UNIVERSITY OF
Southampton
Southampton Statistical
Sciences Research Institute

Working Paper M09/12
Methodology

# Using Field Process Data To Predict Best Times Of Contact Conditioning On Household And Interviewer Influences

Julia D'arrigo, Gabriele B. Durrant, Fiona Steele

Abstract

Establishing contact is an important part of the survey response process and effective interviewer calling behaviours are critical in achieving contact and subsequent cooperation. This paper investigates best times of contact for different types of households and the influence of the interviewer on establishing contact. Recent developments in the survey data collection process have led to the collection of so-called field process or paradata, which greatly extend the basic information on interviewer calls. This paper develops a multilevel discrete time event history model based on interviewer call record data to predict the likelihood of contact at each call. The results have implications for survey practice and inform the design of effective interviewer calling times, including responsive survey designs.

# Using field process data to predict best times of contact conditioning on household and interviewer influences

**Julia D'Arrigo[1], Gabriele B. Durrant[1] and Fiona Steele[2]**

[1]Southampton Statistical Sciences Research Institute (S3RI)
University of Southampton, UK
(g.durrant@southampton.ac.uk)

[2]Centre for Multilevel Modelling
University of Bristol, UK

**Summary**

Establishing contact is an important part of the response process and effective interviewer calling behaviours are critical in achieving contact and subsequent cooperation. This paper investigates best times of contact for different types of households and the influence of the interviewer on establishing contact. Recent developments in the survey data collection process have led to the collection of so-called field process or paradata, which greatly extend the basic information on interviewer calls. This paper develops a multilevel discrete time event history model based on interviewer call record data to predict the likelihood of contact at each call. The results have implications for survey practice and inform the design of effective interviewer calling times, including responsive survey designs.

**Key Words:** paradata, interviewer call-record data, responsive survey design, multilevel discrete-time event history models.

Address for correspondence: Gabriele Durrant, Southampton Statistical Sciences Research Institute, University of Southampton, SO17 1BJ, Southampton, g.durrant@southampton.ac.uk

## 1. Introduction

In recent years many surveys have seen a decline in response rates (De Heer, 1999). Survey agencies have to undertake great efforts to increase response rates and, at the same time, to reduce the costs of survey data collection. Establishing contact is an important part of the response process, which is often costly and time-consuming (Weeks et al., 1980; Groves and Couper, 1998; Cunningham et al., 2003). Effective interviewer calling behaviours are therefore critical in achieving contact and subsequent cooperation. Although survey agencies have become increasingly interested in understanding and improving the process of data collection, research so far has analysed primarily the final outcome of contact/non-contact rather than the process leading to contact (Weeks et al, 1980; O'Muircheartaigh and Campanelli, 1999; Durrant and Steele, 2009).

The increasing interest in the data collection process has led more recently to the development of so-called field process data or *paradata* (Couper, 1998). The term is used to describe empirical measurements about the process generating the survey data, such as time and day of the call and, for face-to-face surveys, interviewer observations about the physical and social characteristics of the selected housing unit and the neighbourhood. An increasingly important area for the use of paradata in survey organisations is responsive survey design (Groves and Heeringa, 2006; Laflamme et al., 2008), where the continuous measurement and monitoring of the process and survey data offers the opportunity to alter the design during the course of the data collection to reduce costs and to increase the quality of the survey data. So far, however, only few studies have used paradata for progress updates or as decision-making tools during data collection or for adjustment at the data analysis stage.

To date, analyses of paradata and interviewer calling behaviour, in particular for face-to-face surveys, have been limited. Much of this research has focused on the average best times of day and days of the week to establish contact, without controlling for household characteristics and prior call information (e.g. Weeks et al., 1980). Greenberg and Stokes (1990) and Kulka and Weeks (1988) conditioned on previous call times but did not have household-level information available. Some studies controlled for basic information about the household or area, but without deriving household-specific estimates of the probability of contact (Purdon et al., 1999; Groves and Couper, 1998; Brick et al. 1996; O'Muircheartaigh and Campanelli, 1999). Most research on optimal calling scheduling has been carried out in the context of telephone surveys (e.g. Weeks et al., 1987; Greenberg and Stokes, 1990; Brick et al. 1996) rather than face-to-face surveys, although the latter offer a much wider range of observational information available for each household and call (Groves and Couper, 1998; Greenberg and Stokes, 1990). Techniques to analyse such data have often been limited to descriptive statistics and simple logistic regression modeling, and usually only one survey was considered (e.g. Weeks et al., 1987; Purdon et al., 1999; Groves and Couper, 1996; Wood et al., 2006; Elliott et al., 2000). Although often acknowledged as important for securing cooperation, few studies have considered the role of the interviewer on the contact process (for examples see Purdon et al., 1999; Groves and Couper, 1998; Blom and Blohm, 2007), and those that have, used basic analysis techniques or had only limited information about interviewers.

A major advantage of this study is that we have access to rich paradata including information recorded by the interviewer at each call to the household (even if contact was not made), interviewer observations about the household and neighbourhood, and detailed information about the interviewers themselves. The dataset combines call-record data from six major UK face-to-face surveys, which allows more general inferences to be made than in previous work. A key strength of these data is that individual and household characteristics from the UK 2001 Census are linked to the paradata for both contacted and non-contacted households. The resulting data have a multilevel structure with households nested within a cross-classification of interviewers and areas. As identified by Groves and

Heeringa (2006, p. 455), research is needed to establish how best to use such paradata to inform nonresponse processes, as well as further methodological development in the specification of models based on such data.

This paper aims to build and improve response propensity models based on paradata to predict the likelihood of contact at each call, conditioning on household and interviewer characteristics. We use multilevel discrete-time event history analysis (Steele et al., 2004) to model the propensity of contact, allowing for household, interviewer and area effects in a cross-classified model. The model conditions on information available for each household, such as from administrative data and prior calls, and includes call record data as time-varying covariates. The key research questions are:

1. What are the best times of the day and days of the week to establish contact?
2. What are the best times to establish contact with certain types of households, in particular households that are generally more difficult to contact?
3. To what extent does establishing contact and the success of the timing of the call depend on interviewer characteristics?

The paper aims to provide guidance to academic researchers and survey practitioners on how to model and use interviewer call record data for the design of effective and efficient interviewer calling strategies. It is anticipated that this research will inform the improvements of responsive survey designs and the design of call-backs and follow-ups of nonrespondents, with implications for survey agencies for the allocation of time and staff resources. Although survey organisations may not have access to information such as the census variables considered in this study, the analysis provides useful information about the type of data that could be beneficial for predicting contact and survey organisations could explore proxies for such variables from available data sources. It would also be possible to train interviewers to collect relevant observation data on earlier calls. If some attributes of the households are observable, survey designs might be altered to improve efficiency, reduce costs and increase contact rates (Groves and Couper, 1998). The paper is organised as follows. Section 2 describes the data available. The methodology for the analysis is presented in Section 3. Section 4 outlines the rationale for the modelling, the choice of variables and the modelling strategy. Section 5 discusses the results. A summary of the findings with implications for survey practice is provided in Section 6.

## 2. Data

### 2.1 Field process data (paradata)

This study takes advantage of comparatively rich field process data (paradata) captured during the data collection period of six face-to-face UK government surveys in 2001. In each survey interviewers recorded information on each call to a household via an interviewer observation questionnaire. The key advantage of these data is that they have been linked to individual and household information from the UK 2001 Census, interviewer information from a survey of all face-to-face interviewers working for the UK Office for National Statistics (ONS) in 2001, and area information from registers and aggregated census information. The timing of the study was chosen to coincide with the last UK Census in 2001. However, the data have only recently become available for more detailed analysis.

The available paradata include records of calls and interviewer observations about the household and neighbourhood captured by the interviewer during data collection. The call record data include the time and day of call, brief information on the contact strategy used at the call, and the outcome of the call. In the interviewer observation questionnaire, the interviewer also recorded their observations about the household and neighbourhood, such as if there were any physical barriers to the house, type of accommodation, quality of housing and information about the household composition, such as any signs of the presence of children. The interviewer observation data are available even if no contact was made with the household. (Information that was recorded by the interviewer only after contact had been established is not discussed in this paper.)

The interviewer is said to have made *contact* with a household at a given call - the dependent variable in our analysis - if he/she was able to talk to at least one responsible resident at the sampled household, either face-to-face (door/window) or through an entry phone. The guidelines provided to interviewers by the survey organisation state that the final response outcome for an address cannot be coded as 'non-contact' until at least four calls have been made. At least two of these calls should be in the evening or on a Saturday. In our dataset the maximum number of calls made to a household is 15. The study includes households selected for interview in one of the six surveys during May-June 2001, the months immediately following the 2001 Census. The call record data are available for 16,799 households (after excluding vacant and non-residential addresses, re-issues and unusable records, as described in detail in Durrant and Steele, 2009), of which 1,017 households were never contacted. This results in an average final non-contact rate of about 6%. Although the non-contact rate may not appear very large in comparison to the refusal rate (for the surveys considered here around 15-30%), establishing contact is a costly and time-consuming process. Our dataset contains a total of 69,619 calls to households of which more than half alone (37,879 calls) are made to establish first contact or until the household was coded as a non-contact.

The six face-to-face household surveys for which the interviewer call record data were collected 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). The contact rates for the six surveys range from 3% to about 10% which may be explained by differences in the survey design, length of data collection period, minimum number of calls to be made, interviewer workload, interviewer qualifications and interviewer training. Further details about these surveys can be found in Durrant and Steele (2009) and at www.statistics.gov.uk.

