and high SES because they have received fewer government services. However, the empirical evidence from most earlier studies suggests SES effects in the opposite direction to what has been hypothesised. For example, Groves and Couper (1998), using indicators of education of the reference person and housing costs, have found support for higher cooperation among lower SES households, although the effect of education becomes non-significant once other factors are controlled. Using indicators of income, De Maio (1980) found that low-income households were least likely to refuse. To the extent that qualifications, employment status, household condition and safety of the area of residence are indicators of SES, our findings suggest lower participation rates among low SES groups, which is consistent with the theory of social exchange. However, we do not find support for a curvilinear relationship predicting lower cooperation rates for high SES groups.

We also find that households that do not own a car are less likely to participate in the Omnibus, NTS and EFS. As far as the absence of a car indicates a household with low means (after controlling for geographic location and other household characteristics such as the presence of children) this finding is consistent with the effects of our SES indicators, although there is evidence that not having a car predicts higher cooperation with the FRS.

It should be noted that for a number of reasons it is difficult to compare results from different studies, as also recognised by Groves and Couper (1998). Different indicators are used, the indicators may be imperfect measures of SES, they may be subject to missing data and the conclusions reached may be sensitive to which other variables have been included in the model.

A lower participation rate among households with an unemployed or uneducated HRP may also be predicted by the notion of social isolation (Goyder, 1987). According to this theory those who are alienated or isolated from the broader society are less likely to respond. Lower SES groups should therefore be less likely to respond to a survey request, while higher SES groups would have a higher propensity to respond due to a greater sense of civic obligation and feeling that participation is important. To the extent that employment status and education are suitable indicators, we find support for this theory. In contrast, however, Groves and Couper (1998) find a negative relationship between SES and cooperation, using the education of the household reference person as a measure of SES.

Household composition and household type may also be related to social isolation (Goyder, 1987). Previous research, based on bivariate analyses investigating the relationship between cooperation and one covariate at a time, provides some indirect support for this theory with evidence of lower cooperation among single households and people living in flats (Goyder, 1987; Groves and Couper, 1998). In contrast we find, after controlling for other factors, no significant differences in participation between single and other households or between houses and flats. Gender of the HRP was also not significant for explaining refusal.

Investigating the impact of the presence of children, we find that households with at least one dependent child are more likely to cooperate than childless households. There is no significant effect of the number and age of children. This is in line with previous research which consistently found higher cooperation rates among households with children (Ekholm and Laaksonen, 1991; Groves and Couper, 1998), but no effect of the age and number of children. It may be argued that a child's carer is more likely to be at home than a person in full-time employment – at least at certain times during the day – and it may be hypothesised that a carer may have more time to participate in a survey. Another possible explanation for this relationship is that the presence of children in a household may be associated with higher levels of social integration and social obligation, as argued by Glorioux (1993) and Groves and Couper (1998). Families with children may have a higher degree of social integration due to attendance at nurseries, schools, and greater involvement with community and family activities. Such activities may be indicators of social duty (Glorioux, 1993).

We find that the presence of a carer in the household who looks after an elderly or disabled person is associated with a lower probability of refusal, an effect which is constant across surveys (implied by the non-significant interaction between carer and survey). The effect may be explained partly by a carer being more likely to be at home and possibly having more time available or welcoming the interruption. Helping to care for a person in need may also be viewed as an indicator of civic duty as in Couper et al. (1998). The notions of civic duty (Brehm, 1993; Groves et al., 2000) and helping tendency (Groves et al., 1992) suggest that social norms lead to a feeling of obligation to provide help, e.g. agree to a survey request, in the belief that participation serves the common good.

The presence of a pensioner in the household is associated with a lower probability of refusal. The effect of the age of the HRP indicates no significant difference in the response rates of HRPs aged 50 years and older and those who are younger than 35. Similar indicators were used by Groves and Couper (1998) who considered the age of the reference person and differences between 'young' and 'old' households, based on the age composition of household members. Groves and Couper were unable to find significant effects or consistent trends in the effect of age. While some previous research has found higher refusal rates among the elderly - which is often interpreted as support for the social isolation theory (Krause, 1993) - the findings here may show greater support for an effect related to a higher level of civic duty amongst the elderly. As argued by Groves and Couper, higher cooperation rates among households with pensioners could provide support for the civic duty theory whereby older people might feel a stronger obligation to contribute to the good of society. When comparing different studies it should be noted, however, that much of the previous research has been based on simpler analyses relating the response outcome to only one variable at a time rather than controlling for other influences in a model. For example, some studies that found a positive association between being a pensioner and the probability of refusal may not have allowed for health-related factors (e.g. Krause, 1993). In our study we allow for other factors in the model, including an indicator of self-reported health. Further, previous studies of participation among the elderly may have investigated individual level response whereas our study and Groves and Couper (1998) have investigated household nonresponse using characteristics of the household members as predictors.

