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Abstract

This paper analyses household unit nonresponse and interviewer effects 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 survey dependent and independent effects of household and interviewer characteristics, providing an empirical exploration of the leverage-salience theory. The analysis is based on the 2001 UK Census Link Study, a unique data source containing an unusually rich set of auxiliary variables, linking the response outcome of six surveys to census data, interviewer observation data and interviewer information, available for respondents and nonrespondents.

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

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Summary.

This paper analyses household unit nonresponse and interviewer effects 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 survey dependent and independent effects of household and interviewer characteristics, providing an empirical exploration of the leverage-salience theory. The analysis is based on the 2001 UK Census Link Study, a unique data source containing an unusually rich set of auxiliary variables, linking the response outcome of six surveys to census data, interviewer observation data and interviewer information, available for respondents and nonrespondents.

Key Words: multilevel multinomial models, survey unit nonresponse, noncontact, refusal, theories of survey participation, census link study, interviewer effects.

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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 and Peytcheva, 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 causes 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 of 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), concerned with the role of individual and household characteristics on survey cooperation. A more recent theory is the leverage-salience theory (Groves, Singer and Corning, 2000), focusing on the interaction between individual sample member characteristics and survey design features. These theories incorporate important phenomena to explain survey participation, such as the distinction between influences on access to the sample unit and cooperation of the sample unit with the survey request, the influence of the social context on individual action, the interplay of multiple effects on survey participation, and the 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 and, if ignored, interviewer effects will lead to clustering of nonresponse rates for sample units allocated to the same interviewer. In particular, the interaction between the household and the interviewer has been noted as an important part in the survey response process, supporting notions of tailoring of interviewing approaches to sample members (Groves and McGonagle, 2001; Snijkers, Hox and De Leeuw, 1999).

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 explore the extent to which between-interviewer variation in the probability of each type of nonresponse can be explained by interviewer characteristics, allowing for cross-level interactions between household and interviewer attributes. Analysing several surveys simultaneously, one key feature of the analysis, and a major advantage of the data used, is the identification of survey specific versus survey independent effects by testing for interactions between characteristics of the sample unit and/or interviewer and surveys which vary in their design and subject matter. 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 use of several surveys simultaneously allows us both to identify general results and to test for variation in response correlates and interviewer effects across and within surveys. This work also provides one of the first empirical explorations of the leverage-salience theory.

Previous empirical research has largely investigated influences of a small number of factors, primarily using simple methodology such as bivariate analyses or logistic regression (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, Singer, Corning, 2000). Recent studies have used multilevel modelling approaches to allow simultaneously for different types of nonresponse and interviewer effects. However, these studies are limited with regard to the data available or the methodology 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, Loosveldt and Carton, 2001; O'Muircheartaigh and Campanelli, 1999), suffered from convergence problems (Pickery, Loosveldt and Carton, 2001; O'Muircheartaigh and Campanelli, 1999), and interaction effects were not considered (O'Muircheartaigh and Campanelli, 1999; Pickery and Loosveldt, 2002 and 2004; Pickery, Loosveldt and Carton, 2001). The study here will address all of 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 containing a rich set of auxiliary variables, including census data and detailed interviewer information, available for respondents and nonrespondents for six major UK government surveys. 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 this earlier work. The database is considerably richer than other sources, in that it includes individual level information in addition to the usual household information, interviewer observation data, and unusually detailed information on interviewers and interviewer calling strategies and fieldwork process data. The data have been collected and made available by the UK Office for National Statistics (ONS) and the work has been carried out in collaboration with ONS.

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 and plans for further research 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. 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 smaller scale.

2.1 The Surveys

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). All survey data are treated as cross-sectional data; 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 survey designs 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 to 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, apart from the Omnibus survey, specify that all household members of a certain age take part in the interview, referred to as full cooperation. If the interviewer is not able to obtain information from all household members it 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, only requiring response from one household member, is regarded as a special case of partial 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 partly due 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 partly caused by 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 fully linked dataset contains the following information:

- *2001 UK census information*. Survey records of respondents and nonrespondents are linked to their census record, both for households and individuals within households. This comprises primarily socio-demographic and some attitudinal information about the individuals within a household, and household characteristics;
- *interviewer observation data*. The interviewer recorded information about the household 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 alarm), any information about the household composition, the quality of housing and observations of the surrounding neighbourhood.
- *Field-process and interviewer calling data* - also referred to as paradata (Couper, 1998). This comprises primarily information on the frequency of calls to the household, the time and date and the outcome of each call, as well as information about the interaction between the interviewer and the household at the 'doorstep' if contact was made. This information was recorded by the interviewer at the survey data collection stage.