It should be noted that the ideal dataset for such an analysis would be based on fully randomized calling times for all sample units. Such a design would, however, be practically impossible, at least for face-to-face surveys; it could be achieved to some extent for telephone surveys (Groves and Couper, 1998). The dataset here, similarly to previous work on this topic, is based on observed calling times, i.e. on the timings that the interviewer chooses to call on a household. If an interviewer's decision to call at a particular time can be regarded as independent of the characteristics of the sample unit, a departure from fully randomised calls should not be important. It is probably realistic to assume that for the first call the interviewer chose calling times without or with at least not much prior knowledge about the sampling units. However, subsequent calls, may condition on additional knowledge that the interviewer obtained at an earlier call. To the extent that we control in our models for characteristics of the households that are related to differential interviewer calling strategies, in particular household and area characteristics from both the census and the interviewer observation data, our models should also produce unbiased estimates. This issue has been discussed further in Purdon et al. (1999, p. 201), Groves and Couper (1998, p. 82) and Kulka and Weeks (1988).

### 2.2 Linked data

The field process data recorded for every household were linked to demographic and socio-economic individual and household level information from the UK 2001 Census, available for both contacted and non-contacted households of the surveys. (Further details on the variables considered are given in Section 4). It should be noted that some of the information from the interviewer observation data also coincide with information recorded via the census (e.g. type of accommodation) and wherever possible we used the interviewer observation variables.

Detailed information about the interviewer was linked to the household level information. These data were obtained via a separate face-to-face survey (Interviewer Attitude Survey) of ONS interviewers during June 2001, at around the time of the survey and census data collection period. The information on interviewers includes socio-demographic characteristics, and employment background, such as pay grade and experience, workload and planning, attitudes, strategies and behaviours for dealing with noncontacts as well as information about doorstep approaches.

Area information is available from aggregated census data, where area is defined as the local authority district. In total, the dataset contains 565 interviewers and 392 areas. It should be noted that in clustered survey designs an interviewer is normally assigned to one primary sampling unit (PSU) and their workload consists of all sampled households in that PSU. Interpenetrated sampling designs may be used to avoid confounding of area and interviewer effects, where interviewers are allocated at random to households. Such designs enable, at least to some extent, a separation of interviewer and PSU effects. However, due to the high costs of implementing interpenetrated designs, only very few studies of this kind exist (O'Muircheartaigh and Campanelli, 1999; Schnell and Kreuter, 2001). Usually, if no such design has been employed, area effects are ignored in the analysis or area information is not available (e.g. Pickery and Loosveldt, 2004). The surveys included in this study did not employ an interpenetrated sampling design where households are allocated to interviewers fully at random due to the high costs involved. However, a complete confounding of area and interviewer effects was avoided because most interviewers work on a number of surveys and some interviewers work across PSUs, leading to a structure where households are nested within a cross-classification of interviewers and PSUs. We also allow for area effects in our models where areas are defined at the local authority district level, a geographical area slightly larger than a PSU. As described in Section 3 we use a multilevel cross-classified model to analyse this type of data. Nevertheless, we do not claim to be able to fully disentangle interviewer and area effects and some confounding may possibly remain. For another example of the use of a multilevel cross-classified model and a detailed discussion of different forms of (partial) interpenetrated sampling designs that are less restrictive than the traditional interpenetrated approach, including the case of nonrandom allocation of interviewers to areas, see von Sanden (2004) and Durrant et al. (2009).

The linkage of the various data sources was carried out and quality assured by ONS. More detailed information about the rationale of the study, the data and the linkage of the different datasets can be found in Durrant and Steele (2009) and Beerten and Freeth (2004).

## 3. Multilevel discrete time hazard model for the probability of contact

Multilevel event history analysis (see, for example, Steele, Diamond and Amin, 1996) was used to model the probability of contact at a particular call, given that no contact was made prior to that call (i.e. we model first contact). Households that were not contacted by the end of the data collection period have right-censored contact histories.

Denote by $y_{i(jk)t}$ the binary indicator of contact, coded 1 if contact is made with household $i$ of interviewer $j$ in area $k$ at call $t$ and 0 if the contact attempt fails. The grouping of the $j$ and $k$ indices in parentheses, $(jk)$, indicates a cross-classification of interviewers and areas. The conditional probability of contact at call $t$ given no contact before $t$ – commonly referred to as the discrete-time hazard function – is defined as $\pi_{i(jk)t} = \Pr(y_{i(jk)t} = 1 \mid y_{i(jk)t-1} = 0)$. The multilevel cross-classified discrete-time hazard model, allowing for clustering of households within interviewers and the cross-classification of interviewers within areas, may be written

$$\log\left(\frac{\pi_{i(jk)t}}{1-\pi_{i(jk)t}}\right) = \alpha_t + \boldsymbol{\beta}' \boldsymbol{x}_{i(jk)t} + u_j + v_k . \qquad (1)$$

$\boldsymbol{x}_{i(jk)t}$ is a vector of covariates, with coefficients $\boldsymbol{\beta}$, including time-varying attributes of calls (e.g. time and day of contact attempt), time-invariant characteristics of households, interviewers and areas, and two-way interactions between call and household-level variables. $\alpha_t$ is a function of the call number $t$ ('time') which allows the probability of contact to vary across calls; here $\alpha_t$ was initially fitted as a step function, i.e. $\alpha_t = \alpha_1 D_1 + \alpha_2 D_2 + ... + \alpha_T D_T$ where $D_1, D_2, \ldots, D_T$ are dummy variables for calls $t = 1,\ldots,T$ with $T$ the maximum number of calls, but simpler monotonic functions were also explored. Unobserved interviewer and area characteristics are represented respectively by the random effects $u_j$ and $v_k$, assumed to follow normal distributions: $u_j \sim N(0,\sigma_u^2)$ and $v_k \sim N(0,\sigma_v^2)$.

After restructuring the data so that, for each household, there is a record for every contact attempt, the multilevel discrete-time event history model (1) can be estimated as a cross-classified model for the binary responses $y_{i(jk)t}$. Estimation is carried out using Markov chain Monte Carlo (MCMC) methods as implemented in the MLwiN software (Browne, 2009; Rasbash et al., 2009).

To aid interpretation of the fitted model, predicted probabilities of contact are calculated for each value of the categorical covariates, holding constant the values of all other covariates in the model. To obtain mean probabilities, we average across interviewer and area-specific unobservables by taking random draws from the interviewer and area random effect distributions. The simulation approach involves generating a large number of pairs of random effect values from independent normal distributions with variances $\hat{\sigma}_u^2$

and $\hat{\sigma}_v^2$, calculating a predicted probability based on each pair of generated values and the estimated coefficients, and taking the mean across the simulated values. This procedure is implemented in MLwiN and described in Rasbash et al. (2009).

## 4. Choice of explanatory variables and modelling strategy

The conceptual framework by Groves and Couper (1998, Ch. 4) on household survey nonresponse identifies a number of important influences on the process of contacting a household, including the timing and frequency of the calls, social environmental attributes, socio-demographic attributes, at home patterns of the householders and any physical impediments to gaining access to the household. Such attributes may be separated into factors that are under the control of the interviewer or survey organisation and factors outside their control. Our analysis aims to control for all of these effects. Examples of variables under the direct control of the interviewer are the timing of the call, i.e. the time of day, day of the week and the time between calls (Purdon, et al. 1999; Groves and Couper, 1998). These may also be influenced by decisions of the survey organisation. For example, as part of responsive survey designs, the survey agency could direct the interviewer to certain types of households who are known to be difficult to contact at particular times, such as calling on households without children during the day. Contact strategies and interviewer behaviours, such as attempting to establish contact by telephone or leaving a card or message at a call, are further examples of variables under the control of the interviewer or survey organisation. Such call-specific variables are included in the models as time-varying covariates. Some further time-varying variables, such as the time between calls, were derived from the call record history. An interesting question for survey agencies is whether changing the timing of the call increases the likelihood of contact. Our model investigates the influence of the call history by conditioning on the timing of the previous call including any potential interaction effects with the current call time (see also Purdon et al., 1999; Groves and Couper, 1998 and Kulka and Weeks, 1988). A separate indicator for the first call was included and variables relating to earlier calls, such as the time of the previous call, were coded zero for the first call in our model. This coding allows the coefficients of these call history variables to be interpreted as effects for second and subsequent calls.

Factors that are outside the direct control of the interviewer include characteristics of the household or area that indicate at home patterns and lifestyle of household members, attributes of the social environment, socio-demographic characteristics and indicators of physical impediments to accessing the household. Our model investigates the influence of variables that may be regarded as proxies for the time spent at home and lifestyle, such as indicators for a single-person household, presence of dependent children, pensioners, carers or a person with a limiting long-term illness and adults in employment. The social environmental and socio-demographic attributes considered include for example gender and age of the main householder, number of people in the household and type of accommodation; at the area level we considered an urban vs rural indicator, population density, percentage of people living in houses/flats, percentage of ethnic minority residents, percentage belonging to particular religious groups, percentage of students, pensioners or children and unemployment rate. Most of these variables were taken from the 2001 Census.

Of particular interest are the relevance of interviewer observation variables, which allow the survey agency to collect further information about each household, even if not contacted. These include information about physical barriers to accessing the household, such as a locked common entrance, locked gates or entry phones and the presence of security devices, such as security staff, CCTV cameras or burglar alarms – all hypothesised to be important for the probability of establishing contact (Groves and Couper, 1998).

Further interviewer observations are indications about boarded-up or uninhabitable buildings in the area, how safe the interviewer feels walking along in the area after dark and the quality of the housing.

Most previous research has analysed the average best times to contact and found that evening and weekend calls are optimal (Weeks et al., 1980; Swires-Hennessy and Drake, 1992). Survey agencies, however, need to allocate staff and time resources and not all calls can be made in the evenings and at weekends; some have to be made during the day and on weekdays. A logical question to ask is which households have the highest chance of contact during the day, so that evening and weekend times can be reserved for more difficult cases. The interviewer or survey organisation may then refine the calling strategy in light of information available about a household. For example, a household with children may be easier to contact during the day than a single household. We therefore explore interactions between call and household characteristics to determine best times of contact for different types of households.