Self-reported health has an interesting effect on participation with a lower refusal rate among households whose reference person is content with his or her health (see Table 4). Happiness and a positive attitude to life, which are likely to be associated with good health, have been found to be connected to the decision to help other people, thus increasing the probability of cooperation (Groves et al., 1992). However, it is difficult to say to what extent the result here may be indicative since the characteristic refers only to the HRP.

Our measure of household mobility (whether the household moved during the last year) may be regarded as an indicator of social isolation, with more mobile households being less well integrated and therefore less likely to respond, as was initially hypothesised by Groves and Couper (1998). However, our results show lower refusal rates among movers than non-movers (even after controlling for type of accommodation) which is consistent with findings from other studies (Comstock and Helsing, 1973) including the findings in Groves and Couper (1998). A possible explanation for this effect is that a recently relocated household may need to make a greater effort to fit in with its new environment and neighbourhood, leading to a higher degree of social integration.

Compared to households in other parts of the UK, Londoners are less likely to participate in the EFS, Omnibus, NTS and LFS (see Tables 4 and 5). After controlling for London residence, however, an urban-rural difference in participation is evident in only one of the surveys (the GHS - see Table 4). One might expect the London effect to be partly explained by longer commutes in the capital but, as noted earlier, travel-to-work time was considered as a predictor and found not to be significant. Another possible explanation is that feelings of social isolation may be more prevalent in London, while civic duty may be weaker.

It has been argued that the time available to answer a survey is an important factor for cooperation rates. As discussed earlier, we find that households with an unemployed HRP are less likely to respond than those whose reference person is in employment. Refusal rates among the self-employed are comparatively high for five of the six surveys (with the exception of the LFS – see Table 5). To the extent that the self-employed have less free time than those in the other economic activity categories, the opportunity cost theory would predict a lower cooperation rate among self-employed persons. Such an effect would support the opportunity cost hypothesis which is based on the idea that survey participation is a rational decision depending on factors such as the time available to the sample unit. However, the opportunity cost hypothesis would also lead us to expect a higher participation rate among unemployed persons than for those in employment; as noted earlier, the reverse is true. Furthermore, the travel-to-work time, another proxy for the availability of discretionary time, was not statistically significant once other factors were controlled. It may be argued that variables such as the presence of a carer or pensioner in the household could be used as (imperfect) indicators of time available to answer a survey, with carers and pensioners having potentially more time to participate. Our findings indicate that households with carers or pensioners are indeed more likely to take part. To conclude, we find, as do Groves and Couper (1998), no consistent support for the hypothesis that less time available may lead to a lower probability of cooperation. However, our results should be interpreted with some caution because, for example, our measure of economic activity refers to the HRP who may not be the person with whom the initial contact was made. It is also possible that processes of social exchange or civic duty exert a stronger influence on an employed or unemployed person's decision about whether or not to participate in a survey.

A particular strength of the Census Link Study is that it provides data on respondents and nonrespondents to six major UK surveys. We can therefore test whether the effects of household characteristics on nonresponse are the same for each survey. The leverage-salience theory (Groves et al., 2000) posits that the effect of a particular survey design feature on a sample person's decision to participate will depend on the importance that he or she places on that feature. For example, one would expect the effect of offering incentives to be weaker among people who are highly involved in the community (an indicator of civic duty). The theory may therefore give insights as to why the effectiveness of some survey design features should work for some subgroups in the population but not for others. Unfortunately we do not have experimental data with which to test hypotheses about the effects of specific design features on participation rates, and whether their effects differ across subgroups of households. Nevertheless, evidence of an interaction between survey and a household characteristic, together with information about the design and topic of each survey, may suggest survey attributes that are more important for some subgroups than for others.

Throughout the paper we have highlighted which effects of household characteristics are survey specific and which are constant across surveys. For example, by considering the interaction between survey and the economic status of the HRP (and predicted probabilities of refusal for combinations of categories of these variables) we find particularly high refusal rates among the self-employed for the EFS, GHS, OMN, NTS and to a lesser extent for the FRS (see Table 5). The EFS, NTS, FRS and GHS all have long interviews compared to the LFS (Table 1). As indicated earlier, the self-employed may work longer hours, and may therefore have less time available to participate in a survey than other economic groups. The high refusal rates for the EFS and NTS may also be due to the extra burden of completing a diary for these surveys. Diary keeping could be more burdensome for the self-employed because they may have more complex expenditure and travel patterns, and because of the competing demands of maintaining financial records for budgetary and tax purposes. The interaction between economic activity and survey may indicate that the self-employed are more sensitive to the response burden of a survey than other economic groups; the time factor may be especially important for the self-employed. Such a finding may have consequences for the survey design. A short questionnaire, for example, may be advisable to obtain information from the self-employed. We also find survey-specific effects for car ownership. However, the interpretation and theoretical implications appear more difficult. For the EFS, Omnibus and NTS we find higher refusal rates among households with no car, whereas for the FRS refusal rates are higher for households with at least one car (see Table 5). In the case of the EFS and NTS this could possibly reflect sensitivity to the survey topics of expenditure and travel respectively.