- *interviewer information*. This information was obtained via a separate comprehensive survey (Interviewer Attitude Survey) of face-to-face ONS interviewers during June 2001, at around the time of the survey and census data collection period. Interviewers were asked about their socio-demographic background, work experience, interviewing strategies and behaviours, and attitudes towards their work and towards gaining contact and cooperation (Freeth, Kane and Cowie, 2002). A similar survey of ONS interviewers was carried out in 1998 as part of an international project (Hox and De Leeuw, 2002).

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, with about 95% of all households being 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, Freeth and Martin (2001), Beerten and Freeth (2004), Freeth (2004), Freeth and Sowman (2003a, 2003b, 2005) and Freeth, Sowman and Greenwood (2004).

2.3 Analysis Sample and Definition of Explanatory Variables

Households selected for interview in one of the surveys during May-June 2001, the months immediately following the 2001 Census, were included in the study. The following cases were excluded from the analysis sample: all persons under 16 (to exclude ineligible cases); sample units that were unable to respond due to language problems; 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. Only households for which all data components could be linked successfully to the survey data were included in the analysis sample. The final dataset on which the following analysis is based, contains 18,530 households and 565 interviewers.

The explanatory variables of major interest are household and interviewer characteristics, including individual and household characteristics from the census, observations recorded by the interviewer on the household and the area in which it is situated, interviewer characteristics such as their socio-economic background, and work experience, attitudes and behaviour of the interviewer. Table 2 shows the coding and percentage distributions 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 response variable of interest, individual level information for the household reference person (HRP) is used to obtain variables that represent the household. The HRP is defined as the person who exerts the major influence on the household's living patterns and circumstances. This person 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).

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 sampling 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

A multilevel multinomial model is used to explore the effects of household and interviewer characteristics on household nonresponse, distinguishing refusal and noncontact. A multilevel model allows for similarity in nonresponse rates for households allocated to the same interviewer that cannot be explained by observed interviewer characteristics alone. Failure to account for clustering by interviewer leads to underestimated standard errors and therefore incorrect inferences, particularly for coefficients of interviewer-level variables. 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 and interviewer 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

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

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 probability of refusal versus cooperation as a function of covariate and interviewer effects, and the second $(s = 2)$ models the probability of noncontact versus 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. $\mathbf{u}_j = (u_j^{(1)}, u_j^{(2)}) \sim N(\mathbf{0}, \boldsymbol{\Omega})$ where

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

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. Model (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.

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 estimates obtained from the 2nd order penalised quasi-likelihood (PQL) procedure as starting values for the sampling.

Predicted probabilities of cooperation, refusal and noncontact can be calculated to aid model interpretation. A reorganisation of (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 2-level binary logit model; details of the procedure for a multilevel multinomial model are given in the appendix. 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.

4. Results

4.1 Modelling Strategy

We consider three specifications of the multilevel multinomial model for survey participation, each allowing for interviewer effects. All models include dummy variables for survey to control for design differences among the six surveys. The 'null' model (Model 1) allows only for survey differences and interviewer effects on noncontact and nonresponse rates. This model is then extended by introducing 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 final model (Model 3) includes interviewer-level variables and their interactions with the household-level variables of Model 2 and the survey indicators. The presence of either type of interaction may suggest ways of tailoring interviewing strategies for particular types of respondent or survey. Information on cross-level interactions between household and interviewer characteristics may be used to match interviewers to sample units. There has been little exploration of the statistical interactions between interviewers and householders in previous research on nonresponse (Groves and Couper, 1998; O'Muircheartaigh and Campanelli, 1999; Pickery and Loosveldt, 2002, 2004).

The selection of variables for inclusion in Models 2 and 3 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.

4.2 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). From Model 1 we find significant between-interviewer variation in both noncontact and nonresponse rates. 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, but little change in the random effect variance and covariance estimates. There is a further large reduction in the DIC statistic after adjusting for observed interviewer characteristics (Model 3) and the random effect variances and correlation are considerably smaller. Nevertheless, there remains some unexplained interviewer variation.

[Table 3 about here]

4.3 Effects of Household and Interviewer Characteristics

We now turn to the interpretation of the final model (Model 3). Table 4 presents the estimated coefficients of the household and interviewer variables and their interactions. The missing value categories have been suppressed 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.

