

# A PRIORITY SYSTEM TO IMPROVE CALLBACK SUCCESS IN TELEPHONE SURVEYS

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## INTRODUCTION

Collecting survey data by telephone rather than face-to-face has become an attractive option for survey researchers. This mode of data collection has always had the advantage of lower costs. The high telephone ownership rate in the United States has lowered concerns about coverage bias. Development of computer assisted telephone interviewing systems (CATI) has increased data processing efficiency. Although telephone callbacks are less expensive than face-to-face callbacks, the number of callbacks required by telephone is still greater than in face-to-face surveys (Groves and Kahn 1979, p. 57). The cost and timeliness of telephone surveys could be improved if the number of callbacks required could be reduced.

At any point in the surveying period, there is limited, but well-defined information about each unreached telephone number in the sample. This information, which includes the time and outcomes of unsuccessful calls to the number, could potentially be helpful for scheduling callbacks. Likewise, the actions a scheduler might take are few; they include only when, if ever, the next call to that number is to be made. The small number and objectivity of the available cues and options suggest that a generalizable method for improving the efficiency of callback scheduling may be possible to develop.

Much of the previous research on call scheduling has concentrated on the question of when to make the first attempt so that the probability of obtaining an interview or contacting a respondent is maximized (Falthezik 1972, Weber and Burt 1972, Weeks, et al. 1980). But first calls make up less than 30% of all calls made in many demographic surveys (Groves and Kahn 1979). So there is potential for improving the efficiency of data collection by wise scheduling of callbacks. Vigderhous (1981) and Kerin and Peterson (1983) used all calls in their analysis, but ignored the effect of the timing and outcome of earlier calls on the outcome of later calls. Weeks, et al. (1987) have recognized this possibility and have investigated the effect of the timings of the first and second calls on the outcome of the second call. They present evidence that second calls (in addition to first calls) should ideally be scheduled on weekday evenings or weekends. However, as they note, this strategy ignores factors such as the availability of qualified interviewers and the capacity of the interviewing facility. In their investigation of the same problem, Warde (1989) have considered how long to wait before making a second attempt after receiving a busy signal or unanswered ring on the first call.

Typically, until very late in the survey period, there are more telephone numbers remaining in the sample than can be called on a single shift. By setting priorities, the available interview resources of the survey organization can be efficiently utilized. The goal of this research was to develop a scoring system for determining a priority order for cold callback cases, which are those cases that have not been previously contacted. To do this, we analyzed data from 4192 calls made in a random digit dial telephone survey to determine the factors that are useful for computing priority scores. Our method is to assign a score that is the predicted probability of success (defined in our example as an interview or a household contact) to each unreached telephone number in the sample. These scores are to be recomputed each shift for each case, and their calling order is determined by ranking the scores from highest to lowest.

Weeks (1988) describes several scheduling methods currently in use by large survey organizations. Our method is a combination of the two he describes as the "conditional probabilities" and "priority scores" approaches. Our approach augments these earlier efforts by replacing the ad hoc methods frequently used for determining the scores or conditional probabilities using a strategy based on statistical modeling. We use a logistic regression model that has as its dependent variable the probability of success and as its explanatory variables characteristics of the call history of the case, as well as the current shift.

The use of a model to predict success probabilities has the advantage of requiring fewer parameter estimates than would the approach of simply using observed success rates for each call history. Our model, whose fit requires estimation of only 16 parameters, can predict conditional success probabilities for more than 1000 different call history and shift combinations. A well-fitting model also allows for accurate assessment of the simultaneous impact of several factors of a call history, rather than the one or two at a time that previous investigations have addressed.

The characteristics of call history that were found useful for explaining success probabilities in our data are consistent with those suggested by previous research. Groves and Kahn (1977) found, as we did that the chance of success decreases as the number of previous attempts increases. Warde (1989) found that the time since the last call was important; however since they were not able to control for other factors, we found that the magnitude of this effect was different from what they predicted. Weeks et al. (1987) used the timing of previous unanswered calls as a predictor of success in different shifts. We applied this idea using the timing of previous unsuccessful attempts and also tested the idea with only unanswered ring outcomes and discovered that using the timing of previous calls with only unanswered ring outcomes worked somewhat better. Finally, we determined that the outcome of the previous unsuccessful attempt (e.g., busy or unanswered ring) is a strong predictor of success as well.