It is possible that some prior knowledge about a household, or at least about the area, may be available to the survey agency prior to the start of fieldwork. This information could potentially come from the sampling frame, census, register or administrative data - possibly only at an aggregated level- or in case of a longitudinal survey from a previous wave. The availability of such data may depend on the country: in particular, Scandinavian countries and the Netherlands have access to rich administrative and register data (for an example of the enrichment of survey data by household-level administrative data see Cobben and Schouten, 2007). Any such prior information may be used by the survey agency to direct the calling efforts of interviewers at the start of the data collection period. Furthermore, interviewers may already have some prior knowledge about the areas and the type of households they have to contact. After the first call the interviewer should be able to gather more information about each particular household, e.g. based on visual observations or by talking to neighbours. Subsequent calls may then depend on this information. In this paper, we aim to investigate the potential use of such additional data to inform contact strategies.

Previous research on the influence of the interviewer on the nonresponse process has focused on the cooperation/refusal stage (Durrant et al., 2009; O'Muircheartaigh and Campanelli, 1999; Groves and Couper, 1998). However, only a few studies exist that consider the role of interviewers in establishing contact (Purdon et al., 1999; Groves and Couper, 1998; O'Muircheartaigh and Campanelli, 1999). Purdon et al. (1999) and Groves and Couper (1998) argue that, at least theoretically, the impact of interviewer characteristics should operate through the time, day and frequency of the call, as the only parts of the contact process that interviewers can control. After adjusting for the timing of the call the interviewer should not play a significant role. Groves and Couper (1998) nevertheless investigate if there are any further net effects of interviewer characteristics, such as interviewer experience, and explore simple relationships between interviewer attributes and the probability of contact. Purdon et al. (1999) find a significant influence of interviewer pay grade (although it should be noted that only a single level model was used which did not allow for unmeasured interviewer characteristics). In this paper, we hypothesise that characteristics such as the qualification, pay grade and experience of the interviewer may play a role in establishing contact. Such variables may be indicators of an interviewer's ability to judge best times of contact for different households. Another mechanism through which attributes of the interviewer may impact on establishing contact could be through knowledge of the area and types of households. Also some interviewers may be better than others at organising their workload and prioritising their cases, leading to higher contact rates. Since survey agencies are particularly interested in behavioural differences between interviewers we also explore the extent to which interviewer strategies may influence the probability of contact. The survey organisation may also have limited influence over certain interviewer characteristics. For example, more experienced interviewers may be allocated to more difficult cases or areas. Interactions between interviewer and household characteristics were investigated to see which interviewers may be better at establishing contact with generally harder to reach households. To analyse differences in effectiveness of interviewers at certain times of the day, interactions between interviewer and call characteristics were explored.

Due to the large number of variables available, testing of main effects and interactions was primarily guided by theories of contact and interpretation (Durrant and Steele, 2009; Groves and Couper, 1998). Variables that were not significant at the 10% level, and did not interact significantly with other variables, were excluded from the final model. Some variables in the dataset are subject to a small amount of item nonresponse. To maximise the size of the analysis sample we allowed for a missing category for those variables subject to item nonresponse. The coefficients of dummy variables for these categories were not significant in the final model and, for space reasons, are not shown in the tables of results.

We investigated a series of models starting with a simple specification including only dummy variables for survey to control for differences among the six surveys, the previous call indicator and the number of previous calls. We then added interviewer and area random effects in a cross-classified multilevel model. Next, we entered time-invariant household and time-varying call-level variables and two-way interactions between household and call characteristics. Finally, we include interviewer-level variables to examine the extent to which these may explain between-interviewer variance in the contact rate.

# 5. Results

## 5.1 The hazard rate and average best times of contact

We first present descriptive statistics on the contact process and results from preliminary models that informed the specification of the final multilevel model. Figure 1 shows the hazard of contact at each call, based on a simplified version of model (1) with only dummy variables for call number. In line with previous studies (e.g. Purdon et al., 1999; Groves and Couper, 1998), we can see a monotonic decline in the contact rate as the number of calls increases, here until about call 9. The contact rate is highest at the first call, when about 50% of households were contacted, and decreases with each additional call. The slight increase in the contact rate for call 9 and 10, and the increase for calls 13 and 15, may indicate that interviewers change their calling strategy and put in a greater effort to secure contact towards the end of their contact attempts. Another reason could be that interviewers have additional information that leads them to believe there is a chance of contact even after many failed attempts. It should be noted that from call 13 onwards the estimated probabilities of contact are based on fewer than 100 households. Based on the monotonic relationship between the probability of contact and call number, we simplified the specification of the baseline logit hazard, $\alpha_t$ in (1), by including the number of previous calls as a linear term.

*[Figure 1 about here]*

Table 1 shows the probability of contact at the first call by time of day and day of the week. The most popular times to call are by far weekday afternoons, followed by weekday evenings and weekday mornings, with a clear decline in the frequency of calls from the beginning to the end of the week for all times of the day. It should be noted that only few calls are made at the weekend, in particular on a Sunday. The highest contact probabilities can be found for evening calls, especially for Sunday to Wednesday evenings with a probability of more than 0.6. The chance of making contact in the evening decreases as the week progresses, with a comparatively low probability for Saturday evening of 0.43. On weekdays, the probability of making contact during the day is below 0.5, with a particularly low probability for Wednesday morning. For all weekdays, afternoons show a higher chance of contact than mornings. At the weekend the daytime contact probability is comparatively high at around 0.5.

*[Table 1 about here]*

We also explored the probability of contact at the second call conditioning on the time of the previous call using descriptive statistics (Table 2). The results may suggest that the best time for the second call is a weekday evening, regardless of the time of the first call, which supports earlier findings by Purdon et al. (1999), Groves and Couper (1998) and Kulka and Weeks (1988). The effect is greatest if the previous call was at a weekend, followed by weekday day times. The effect is smallest if the previous call was also made on a weekday evening. We found a very similar pattern for the timing of the third call conditioning on the time of the second call, with again weekday evenings achieving the highest probability of contact (results not shown).

*[Table 2 about here]*

We investigated the effect of day of the week and time of day in a cross-classified multilevel discrete-time hazard model controlling for household, area and interviewer characteristics, but excluding any interaction effects. The estimated coefficients for each category of the time of call variable are provided in Table 3. The results confirm the indicative findings of Table 1, and largely support the conclusions of previous research, that evenings and weekends are optimal times to call (Weeks et al., 1980; Swires-Hennessy and Drake, 1992; Purdon et al. 1999; Groves and Couper, 1998). There is pervasive evidence that calling on weekday evenings yields the highest probability of contact, with a particularly high probability towards the beginning of the week and decreasing thereafter. Calling at the weekend, in particular on a Sunday, also leads to a higher probability of response, with Sunday evenings showing a similar pattern to early weekday (Mon-Wed) evenings. (Due to this finding and the very small number of calls made on a Sunday evening, this category was combined with 'early weekday evening' in later models, see Table 4). The next most successful times to call are weekday afternoons. Weekday mornings are generally the worst times to establish contact. During the week, afternoons are better than mornings but it is the other way round at the weekend. These results informed the categorisation of the calling time variable in the final model (Table 4) which distinguishes eight calling times: early week (Mon-Wed) and late week (Thu-Fri) morning, afternoon and evening and weekend daytime and evening.

*[Table 3 about here]*

### 5.2 Best times of contact for different types of households

So far we have considered the average best times to call on a household. However, the chance of making contact at a given time of day will depend on the characteristics of the household that indicate the householder's at-home patterns. We now investigate the best times to establish contact with certain types of households, in particular those households that are generally more difficult to contact. Table 4 presents parameter estimates of the final multilevel discrete-time hazard model which takes account of household, area and interviewer characteristics and interactions between time-varying variables and household and interviewer characteristics.

*[Table 4 about here]*

From Table 4 we see that the probability of contact is highest for the first call. The highly significant negative coefficient on number of previous calls after the first call indicates a decrease in the odds of contact by 10% for each additional call, in line with the descriptive analysis shown in Figure 1.

*Household Characteristics from the Census*

In the following we distinguish between census and interviewer observation variables, although in practice at least some of the census variables may be obtained from interviewer observation data. It is well known that single-person households, households without children or with primarily young people, and households in urban areas and in flats are the most difficult to contact (Durrant and Steele, 2009; Groves and Couper, 1998), and our results confirm these findings (see also Table 4). To aid interpretation of the interaction terms, predicted probabilities are provided in Table 5. (These have been calculated for call 1 but the pattern in probabilities is exactly the same for subsequent calls because the lack of interactions with the number of previous calls implies that all effects are constant across calls.) From Table 5, we can see that for almost all call times the probability of contact is higher for households with children, with particularly high probabilities on weekday evenings, all afternoons and Mon-Wed mornings. The fact that weekday afternoons are good times may be related to children being back home from school. For households without children, calls made on weekdays during the day are the least likely to result in contact, whereas weekday evenings are the most promising. In practice, indications of the presence of children may be obtained via interviewer observations or, at least in some countries, from administrative or register data, such as from child benefit records (for an example see Cobben and Schouten, 2007).

*[Table 5 about here]*

As might be expected, the contact rate for weekday mornings (Mon-Wed) or afternoons (Mon-Fri) is higher for households without any adults in employment than for households with at least one employed resident, and the probability of contact decreases with the number employed (Table 5). The reverse effect is found for the evenings. The more adults there are in employment the higher is the probability of contact for both weekday and weekend evenings in comparison to households in unemployment. There is a lower chance of contact for households with adults in employment on weekend mornings but weekend afternoons perform very similarly across the three groups. The contact rate for Saturday evenings is higher for households with employed adults than for those with no one in employment. (For an example where information on employment status and unemployment allowance is recorded on the administrative data file see Cobben and Schouten, 2007.)

