Original Article:

The Elicitation of Prior Distributions for Bayesian Responsive Survey Design:

Historical Data Analysis vs. Literature Review

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Summary

Responsive Survey Design (RSD) aims to increase the efficiency of survey data collection via live monitoring of paradata and the introduction of protocol changes when survey errors and increased costs seem imminent. Unfortunately, RSD lacks a unifying analytical framework for standardizing its implementation across surveys. Bayesian approaches would seem to be a natural fit for RSD, which relies on real-time updates of prior beliefs about key design parameters. Using real survey data, we evaluate the merits of two approaches to eliciting prior beliefs about the coefficients in daily response propensity models: analyzing historical data from similar surveys and literature review.

Key Words

Responsive Survey Design, Bayesian Analysis, Response Propensity Modeling, Elicitation of Prior Distributions, National Survey of Family Growth
1. Introduction

In an effort to minimize survey errors and survey costs, survey methodologists have developed a conceptual framework for survey data collection known as responsive survey design (RSD; Groves and Heeringa, 2006). RSD monitors the quality and cost efficiency of a survey data collection in real time, enabling informed decisions about design changes in response to the large uncertainties that accompany survey research. Unfortunately, current implementations of RSD are often ad hoc and simplistic, failing to integrate prior knowledge of data collection outcomes with incoming real-time information. The present study aims to begin formalizing the decision framework of RSD by considering alternative methods for eliciting the prior information necessary to implement a Bayesian approach to RSD. These approaches will take advantage of information from earlier surveys - either through data from previously conducted surveys or via a review of the literature - to implement RSD more effectively in current studies.

RSD methods rely on the accurate prediction of future outcomes to make important design decisions in real time. For example, a survey organization may target cases with a high predicted response propensity as a cost savings measure, or draw subsamples of active cases once the average estimated propensity has fallen below a specified threshold for certain subgroups in order to implement a design that will increase the response propensity among these subgroups. Unfortunately, sparse production data early on in a field period could bias these predictions in many applications. For example, there may be bias in the estimates of the coefficients of response propensity models fitted early in a data collection using only production data available at that point in time. These inaccuracies can reduce the efficiency of RSD by suggesting design changes at less-than-optimal points in time. The Bayesian approach provides a framework for
taking advantage of prior information in addition to the data currently available from the field to develop the accurate predictions needed to make RSD function as efficiently as possible. The application of RSD to existing data collections has increased cost efficiency by up to 25% (Wagner et al., 2012; Kirgis and Lepkowski, 2013); even greater gains in efficiency may be possible by using Bayesian methods to improve the accuracy of predicted data collection outcomes.

As a first step in the development of a Bayesian approach to RSD, the present study aims to evaluate alternative approaches to the elicitation of reasonable prior distributions for the coefficients in response propensity models that survey organizations often use in RSD. These approaches include analyzing previous data sets from similar surveys and intensive literature review. Historical data from similar surveys may not always be available, meaning that a review of the relevant literature may be one of the only options available to practitioners. We evaluate the prior distributions generated from these two alternative approaches with respect to their ability to improve predictions of response propensity at different points in time for a real survey, relative to more “standard” approaches that ignore prior information and only leverage information from the current data collection.

2. Background

In general, RSD refers to a set of practical tools and strategies developed by survey methodologists to reduce survey errors and costs in a principled, scientific manner. RSD principles enable survey managers to monitor key indicators of survey errors and costs in real time and react to patterns in these indicators as data collection proceeds, altering design
parameters to increase data quality while reducing costs. Groves and Heeringa (2006) outlined a conceptual framework for RSD, defining five key steps:

1) Pre-identify a set of design features affecting the costs and errors of survey statistics (e.g., number of calls made to a sampled unit; over-sampling ethnic groups);
2) Identify a set of indicators of the cost and error properties of those features (e.g., response rates over time for various ethnic groups), generally referred to as paradata (Kreuter, 2013);
3) Monitor those indicators during initial phases of data collection;
4) Alter the active features of the survey in subsequent phases based on cost/error tradeoff decision rules (e.g., ask interviewers to increase their efforts for a particular ethnic group); and
5) Combine data from the separate design phases into a single estimator.