## DATA COLLECTION

The data from which our conclusions are drawn were collected by the U.S. Bureau of the Census during a random digit dial telephone survey. The telephone numbers represent a national sample of households selected using a Waksberg-Mitofsky design (Waksberg 1978) collected in a two week period. Details of the design and the calculation of response rates are described in Mulry and Chapman (1982) and DeMaio (1983). The data consists of certain characteristics of each call made to the numbers, such as the time it was made and its outcome.

The call outcomes assigned were non-working, business or other out-of-scope, unanswered ring, busy signal, other non-contact, contact, and interview. Other non-contact includes all calls other than busy signals and unanswered rings in which no party was reached, such as fast busies or silence. A call was classified as an interview only if the entire questionnaire was completed. Every other call in which a residential respondent answered the telephone (partial interviews, refusals, and calls resulting in appointments) was classified as a contact.

Information concerning the final disposition of each telephone number was also available, i.e., whether it was classified by the end of the survey as a non-working number, business or other out-of-scope, residence, or undetermined. Since no strategy for timing the calls to

non-working numbers was likely to improve the efficiency of identifying them as such, all calls to these numbers were removed from our data and analysis. Also, we were concerned only with developing a strategy for efficient timing of calls to uncontacted numbers, so all calls to numbers after the first contact were discarded. This left a total of 4192 calls to 1474 numbers, of which 277 were identified as a business or other out of scope.

### FACTORS AFFECTING SUCCESS

Table 1 describes the results of first dialings to those 1474 numbers. The shift classifications shown are: day (9:00 a.m. - 5:00 p.m. weekdays), evening (5:00 p.m. - 9:00 p.m. weekdays) and Saturday (10:00 a.m. - 4:00 p.m.). A contact or interview was achieved in about 47% of the first calls made during the evening, about 41% of those made during the day, and only 30% of those made on Saturday. These results are consistent with those of earlier studies, most of which show evening to be the preferable time to make first calls (Weber and Burt 1972, Weeks, et.al. 1980, Vigerhous 1981, Weeks, et.al. 1987, Warde 1988).

Data on timing and outcome of the additional 2718 calls made to those 1474 numbers reveal that certain characteristics of a number's call history are helpful for predicting the outcome of future calls. Some scheduling choices resulted in higher proportions of contacts or interviews than others, for a given call history. The characteristics of call history that appear to be good predictors of outcome for a given call are:

- (1) the number of calls made previously to the telephone number,
- (2) when calls with unanswered ring outcomes were made,
- (3) how recently a call had been made, and
- (4) the outcome of the most recent call.

The kind of influence each of these factors has, and the evidence for it, is now discussed.

#### Number of calls previously made

Figure 1 shows the relationship between number of calls previously made to a sample unit and the proportion of contact or interview outcomes, which we call successes. The graph shows that the chance of recording one of these outcomes decreases sharply with the number of attempts. This effect has been noted by others (for example, Groves and Kahn 1979).

#### Timing of previous unanswered ring outcomes

We found that the timing of calls resulting in unanswered rings was helpful in predicting success rates in subsequent shifts. Specifically, if an unanswered ring outcome had been obtained in the evening shift, but not at all in the day, the next call has the best chance of being a contact or interview if attempted during the day. Similarly, if an unanswered ring outcome had been obtained during the day but not in the evening, the proportion of successful next attempts is higher during the evening or Saturday than for another day attempt. This observation is intuitively reasonable. It suggests that people are consistent in their at home pattern. Once it has been discovered that they are not