The interviewer also has a good chance of finding someone at home during the week if there is at least one pensioner present. We see particularly high probabilities of contact during the day in the early part of the week. Weekday evenings are also good times to establish contact with pensioners. Compared to other types of households, the contact rate for households with pensioners is relatively low at the weekend, particularly mornings. This may be partially explained by older people being more likely to have religious commitments on a Sunday for example. For households without a pensioner weekday evenings and weekend mornings are the best times to call. There was also a suggestion of a similar effect for households with an older household representative, where householders older than 50 are more easily contacted during the day on weekdays whereas the daytime contact rate is quite low for householders younger than 35; however, this effect was not significant any more once we controlled for the interaction effect of pensioners. For any time and day, we find that the older the household representative the more likely it is to establish contact, whereas householders aged below 35 are the most difficult to contact (Table 4).

From Table 4 we see that the number of people in the household has a significant effect on the probability of contact, with larger households being easier to contact than single-person households. This may be expected since it will be more likely to find at least one person at home for larger households. The interaction between timing of call and number of people in the household was significant in initial modelling, but not after controlling for other markers for at-home patterns such as the presence of children and household members in full-time employment.

Households with at least one person with a limiting long term illness (LLTI) have high probabilities of contact throughout the week as would be expected since such persons may be more likely to be at home due to their restricted daily activities and some may have a carer present. The probabilty of contacting these households is particularly high during the week (Mon-Wed), which is almost as good a time to call as evenings and weekends. In preliminary analysis, we found a very similar effect for households with a carer present, but due to collinearity with the LLTI variable this variable was not included in the final model. Information on carers or persons with a long-term illness present can be recorded by register or administrative data (for an example see Cobben and Schouten, 2007), although there might be restrictions in the use of such variables due to confidentiality concerns. Alternatively, some crude indicators may be captured by the interviewer, for example via observations regarding wheelchair access to the house or a disabled parking permit visible in the car.

Geographical location and type of area are usually regarded as important predictors of non-contact (Groves and Couper, 1998). However, after controlling for household characteristics and random area effects the London and urban-rural indicators were no longer significant. We also allowed for interactions between the geographical variables and the timing of the call. The interaction with the London indicator was significant in a simple model, but not after adjusting for all household effects and their interactions. In addition, area-level variables, such as long-term unemployment rate, percentage of older people and children and percentage of houses were all significant in predicting noncontact before controlling for household and call-level information, but not in the final model. This implies that area variables may be regarded as weak proxies for household characteristics, in line with the findings of O'Muircheartaigh and Campanelli (1999). In the absence of other information, knowledge about the area would therefore be advantageous and predictive of contact.

*Household and neighbourhood characteristics based on interviewer observations*

In addition to the census variables we considered the effects of a range of interviewer observations. All of these variables were predictive of contact in initial modelling (i.e. before controlling for household and interviewer effects), which suggests such variables are useful for guiding the process of establishing contact in the field, in particular in the absence of additional administrative data, i.e. when the survey agency can only rely on recordings by the interviewers to obtain information about nonresponding households.

Table 4 shows the effects of variables that remained significant in the final model. As may be expected, houses with no security device visible - such as a security gate, burglar alarm, CCTV cameras or security staff - were easier to contact. An observation that can be relatively easily recorded by the interviewer is whether the household lives in a house or a flat. For almost all times, it is easier to establish contact with householders living in a house rather than a flat, and this is true even after controlling for household characteristics such as location, number of people in the household and presence of children. We also explored interactions between interviewer observation variables and time of call, of which a number were found significant in initial modelling. Two interactions remained significant in the final model adjusting for all other household level characteristics; these are the interaction between timing of call and type of accommodation as well as state of repair of houses in the area. The interaction term between the timing of the call and the type of accommodation (Table 5) reveals that on afternoons, for any day of the week, it is easier to make contact with residents of houses than of flats. Householders living in flats are most likely to be contacted in the evenings and on Saturday and Sunday mornings. Contact was found on average to be more difficult when the interviewer recorded that houses in the area were in a fair or bad state of repair and that the house was in a worse condition than others in the area (Table 4). The interaction term between timing of the call and state of repair of houses in the area provides some indication that the contact rate is better for houses in a fair or bad state of repair for Thursday to Sunday mornings (Table 5).

We also found indications that contact is more difficult to establish if there are any boarded-up or uninhabitable buildings in the area, if the interviewer does not feel safe walking along in the area after dark or if physical barriers exist, such as a locked common entrance, locked gates or entry phone. However, none of these effects were significant after controlling for other interviewer observations and household characteristics from the census. It should be noted that interviewers were also asked to record indicators of the presence of children, which is (at least in principle) the same information that we have available from the census data. We decided to use the census variable in our model due to the potential higher data quality and less item-nonresponse of this variable.

Two other call-specific variables that are under the control of the survey organisation, and that may determine best times of contact, are the timing of the previous call and the length of time since the last call. Considering the main effect of time of previous call only (without the interaction term with time of current call in the model) we found that if the previous call was already a weekday evening call then establishing contact at the next call becomes increasingly less likely, indicating a potentially difficult to contact household. We found some indications for a significant interaction term between time of current call and time of previous call (Tables 4 and 5). If the previous call was a weekend call, it seems advisable to call early during the week either in the morning or evening, or on a weekend morning. If the previous call was on a weekday afternoon, promising times to call are evening and weekend and Mon-Wed mornings. If the previous call was made during the evening, calling again during the evening is the most likely to lead to contact, although in comparison to other previous calling times the contact rate for such repeated evening calls is smaller. We may conclude that there is some indication for varying the timing of the call. Overall, however, evenings and weekends are reliably good times to call. This indicates that interviewers may have some (although limited) options in increasing contact rates by changing the time of the call, in particular if it is to an evening or weekend. Similar conclusions were drawn by Weeks and Kulka (1988), although they present only descriptive statistics for the timing of the first three calls. Purdon et al. (1999) did not find a significant interaction between time of current and time of previous call. They conclude that if a household is repeatedly called upon during the evening the contact probability decreases, indicating a more difficult household. Groves and Couper (1998) did not find interpretable conditional effects of the timing of previous calls.

The effect of the number of days between calls (Table 4) suggests that leaving a few days between calls, ideally about one or two weeks, increases the probability of contact compared to returning on the same day. The increased probability of contact for call-backs after one or two weeks may reflect effects of additional knowledge about the household gathered by the interviewer at the earlier call which led them to adopt such a calling schedule. For example, interviewers may have found out from neighbours that the household was on holiday. Unfortunately, this type of information was not recorded for each call.

The above findings are based on a pooled analysis of six UK surveys which are expected to differ in their contact rates, for example because of differences in their design, such as length of data collection period (see also Section 2.1). We find that the LFS has a significantly higher probability of contact than the other surveys considered. This may be due to a number of factors, such as LFS interviewers working only on that survey whereas normally interviewers may be expected to work on several surveys. They also have a comparatively lower workload, in terms of the number of addresses, and receive more intensive interviewer training, although it should be noted that the LFS also has shorter data collection period than the other surveys.

### 5.3 Influences of the interviewer on the process of contact

There is significant variation between interviewers in their contact rates in all models. The inclusion of the interviewer characteristics reduced the between-interviewer variance from 0.11 to 0.08, explaining about 27% of the interviewer variance. The between-area variance was found to be substantially smaller than the between-interviewer variance, and controlling for household-level and call-level variables halved the between-area variance; in the final model area effects are only marginally significant at the 10% level (see Table 4).

The effects of a number of interviewer characteristics were investigated in an attempt to explain the between-interviewer variance in contact rates, including socio-demographic characteristics, experience and work background and interviewer strategies. It may be argued that more experienced and higher qualified interviewers may be better at establishing contact (for a preliminary analysis see Groves and Couper, 1998, p. 95). We found pay grade of interviewers to be an important factor in explaining part of the differences between interviewers, with interviewers in higher pay grades being better at establishing contact. A similar effect was found in Purdon et al. (1999) - although contrary to their a priori hypothesis of no interviewer effects after controlling for the timing of the call. We also found that interviewers with a higher qualification such as a University degree or postgraduate education have higher contact rates. This may indicate that certain types of interviewers may be better at judging the best times to call, for example through gathering information about the household from observation and talking to neighbours, and using such information to tailor their calling strategy to maximise the chance of contact.

We also find that older interviewers (50 years and over) are more successful at establishing contact which may possibly reflect their greater experience. Another explanation may be that older interviewers may have fewer time-constraining commitments outside their job, such as looking after young children, allowing greater flexibility on calling times. We also explored the interaction between age of the interviewer and timing of the call (see Table 5), and found some evidence that older interviewers may be better in judging the best timing of the call for certain types of households: older interviewers are more likely than younger interviewers to achieve contact on weekday evenings, in particular Thursday and Friday, and on weekend mornings.

Slightly surprisingly, we did not find any significant main or interaction effects of the number of years of interviewer experience after controlling for the timing of the call as well as household and area characteristics, even if this was the only interviewer level effect in the model. This is in line with Groves and Couper (1998) who also did not find an effect of interviewer experience. The expected positive association between experience and the probability of contact might be more adequately captured by pay grade and qualification and, to some extent, age which were all found to be significant. It may be argued that the pay grade of the interviewer captures a combination of length of experience and interviewer performance, with better performing interviewers expected to be on higher pay grades. This combination of characteristics may therefore be more important in explaining differences between interviewers rather than simply the length of time an interviewer has been in the job (for a similar effect on refusal see Durrant et al, 2009).