Effective implementation of RSD can substantially increase the efficiency of survey data collection, from the perspectives of both costs and errors. The 2002 National Survey of Family Growth (NSFG) implemented an early version of RSD (Axinn et al., 2011; Lepkowski et al., 2006). Learning from these experiences, NSFG managers incorporated improved RSD ideas into the 2006-2010 NSFG, resulting in substantial cost savings and increasing data collection yield relative to 2002 (Kirgis and Lepkowski, 2013). Indeed, the 2006-2010 NSFG completed nearly 10,000 additional interviews for roughly the same cost as the 2002 NSFG, using almost an identical questionnaire. The “standard” NSFG RSD includes two-phase sampling of nonrespondents after a fixed amount of time in each data collection quarter (10 weeks), where the data collection protocol changes in the second phase to recruit cases for which the first phase
protocol was ineffective. The second phase design takes a subsample of active cases so that interviewers can expend more effort per case, doubles the incentive (from $40 to $80), and includes a new mailing explaining the importance of the survey. Overall, these design features allowed the 2006-2010 NSFG to control costs, making them quite predictable, and yielded the aforementioned larger overall sample size (Lepkowski et al., 2010; Wagner et al., 2012; Kirgis and Lepkowski, 2013; Lepkowski et al., 2013).

In addition to increasing cost efficiency, RSDs can also reduce the bias and variance of survey estimates. For example, one indirect measure of nonresponse bias is the variation in demographic subgroup response rates. The NSFG defines 12 key subgroups based on age, sex, and race/ethnicity. As described by Wagner et al. (2012), NSFG managers monitor response rates for each subgroup during the NSFG field period, and if the response rate for a subgroup drops far below the response rates of the other subgroups, interviewers prioritize that subgroup with their efforts, ultimately reducing variance in the subgroup response rates.

RSD techniques have also been successfully implemented in the Health and Retirement Study (Dworak and Guyer, 2013), a large panel survey that studies the health and well-being of the elderly U.S. Population; the National Health Interview Survey (Miller, 2013); the National Survey of College Graduates (Miller, 2013); the Relationship Dynamics and Social Life study (Barber et al., 2011); and the American Community Survey (ACS; Slud and Erdman, 2013). Researchers have also described successful implementations of RSD techniques (resulting in reductions of errors and costs) for several face-to-face surveys conducted in various countries (Heeringa et al., 2004; De Keulenaer, 2005; Durrant et al., 2011). Of particular interest to survey
researchers conducting smaller studies are the benefits reaped from applying RSD ideas to telephone surveys, both nationally and internationally (Mohl and Laflamme, 2007; Peytchev et al., 2009; Tabuchi et al., 2009; Kleven et al., 2010; Laflamme and Karaganis, 2011; Lundquist and Sarndal, 2013). Researchers working with limited budgets also have much to gain from recent experiences with using RSDs in mixed-mode surveys that seek to minimize costs while maintaining high quality data (Barber et al., 2011; Schouten et al., 2011; Calinescu et al., 2013; Luiten et al., 2013; Finamore et al., 2013; Bianchi and Biffignandi, 2014; Wagner et al., 2014).

Unfortunately, despite these success stories, the analytic techniques used to implement RSD strategies to date have been extremely simplistic in nature, failing to use advanced statistical methods to take full advantage of the real-time data collection and monitoring inherent to RSDs. The “standard” RSDs employed by surveys generally rely on arbitrary decision rules rather than real-time patterns in error and cost indicators combined with prior knowledge. For example, in the NSFG RSD, the end of the first phase always occurs 10 weeks into a given data collection quarter, even though the response rates, costs, and estimates of key statistics at that fixed time point vary across the quarters. These “fixed” approaches to RSD, which fail to integrate new data with prior beliefs and lack any coherent analytical framework, could lead to designs that are inefficient both financially and statistically. Tourangeau et al. (2017) recently reviewed a number of studies that presented mixed evidence of the effectiveness of RSD. Among possible explanations for this mixed evidence were the generally difficult climate in which surveys are currently conducted, the high costs involved with varying powerful design features (e.g. high incentives or new modes), and inefficient designs. Imprecise timing of interventions could also be one source of inefficiency. These inefficiencies can lead to higher costs or mitigate bias
reduction. For example, unstable estimates of response propensity early in a fieldwork period can lead to a misallocation of field efforts that increases bias rather than reducing it. Similarly, targeting cases solely based on estimated response propensities, when those estimates are inaccurate, does not necessarily allocate effort toward bias reduction.