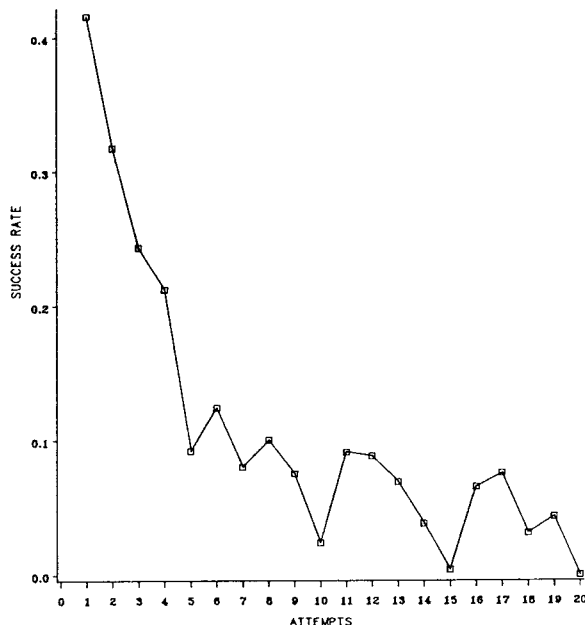


Figure 1. This figure shows the relationship between callback success rates and number of previous call attempts made to the sample unit.

home during a particular shift (by calling and obtaining an unanswered ring), it is best to call in a different shift.

Figure 2 shows the magnitude of these effects. There, we have used values of indicator variables as labels. The variable  $D$  is an indicator of whether or not a call attempt that resulted in an unanswered ring was ever made to the number during a day shift. If it has,  $D = 1$ ; otherwise,  $D = 0$ . Likewise  $E$  describes whether or not an unanswered call was previously made during a evening shift. Four categories of timing of previous unanswered ring outcomes are shown in Figure 2, and these distinguish whether a case has been called during the day and/or evening shifts. Knowledge that a Saturday call resulted in an unanswered ring outcome did not appear to change the pattern of success for the three shifts.

The fact that the lines of the figure are not parallel indicates that the timing of unanswered ring outcomes have unequal impact on success rates for the different shifts. The figure also shows that having obtained an unanswered ring in both day and evening shifts portends a very low success rate. When the unanswered ring was obtained only during the day shift, the chance of a subsequent success in the evening is highest of all, higher even than for a first call. Part of the added probability of success for second calls in this case can be attributed to the fact that business numbers, which are more likely to be screened out by a first call made during the day, are included in the random digit dial frame. Thus evening calls made to numbers that have been called once in the day are more likely, at least, to be

TABLE 1  
OUTCOME DISTRIBUTIONS OF FIRST CALLS BY SHIFT OF ATTEMPT

SHIFTS	OUTCOMES					
	BUSINESS	BUSY	UNANSWERED RING	OTHER NON-CONTACT	CONTACT	INTERVIEW
DAY (n=1102)	10.5%	5.1%	37.0%	6.5%	24.1%	16.8%
EVENING (n=306)	9.5%	3.9%	36.9%	2.9%	26.8%	19.9%
SATURDAY (n=66)	10.6%	4.5%	50.0%	4.5%	15.2%	15.2%

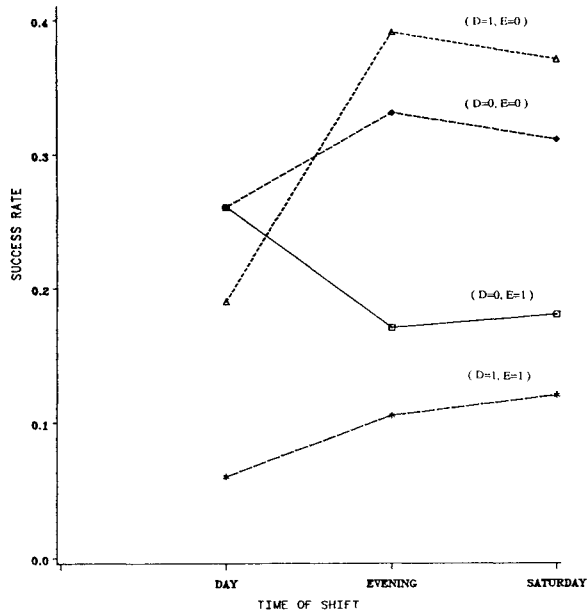


Figure 2. This figure shows the relationship between timing of the previous calls and callback success rates for the three shifts.

residences than first calls. For all four categories shown in Figure 2, the probability of success for calls made on Saturdays is approximately the same as for calls made on weekday evenings.