Since survey agencies are particularly interested in behavioural differences between interviewers, we also explored the extent to which interviewer strategies influence the probability of contact. We found that interviewers who report that they at least sometimes wait to explain the survey, rather than simply leaving behind information, are more likely to establish contact (Table 4), which suggests that interviewers who put in more effort and dedicate more time to each sample unit may be more successful at securing contact. We also found that interviewers who always or frequently use the phone to establish contact, rather than visiting the household in person, perform worse than interviewers who rarely or never use the phone. Again, this variable may be an indicator of interviewer effort. Somewhat surprisingly some interviewer strategies, such as how often they check with neighbours, were not found to explain differences amongst interviewers. However, it should be noted that these measures of interviewer practice are self-reported rather than from direct observation. This non-significant effect may have been caused by the fact that most interviewers responded to these types of questions in a similar way (i.e. in the way the survey agency would expect them to respond). This may highlight a potential downside of self-recorded interviewer behaviour. As suggested by Groves and Couper (1998), in the context of interviewer effects on cooperation given contact, it may be preferable to ask interviewers to record their strategy for each call or household. We find some support for their recommendation: the variable indicating whether it is the interviewer's general practice to leave a card or message behind had no significant effect on contact, while the time-varying covariate capturing the same information for each call was found to be significant, showing an increase in the probability of contact at the next call if a card or message was left (see Table 4).

It may be argued that more experienced interviewers and interviewers on higher pay grades are better at establishing contact with harder-to-reach households. Effects of this type could help to inform the allocation of certain interviewers to potentially more difficult households. We therefore explored interaction effects between interviewer characteristics and type of household, focusing on households that previous research identified as being harder to contact, such as single households, younger people or households without children. However, none of the effects explored were found to be significant after controlling for the timing of the call and household characteristics. Also a number of other interviewer characteristics considered were not found to be associated with the probability of contact, including gender of the interviewer, whether they worked for another survey organisation or had other paid employment, and indicators of whether the interviewer is happy to travel, to work evenings and weekends, or to stay overnight.

## 6. Summary and Discussion

This paper uses multilevel discrete-time event history analysis to model the process of establishing contact with sample members in face-to-face surveys. Our unique data allow exploration of the best times to contact different types of households, controlling for interviewer effects. Our findings can be summarised as follows:

1. The results support earlier findings that weekday evenings and weekend daytimes are, on average, the best times to call (Weeks et al., 1980; Swires-Hennessy and Drake, 1992; Purdon et al. 1999). Furthermore, we find that the best times to call depend on household characteristics, especially markers for at home patterns. For example, differences in optimal calling times have been found by type of accommodation, the state of repair of the house, and the presence of children, pensioners or unemployed persons.
2. There is substantial evidence that interviewer observations about a household and neighbourhood are useful for predicting best times of contact at the next call. Interviewer observation variables were predictive of contact before controlling for additional information about a household (such as here from the census) and some of these variables remained significant in the final model.
3. We find that area-level variables are predictive of contact before controlling for other household and calling variables, although they were not significant any more in the final model. Therefore, in the absence of additional information, area characteristics are useful in predicting contact.

4. We have found significant effects of interviewer characteristics on contact. Important in explaining differences among interviewers are pay grade, qualifications and age of the interviewer. Interviewer experience was not found to be important after controlling for these factors, suggesting that the length of time an interviewer has been in the job may be less critical than, for example, a performance-related indicator such as pay grade. There is evidence that some interviewers may be more effective in establishing contact at certain times, which may indicate better judgement of when best to call. There is, however, little empirical support for the hypothesis that some interviewers are more successful in establishing contact with more difficult households, such as single households.
5. It is of interest to know whether certain interviewer strategies are helpful in establishing contact. Our model showed some significant effects of such strategies, for example the probability of contact was higher at the next call if the interviewer left a card or message. Our results also suggest that interviewer strategies measured at the call or household level have greater predictive power than measurements at the interviewer level. We also found some indication that changing the time of the call may lead to higher contact rates, in particular when changing to evening and weekend calls.

The results have wide ranging implications for survey practice. They may inform the design of efficient and effective calling behaviours and follow-ups as well as responsive survey designs to increase response rates and to potentially reduce nonresponse bias. The type of model presented may be used to predict the likelihood of contact at the next call, conditioning on information known to the survey organisation and/or interviewer at each point in time - even in the absence of information like here from the census. Furthermore, probabilities of contact for different types of households can be derived conditioning on households characteristics that may be known to the survey organisation prior to or during data collection. Due to limited time and staff resources, not all calls can be made in the evenings and at weekends and survey organisations need to make informed decisions which households to call upon during daytimes. By identifying the types of household that have a high chance of being contacted during the day, survey agencies can allocate staff and time resources more efficiently. The focus of this paper is on face-to-face surveys but some findings may also apply to telephone surveys.

The study highlights the benefits of additional information for improving prediction of contact, and survey agencies should exploit possibilities of data linkage to boost information available about each household or area. Such additional information may come from the sampling frame, registers or administrative data, as well as previous waves in the case of a longitudinal study - available prior to data collection. Information may also come from interviewer observation data, obtained during data collection. The availability of such additional data may depend on the country and some limitations of such data linkage may apply due to confidentiality and data disclosure concerns. The analysis highlights the usefulness of field process data (paradata) to inform interviewing calling strategies. This also has implications for interviewer training and interviewers will need to receive guidance on the type of data to be collected. In particular, careful consideration should be given to what kind of data should be recorded at the *call-level*, such as interviewer observations about the household and information obtained from neighbours.

The significant interviewer effects imply that survey agencies may have a greater choice than previously thought regarding how best to contact a household, rather than, as was hypothesised in Purdon et al. (1999), simply decisions on the timing of calls. For example, certain interviewers may be allocated to more difficult times or cases – at least within field work constraints such as travelling times and costs. It may also be advantageous for the survey organisation to be aware of other time commitments of interviewers; for example interviewers who have only a limited capacity to make evening and weekend calls may need additional support or may be allocated certain cases or areas.

The paper also provides guidance to academic researchers and survey practitioners on how best to use paradata collected in the field and contributes to the methodological developments in the specification of response propensity models based on such data. The paper aims to contribute to the development of a theoretical framework for the analysis and definition of interviewer calling behaviours and strategies to establish contact. The estimated response propensities obtained from the event history models may ultimately be used for adjustment and estimation at the data analysis stage. Further research is currently under way to explore these options.

## 7. Acknowledgement

The research is funded by the Economic and Social Research Council (ESRC), UK, titled 'Hierarchical analysis of unit nonresponse in sample surveys', grant number: RES-062-23-0458. This work contains statistical data from ONS which is Crown copyright and reproduced with the permission of the controller of HMSO and Queen's Printer for Scotland. The use of the ONS statistical data in this work does not imply the endorsement of the ONS in relation to the interpretation or analysis of the statistical data. This work uses research datasets which may not exactly reproduce National Statistics aggregates.

## References

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

Blom, A.G. and Blohm, M. (2007) The Effects of First Contact by Phone: Evidence for the European Social Survey. Paper presented at the *18th International Workshop on Survey Household Nonresponse*, Southampton, UK.

Brick, J.M. and Allen, B. and Cunningham, P. (1996) Outcomes of a Calling Protocol in a Telephone Survey. *Proceedings of the Survey Research Methods Section, American Statistical Association,* 142-149.

Browne, W.J. (2009) *MCMC Estimation in MLwiN v2.10*. Centre for Multilevel Modelling, University of Bristol.

Cobben, F. and Schouten, B. (2007) A follow-up with basic questions of nonrespondents to the Dutch Labour Force Survey. *Discussion paper 07011, Statistics Netherlands*, available from: http://www.cbs.nl/NR/rdonlyres/42B0DC4A-D071-46F8-A249-408D7786E2F3/0/200711x10pub.pdf

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

Cunningham, P., Martin, D. and Brick, M. (2003) An Experiment in Call Scheduling. *Proceedings of the Section on Survey Research Methods, American Association for Public Opinion Research*, 2003, 59-66.

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

Durrant, G.B. and Steele, F (2009) Multilevel Modelling of Refusal and Noncontact Nonresponse in Household Surveys: Evidence from Six UK Government Surveys. *J. R. Statist. Soc. A,* 172, 2, 361-381.

Durrant, G.B., Groves, R., Staetsky, L. and Steele, F. (2009) Effects of Interviewer Attitudes and Behaviours on Refusal in Household Surveys, *under revision with Public Opinion Quaterly*, *S3RI Methodology Working Paper Series, M09/05*, 1-34.

Elliott, M.R., Little, R.J.A. and Lewitzky, S. (2000) Subsampling Callbacks to Improve Survey Efficiency. *Journal of the American Statistical Association*, *Applications and Case Studies*, 95, 451, 730-738.

Greenberg, B.S. and Stokes S.L. (1990) Developing an Optimal Call Scheduling Strategy for a Telephone Survey. *Journal of Official Statistics,* 6**,** 4, 421-435.

Groves, R.M. and Couper, M.P. (1996) Contact-Level Influences on Cooperation in Face-to-Face Surveys. *Journal of Official Statistics*, 12, 1, 63-83.

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

Groves, R.M. and Heeringa, S.G. (2006) Responsive Design for Household Surveys: Tools for Actively Controlling Survey Errors and Costs, *J. R. Statist. Soc. A,* 169, 3, 439-459.

Kulka, R.A. and Weeks, M.F. (1988) Towards the Development of Optimal Calling Protocolls for Telephone Surveys: A Conditional Probabilities Approach. *Journal of Official Statistics*, 4,4, 319-358.

Laflamme, F., Maydan, M. and Miller, A. (2008) Using Paradata to Actively Manage Data Collection Survey Process, *Proceedings of the Survey Research Methods Section, American Statistical Association*, forthcoming.