[Table 4 about here]

Factors influencing the likelihood of contact

We 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 interviewing strategies for contacting sample members. The results show that the likelihood of contact is higher, for example, among households living in a house rather than a flat (with the effect being significant for the EFS, FRS and Omnibus) and for couple households as opposed to single or multiple households (with particularly low noncontact rates for the GHS, NTS, EFS and LFS and high rates for the Omnibus). The differences across surveys may reflect the different lengths of data collection periods and interviewer workloads. Information based on interviewer observations, such as the presence of physical impediments (e.g. intercom systems), noted in the literature as highly important variables (Groves and Couper, 1998), were found significant in earlier bivariate analysis but not in the final model once other factors had been controlled. This may be explained by the fact that flats and multi-unit structures are more likely to have, for example, intercom systems installed, and controlling for type of accommodation may wipe out the significance of physical barriers. Other types of interviewer observation data, such as the condition of the house or if the interviewer feels safe in the area, have a significant effect on explaining noncontact even after controlling for other variables, with houses in a worse condition having higher noncontact rates. Geographical location, as measured by urban-rural and London indicators, often stressed in the Literature as important factors, were found highly significant in bivariate analysis. However, part of their effect can be explained by variables such as accommodation type, leading to non-significance of both variables as main effects. Some survey specific geographic effects have been found, with a particularly low noncontact rate in London areas for the FRS and comparatively high rates for the EFS and Omnibus.

Indicators of a single-person household, and the presence of dependent children, pensioners and adults in employment may be regarded as proxies for the time spent at home and lifestyle. 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 adults in employment are less likely to be found at home. In contrast to the US, multiple households in the UK are no more or less likely to be contacted than single households, which may reflect the fact that multiple households often consist of a number of students or young professionals whose lifestyles are closer to those of single-person households than of families. Of the socio-demographic variables considered, such as qualifications, economic activity and gender of the HRP, only age was found to have an effect on contactability.

As might be expected, interviewing strategies and interviewer experience are associated with the probability of contact. We find support for the idea of tailoring approaches to specific situations or households. Interviewers who either always or never use a contact strategy, such as leaving a phone number behind, seemed to be less successful at making contact than interviewers who adopt a strategy only sometimes depending on the situation. We also find that interviewers in higher pay grades, reflecting a higher level of qualifications and experience, seem to perform better in establishing contact. As may be expected, cross-level interactions between respondent and the interviewer characteristics do not play a role in establishing contact.

Factors influencing the likelihood of survey participation

Our choice of variables for consideration as predictors of survey participation was guided by the socio-psychological concepts and theories proposed in the survey research literature. The results from the statistical model are discussed in terms of the support they provide for these theories. We note, however, that we expect 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 may be difficult. Often only proxy indicators can be used to investigate a theory, and these might be imperfect measures. The analysis also focusses on the identification of the response behaviour of different subgroups within the population.

Based on the theory of s*ocial exchange* (Goyder, 1987; Groves, Cialdini and Couper, 1992; Dillman, 2000) individuals receiving fewer services from government and those feeling disadvantaged may also feel least obligated to respond to a government request, for example to take part in a survey. According to this theory, effects of socio-economic status may broadly reflect exchange influences on survey cooperation. Our results show a lower rate of survey participation among disadvantaged groups, including households where the HRP is unemployed or poorly qualified, or where the house is in a worse condition than others in the area. Our analysis shows, for the first time, consistent support for this hypothesis, whereas past research has reported contradictory effects. For example, Groves and Couper (1998, Ch. 5.3) found indications for higher cooperation rates amongst people from lower socio-economic and lower education groups. This finding, however, was not consistent for all indicators investigated.

The theory of *leverage-salience* (Groves, Singer and Corning, 2000) specifies the mechanisms by which individual householder differences themselves affect the performance of survey design features. The theory may give insights on why the effectiveness of some survey design features (e.g. incentives to increase response rates) may work for some subgroups in the population but not for others. We extend the work of Groves and Couper (1998) by testing for interactions between the characteristics of the sample unit and the type of survey or survey design, thereby allowing for the possibility that the effects of design and topic may vary across different subgroups. We note, however, that the design of the Census Link Study does not allow us to identify directly why survey specific effects arise since the information is not based on an experimental design. By considering the interaction between survey and the economic status of the HRP for example, we find particularly high refusal rates among the self-employed for the EFS and NTS (see Table 5), which is possibly due to the extra burden of completing a diary for these surveys. In contrast, the LFS, which has a short interview and therefore a low response burden, has the lowest refusal rate for the self-employed. This may indicate that the self-employed are more sensitive to the response burden of a survey than other economic groupings and a short questionnaire, for example, may be advisable to obtain information from this group. We also find survey specific effects of car ownership which, after controlling for geographic location, may be viewed as a proxy for income. Households without a car have a high probability of refusal for the EFS, possibly reflecting sensitivity to the survey topic of income and expenditure.

[Table 5 about here]

The idea behind the *civic duty* (Brehm, 1993; Groves, Singer and Corning, 2000) or *helping tendency theory* (Groves, Cialdini and Couper, 1992) is that social norms lead to a feeling of obligation to provide help or to agree to a survey request in the belief that participation serves the common good. Indicators of civic duty include helping to care for a person in need, and volunteering to work for a community group or a neighbourhood initiative (Couper, Singer and Kulka, 1998). We find that the presence of a carer in the household who looks after an elderly or disabled person is associated with a lower likelihood of refusal, an effect which is constant across surveys. Self-reported health has an interesting effect on participation. A person who is content with his/her health and indicates a positive attitude towards life is less likely to refuse. Happiness and a positive attitude to life have been found to be connected to the decision to help other people, thus increasing the probability of cooperation (Groves, Cialdini and Couper, 1992).