#### Time since the last call

A third effect noticeable in the data was that knowledge of the time elapsed since the previous call to a number was helpful in predicting the probability of a successful attempt. Each call was classified into one of four categories describing the time since the last call. They are:

- (1) Calls made within about two hours of a previous one (called redials);
- (2) Calls made within the same day, but later than redials;
- (3) Calls made on the next day;
- (4) Calls made two or more days after a previous call.

In order to see the effect of elapsed time in the raw data, one must control for certain other variables that affect the success rate. Otherwise, as Warde (1989) mention, the effect of waiting a few hours to make a second call is exaggerated when the first call is made during the day and the second call is made in the evening. Figure 3 illustrates the advantage of waiting by showing the relationship between elapsed time and the success rate for each of three large groups of cases having some common characteristics in their call histories. These groups are, from top to bottom of Figure 3, day calls having  $D = 1$  and  $E = 0$ , evening calls having  $D = 1$  and  $E = 1$ , and day calls having  $D = 1$  and  $E = 1$ . The other groups are not presented because they

each had too few cases. The monotone increasing shape of the curves suggests that the longer it has been since the previous call, the higher the proportion of successful outcomes. This effect may have been exaggerated in our survey because of the time of year it was conducted, which was July and August. Since more people are out of town, there might be more advantage in waiting longer to make a callback attempt in the summer months than at other times.

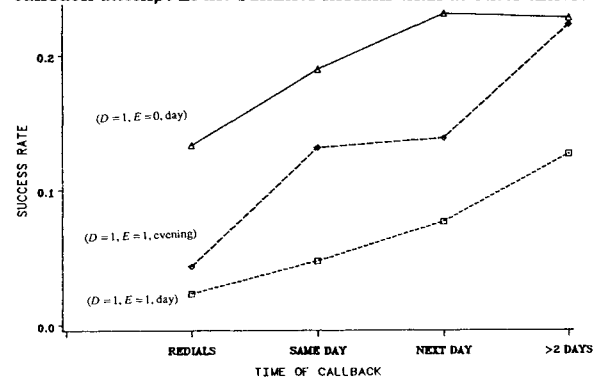


Figure 3. This figure shows how waiting time between calls affects callback success. The groups represented are, from top to bottom, day calls having ( $D = 1, E = 0$ ), evening calls having ( $D = 1, E = 1$ ), and day calls having ( $D = 1, E = 1$ ).

#### Previous outcome

Finally, the data showed that the outcome of an unsuccessful call to a number was predictive of the success rate of the next call to the number. The magnitude of this effect is seen in Table 2, which shows the proportion of callbacks resulting in each outcome following a busy, unanswered ring, or other non-contact. A busy outcome was the most promising (i.e., had the highest rate for) a success on callback, while an unanswered ring was the least promising.

Figure 4 shows the same data as Table 2, but further conditioned on the time elapsed since the previous call. Once again, it is clear that busy signals are the most encouraging outcomes for a success on callback, and this remains true whether the callback is a redial or not. Further, and surprisingly, the data showed that success rate for redials was uniformly smaller than that for non-redials, regardless of the previous outcome. The parallel nature of the lines in Figure 4 indicates that there is no evidence of an interaction between the last outcome and the time elapsed since the last call.

A policy of the field operation in the Census survey, as in many telephone surveys, was to redial within an hour or two any number that had a busy outcome. The justification was that a busy signal indicates that someone is at home, and therefore suggests that an interview or contact is likely. Our results suggests that this policy is not wise if the cost of a redial is no less than a later callback.