O'Muircheartaigh, C. and Campanelli, P. (1999) A Multilevel Exploration of the Role of Interviewers in Survey Nonresponse. *J. R. Statist. Soc. A,*162, 3, 437-446.

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.

Purdon, S., Campanelli, P. and Sturgis, P. (1999) Interviewer's Calling Strategies on Face-to-Face Interview Surveys. *Journal of Official Statistics,* 15, 2, 199-216.

Rasbash, J., Steele, F., Browne, W.J. and Goldstein, H. (2009) *A User's Guide to MLwiN v2.10*. Centre for Multilevel Modelling, University of Bristol.

Schnell, R. and Kreuter, F. (2001) Separating Interviewer and Sampling Point Effects. *Journal of Official Statistics*, 21, 3, 389-410.

Steele, F., Diamond, I. and Amin, S. (1996) Immunization Uptake in Rural Bangladesh: a Multilevel Analysis. *J. R. Statist. Soc. A,* 159, 289-299.

Steele, F., Goldstein, H. and Browne, W. (2004). A General Multistate Competing Risks Model for Event History Data, with an Application to a Study of Contraceptive Use Dynamics. *Statistical Modelling*, 4, 2, 145-159.

Swires-Hennessy, E. and Drake, M. (1992). The Optimum Time at Which to conduct Interviews, *Journal of the Market Research Society*, 34, 1, 61-72.

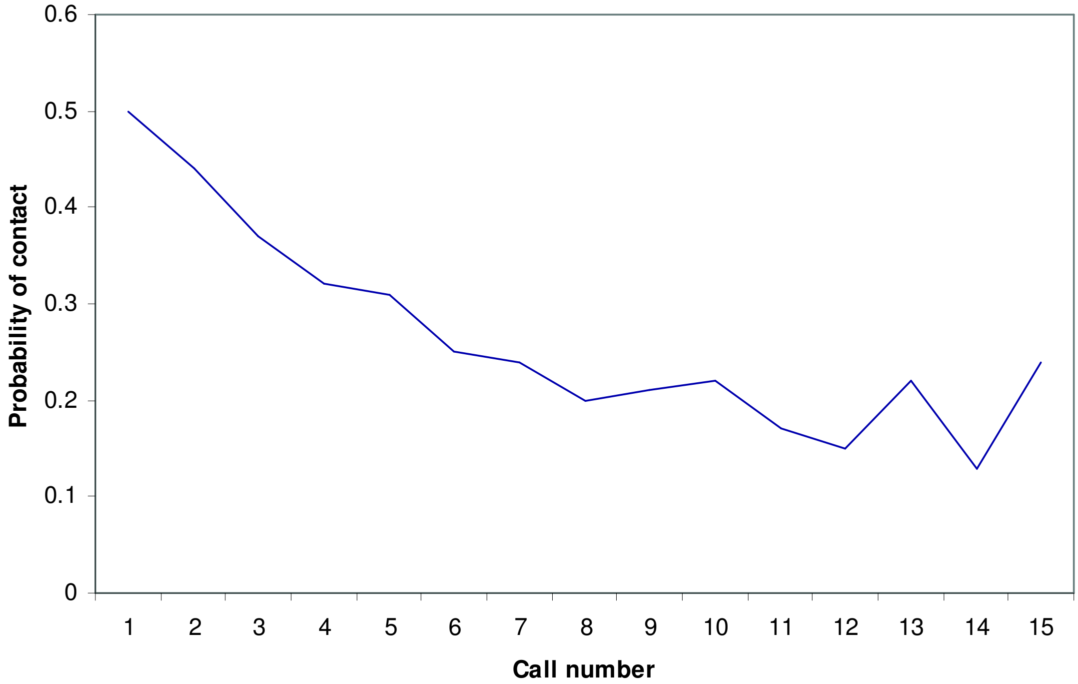
von Sanden, N. D. (2004) *Interviewer Effects in Household Surveys: Estimation and Design*, PhD Thesis, University of Wollongong. Available from: http://www.library.uow.edu.au/adt-NWU/public/adt-NWU20051202.102014/index.html

Weeks, M.F., Jones, B.L., Folsom, R.E. and Benrud, C.H. (1980) Optimal Times to Contact Sample Households. *Public Opinion Quarterly*, 44, 1, 101-114.

Weeks, M.F., Kulka, R.A. and Pierson, S.A. (1987) Optimal Call Scheduling for a Telephone Survey. *Public Opinion Quarterly,* 51, 4, 540-549.

Wood, A.M. and White, I.R. (2006). Using Number of Failed Contact Attempts to Adjust for Non-ignorable Non-response. *J. R. Statist. Soc. A,* 169, 3, 525-542.

**Figure 1:** Estimated probabilities of contact for each call (hazard rate).†




† The sample sizes for calls 13-15 are less than 100 households.

**Table 1:** Probability of contact at first call, by day and time of call.

| | | Contact probability | Total number of first calls made | % of all calls |
|---|---|---|---|---|
| Monday | Morning | 0.46 | 682 | 4.1 |
| | Afternoon | 0.49 | 3310 | 19.8 |
| | Evening | 0.67 | 947 | 5.7 |
| Tuesday | Morning | 0.39 | 505 | 3.0 |
| | Afternoon | 0.48 | 2796 | 16.7 |
| | Evening | 0.63 | 810 | 4.8 |
| Wednesday | Morning | 0.36 | 327 | 2.0 |
| | Afternoon | 0.47 | 2176 | 13.0 |
| | Evening | 0.61 | 683 | 4.1 |
| Thursday | Morning | 0.44 | 290 | 1.7 |
| | Afternoon | 0.46 | 1864 | 11.1 |
| | Evening | 0.59 | 492 | 2.9 |
| Friday | Morning | 0.39 | 221 | 1.3 |
| | Afternoon | 0.42 | 1014 | 6.1 |
| | Evening | 0.57 | 286 | 1.7 |
| Saturday | Morning | 0.50 | 60 | 0.4 |
| | Afternoon | 0.53 | 202 | 1.2 |
| | Evening | 0.43 | 51 | 0.3 |
| Sunday | Morning | 0.50 | 10† | <1.0 |
| | Afternoon | 0.50 | 16† | <1.0 |
| | Evening | 0.67 | 9† | <1.0 |
| Total | | -- | 16799 | 100 |

Morning: 0.00-12.00, Afternoon: 12.00-17.00, Evening: 17.00-0.00
† indicates cells with a sample size of less than 30

**Table 2:** Probability of contact at second call conditional on timing of the previous call

| Second call | | First Call | | | | |
|---|---|---|---|---|---|---|
| | | Weekend | Weekday Morning | Weekday afternoon | Weekday Evening | Overall |
| Weekend | (239) | 0.33 | -- | 0.38 | 0.30 | 0.39 |
| Weekday morning | (487) | -- | 0.31 | 0.35 | 0.28 | 0.34 |
| Weekday afternoon | (3717) | 0.35 | 0.34 | 0.37 | 0.39 | 0.37 |
| Weekday evening | (3667) | 0.65 | 0.54 | 0.53 | 0.50 | 0.53 |

-- indicates cells with a sample size of less than 30.
The number of second calls made per calling time are given in parentheses.
All cases where contact was made at the first call are excluded.

**Table 3:** Estimated coefficients for the variable 'day and time of call' when included as a main effect only in the cross-classified multilevel discrete-time hazard model, controlling for household, area and interviewer characteristics, but without any interaction effects.

| | | $\hat{\beta}$ $(ste)$ |
|---|---|---|
| Monday | Morning | -0.861 (0.085)*** |
| | Afternoon | -0.756 (0.051)*** |
| | Evening | Reference |
| Tuesday | Morning | -1.084 (0.090) |
| | Afternoon | -0.800 (0.052)*** |
| | Evening | -0.063 (0.054) |
| Wednesday | Morning | -1.040 (0.101) *** |
| | Afternoon | -0.784 (0.055) *** |
| | Evening | -0.059 (0.055) |
| Thursday | Morning | -0.879 (0.102) *** |
| | Afternoon | -0.851 (0.058) *** |
| | Evening | -0.155 (0.059) *** |
| Friday | Morning | -0.998 (0.116) *** |
| | Afternoon | -0.871 (0.066) *** |
| | Evening | -0.187 (0.073) *** |
| Saturday | Morning | -0.419 (0.140) *** |
| | Afternoon | -0.682 (0.096) *** |
| | Evening | -0.508 (0.201) *** |
| Sunday | Morning | 0.122 (0.527) |
| | Afternoon | -0.422 (0.336) |
| | Evening | 0.645 (0.453) |

*** significant at the 1% level

**Table 4:** Estimated coefficients (and standard errors in parentheses) of multilevel cross-classified logistic model for non-contact.