The *opportunity cost hypothesis* is based on the idea that survey participation is a rational decision, made after weighing up the pros and cons of cooperation. Factors in this decision might be the time available to the sample unit, with a higher cooperation rate among those with more free time. Using employment status as a proxy for the amount of time available, however, we find that households with the HRP in employment are more likely to cooperate than are those with an unemployed HRP. The time take to commute to work, another proxy for the availability of discretionary time, was not significant once other factors were controlled. We therefore find, as do Groves and Couper (1998), little support for the hypothesis that less time available may lead to lower likelihood of cooperation.

Socio-economic status and the level of qualifications may also be regarded as indicators for the *social isolation theory* (Goyder, 1987). According to this theory those who are alienated or isolated from the broader society are less likely to respond. Lower socio-economic groups should therefore be less likely to respond to a survey request. The results for employment status and qualification reported earlier indicate support for the social isolation theory and our study gives stronger support for this theory than, for example, the findings of Groves and Couper (1998) would suggest. Other indicators, such as household composition (e.g. single or couple households) and the presence of children, provide further support for this hypothesis; households with dependent children have a higher probability of cooperation which may reflect higher levels of social integration and social obligation. There is no effect of age or number of children in the household. Although previous bivariate analyses found evidence of lower cooperation from single households and people living in flats (Goyder, 1987; Groves and Couper, 1998) we find, after controlling for other factors, no significant differences in participation between single and other households or between houses and flats.

Rather than supporting the isolation theory which would predict lower cooperation rates among the elderly, we find that households with pensioners are more likely to respond. This result provides evidence for the civic duty theory, whereby older people might feel a stronger obligation to contribute to the good of society. The 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. However, the results show lower refusal rates among movers than non-movers (even after controlling for type of accommodation) which, although not supporting the isolation theory, is in line with findings in other studies (Groves and Couper, 1998). This could be because moving households are more likely to be in employment and may have higher qualifications.

Interviewer effects on survey cooperation

Groves and Couper (1998, p. 198) argue that it may be difficult to interpret main effects of socio-demographic interviewer characteristics, but where such variables may come into play is in their interaction with household characteristics. Due to data limitations on socio-demographic interviewer characteristics Groves and Couper were, however, unable to test this hypothesis. One of the advantages of the Census Link Study is that its rich information on interviewers, linked to individual and household characteristics, permits such an analysis. Our results show that main effects of variables such as age and gender of the interviewer are not significant in explaining interviewer differences but, in the case of refusal, there is a significant interaction between the gender of the HRP and the interviewer. Households with a female HRP are significantly more likely to respond if the interviewer is also female, while interviewer gender has no effect among male sample units (Table 5). This finding may be explained by a potential fear of crime of a woman towards a male stranger. It could also be explained by the *theory of liking* (Groves, Cialdini and Couper, 1992), which hypothesises that people are favourably inclined towards those individuals who they like or have something in common with, such as similar characteristics or attitudes.

There has been much debate about the effects of *interviewer experience*, usually measured as the length of time the interviewer has worked in the job. A common argument is that refusal rates decrease with increasing length of interviewer experience (Groves and Couper, 1998; Pickery and Loosveldt, 2002; Hox and De Leeuw, 2002). Here, we have been able to separate out the effects of the number of years of experience and the pay grade of the interviewer. The results indicate that the higher the pay grade the lower is the refusal rate. After controlling for the effect of grade, the number of years of experience does not necessarily lead to a lower refusal rate. Although there is a suggestion that the probability of refusal declines after 1-2 years experience (effect not significant at the 5% level), interviewers who have been in the job for 9 years or more seem to perform significantly less well. This could indicate that, after controlling for grade, long-time interviewers may have settled into the routine of their job, may be less ambitious or may be less responsive to interviewer training and new interviewing strategies, resulting in lower performance. This implies a curvilinear relationship between performance and length of experience, which has been hypothesised but has not before been supported by empirical evidence (Groves and Couper, 1998, p. 203).