TABLE 2  
OUTCOME DISTRIBUTIONS OF CALLBACKS BY PREVIOUS OUTCOME

PREVIOUS OUTCOME	OUTCOMES					
	BUSINESS	BUSY	UNANSWERED RING	OTHER NON-CONTACT	CONTACT	INTERVIEW
BUSY (n=193)	7.3%	22.3%	30.6%	9.3%	17.1%	13.5%
UNANSWERED RING (n=2305)	3.6%	3.0%	74.3%	2.3%	8.4%	8.3%
OTHER NONCONTACT (n=217)	11.1%	5.5%	29.0%	31.8%	13.8%	8.8%

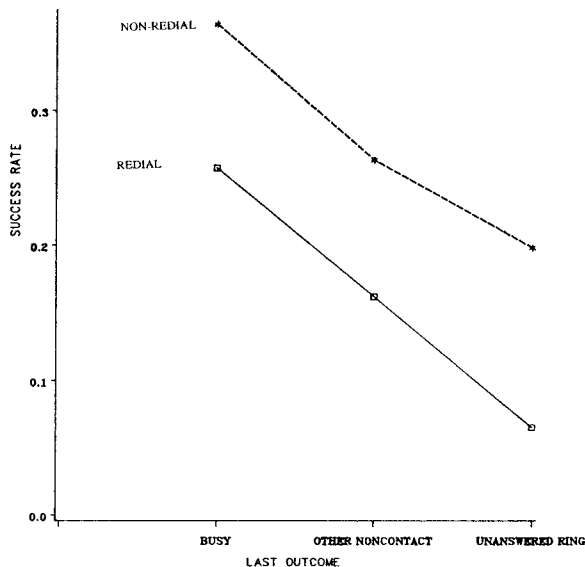


Figure 4. This figure shows the lack of interaction between the outcome of the previous call to a number and the elapsed time since it was last attempted.

#### A MODEL FOR OUTCOMES

In the previous section, evidence of the impact of certain characteristics of a number's call history on the chance of a successful outcome was suggested by the raw data. Results from raw data can be misleading, however, when more than one characteristic at a time affects the outcome. For a proper examination of the impact of a single characteristic of call history on outcome, the others must be controlled to be constant, or nearly so. One good way of doing this is by building a regression model for call outcome that has as its explanatory variables likely determinants of success. Since the call outcome of interest to us is dichotomous (success/no success), a logistic regression model was selected. This model assumes the number of successful outcomes (out of  $m_i$  attempts) for a case having call history  $X_i$  (which is a vector of characteristics) is binomial with probability of success

$$p_i = \frac{e^{X_i\beta}}{1 + e^{X_i\beta}} \quad (1)$$

where  $\beta$  is a vector of parameters to be estimated.

Once  $\beta$  is estimated, the model is used to predict the probability of success conditional on the unit having a specified call history  $X_i$ . Such predictions from a model are smoother and subject to less sampling variation than those from raw data, any one of which may be based on only a few observations. The model can even be used to predict conditional success probabilities for call histories that did not occur in the raw data. This should not be done, of course, for call histories having characteristics outside the range of values from which the model was built.

In this section, we report the results of fitting a logistic regression model to the Census callback data, that is, all second and subsequent calls to the 1474 telephone numbers. The explanatory variables considered were those identified in the previous section:

- (1) *SHIFT* (having the three levels: day, evening, and Saturday),
- (2) number of previous attempts (a variable we call *ATTEMPTS*),
- (3) a proxy variable (*LAGDAY*) representing time since last call (1 = redial, 2 = same day, 3 = next day, 4 = 2 or more days later),
- (4) previous outcome (*PREVOUT*, having the three levels: busy, unanswered ring, and other non-contact), and

- (5) the timing of previous calls (*PAST*, having the four levels: ( $D=0, E=0$ ), ( $D=1, E=0$ ), ( $D=0, E=1$ ), and ( $D=1, E=1$ )).

Interactions among several pairs of variables were also considered. The models were fit by maximum likelihood.

The results showed that all the main effects listed above, with the exception of *SHIFT*, are helpful in explaining the variation of success rates among groups. In addition, the interaction between shift and the time of previous calls, which was observed in the raw data from Figure 2, was significant; no other interactions were. An analysis of variance table for this model is shown in Table 3.