| Variable<br>(0 = Reference category) | Categories | $\hat{\beta}$ $(ste(\hat{\beta}))$ |
|---|---|---|
| Constant | | -0.891 (0.110)*** |
| **Time variant variables** | | |
| Previous call indicator<br>(0 = First call) | 1 Call previously made | -0.550 (0.060)*** |
| Number of calls previously made | | -0.110 (0.009)*** |
| Day and time of call †<br>(0 = Sun, Mon, Tue, Wed evening) | 1 Mon, Tue, Wed morning<br>2 Mon, Tue, Wed afternoon<br>3 Thur, Fri morning<br>4 Thur, Fri afternoon<br>5 Thur, Fri evening<br>6 Sat, Sun morning<br>7 Sat, Sun afternoon<br>8 Sat evening | -0.278 (0.186)<br>-0.443 (0.109)***<br>-1.125 (0.283)***<br>-0.599 (0.143)***<br>-0.097 (0.147)<br>-0.298 (0.521)<br>-0.348 (0.317)<br>-2.383 (1.399)* |
| Time of previous call<br>(0 = Weekday evening) | 1 Weekend<br>2 Weekday morning<br>3 Weekday afternoon | 0.623 (0.140)***<br>-0.025 (0.103)<br>0.169 (0.051)*** |
| Number of days between calls<br>(0 = Same day) | 1 1-3 days<br>2 4-8 days<br>3 9-14 days<br>4 15+ days | 0.097 (0.042)**<br>0.246 (0.045)***<br>0.311 (0.080)***<br>0.287 (0.155)* |
| Card/message left<br>(0 = No card/message left) | 1 Card/message left | 0.099 (0.035)*** |
| **Household-level variables (time invariant)** | | |
| Survey indicator<br>(0 = EFS) | 1 FRS<br>2 GHS<br>3 OMN<br>4 NTS<br>5 LFS | 0.078 (0.051)<br>0.022 (0.045)<br>0.068 (0.046)<br>-0.006 (0.047)<br>0.281 (0.057)*** |
| Age (HRP)<br>(0 = 16 - 34) | 1 35 - 49<br>2 50 - 64<br>3 65 - 79<br>4 80 and older | 0.172 (0.034)***<br>0.398 (0.038)***<br>0.454 (0.069)***<br>0.550 (0.080)*** |
| Household type<br>(0 = Single household) | 1 Couple household<br>2 Multiple household | 0.436 (0.030)***<br>0.404 (0.076)*** |
| Dependent children present †<br>(0 = Not present) | 1 Present | 0.538 (0.054)*** |
| Adults in employment †<br>(0 = No adults) | 1 One adult<br>2 Two or more adults | 0.054 (0.067)<br>0.235 (0.073)*** |
| Pensioner in household †<br>(0 = No pensioner in household) | 1 Pensioner in household | 0.134 (0.081)* |
| Person with a limiting long term illness present (LLTI) †<br>(0 = Not present) | 1 Household with one or more people with LLTI | 0.085 (0.054) |
| **Interviewer Observations (time invariant)** | | |
| Security device<br>(0 = security device visible) | 1 No security device visible | 0.193 (0.031)*** |
| Type of accommodation †<br>(0 = Not house, i.e. flat, mobile home, other) | 1 House | 0.325 (0.058)*** |
| Houses in area in good or bad state of repair †<br>(0 = Good) | 1 Fair-Bad | -0.166 (0.051)*** |
| House in a better or worse condition than others in area<br>(0 = Better) | 1 About the same<br>2 Worse | -0.069 (0.039)*<br>-0.273 (0.055)*** |

| | | |
|---|---|---|
| **Interviewer-level Variables (time invariant)** | | |
| Pay grade<br>(0 = Merit 1 and 2) | 1 Interviewer and advanced interviewer<br>2 Merit 3 and field manager | 0.081 (0.047)*<br>0.129 (0.056)** |
| Interviewer qualification<br>(0 = Degree or postgraduate, other higher education) | 1 A levels<br>2 GCSE, qualifications below this level, no qualification | -0.144 (0.058)**<br>-0.129 (0.078)* |
| Interviewer Age †<br>(0 = 50 years or more) | 1 Under 50 years | -0.144 (0.062)** |
| Wait to explain survey rather than leaving behind information<br>(0 = Always, frequently, sometimes) | 1 Rarely<br>2 Never | -0.157 (0.055)***<br>0.069 (0.071) |
| Use phone to make appointment<br>(0 = Always, frequently, sometimes) | 1 Rarely, never | 0.106 (0.041)*** |
| **Interactions between interviewer observations and household characteristics** | | |
| Day and time of call * Dependent children present<br>(0 Sun, Mon, Tue and Wed Evening and 0 Not present) | 1*1 Mon, Tue, Wed morning - Present<br>2*1 Mon, Tue, Wed afternoon - Present<br>3*1 Thur, Fri morning - Present<br>4*1 Thur, Fri afternoon - Present<br>5*1 Thur, Fri evening - Present<br>6*1 Sat, Sun morning - Present<br>7*1 Sat, Sun afternoon - Present<br>8*1 Sat evening - Present | -0.047 (0.126)<br>0.177 (0.069)***<br>-0.074 (0.189)<br>0.094 (0.089)<br>-0.144 (0.097)<br>-0.573 (0.364)<br>-0.098 (0.209)<br>-0.256 (0.529) |
| Day and time of call * Adults in employment<br>(0 Sun, Mon, Tue and Wed Evening and 0 No adults) | 1*1 Mon, Tue, Wed morning - One<br>2*1 Mon, Tue, Wed afternoon - One<br>3*1 Thur, Fri morning - One<br>4*1 Thur, Fri afternoon - One<br>5*1 Thursday, Friday evening - One<br>6*1 Sat, Sun morning - One<br>7*1 Sat, Sun afternoon - One<br>8*1 Sat evening - One<br><br>1*2 Mon, Tues, Wed morning - Two or more<br>2*2 Mon, Tues, Wed afternoon - Two or more<br>3*2 Thur, Fri morning - Two or more<br>4*2 Thur, Fri afternoon - Two or more<br>5*2 Thur, Fri evening - Two or more<br>6*2 Sat, Sun morning - Two or more<br>7*2 Sat, Sun afternoon - Two or more<br>8*2 Sat evening - Two or more | -0.333 (0.150)**<br>-0.451 (0.087)***<br>-0.025 (0.218)<br>-0.420 (0.112)***<br>0.050 (0.123)<br>-0.268 (0.389)<br>0.066 (0.261)<br>2.328 (1.289)*<br><br>-0.872 (0.157)***<br>-0.807 (0.090)***<br>-0.177 (0.232)<br>-0.849 (0.118)***<br>-0.026 (0.130)<br>-0.542 (0.429)<br>-0.156 (0.274)<br>2.642 (1.309)** |
| Day and time of call * Household with a person with limiting long term illness (LLTI)<br>(0 Sun, Mon, Tue and Wed Evening and 0 Not present) | 1*1 Mon, Tue, Wed morning - Present<br>2*1 Mon, Tue, Wed afternoon - Present<br>3*1 Thur, Fri morning - Present<br>4*1 Thur, Fri afternoon - Present<br>5*1 Thur, Fri evening - Present<br>6*1 Sat, Sun morning - Present<br>7*1 Sat, Sun afternoon - Present<br>8*1 Sat evening - Present | 0.140 (0.117)<br>0.307 (0.069)***<br>0.196 (0.168)<br>0.117 (0.089)<br>-0.050 (0.102)<br>0.363 (0.297)<br>0.272 (0.199)<br>0.507 (0.544) |
| Day and time of call * Pensioner in household<br>(0 Sun, Mon, Tue and Wed Evening and 0 Not present) | 1*1 Mon, Tue, Wed morning - Present<br>2*1 Mon, Tue, Wed afternoon - Present<br>3*1 Thur, Fri morning - Present<br>4*1 Thur, Fri afternoon - Present<br>5*1 Thur, Fri evening - Present<br>6*1 Sat, Sun morning - Present<br>7*1 Sat, Sun afternoon - Present<br>8*1 Sat evening - Present | 0.276 (0.150)*<br>0.272 (0.086)***<br>0.618 (0.217)***<br>0.195 (0.113)<br>0.015 (0.127)<br>-0.744 (0.391)*<br>0.051 (0.266)<br>1.475 (1.334) |
| Day and time of call * Indicator if house<br>(0 Sun, Mon, Tue and Wed Evening and 0 Not house) | 1*1 Mon, Tue, Wed morning - House<br>2*1 Mon, Tue, Wed afternoon - House<br>3*1 Thur, Fri morning - House<br>4*1 Thur, Fri afternoon - House<br>5*1 Thur, Fri evening - House | -0.464 (0.144)***<br>-0.149 (0.080)*<br>-0.129 (0.204)<br>0.106 (0.102)<br>0.051 (0.102) |