The effects of *interviewer attitudes and expectations* have been studied by previous researchers, but their findings are based on bivariate or single-level analyses, usually with the interviewer-level response rate as the dependent variable (e.g. Groves and Couper, 1998, Ch. 7.7; Hox and De Leeuw, 2002). In our analysis of household response, and after controlling for household and area characteristics, we find a significant effect of the attitude of the interviewer towards persuasion of reluctant respondents. Interviewers who are less confident in their ability to persuade reluctant respondents, or who believe that reluctant respondents should not be persuaded, show an increased probability of refusal. The effect of interviewer confidence is particularly strong for the EFS, but is also apparent for the GHS and OMN, resulting in low refusal rates for more confident interviewers (see Table 5). This may reflect differences in interviewer training, whereby surveys providing more detailed interviewer training (NTS and LFS) show smaller effects of interviewer confidence. Other factors that might explain between-interviewer variation are *interviewer behaviours and interviewing strategies*, which include habits, procedures and working rules. We find, however, that, after controlling for household characteristics, such variables had either non-significant or non-interpretable main effects on refusal. Groves and Couper (1998) argue that main effects of interviewer behaviour on survey cooperation may be unlikely because it is not whether certain strategies are adopted *in general* that is important, but whether strategies are *tailored* towards a sample unit. Further exploration of interviewer effects, and their variation by survey, household and individual characteristics, is planned in future research.

5. Discussion and Further Research

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 different 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 predominantly by individual characteristics, such as the socio-economic status, qualifications and attitudes of the HRP, rather than general or factual characteristics of the household. This may be expected because refusal is a decision that is more likely to be made at an individual rather than a household level. The analysis also reveals that some predictors have opposite effects on the probability of noncontact and refusal. For example, there is some indication that households with an unemployed HRP are more likely to be found at home, but are less likely to participate. Effects may therefore 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 provide empirical evidence 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.

The analysis of interviewer effects may inform interviewer allocation, training and performance. We investigated the ways in which interviewer characteristics and strategies interact with household level variables and with different surveys. The results suggest the matching of design alternatives and interviewer characteristics to different subgroups of the population, which may be of particular relevance for the design of interviewer call-backs, re-issues and follow-ups. We also find support for the idea of tailoring interviewing strategies to sample units or subgroups rather than the use of general interviewing strategies. The importance of interviewer confidence and a positive attitude towards persuasion of reluctant respondents, and in particular the survey specific effects of interviewer confidence, may have implications for interviewer training. Strategies for enhancing interviewer confidence may possibly reduce refusal rates.

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 strategies and interviewing. 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. In this paper, we have not specifically investigated the relationship between nonresponse rates and nonresponse bias. However, the results suggest that characteristics of sample units that affect response rates may influence the composition of the sample. 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.

Future research will consider multilevel cross-classified models to separate interviewer and area effects for surveys where the assignment of interviewers crosses areas. Another avenue for further work is the development of models to investigate the contextual response behaviour of individuals within households, taking account of potential clustering of individuals within households and interviewers. Such contextual response effects have not been fully explored, partly because of a lack of appropriate data. The Census Link Study also provides a unique opportunity to investigate para- and interviewer observation data. Research is needed to establish how best to use such data to inform nonresponse processes, as well as further methodological development in the specification of response propensity models. So far, this area is not well researched and little is known about the benefits of paradata for data collection, adjustment and analysis. This work will include analysis of interviewer calling patterns and strategies as well as the initial interaction process between the household and the interviewer. The findings will inform research on the reduction of nonresponse, the relationship between nonresponse rates and nonresponse bias and the improvement of nonresponse adjustment methods for data analysis.

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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 lengths 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. Further information on the different surveys can be obtained from the ONS website, www.statistics.gov.uk)

Information collected by survey:

EFS: core topics include: household expenditure, rent and mortgage payments, taxes, benefits, detailed information about income of each household member, 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, income.

NTS: aims to provide a comprehensive picture of personal travel behaviour. Questions include information about 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, 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.