5. Discussion

The findings indicate a systematic correlation between different types of nonresponse and socio-economic and demographic individual and household characteristics. A comparison of the results for refusal and noncontact reveals two quite distinct underlying nonresponse processes. Noncontact was found to be related to household and lifestyle characteristics, primarily ‘factual’ variables and factors relating to the propensity of being at home. In contrast, refusal seems to reflect a more complex social phenomenon explained by individual characteristics, such as the socio-economic status, qualifications and attitude of the HRP. This may be expected because refusal is a decision that is more likely to be made at an individual rather than a household level. In some situations we were only able to use characteristics of the HRP as an indicator of characteristics of the household as a whole, which may in some cases be an imperfect measure of the social constructs proposed in the survey literature.

Some predictors have opposite effects on the probability of noncontact and refusal (Groves and Couper, 1998). We find, for example, that households with an unemployed HRP are more likely to be found at home, but are less likely to participate (although the effect was only significant for refusal once other factors were controlled). Effects on refusal and noncontact may counteract one another, supporting the view that it is important to distinguish noncontact and refusal in order to understand nonresponse processes and their potentially different effects on nonresponse bias, with the goal of informing different strategies for reducing and adjusting for nonresponse.

The selection of explanatory variables was guided by existing conceptual frameworks for survey participation and the results provide support for some of these theories. In particular, there is evidence of interactions between characteristics of the sample unit and survey, which suggests that the effects of survey design and subject matter vary across subgroups of households. These interaction effects may provide some empirical support for the leverage-salience theory. The results have potential implications for survey practice and may provide guidelines on how different designs and survey topics may work for different subgroups of the population, and how best to approach certain sample units.

Some of the variables considered here are unlikely to be known to the interviewer prior to the data collection stage, for example from the sampling frame or registers. Information about a sampling unit can, however, be enriched by interviewer observation data and some of these types of variables, available in the Census Link Study, have proven useful in explaining the response outcome. The collection of interviewer observation data, or more generally paradata (Couper, 1998), may be recommended as a standard tool to obtain further information about potential nonrespondents and to guide calling and interviewing strategies. This information could also contribute to the tailoring of contact and interviewing strategies to particular sampling units.

The aim of the research was to contribute to a better understanding of the nonresponse process and the influence of factors associated with nonresponse. The findings will inform not only the design of strategies to reduce nonresponse prior to survey data collection, but also models for post-survey nonresponse adjustment. We have not specifically investigated the relationship between nonresponse rates and nonresponse bias. However, the analysis has shown that rules for survey participation may vary by subgroups. Serious nonresponse bias may occur if a variable indicating differential nonresponse propensities is correlated with the survey target variable on which an estimate is based.

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References

Beerten, R. and Freeth, S. (2004) Exploring Survey Nonresponse in the UK: The Census-Survey Nonresponse Link Study, *ONS working paper*, 1-16.

Brehm, J. (1993) *The Phantom Respondents: Opinion Surveys and Political Representation.* University of Michigan Press.

Browne, W.J. (2004) *MCMC Estimation in MLwiN*, Centre for Multilevel Modelling.

Comstock, G.W. and Helsing, K.J. (1973) Characteristics of Respondents and Nonrespondents to a Questionnaire for Estimating Community Mood, *American Journal of Epidemiology*, 97, 4, 233-239.

Couper, M.P. (1998) Measuring Survey Quality in a CASIC Environment, *Proceedings of the Survey Research Methods Section, American Statistical Association*, 48, 743-772.

Couper, M.P., Singer, E. and Kulka, D.A. (1998) Nonresponse to the 1990 Census: Politics, Privacy and/or Pressures, *American Politics Quarterly*, 26, 59-80.

De Heer, W. (1999) International Response Trends: Results of an International Survey, *Journal of Official Statistics*, 15, 2, 129-142.

DeMaio, T.J. (1980) Refusals, Who, Where and Why?, *Public Opinion Quarterly*, 44, 223-233.

Dillman, D.A. (2000) *Mail and Internet Surveys: the Tailored Design Method,* 2nd edition, New York, Wiley.

Ekholm, A. and Laaksonen, S. (1991) Weighting Via Response Modelling in the Finnish Household Budget Survey, *Journal of Official Statistics*, 7, 3, 325-337.

Foster, K. (1998) Evaluating Non-Response on Household Surveys, Report of a Study Linked to the 1991 Census, Government Statistical Service, Methodology Series No. 8.

Freeth, S. (2004) The Labour Force Survey, Report of the 2001 Census-Linked Study of Survey Nonresponse, *Office for National Statistics working paper*, London.

Freeth, S. and Sowman, P. (2003a) The Expenditure and Food Survey, Report of the 2001 Census-Linked Study of Survey Nonresponse, *Office for National Statistics working paper*, London.