To date, several RSDs have used estimated response propensities as inputs (e.g., Rosen et al., 2014), where response propensity is assumed to assess the “quality” of the active sample (Groves and Heeringa, 2006; Groves et al., 2009; West and Groves, 2013). Other surveys have used response propensity models to make decisions about design features (Peytchev et al., 2009; Wagner, 2013). For example, Wagner (2013) used estimated contact propensities to trigger decisions about the timing of the next call for each active case. The models producing these estimates used the data available at each point in the data collection process. However, early in the field period, there may be a relatively high prevalence of “easy” early responders, and estimates of response propensity may be both biased and noisy due to the limited accumulation of helpful paradata (Wagner and Hubbard, 2014). Early responders may also be different from late responders in ways that are not observable early in the period, and in face-to-face surveys, interviewers may select cases to attempt based on features not shown in the paradata (Kennickell, 2003). Any of these situations may lead to estimated models that generate inaccurate predictions.

Survey managers can improve these predictions with a Bayesian approach that incorporates relevant prior information. Because RSDs lead to real-time management decisions based on continuously updating prior beliefs about uncertain survey design parameters with new data, the
Bayesian analysis framework is a natural fit for improving the science of RSD. For example, Bayesian approaches that update prior assumptions with current data might suggest that specific subgroups of the NSFG sample have a higher probability of cooperating in response to the second-phase protocol considerably earlier than the current fixed period (10 weeks). Clinical trials have had great success using this approach as a way of incorporating known information from previous trials (Spiegelhalter and Best, 2003; Spiegelhalter et al., 2004; Thall and Wathen, 2008; Hiance et al., 2009). However, specifying priors for survey parameters, including the coefficients of response propensity models, is not a simple task to carry out. Even for clinical trials, this has been an area of debate and discussion. Of particular interest are parameters for which there are not pre-existing data. In this case, prior knowledge does not exist in the form of data from a previous study, and may only exist in the form of published literature.

The development and evaluation of Bayesian approaches to RSD will require the sound specification of prior distributions for the parameters of these response propensity models. With this study, we aim to begin formalizing this process and prevent the risk of prior information overpowering real signals in the accumulating data. For example, in the contact models used by Wagner (2013), the use of too much prior data led to suppressed estimates of current contact rates. With careful proper specification of these priors, it will be possible to improve the accuracy of these types of daily predictions used in an RSD framework, and improve the reproducibility of RSD research. Understanding the consequences of choosing a less-than-optimal prior is important for practitioners, and we aim to provide this practical guidance with the present study.
3. Methods for Eliciting Prior Distributions

3.1 Overview of the NSFG RSD

The NSFG selects a national sample of U.S. housing unit addresses each quarter of the year, and attempts to collect fertility and family formation data from randomly selected persons living at the sampled addresses. The target population from which the NSFG selects these four independent national samples is persons living in the U.S. who are between the ages of 15 and 49. Interviewers first visit randomly sampled households and attempt to screen the households for eligibility. Within eligible households, one of the eligible individuals is randomly selected to complete the main survey interview, which usually takes 40-80 minutes and covers a variety of fertility-related topics. NSFG managers analyze paradata on a daily basis, modeling the probability that active households will respond to either the screening interview or the main interview. The managers might use these predictions for prioritization of active cases (e.g., Wagner et al., 2012) or when selecting a subsample of active cases for the new data collection protocol after 10 weeks (where managers may over-sample high-propensity cases). Accurate model-based predictions are thus essential for maximizing the efficiency of the data collection effort in any given quarter. For purposes of this study, we focus on models for the probability of responding to the initial screening interview.