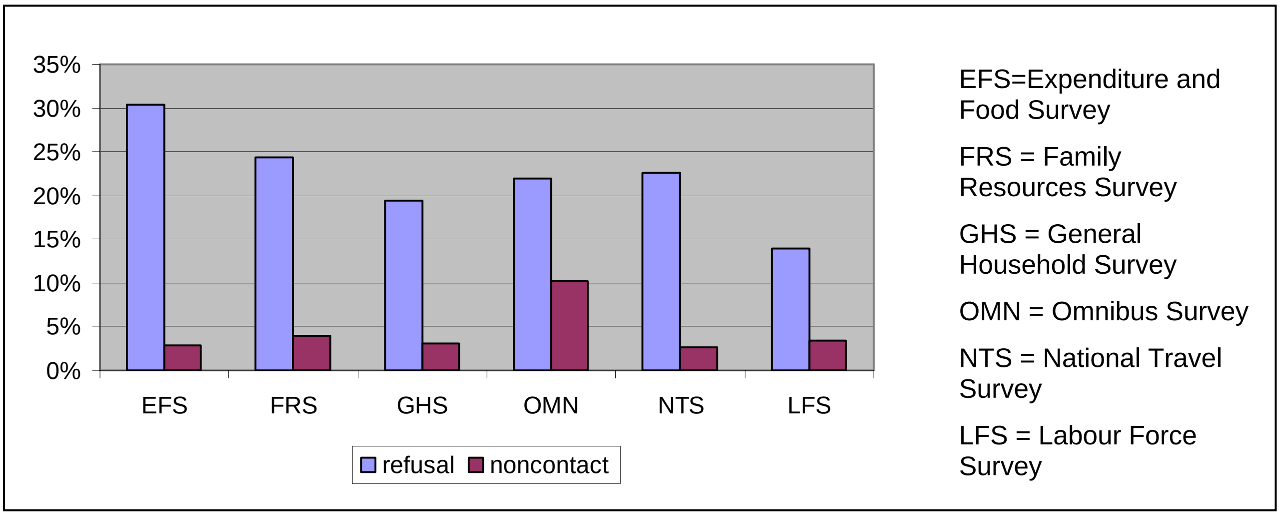

Table 2: Distribution of explanatory variables included in final models. †

Variable	Categories	Cooperation (%)	Refusal (%)	Noncontact (%)
Household level variable				
Survey indicator	EFS	18.1	27.3	12.6
	FRS	11.7	13.2	10.8
	GHS	19.4	16.1	13.1
	OMN	16.5	17.7	41.5
	NTS	14.5	14.6	8.4
	LFS	19.8	11.0	13.7
Highest qualification (HRP)	No academic qualification	27.5	32.5	28.2
	O-levels, GCSEs, A-levels	38.9	33.4	40.4
	First or Higher degree	16.7	13.1	20.0
	Other qualifications	5.6	5.9	4.7
	Missing	11.5	15.1	6.8
Indicator if house	Other (flat, mobile home,…)	15.6	17.9	35.3
	House	84.4	82.1	64.7
Dependent children present	not present	68.2	74.4	77.1
	present	31.8	25.6	22.9
London indicator	not London	90.1	86.5	83.9
	London	9.9	13.5	16.1
Rural indicator	Urban	88.3	90.7	93.6
	Rural	11.0	9.0	6.2
	Missing	0.7	0.3	0.2
Gender (HRP)	Male	61.0	58.6	62.6
	Female	39.0	41.4	37.4
Economic Activity (HRP)	Employee	51.3	45.6	59.6
	Self employed	8.8	10.4	9.1
	Unemployed	2.2	2.6	4.6
	Retired	16.9	16.5	8.6
	Looking after family	2.8	2.3	2.0
	Other (incl. student, ill etc)	6.5	7.5	9.4
	Missing	11.5	15.1	6.8
Pensioner in household	No pensioner in household	66.7	62.4	82.8
	Pensioner in household	33.3	37.6	17.2
Perception on health (HRP)	Good	60.0	54.5	63.8
	Fairly good	28.3	31.7	25.5
	Not good	11.7	13.8	10.7

Carers in household	No Yes	80.9 19.1	82.7 17.3	86.6 13.4
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
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
Age (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
Car Ownership	One car or more No car	75.2 24.8	70.3 29.7	65.8 34.2
Household moved during last year	No Yes	92.0 8.0	94.0 6.0	88.8 11.2
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
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
Interviewer level variables				
Pay grade	Interviewer Advanced Interviewer Merit 1 Merit 2 Merit 3 Field Manager Missing	47.4 11.4 12.1 10.3 17.8 0.7 0.2	42.6 8.7 17.4 12.2 17.4 0.0 1.7	59.1 9.1 4.5 9.1 18.2 0.0 0.0
Years of experience	Less than 1 year 1 to 2 years 3 to 8 years 9 years or more	20.3 28.7 27.1 23.8	18.3 22.6 28.7 30.4	27.3 22.7 31.8 18.2
Interviewer gender	Male Female	60.3 39.7	61.7 38.3	50.0 50.0
Can convince reluctant respondents	Less confident More confident Missing	82.5 17.3 0.2	85.2 14.8 0.0	81.8 18.2 0.0
Should persuade most reluctant respondents	Strongly agree Agree Neither agree nor disagree Disagree Strongly disagree Missing	30.8 47.4 8.4 11.2 1.9 0.2	31.3 44.3 7.8 11.3 5.2 0.0	22.7 40.9 13.6 22.7 0.0 0.0
Refusal should be accepted	Strongly agree Agree Neither agree nor disagree Disagree Strongly disagree Missing	1.2 16.8 31.3 43.0 7.5 0.2	5.2 11.3 31.3 39.1 13.0 0.0	0.0 9.1 50.0 36.4 4.5 0.0
How often do you leave phone number behind	Always Frequently Sometimes Rarely Never Missing	27.1 24.8 23.6 17.1 7.0 0.5	27.0 23.5 24.3 14.8 10.4 0.0	27.3 31.8 13.6 22.7 4.5 0.0