TABLE 3  
ANALYSIS OF VARIANCE TABLE  
FOR LOGISTIC REGRESSION MODEL

SOURCE	DF	CHI-SQUARE	P-VALUE
INTERCEPT	1	2.39	.122
<i>SHIFT</i>	2	2.56	.278
<i>PAST</i>	3	8.05	.045
<i>ATTEMPTS</i>	1	21.49	< .001
<i>LAGDAY</i>	1	32.11	< .001
<i>PREVOUT</i>	2	14.74	< .001
<i>SHIFT</i> × <i>PAST</i>	6	12.06	.061

The data for building our model came from an observational study, rather than an experiment designed to investigate the factors affecting success of callbacks. Consequently, the number of observations in the category levels is very unbalanced, even for variables like *SHIFT*, for which these numbers could have been controlled. This induces collinearity among the explanatory variables in the model, which makes tests of individual effects dependent. The main effects for *SHIFT* and *PAST*, especially, suffer from this problem. Therefore we have retained *SHIFT* in our predictive model because we believe its non-significance is an artifact of the way the data were collected. Examination of our first call data (Table 1), as well as the work of previous authors, shows that shift is related to success for first calls, and we see no logical reason this should change for subsequent calls. Removing this effect from our model would have virtually no effect on the predicted conditional success probabilities, of course.

Other models are possible for describing the relationship between explanatory variables and the probability of success. The logistic model is commonly used for modeling dichotomous data because of its attractive mathematical properties (McCullagh and Nelder, 1983). Since an ill-fitting model can produce biased estimates, care must be taken to ensure that the chosen model fits adequately. For the data we investigated, the logistic regression model provided an excellent fit. The deviance statistic had a value of 383.18 on 438 degrees of freedom, a small value. (This statistic is an index of lack of fit of the model, although not a test statistic in this case because of the large number of sparse cells.) Residual plots of the weighted residuals against the predicted values of  $p_i$ , against *LAGDAY*, against *ATTEMPTS*, and against *PAST* all appear to have no discernible pattern, with one exception. The model is a bit too pessimistic for cases having very small predicted values. In other words, even for those cases with predicted value of success near 0 (say less than .01), an interview or contact is occasionally obtained. There are so few cases of this type in the data, that their impact on the scheduling decisions will be small.

The relative impacts of the various characteristics in our model are illustrated in Figures 5 and 6. Figure 5 shows model-based estimates of conditional success probabilities for those cases having their first call in the day. It illustrates how much the outcome of the previous call, the timing of the call, and waiting between calls affects the probability. From the figure, it is easy to see the relative

- strength of these three predictive effects:
- (1) the advantage of calling in the evening shift instead of the day
  - (2) the advantage of waiting to make the next attempt, and
  - (3) the higher probability of success after a busy signal.

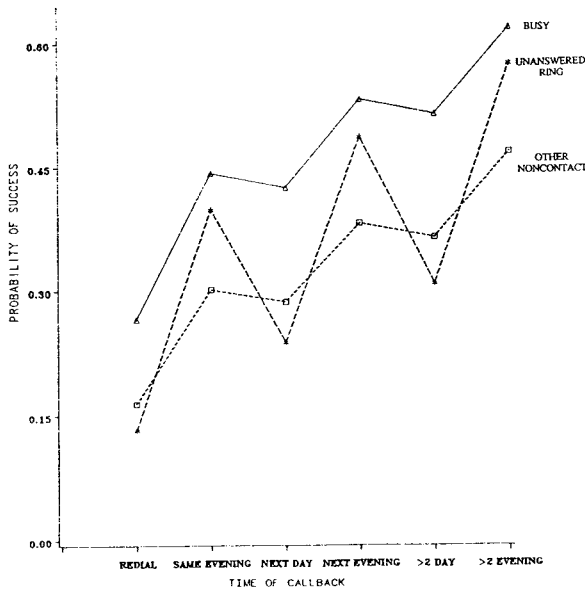


Figure 5. This figure shows the cumulative effect on model-based success probabilities of several characteristics of a sample unit's call history: the previous outcome, elapsed time between calls, and the shift.