| | | |
|---|---|---|
| | 6*1 Sat, Sun morning - House<br>7*1 Sat, Sun afternoon - House<br>8*1 Sat evening - House | 0.353 (0.365)<br>-0.066 (0.217)<br>-0.198 (0.577) |
| Day and time of call * Indicator if house in a good or bad state of repair<br>(0 Sun, Mon, Tue and Wed Evening and 0 Good ) | 1*1 Mon, Tue, Wed morning - Fair/bad<br>2*1 Mon, Tue, Wed afternoon - Fair/bad<br>3*1 Thur, Fri morning - Fair/bad<br>4*1 Thur, Fri afternoon - Fair/bad<br>5*1 Thur, Fri evening - Fair/bad<br>6*1 Sat, Sun morning - Fair/bad<br>7*1 Sat, Sun afternoon - Fair/bad<br>8*1 Sat evening - Fair/bad | -0.014 (0.120)<br>0.118 (0.065)*<br>0.621 (0.167)***<br>0.157 (0.085)*<br>0.111 (0.091)<br>0.462 (0.334)<br>-0.160 (0.200)<br>-0.173 (0.486) |
| Day and time of call * Time of previous call<br>(0 Sun, Mon, Tues and Wed Evening and 0 Weekday evening) | 1*1 Mon, Tues, Wed morning - Weekend<br>2*1 Mon, Tues, Wed afternoon - Weekend<br>3*1 Thur, Fri morning - Weekend<br>4*1 Thur, Fri afternoon - Weekend<br>5*1 Thur, Fri evening - Weekend<br>6*1 Sat, Sun morning - Weekend<br>7*1 Sat, Sun afternoon - Weekend<br>8*1 Sat evening -Weekend<br><br>1*1 Mon, Tues, Wed morn. - Weekday morning<br>2*1 Mon, Tues, Wed aftern.- Weekday morning<br>3*1 Thur, Fri morning - Weekday morning<br>4*1 Thur, Fri afternoon - Weekday morning<br>5*1 Thur, Fri evening - Weekday morning<br>6*1 Sat, Sun morning - Weekday morning<br>7*1 Sat, Sun afternoon - Weekday morning<br>8*1 Sat evening - Weekday morning<br><br>1*1 Mon, Tues, Wed morn. - Weekday aftern.<br>2*1 Mon, Tues, Wed aftern. - Weekday aftern.<br>3*1 Thur, Fri morning - Weekday afternoon<br>4*1 Thur, Fri afternoon - Weekday afternoon<br>5*1 Thur, Fri evening - Weekday afternoon<br>6*1 Sat, Sun morning - Weekday afternoon<br>7*1 Sat, Sun afternoon - Weekday afternoon<br>8*1 Sat evening - Weekday afternoon | 0.013 (0.419)<br>-0.589 (0.220)***<br>-0.229 (0.784)<br>-0.046 (0.462)<br>-0.707 (0.437)<br>0.056 (0.669)<br>-0.776 (0.303)**<br>-1.251 (0.598)**<br><br>0.086 (0.245)<br>0.163 (0.136)<br>0.498 (0.301)*<br>0.041 (0.168)<br>0.353 (0.186)**<br>0.445 (0.528)<br>0.226 (0.510)<br>-0.626 (1.632)<br><br>0.206 (0.145)<br>-0.006 (0.067)<br>-0.070 (0.182)<br>0.020 (0.086)<br>-0.022 (0.084)<br>0.868 (0.313)**<br>-0.451 (0.202)**<br>0.006 (0.600) |
| **Interactions between interviewer observations and interviewer characteristics** | | |
| Day and time of call * Interviewer Age<br>(0 Sun, Mon, Tue and Wed Evening and 0 50 years or more) | 1*1 Mon, Tue, Wed morning - under 50 years<br>2*1 Mon, Tue, Wed afternoon - under 50 years<br>3*1 Thur, Fri morning - under 50 years<br>4*1 Thur, Fri afternoon - under 50 years<br>5*1 Thur, Fri evening - under 50 years<br>6*1 Sat, Sun morning - under 50 years<br>7*1 Sat, Sun afternoon - under 50 years<br>8*1 Sat evening - under 50 years | 0.114 (0.121)<br>0.042 (0.066)<br>0.133 (0.171)<br>-0.002 (0.086)<br>-0.205 (0.091)**<br>-0.714 (0.336)**<br>0.029 (0.195)<br>-0.154 (0.448) |
| **Interviewer variance** | -- | 0.080 (0.011)*** |
| **Area variance** | -- | 0.009 (0.005)* |

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 10% level
** significant at the 5% level
*** significant at the 1% level
† interaction between interviewer observations and either household or interviewer characteristics
HRP information based on household reference person

**Table 5:** Predicted probabilities of contact (in %) for two-way interactions.†

| **Interaction between day and time of call and dependent children in household** | | | |
|---|---|---|---|
| | | **Dependent children present** | |
| | | Present | Not present |
| **Day and time of call** | Mon, Tue, Wed morning | 55.5 | 43.6 |
| | Mon, Tue, Wed afternoon | 56.9 | 39.7 |
| | Sun, Mon, Tue, Wed evening | 63.2 | 50.4 |
| | Thu, Fri morning | 34.7 | 25.2 |
| | Thu, Fri afternoon | 51.2 | 36.1 |
| | Thu, Fri evening | 57.6 | 48.0 |
| | Sat, Sun morning | 42.3 | 43.1 |
| | Sat, Sun afternoon | 52.6 | 41.9 |
| | Sat evening | 12.4 | 9.7 |

| **Interaction between day and time of call and adults in employment** | | | | |
|---|---|---|---|---|
| | | **Adults in employment** | | |
| | | No adult | One adult | Two or more adults |
| **Day and time of call** | Mon, Tue, Wed morning | 51.2 | 44.4 | 36.0 |
| | Mon, Tue, Wed afternoon | 49.2 | 37.7 | 33.8 |
| | Sun, Mon, Tue, Wed evening | 57.9 | 59.2 | 63.4 |
| | Thu, Fri morning | 32.4 | 32.0 | 32.6 |
| | Thu, Fri afternoon | 45.4 | 34.9 | 29.6 |
| | Thu, Fri evening | 55.6 | 58.1 | 60.6 |
| | Sat, Sun morning | 50.7 | 45.5 | 43.2 |
| | Sat, Sun afternoon | 49.5 | 52.4 | 51.4 |
| | Sat evening | 12.8 | 60.3 | 71.1 |

| **Interaction between day and time of call and pensioner in household** | | | |
|---|---|---|---|
| | | **Pensioner in household** | |
| | | Present | Not present |
| **Day and time of call** | Mon, Tue, Wed morning | 55.6 | 45.6 |
| | Mon, Tue, Wed afternoon | 51.5 | 41.6 |
| | Sun, Mon, Tue, Wed evening | 55.7 | 52.4 |
| | Thu, Fri morning | 43.3 | 26.8 |
| | Thu, Fri afternoon | 45.8 | 38.0 |
| | Thu, Fri evening | 53.7 | 50.0 |
| | Sat, Sun morning | 31.2 | 48.1 |
| | Sat, Sun afternoon | 48.4 | 43.9 |
| | Sat evening | 36.3 | 10.4 |

| **Interaction between day and time of call and person with limiting long term illness (LLTI)** | | | |
|---|---|---|---|
| | | **Person with LLTI** | |
| | | Present | Not present |
| **Day and time of call** | Mon, Tue, Wed morning | 51.5 | 46.0 |
| | Mon, Tue, Wed afternoon | 51.6 | 42.1 |
| | Sun, Mon, Tue, Wed evening | 54.9 | 52.8 |
| | Thu, Fri morning | 39.9 | 27.1 |
| | Thu, Fri afternoon | 43.2 | 38.4 |
| | Thu, Fri evening | 51.3 | 50.5 |
| | Sat, Sun morning | 56.5 | 45.6 |
| | Sat, Sun afternoon | 53.1 | 44.4 |
| | Sat evening | 17.6 | 10.6 |

| Interaction between day and time of call and type of accommodation | | | |
|---|---|---|---|
| | | Type of accommodation | |
| | | House | Flats, other |
| Day and time of call | Mon, Tue, Wed morning | 39.3 | 42.5 |
| | Mon, Tue, Wed afternoon | 42.8 | 38.6 |
| | Sun, Mon, Tue, Wed evening | 57.2 | 49.3 |
| | Thu, Fri morning | 28.1 | 24.4 |
| | Thu, Fri afternoon | 45.2 | 35.1 |
| | Thu, Fri evening | 56.1 | 46.9 |
| | Sat, Sun morning | 58.5 | 45.1 |
| | Sat, Sun afternoon | 47.1 | 40.9 |
| | Sat evening | 10.4 | 9.3 |

| Interaction between day and time of call and state of repair of houses in area | | | |
|---|---|---|---|
| | | State of repair of houses in area | |
| | | Good | Fair-Bad |
| Day and time of call | Mon, Tue, Wed morning | 48.3 | 44.0 |
| | Mon, Tue, Wed afternoon | 44.3 | 43.2 |
| | Sun, Mon, Tue, Wed evening | 55.1 | 51.1 |
| | Thu, Fri morning | 29.0 | 38.9 |
| | Thu, Fri afternoon | 40.6 | 40.4 |
| | Thu, Fri evening | 52.8 | 51.4 |
| | Sat, Sun morning | 47.9 | 55.1 |
| | Sat, Sun afternoon | 46.6 | 38.8 |
| | Sat evening | 11.5 | 8.5 |

| Interaction between day and time of call and time of previous call | | | | | |
|---|---|---|---|---|---|
| | | Time of previous call | | | |
| | | Week end | Wkday morning | Wkday aftern. | Wkday evening |
| Day and time of call | Mon, Tues, Wed morning | 61.8 | 47.9 | 55.6 | 46.4 |
| | Mon, Tues, Wed afternoon | 43.3 | 45.8 | 46.4 | 42.5 |
| | Sun, Mon, Tues, Wed evening | 67.7 | 52.6 | 57.3 | 53.2 |
| | Thu, Fri morning | 35.8 | 37.6 | 29.4 | 27.4 |
| | Thu, Fri afternoon | 52.7 | 39.2 | 43.3 | 38.8 |
| | Thu, Fri evening | 48.8 | 58.8 | 54.5 | 50.9 |
| | Sat, Sun morning | 62.3 | 56.2 | 70.1 | 46.0 |
| | Sat, Sun afternoon | 41.1 | 49.7 | 38.1 | 44.8 |
| | Sat evening | 6.1 | 5.9 | 12.5 | 10.8 |

| Interaction between day and time of call and interviewer age | | | |
|---|---|---|---|
| | | Interviewer age | |
| | | Under 50 years | 50 years or more |
| Day and time of call | Mon, Tue, Wed morning | 50.0 | 50.8 |
| | Mon, Tue, Wed afternoon | 44.3 | 46.7 |
| | Sun, Mon, Tue, Wed evening | 54.0 | 58.5 |
| | Thu, Fri morning | 30.8 | 31.0 |
| | Thu, Fri afternoon | 39.5 | 43.0 |
| | Thu, Fri evening | 46.7 | 55.2 |
| | Sat, Sun morning | 30.4 | 50.3 |
| | Sat, Sun afternoon | 46.3 | 49.1 |
| | Sat evening | 9.7 | 12.6 |

† Predicted probabilities are calculated by varying the values of the two interacting variables, 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.

The call indicator variable has been fixed for call 1 to obtain these predicted probabilities but the trend in predicted probabilities would be the same for subsequent calls since interactions with the call-variable were not included.