† 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)	**Model 3** (Model 2 + interviewer variables)
Refusal, $\mathrm{var}(u_j^{(1)})$	0.095 (0.065; 0.130)	0.085 (0.056; 0.119)	0.055 (0.030; 0.087)
Noncontact, $\mathrm{var}(u_j^{(2)})$	0.539 (0.388; 0.721)	0.453 (0.312; 0.626)	0.394 (0.254; 0.531)
$\mathrm{cov}(u_j^{(1)}, u_j^{(2)})$	0.076 (0.022; 0.132)	0.050 (-0.002; 0.104)	0.028 (-0.018; 0.078)
$\mathrm{co}\,r(u_j^{(1)}, u_j^{(2)})$	0.336	0.254	0.193
DIC diagnostics	24971	24334	24123

† 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).

Table 4: Estimated coefficients (and standard errors in parentheses) of multilevel multinomial model (Model 3). †

Variable (0 = Reference category)	**Categories**	$\hat{\beta}$ $(ste(\hat{\beta}))$ **refusal**	$\hat{\beta}$ $(ste(\hat{\beta}))$ **noncontact**
Constant		-0.316 (0.199)	-1.821 (0.675)*
Household level variable			
Survey indicator** (0 EFS)	1 FRS 2 GHS 3 OMN 4 NTS 5 LFS	-0.135 (0.094) -0.504 (0.090)* -0.446 (0.090)* -0.444 (0.093)* -1.110 (0.109)*	0.199 (0.291) -0.548 (0.295) 0.521 (0.238)* -0.872 (0.336)* -0.779 (0.309)*
Highest qualification (HRP) (0 No academic qualification)	1 O/A levels, GCSEs 2 First/Higher degree 3 Other qualifications	-0.204 (0.052)* -0.509 (0.064)* -0.222 (0.085)*	-0.210 (0.117) -0.154 (0.129) -0.157 (0.194)
Indicator if house** (0 not house, e.g. flat, mobile home)	1 House	-0.018 (0.057)	-1.170 (0.224)*
Dependent children present (0 not present)	1 Present	-0.277 (0.053)*	-0.645 (0.108)*
London indicator** (0 not London)	1 London	0.381 (0.137)*	0.508 (0.319)
Rural indicator** (0 Urban)	1 Rural	0.002 (0.130)	-0.299 (0.169)
Gender (HRP)** (0 Male)	1 Female	0.138 (0.055)*	-0.155 (0.111)
Economic Activity** (HRP) (0 Employee)	1 Self employed 2 Unemployed 3 Retired 4 Looking after family 5 Other (incl. student, permanently sick etc)	0.582 (0.130)* 0.229 (0.104)* -0.159 (0.092)* -0.118 (0.130) -0.004 (0.086)	0.098 (0.140) -0.237 (0.299) 0.125 (0.310) -0.563 (0.361) -0.015 (0.269)
Pensioner in household (0 No pensioner in household)	1 Pensioner in household	-0.144 (0.067)*	-0.604 (0.241)*