3.2 Modeling Screening Response Propensity in the NSFG

For this study, we analyzed data from 13 quarters of the NSFG (roughly ranging in time from June 2013 to September 2016). We seek to evaluate predictions of the probability that individuals in each of the five most recent quarters (i.e., June 2015 to September 2016) will respond to a screening interview at a given contact attempt, considering the eight preceding
quarters in each case as historical data that may be useful for defining prior distributions for the response propensity model coefficients. For example, for the data collection quarter from June 2016 to September 2016 (Quarter 20 from the 2011-2019 NSFG), we considered historical data from Quarters 12-19 for our analyses. To identify robust predictors of the daily propensity to respond to the screening interview across these quarters for our models, we initially fitted a discrete-time logit regression model to a stacked data set containing the outcomes of all screening interview attempts by the interviewers during the eight most recent quarters (Quarters 13 through 20). In this model, the dependent variable was a binary indicator of successful completion of a screening interview at that contact attempt. The candidate predictor variables included NSFG paradata, sampling frame information, and linked commercial data, each of which have been employed for the prediction of response propensity in prior studies using NSFG data (West, 2013; West and Groves, 2013; West et al., 2015).

We employed a backward selection approach to identify a common set of significant predictors of screener response propensity at a given contact attempt. After identifying the significant predictors ($p < 0.05$, based on Wald tests), we manually added two predictor variables that were deemed important to monitor by NSFG managers: type of sampling area (non-self-representing units, larger self-representing units, and the three largest MSAs) and socio-demographic domain of the sampled area segment based on U.S. Census data (<10% Black, <10% Hispanic; >10% Black, <10% Hispanic; <10% Black, >10% Hispanic; >10% Black, >10% Hispanic).

Table A1 in the online appendix describes the predictors that we identified as significant after applying the backward selection procedure to the contact attempt data from the eight most recent
quarters. These significant predictor variables, which resulted in a total of 75 coefficients in the model, included a mix of paradata and sampling frame information, as well as linked commercial variables (e.g., variables purchased from Marketing Systems Group, or MSG), which could be used in theory to predict the probability of responding to the screening interview at a given contact attempt. Based on a total of \( n = 119,981 \) contact attempts across these eight quarters, the Nagelkerke pseudo R-squared for the final fitted model was 0.09 (Residual chi-square test \( p > 0.10; \) AUC = 0.66), suggesting a reasonable fit to the observed data. The overall fit of this model, as it currently exists, is not critical for our purposes; we only used this model to standardize our approach and identify an important set of predictors for consideration in each quarter. Our goal is to evaluate whether we can improve the predictive power of a model including these predictors in a given quarter by incorporating prior information. Moving forward, we aim to evaluate alternative methods of eliciting prior information regarding the coefficients for these predictors and their variances, and examine the utility of Bayesian approaches incorporating this information for improving predictions of response propensity at a given contact attempt earlier on in a data collection period.

3.3 Overview of Approaches to Prior Elicitation

Our general approach to eliciting prior information on the coefficients for these predictors in the daily response propensity models involves finding prior specifications that stabilize and improve the accuracy of the estimates of these parameters. One could apply this information to create normal prior distributions for these coefficients, using the mean estimate and the range of the estimates to approximate the mean and variance of this distribution. The effect of this prior will diminish as more data from the current period accumulate, since the posterior is the product of
the (fixed) prior and the likelihood, the latter of which will increase as the incoming data from
the current period increases. We draw on two methods for the development of priors employed in
the clinical trials literature (Spiegelhalter and Best, 2003; Spiegelhalter et al., 2004; Thall and
Wathen, 2008; Hiance et al., 2009):

1) Estimates generated from prior data collection periods for the same survey; and
2) Detailed review of any literature presenting response propensity models that included
similar covariates (e.g., West and Groves, 2013)

**Approach 1: Historical Data Analysis.** For this approach, we fit response propensity models of
the form

\[
\log \left( \frac{P(Y_{it} = 1 | X_{it})}{1 - P(Y_{it} = 1 | X_{it})} \right) = \beta' X_{it} = \sum_{p=0}^{P} \beta_p X_{itp},
\]

where for a given set of historical data, \( Y_{it} \) is an indicator of a completed screening interview at contact attempt \( t \) for sampled NSFG household \( i \), and \( X_{it} \) consists of key predictors from those quarters (\( X_{i0} \) as the intercept). These can include regional factors, including local Census measures of aggregate demographics, as well as paradata measures, such as outcomes of previous call attempts and interviewer observations (see supplementary Table A1 for all predictors considered). We consider forms of
the prior given by

\[
N(\hat{\beta}, \hat{V}(\hat{\beta}))
\]

where \( \hat{\beta} \) is a maximum likelihood estimate of the mean of the normal prior based on a given analysis of the historical data, and \( \hat{V}(\hat{\beta}) \) is the estimated variance-covariance matrix associated with \( \hat{\beta} \).