Freeth, S. and Sowman, P. (2003b) The General Household Survey, Report of the 2001 Census-Linked Study of Survey Nonresponse, *Office for National Statistics working paper*, London.

Freeth, S. and Sowman, P. (2005) The Family Resources Survey, Report of the 2001 Census-Linked Study of Survey Nonresponse, *Office for National Statistics working paper*, London.

Freeth, S., Kane, C. and Cowie, A. (2002) Survey Interviewer Attitudes and Demographic Profile, Preliminary Results from the 2001 ONS Interviewer Attitudes Survey, *Office for National Statistics working paper*, London, 1-18.

Freeth, S., Sowman, P. and Greenwood, C. (2004) The National Travel Survey, Report of the 2001 Census-Linked Study of Survey Nonresponse, *Office for National Statistics working paper*, London.

Glorioux, I. (1993) Social Interaction and the Social Meanings of Action: A Time Budget Approach, *Social Indicators Research*, 30, 149-173.

Goldstein, H. (2003) *Multilevel Statistical Models*, third edition, London, Edward Arnold.

Goyder, J. (1987) *The Silent Minority: Nonrespondents on Sample Surveys*, Boulder, CO: Westview Press.

Groves, R.M. (2006) Nonresponse Rates on Nonresponse Bias in Household Surveys:, *Public Opinion Quarterly*, 70, 5, 646-675.

Groves, R.M. and Couper, M.P. (1998) *Nonresponse in Household Interview Surveys*, New York.

Groves, R.M., Cialdini, R.B. and Couper, M. (1992) Understanding the Decision to Participate in a Survey, *Public Opinion Quarterly*, 56, 475-495.

Groves, R.M., Dillman, D.A., Eltinge, J.L., and Little, R.J.A. (2002) *Survey Nonresponse*, New York, Wiley.

Groves, R.M., Singer, E. and Corning, A. (2000) Leverage-Saliency Theory of Survey Participation, Description and Illustration, *Public Opinion Quarterly*, 64, 299-308.

Hox, J. and De Leeuw, E. (2002) The Influence of Interviewers' Attitude and Behavior on Household Survey Nonresponse: An International Comparison, in: Groves, R.M., Dillman, D.A., Eltinge, J.L., and Little, R.J.A. (2002), *Survey Nonresponse*, New York, 103-119.

Krause, N. (1993) Neighbourhood Deterioration and Social Isolation in Later Life, *International Journal of Aging and Human Development*, 36, 1, 9-38.

Martin, J. and Matheson, J. (1999) Responses to Declining Response Rates on Government Surveys, *Survey Methodology Bulletin*, 45, 33-37.

O'Muircheartaigh, C. and Campanelli, P. (1999) A Multilevel Exploration of the Role of Interviewers in Survey Nonresponse, *Journal of the Royal Statistical Society, Series A*, 162, 3, 437-446.

Pickery, J. and Loosveldt, G. (2002) A Multilevel Multinomial Analysis of Interviewer Effects on Various Components of Unit Nonresponse, *Quality and Quantity*, 36, 427-437.

Pickery, J. and Loosveldt, G. (2004) A Simultaneous Analysis of Interviewer Effects on Various Data Quality Indicators with Identification of Exceptional Interviewers, *Journal of Official Statistics*, 20, 1, 77-89.

Pickery, J., Loosveldt, G. and Carton, A. (2001) The Effects of Interviewer and Respondent Characteristics on Response Behavior in Panel Surveys, *Sociological Methods and Research*, 29, 4, 509-523.

Rasbash, J., Steele, F., Browne, W.J. and Prosser, B. (2005) *A User's Guide to MLwiN version 2.0*, University of Bristol.

Spiegelhalter, D.J., Best, N.G., Carlin, B.P. and van der Linde, A. (2002) Bayesian Measures of Model Complexity and Fit (with discussion), *Journal of the Royal Statistical Society, Series B*, 64, 4, 583-640.

Steeh, C., Kirgis, N., Cannon, B. and DeWitt, J. (2001) Are They Really as Bad as They Seem? Nonresponse Rates at the End of the Twentieth Century, *Journal of Official Statistics*, 17, 227-247.

Walker, A., O'Brien, M., Traynor, J., Fox, K., Goddard, E., and Foster, K. (2002) Living in Britain – 2001, Results from the 2001 General Household Survey, Office for National Statistics, London.

White, A., Freeth, S. and Martin, J. (2001) Evaluation of Survey Data Quality Using Matched Census-Survey Records, *Paper presented at the International Conference on Quality in Official Statistics*, Stockholm, May 2001.

Table 1: Summary of main survey characteristics for the six surveys.