Perception on health (HRP) (0 Good)	1 Fairly good 2 Not good	0.121 (0.045)* 0.126 (0.061)*	-0.066 (0.097) -0.052 (0.148)
Carers in household (0 No)	1 Yes	-0.131 (0.051)*	-0.087 (0.115)
Household type (0 Single household)	1 Couple household 2 Multiple household	0.078 (0.051) 0.185 (0.127)	-1.299 (0.286)* -0.092 (0.471)
Adults in employment (0 No adults)	1 One adult 2 Two or more adults	--	0.506 (0.239)* 0.420 (0.261)
Age (HRP) (0 16 - 34)	1 35 - 49 2 50 - 64 3 65 - 79 4 80 and older	0.134 (0.062)* 0.120 (0.070) 0.028 (0.128) 0.127 (0.165)	-0.167 (0.105) -0.520 (0.126)* -0.777 (0.311)* -0.761 (0.425)
Car Ownership** (0 One car or more)	1 No car	0.239 (0.089)*	0.174 (0.103)
Household moved during last year (0 No)	1 Yes	-0.136 (0.078)*	0.009 (0.130)
Interviewer observations			
House in a better or worse condition than others in area (0 Better)	1 Worse 2 About the same	0.442 (0.090)* 0.104 (0.064)	0.770 (0.177)* 0.069 (0.146)
How safe would you feel walking along in this area after dark? (0 Unsafe)	1 Safe	-0.184 (0.063)*	-0.260 (0.116)*
Household level interactions			
Survey*Self-employed indicator (0 EFS and 0 not self-employed)	1 FRS - self-employed 2 GHS- self-employed 3 OMN- self-employed 4 NTS- self-employed 5 LFS- self-employed	-0.657 (0.211)* -0.222 (0.199) -0.098 (0.196) -0.374 (0.208) -0.849 (0.247)*	--
Survey*London indicator (0 EFS and 0 London)	1 FRS - London 2 GHS- London 3 OMN- London 4 NTS- London 5 LFS- London	-0.141 (0.216) -0.189 (0.191) -0.129 (0.208) 0.151 (0.196) -0.533 (0.245)*	-1.129 (0.503)* -0.860 (0.482) -0.102 (0.380) -0.161 (0.468) -0.364 (0.484)
Survey*Rural indicator (0 EFS and 0 urban)	1 FRS - rural 2 GHS- rural 3 OMN- rural 4 NTS- rural 5 LFS- rural	-0.277(0.240) -0.489 (0.203)* -0.225 (0.205) -0.391 (0.227) -0.180 (0.226)	--
Survey*Car Ownership indicator (0 EFS and 0 car)	1 FRS - no car 2 GHS- no car 3 OMN- no car 4 NTS- no car 5 LFS- no car	-0.635 (0.151)* -0.262 (0.130)* 0.091 (0.128) -0.077 (0.137) -0.402 (0.149)*	--
Survey*House Indicator (0 EFS and 0 not House (flat, mobile home,…))	1 FRS - House 2 GHS- House 3 OMN- House 4 NTS- House 5 LFS- House	--	0.069 (0.338) 0.944 (0.333)* 0.675 (0.268)* 0.977 (0.378)* 0.786 (0.329)*
Survey*Household type (0 EFS and 0 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	--	0.311 (0.375) 0.120 (0.355) 1.003 (0.305)* 0.226 (0.389) 0.540 (0.349) -0.343 (0.780) -2.179 (1.386) -0.098 (0.626) -0.667 (0.824) -1.277 (0.958)

Interviewer level variables			
Pay grade (0 Interviewer)	1 Advanced Interviewer 2 Merit 1 3 Merit 2 4 Merit 3 5 Field Manager	-0.017 (0.097) -0.085 (0.090) -0.185 (0.091)* -0.417 (0.104)* -1.047 (0.892)	-0.385 (0.219) -0.446 (0.208)* -0.243 (0.231) -0.745 (0.249)* -0.879 (1.497)
Years of experience (0 Less than 1 year)	1 1 to 2 years 2 3 to 8 years 3 9 years or more	-0.038 (0.075) 0.019 (0.096) 0.283 (0.114)*	-0.010 (0.156) 0.176 (0.208) 0.483 (0.240)*
Interviewer gender (0 Male)	1 Female	-0.029 (0.060)	-0.161 (0.133)
Can convince reluctant respondents** (0 Less confident)	1 More confident	-0.655 (0.177)*	--
Should persuade most reluctant respondents (0 Strongly agree)	1 Agree 2 Neither agree nor disagree 3 Disagree/Strongly disagree	0.076 (0.054) -0.151 (0.091) 0.156 (0.071)*	--
Refusal should be accepted (0 Strongly agree)	1 Agree 2 Neither agree nor disagree 3 Disagree 4 Strongly disagree	-0.332 (0.158)* -0.406 (0.149)* -0.417 (0.150)* -0.230 (0.166)	--
How often do you leave phone number behind (1 Always)	2 Frequently 3 Sometimes 4 Rarely 5 Never	-0.015 (0.066) -0.050 (0.064) -0.140 (0.073) -0.091 (0.091)	-0.300 (0.156) -0.349 (0.147)* 0.063 (0.161) 0.493 (0.220)*
Interviewer level interaction			
Survey indicator * Interviewer can convince reluctant respondents (0 EFS and 0 Less confident)	1 FRS -more confident 2 GHS-more confident 3 OMN-more confident 4 NTS-more confident 5 LFS-more confident	0.415 (0.239) 0.224 (0.226) 0.362 (0.218) 0.454 (0.221)* 0.554 (0.221)*	--
Cross-Level Interaction			
Gender of household reference person * interviewer gender (0 Male and 0 Male)		-0.176 (0.077)*	-0.196 (0.170)

† 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 5% level

** survey specific effect

HRP information based on household reference person

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

Interaction between survey and economic status of the household representative								
		Survey						
		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 interviewer attitude							
		EFS	**FRS**	**GHS**	**OMN**	**NTS**	**LFS**
Can convince reluctant respondent	Less confident	31.1	28.1	21.8	22.0	22.9	13.3
	More confident	19.1	23.6	15.4	17.4	19.6	12.2
Interaction between gender of the interviewer and household representative							
		Interviewer Gender					
		Male	Female				
Gender of HRP	Male	21.6	21.2				
	Female	24.0	20.7				

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

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