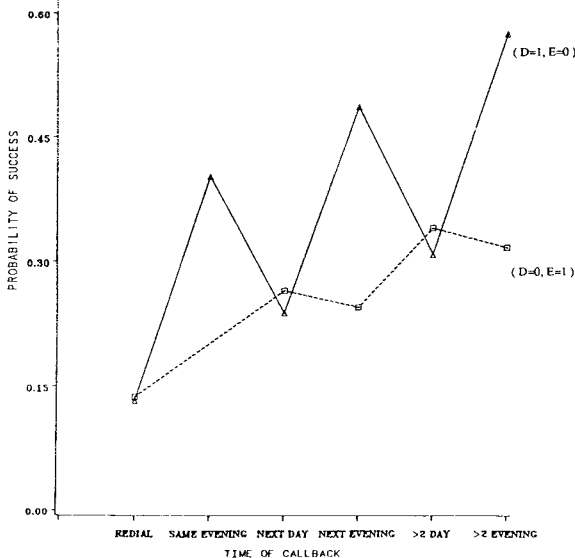


Figure 6. This figure shows the cumulative effect on model-based success probabilities of several characteristics of a sample unit's call history: the timing of previous unanswered rings, elapsed time between calls, and the shift.

Figure 6 shows model-based estimates of success probabilities for cases whose first call resulted in an unanswered ring. It illustrates how much the time of the first attempt affects the probabilities. The upper line shows the success probabilities for those cases whose first call was made in the day and resulted in an unanswered ring; the bottom one shows them for those cases whose first call was an unanswered ring in the evening. After a daytime call

there is about twice the probability of success if the next call is made in the evening instead of the day, and it is advantageous to wait to make that call. Following an unanswered ring in the evening, the difference between making the next call in the evening versus the day are relatively slight, but better in the day. Again, it is advantageous to wait before making the next attempt.

Figures 5 and 6 show that units with certain call histories have very high model-based estimates of success rates for second attempts when compared with the overall success rate for second calls shown in Figure 1. This suggests that reductions could be made in the effort required to accumulate completed interviews (or at least contacts) by concentrating on the most promising cases. A method for doing this is discussed in the next section.

### THE PRIORITY RULE

In a typical telephone survey field operation, until very late in the survey period, there are more uncontacted units remaining from the sample than can be called on a single shift. Therefore it is necessary to set priorities for the uncontacted units to determine the order in which they should be attempted on any shift. A reasonable rule for priority-setting is to make call attempts to the sample units that have the highest probabilities of successful outcomes. This will maximize the expected number of contacts and interviews during a shift. By always calling those units that are most likely to result in interviews or contacts, the overall proportion of successful calls should improve, thus best utilizing the available survey resources.

Although we cannot know the actual probability of success for any unit, the model developed in the previous section provides a straightforward method for predicting the probability conditional on each unit's call history. We suggest using these predicted probabilities as priority scores for determining the order of cold callbacks. For a survey operation using CATI or simply an automated call scheduler, computation of the probability for each unit (using equation (1) with  $\beta$ 's estimated from data collected in a survey with similar frame, target populations, and duration) and sorting of the units by those probabilities to form the queue of numbers to call would be an easy task.

Tables 4, 5, and 6 show, the 15 call histories having the largest model-based probabilities of success for the day, evening, and Saturday shifts, respectively. Numbers that have not been called for at least two days, especially those that resulted in a busy signal on the previous call, are high on all lists. Histories having  $D = 0$  predominate on the day shift list, while the top 15 on the evening shift list contain only those having  $E = 0$ . However, no one effect completely overwhelms all others.

TABLE 4  
PRIORITY RULE FOR ATTEMPTS MADE IN THE DAY SHIFT

PRIORITY LEVEL	HISTORY		PREVOUT	LAGDAY	ATTEMPTS	PROBABILITY OF SUCCESS
	D	E				
1	0	1	BUSY	4	3	0.53
2	0	0	BUSY	4	2	0.51
3	0	1	BUSY	4	4	0.51
4	1	0	BUSY	4	3	0.50
5	0	0	BUSY	4	3	0.49
6	0	1	BUSY	4	5	0.48
7	1	0	BUSY	4	4	0.47
8	0	0	BUSY	4	4	0.46
9	0	1	BUSY	4	6	0.46
10	1	0	BUSY	4	5	0.45
11	0	1	BUSY	3	3	0.44
12	0	0	BUSY	4	5	0.44
13	0	1	BUSY	4	7	0.43
14	0	0	BUSY	3	2	0.42
15	1	0	BUSY	4	6	0.42