Survey Design Characteristic	EFS	FRS	GHS	OMN	NTS	LFS
Maximum number of calls to household	No limit	No limit	No limit	No limit	No limit	No limit
Minimum number of calls to household	4	4	4	4	8	4
Length of data collection period	1 month +1 week	1 month	1 month	3 weeks	2.5 to 6.5 weeks	7+7+2 days (spread over 13 week period)
Interviewer workload in number of addresses	18	24	23	30	23	20
ONS initial interviewer training given	Yes	Yes	Yes	Yes	Yes	Yes
Type of additional interviewer training given	1 day	1 day	briefing	postal	1.5 days	4 days (interviewers work only on this survey)
Advance letter	Yes	Yes	Yes	Yes	Yes	Yes
Purpose leaflet available	Yes: in the field	Yes: in the field	Yes: in the field	Yes	Yes: postal (London only)	Yes: postal
Respondent incentives	Stamps; £10/£5 for diary	Stamps	None	Stamps	Pen and fridge magnet	None
Respondent rules	All house-holders aged 16+	All house-holders aged 16+	All house-holders aged 18+	One house-holder aged 16+	All house-holders aged 16+	All house-holders aged 16+
Proxy response allowed	Yes	Yes	Yes	No	Yes	Yes
Average length of interview (in mins)	70	80	70	26	60	30 (for wave 1)
Diary required (in addition to questionnaire)	Yes: 2 weeks	No	No	No	Yes: 1 week	No

The surveys collect information based on the household as a whole and on the individuals within the households.

Information collected by survey:

EFS: Core topics include: household expenditure, rent and mortgage payments, taxes, benefits, detailed information about the income of each household member, and trends in nutrition.

FRS: Aims to provide information on living standards, people's relationship and interaction with the social security system. The questionnaire seeks information on income and benefits, tenure and housing costs, assets and savings, occupation and employment, health and ability to work, pensions and insurance, childcare and carers.

GHS: Core topics include: accommodation, consumer durables, housing tenure, migration, employment, pensions, education, health, smoking, drinking, family formation, and income.

NTS: Aims to provide a comprehensive picture of personal travel behaviour. Questions include ethnic group, place of work, reliability and frequency of local services such as buses and trains, use of vehicles, long distance journeys and travel outside of Great Britain.

OMN: Multi-purpose survey which aims to obtain information about the general population or about particular groups. The questionnaire is in two parts, including first a set of core classificatory questions and then a series of unrelated modules on varying topics at the request of customers. Core questions include information on demographic details, economic status, job details, employment status, full- or part-time working, tenure, and ethnic origin.

LFS: Aims to provide information about the UK labour market and unemployment. The survey seeks information on respondent's personal circumstances, their labour market status and income.

Figure 1: Refusal and noncontact rates for the six surveys included in the Census Link Study.

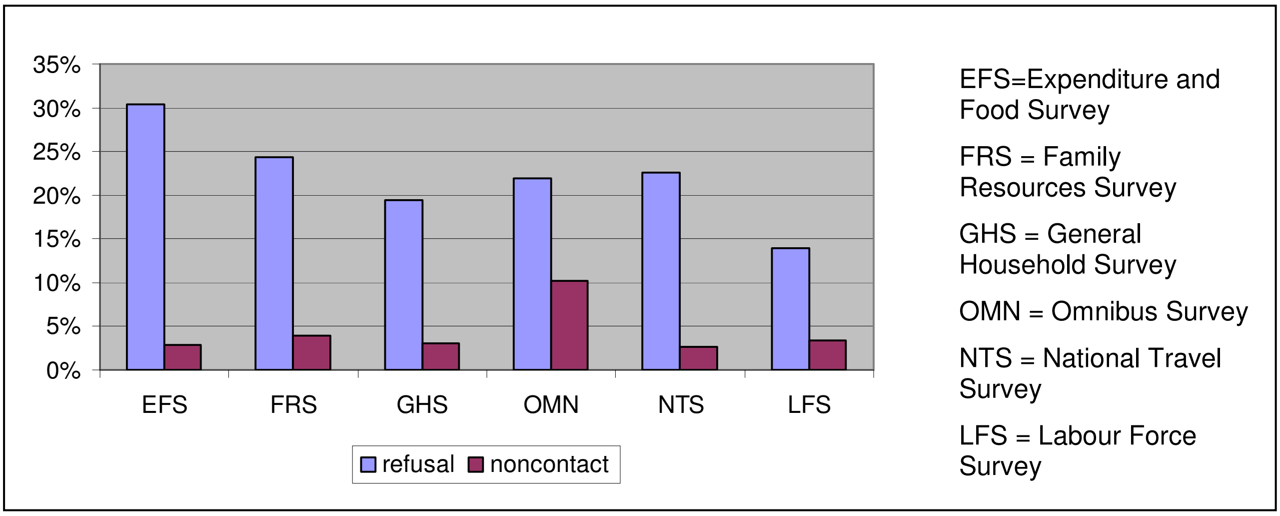

Table 2: Percentage distribution within each type of response status for explanatory variables included in the final model. †