**TABLE 5**  
**PRIORITY RULE FOR ATTEMPTS MADE IN THE EVENING SHIFT**

PRIORITY LEVEL	HISTORY					PROBABILITY OF SUCCESS
	D	E	PREVOUT	LAGDAY	ATTEMPTS	
1	1	0	BUSY	4	3	0.75
2	1	0	BUSY	4	4	0.73
3	1	0	BUSY	4	5	0.71
4	1	0	BUSY	4	6	0.69
5	1	0	BUSY	3	3	0.68
6	1	0	BUSY	4	7	0.67
7	1	0	BUSY	3	4	0.65
8	1	0	BUSY	4	8	0.64
9	1	0	BUSY	3	5	0.63
10	1	0	BUSY	4	9	0.62
11	1	0	OTHER	4	3	0.62
12	0	0	BUSY	4	2	0.62
13	1	0	BUSY	3	6	0.61
14	1	0	BUSY	4	10	0.60
15	1	0	OTHER	4	4	0.60

**TABLE 6**  
**PRIORITY RULE FOR ATTEMPTS MADE IN THE SATURDAY SHIFT**

PRIORITY LEVEL	HISTORY					PROBABILITY OF SUCCESS
	D	E	PREVOUT	LAGDAY	ATTEMPTS	
1	1	0	BUSY	4	3	0.68
2	1	0	BUSY	4	4	0.66
3	1	0	BUSY	4	5	0.64
4	0	0	BUSY	4	2	0.62
5	1	0	BUSY	4	6	0.61
6	1	0	BUSY	3	3	0.60
7	0	0	BUSY	4	3	0.60
8	1	0	BUSY	4	7	0.59
9	1	0	BUSY	3	4	0.58
10	0	0	BUSY	4	4	0.57
11	1	0	BUSY	4	8	0.57
12	1	0	BUSY	2	5	0.55
13	0	0	BUSY	4	5	0.55
14	1	0	BUSY	4	9	0.54
15	1	0	OTHER	4	3	0.54

If a number is called and the attempt is unsuccessful, this will change its call history, and result in a lower priority. In this way, other telephone numbers (especially as the time since they were last attempted increases) will improve their position on the priority list, so that all units will eventually be called. The effect of this strategy can be illustrated by considering the advantage of waiting a day or two between calls to the same unit. At the beginning of the survey, plenty of time remains so that it is sensible to wait between calls to the same unit. At that time there will be many uncontacted units, so ones that have been recently called will be low on the list. At the end of the survey period, however, waiting days between calls is dangerous since it decreases the number of calls that can be made to a unit and increases the risk of running out of time before making a contact. By then, though, there should be far fewer units that have not been contacted, so those that remain will be called more frequently. This strategy should reduce the portion of non-response resulting from never contacting a unit.

**CONCLUSIONS**

Weeks (1988) concludes a description of current capacities and methods for call scheduling saying that the development of optimal formulas for the priority score approach is the key issue for future research. The method we describe in this paper can be used to develop these optimal formulas for other surveys. The model and details of the priority rule we derived were developed specifically for surveys conducted as the Census Bureau's was. They

were also tailored to correspond to our definition of success, which included both interviews and other household contacts.

While the specific results are specialized, the factors that we found to be important and the method of modeling we described are generalizable. Our method may easily be adapted to conform to the specifics of another survey operation if the data describing characteristics of call attempts were available.

It is possible that better models and priority rules could be developed by finer category distinctions for some of the explanatory variables. A large amount of data would be needed for building such a model, and it would be most effective if it could be collected in an experiment designed for the purpose, so that somewhat more independent estimates of the various main effects could be made.

The method presented here assigns priorities to uncontacted cases with the goal of maximizing the number of contacts or interviews during a shift. This scheme does not consider the importance of quickly identifying nonresidential numbers, nor does it give high priority to phone numbers that are difficult to reach. Greenberg and Stokes (1990) address these issues. However, the method presented here does provide an easily implemented, adaptable, and logical way of developing priority scores for cold callbacks in an automated call scheduler. We believe it will be beneficial for improving the efficiency of telephone data collection.

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