Variable	Categories	Cooperation (%) (n=13621)	Refusal (%) (n=4097)	Noncontact (%) (n=812)	Total (%) (n=18530)
Household level variable					
Survey indicator	EFS	18.1	27.3	12.6	19.9
	FRS	11.7	13.2	10.8	12.2
	GHS	19.4	16.1	13.1	18.4
	OMN	16.5	17.7	41.5	17.9
	NTS	14.5	14.6	8.4	14.3
	LFS	19.8	11.0	13.7	17.6
Highest qualification (HRP)	No academic qualification	27.5	32.5	28.2	28.6
	O-levels, GCSEs, A-levels	38.9	33.4	40.4	37.7
	First or Higher degree	16.7	13.1	20.0	16.0
	Other qualifications	5.6	5.9	4.7	5.6
	Missing	11.5	15.1	6.8	12.1
Indicator if house	Other (flat, mobile home,…)	15.6	17.9	35.3	17.0
	House	84.4	82.1	64.7	83.0
Dependent children present	Not present	68.2	74.4	77.1	70.0
	Present	31.8	25.6	22.9	30.0
London indicator	Not London	90.1	86.5	83.9	89.0
	London	9.9	13.5	16.1	11.0
Rural indicator	Urban	88.3	90.7	93.6	89.0
	Rural	11.0	9.0	6.2	10.4
	Missing	0.7	0.3	0.2	0.6
Gender (HRP)	Male	61.0	58.6	62.6	60.6
	Female	39.0	41.4	37.4	39.4
Economic Activity (HRP)	Employee	51.3	45.6	59.6	50.4
	Self-employed	8.8	10.4	9.1	9.2
	Unemployed	2.2	2.6	4.6	2.4
	Retired	16.9	16.5	8.6	16.4
	Looking after family	2.8	2.3	2.0	2.7
	Other (incl. student, ill etc)	6.5	7.5	9.4	6.9
	Missing	11.5	15.1	6.8	12.1
Pensioner in household	No pensioner in household	66.7	62.4	82.8	66.4
	Pensioner in household	33.3	37.6	17.2	33.6

Perception on health (HRP)	Good Fairly good Not good	60.0 28.3 11.7	54.5 31.7 13.8	63.8 25.5 10.7	58.9 28.9 12.1
Carers in household	No Yes	80.9 19.1	82.7 17.3	86.6 13.4	81.6 18.4
Household type	Single household Couple household Multiple household	38.6 59.3 2.2	41.3 56.2 2.5	58.9 38.1 3.1	40.1 57.7 2.3
Adults in employment	No adults One adult Two or more adults	37.0 27.8 35.3	40.2 26.7 33.1	28.4 42.7 28.8	37.3 28.2 34.5
Age in years (HRP)	16 - 34 35 - 49 50 - 64 65 - 79 80 and older	17.7 29.3 25.6 20.5 6.9	14.5 26.8 27.6 21.6 9.4	29.1 33.3 23.4 10.2 4.1	17.5 28.9 25.9 20.3 7.3
Car ownership	One or more car No car	75.2 24.8	70.3 29.7	65.8 34.2	73.7 26.3
Household moved during last year	No Yes	92.0 8.0	94.0 6.0	88.8 11.2	92.3 7.7
Interviewer observations					
House in better or worse condition than others in area	Better Worse About the same Unable to code	10.8 6.4 82.2 0.6	9.3 8.5 79.1 3.1	7.8 13.9 76.0 2.3	10.3 7.2 81.3 1.2
How safe would you feel walking along in this area after dark?	Unsafe Safe Don't know	10.2 89.6 0.2	11.7 87.6 0.8	17.2 82.6 0.1	10.8 88.9 0.3

† HRP= information based on household reference person

Table 3: Estimates (with 95% credible intervals) of the between-interviewer variance-covariance matrix from alternative specifications of the multilevel multinomial model of refusal and noncontact. †

Parameter	**Model 1** (survey effects only)	**Model 2** (Model 1 + household variables)
Refusal, $\mathrm{var}(u_j^{(1)})$	0.095 (0.065; 0.130)	0.085 (0.056; 0.119)
Noncontact, $\mathrm{var}(u_j^{(2)})$	0.539 (0.388; 0.721)	0.453 (0.312; 0.626)
$\mathrm{cov}(u_j^{(1)}, u_j^{(2)})$	0.076 (0.022; 0.132)	0.050 (-0.002; 0.104)
$\mathrm{cor}(u_j^{(1)}, u_j^{(2)})$	0.336	0.254
DIC diagnostic	24971	24334

† The values in each cell are the point estimate (the means of 80,000 MCMC samples, with burn-in of 5,000) and the corresponding 95% interval estimate (the 2.5% and 97.5% points of the distribution). The DIC diagnostics for Model 0 (Model 1 without interviewer random effects) is 25281.

Table 4: Estimated coefficients (and standard errors in parentheses) from the multilevel multinomial model (Model 2).

Variable (0 = Reference category)	**Categories**	$\hat{\beta}$ $(ste(\hat{\beta}))$ **refusal**	$\hat{\beta}$ $(ste(\hat{\beta}))$ **noncontact**
Constant		-0.920 (0.129)*	-1.610 (0.366)*
Household level variable			
Survey indicator † (0 = EFS)	1 FRS 2 GHS 3 OMN 4 NTS 5 LFS	-0.045 (0.090) -0.462 (0.085)* -0.389 (0.085)* -0.403 (0.090)* -0.899 (0.092)*	0.280 (0.295) -0.386 (0.294) 0.697 (0.233)* -0.770 (0.343)* -0.776 (0.290)*
Highest qualification (HRP) (0 = No academic qualification)	1 O/A levels, GCSEs 2 First/Higher degree 3 Other qualifications	-0.192 (0.051)* -0.493 (0.065)* -0.226 (0.085)*	-0.210 (0.107) -0.152 (0.129) -0.158 (0.197)
Indicator if house † (0 = not house, e.g. flat, mobile home)	1 House	-0.022 (0.055)	-1.183 (0.231)*
Dependent children present (0 = not present)	1 Present	-0.272 (0.053)*	-0.634 (0.108)*
London indicator † (0 = not London)	1 London	0.461 (0.136)*	0.700 (0.306)
Rural indicator † (0 = Urban)	1 Rural	-0.015 (0.128)	-0.326 (0.167)
Gender (HRP) (0 = Male)	1 Female	0.066 (0.055)	-0.277 (0.092)*
Economic Activity † (HRP) (0 = Employee)	1 Self-employed 2 Unemployed 3 Retired 4 Looking after family 5 Other (incl. student, permanently sick etc)	0.566 (0.127)* 0.224 (0.103)* -0.166 (0.092)* -0.116 (0.132) -0.001 (0.086)	0.101 (0.142) 0.253 (0.298) 0.129 (0.305) -0.524 (0.356) 0.028 (0.269)
Pensioner in household (0 = No pensioner in household)	1 Pensioner in household	-0.143 (0.066)*	-0.598 (0.236)*
Perception on health (HRP) (0 = Good)	1 Fairly good 2 Not good	0.117 (0.045)* 0.119 (0.060)*	-0.068 (0.096) -0.059 (0.148)
Carers in household (0 = No)	1 Yes	-0.134 (0.051)*	-0.093 (0.115)
Household type † (0 = Single household)	1 Couple household 2 Multiple household	0.080 (0.051) 0.177 (0.127)	-1.249 (0.271)* -0.064 (0.473)
Adults in employment (0 = No adults)	1 One adult 2 Two or more adults	--	0.473 (0.239)* 0.449 (0.261)
Age (HRP) (0 = 16 - 34)	1 35 - 49 2 50 - 64 3 65 - 79 4 80 and older	0.136 (0.061)* 0.133 (0.068) 0.045 (0.120) 0.149 (0.159)	-0.163 (0.106) -0.500 (0.128)* -0.737 (0.305)* -0.732 (0.425)
Car Ownership † (0 = One or more car)	1 No car	0.224 (0.089)*	0.186 (0.101)
Household moved during last year (0 = No)	1 Yes	-0.147 (0.077)*	-0.020 (0.131)

Interviewer observations			
House in a better or worse condition than others in area (0 = Better)	1 Worse 2 About the same	0.435 (0.091)* 0.102 (0.064)	0.757 (0.172)* 0.060 (0.139)
How safe would you feel walking along in this area after dark? (0 = Unsafe)	1 Safe	-0.182 (0.062)*	-0.238 (0.118)*
Household level interactions			
Survey*Self-employed indicator (0 = EFS and not self-employed)	1 FRS - self-employed 2 GHS- self-employed 3 OMN- self-employed 4 NTS- self-employed 5 LFS- self-employed	-0.649 (0.212)* -0.214 (0.197) -0.084 (0.192) -0.357 (0.207) -0.843 (0.248)*	--
Survey*London indicator (0 = EFS and London)	1 FRS - London 2 GHS- London 3 OMN- London 4 NTS- London 5 LFS- London	-0.214 (0.215) -0.196 (0.193) -0.159 (0.206) 0.043 (0.194) -0.590 (0.247)*	-1.192 (0.515)* -0.967 (0.472) -0.051 (0.365) -0.012 (0.454) -0.593 (0.464)
Survey*Rural indicator (0 = EFS and urban)	1 FRS - rural 2 GHS- rural 3 OMN- rural 4 NTS- rural 5 LFS- rural	-0.284(0.240) -0.472 (0.203)* -0.162 (0.203) -0.413 (0.225) -0.164 (0.223)	--
Survey*Car Ownership indicator (0 = EFS and one or more car)	1 FRS - no car 2 GHS- no car 3 OMN- no car 4 NTS- no car 5 LFS- no car	-0.640 (0.151)* -0.269 (0.131)* 0.118 (0.128) -0.064 (0.137) -0.384 (0.148)*	--
Survey*House Indicator (0 = EFS and not house (flat, mobile home,…))	1 FRS - House 2 GHS- House 3 OMN- House 4 NTS- House 5 LFS- House	--	0.096 (0.346) 0.927 (0.341)* 0.646 (0.269)* 0.954 (0.389)* 0.777 (0.331)*
Survey*Household type (0 = EFS and Single household)	1 FRS - Couple 2 GHS - Couple 3 OMN- Couple 4 NTS- Couple 5 LFS- Couple 1 FRS - Multiple 2 GHS- Multiple 3 OMN-Multiple 4 NTS- Multiple 5 LFS- Multiple	--	0.289 (0.364) 0.065 (0.346) 0.939 (0.287)* 0.182 (0.378) 0.500 (0.333) -0.423 (0.781) -2.246 (1.368) -0.159 (0.639) -0.669 (0.820) -1.293 (0.961)

The estimated coefficients and their standard errors are the means and standard deviations of parameter values across 80,000 Markov chain Monte Carlo samples, after the burn-in of 5000 and starting values from second order PQL estimation. The missing value categories have been suppressed to save space.

* significant at the 5% level
† survey-specific effect (i.e. interacts with the survey indicators)
HRP information based on household reference person

Table 5: Predicted probabilities for noncontact and refusal (in %) based on selected two-way interactions.

Interaction between survey and house indicator

		Survey					
Noncontact		**EFS**	**FRS**	**GHS**	**OMN**	**NTS**	**LFS**
Indicator if house	House	1.39	1.88	2.32	4.92	1.73	1.76
	Other (e.g. flat)	4.27	5.34	2.88	7.72	2.08	2.55

Interaction between survey and type of household

		Survey					
Noncontact		**EFS**	**FRS**	**GHS**	**OMN**	**NTS**	**LFS**
Type of household	Single	4.68	5.83	3.14	8.37	2.27	2.77
	Couple	1.31	2.24	0.98	6.31	0.78	1.31
	Multiple	4.06	3.69	0.32	6.79	1.04	0.71

Interaction between survey and London indicator

		Survey					
Noncontact		**EFS**	**FRS**	**GHS**	**OMN**	**NTS**	**LFS**
Indicator if London	London	3.81	1.71	1.20	8.06	2.13	1.83
	Other	2.66	3.34	1.77	4.87	1.27	1.56

Interaction between survey and economic status of the household representative

		Survey					
Refusal		**EFS**	**FRS**	**GHS**	**OMN**	**NTS**	**LFS**
Economic activity of HRP	Employed	30.3	27.4	21.2	21.4	22.3	12.9
	Self-employed	43.5	25.9	27.7	30.4	26.0	10.2
	Unemployed	32.8	28.1	23.3	23.4	24.5	14.3
	Retired	27.0	24.3	18.6	18.8	19.6	11.2
	Looking after family	28.2	25.5	19.4	20.0	20.4	11.7
	Other	30.2	27.4	21.1	21.4	22.2	12.8

Interaction between survey and car ownership

		Survey					
Refusal		**EFS**	**FRS**	**GHS**	**OMN**	**NTS**	**LFS**
Car ownership	One or more car	29.9	27.1	20.9	21.1	21.9	12.7
	No car	34.9	19.9	20.6	26.9	24.8	11.0

Appendix: Simulation method for calculating predicted probabilities

Denote by $(\hat{\boldsymbol{\beta}}^{(s)}, \hat{\boldsymbol{\Omega}})$ the parameter estimates obtained from fitting model (1). The simulation method contains the following steps:

1. Generate M random effect vectors from $N(\mathbf{0}, \hat{\boldsymbol{\Omega}})$, and denote these by

   $$\mathbf{u}_{(m)} = (u_{(m)}^{(1)}, u_{(m)}^{(2)}), \quad m = 1,\ldots,M.$$

2. For $m = 1,\ldots M$ and $\mathbf{x}^{(s)} = \mathbf{x}^{(s)*}$ compute

   $$\pi_{(m)}^{(s)*} = \frac{\exp(\hat{\beta}^{(s)^T}\mathbf{x}^{(s)*} + u_{(m)}^{(s)})}{1 + \sum_{r=1}^{2}\exp(\hat{\beta}^{(r)^T}\mathbf{x}^{(r)*} + u_{(m)}^{(r)})}, \quad s = 1,2\,, \text{ and } \pi_{(m)}^{(0)} = 1 - \pi_{(m)}^{(1)} - \pi_{(m)}^{(2)}$$

3. The mean (population averaged) predicted probabilities are calculated as

   $$\pi^{(s)*} = \frac{1}{M}\sum_{m=1}^{M}\pi_{(m)}^{(s)*}, \quad s = 1,2\,, \qquad \text{and } \pi^{(0)*} = 1 - \pi^{(1)*} - \pi^{(2)*}.$$