We consider three possible methods to forming these priors using historical NSFG data:
1. A standard method that completely ignores prior information when analyzing data from the current data collection quarter (mimicking what is often done in RSD);

2. A precision-weighted prior (PWP) method, where we first fit separate response propensity models to the final accumulated contact attempt data from each of the eight prior NSFG quarters (indexed by $q$). The mean of the normal prior for each coefficient is then defined by $\sum_{q=1}^{8} \hat{\beta}_q / \text{var}(\hat{\beta}_q)$, and the variance of the normal prior for each coefficient is defined by $8 / \sum_{q=1}^{8} 1 / \text{var}(\hat{\beta}_q)$.

3. A most recent period (LAST) prior method, where the mean of the normal prior for each coefficient is defined by the maximum likelihood estimate of that coefficient based on the final accumulated contact attempt data from the most recent quarter, and the variance of the normal prior is defined as the estimated variance of the estimated coefficient from the most recent quarter.

**Approach 2: Literature Review.** For this approach, denoted by LIT moving forward, we reviewed the survey methodological and statistical literature to find any empirical studies of survey response propensity as a function of predictors similar to those under consideration in the present study, at either the case or contact attempt levels. We then extracted estimates of the coefficients and their standard errors reported in these papers. The studies that we ultimately identified included Olson and Groves (2009), Schonlau (2009), Peress (2010), Dahlishamer and Jans (2011), Hill and Shaw (2013), West and Groves (2013), Rosen et al. (2014), and Plewis and Shlomo (2017). Readers can find a Microsoft Excel workbook containing the results of this review in the online supplementary materials. We first established a crosswalk between the
predictors analyzed in a given study and the NSFG predictors under evaluation in this study, and
then computed simple means and variances of the estimated coefficients reported across these
studies. For those predictors that were also considered in at least one other study, the mean of the
reported coefficients (on the log-odds scale) was used as the mean of the normal prior
distribution for a given coefficient, and the mean of the reported variances was used as the
variance of the normal prior distribution.

Of the 75 coefficients identified as significant in our backward selection approach described
earlier, we were able to find prior information in the literature for 33 of them (44%). The means
and variances of the normal prior distributions for the remaining 42 coefficients were set to 0 and
10, respectively, indicating a lack of information in the literature about these coefficients (i.e.,
we used nearly non-informative prior distributions when there was no evidence available in the
literature).

3.4 Analytic Approach

For each of the five most recent NSFG quarters (Quarters 16 through 20), we first generated the
alternative prior distributions for the response propensity model coefficients as described above.
We then fit a discrete time hazard model to the final accumulated contact attempt data for one of
the five quarters, using all available information from that quarter for the final set of predictors
described earlier. We used this model to compute a “final” predicted probability of response for
each case at the last contact attempt made to that case, using all available information from that
quarter. These “final” predictions served as our benchmarks; we sought to evaluate the ability of
the alternative Bayesian approaches to approximate these “final” predictions (based on all data from a quarter) for each case *earlier on* in the quarter, when current information was sparse.

For each alternative prior elicitation approach, we then followed these steps:

1. Beginning on Day 7 of the current quarter (allowing for the accumulation of one week of information), we used PROC MCMC in the SAS software (Version 9.4; 100 tuning steps, and 5000 Monte Carlo simulations) to simulate posterior draws of the logistic regression model coefficients, given the prior specifications and the likelihood based on the current cumulative data on that day.

2. We then averaged the draws for each coefficient, and used the average draws to compute predicted probabilities of responding to the screening interview request on that day for each case in the data set.

3. For each case, we computed the difference between their predicted probability of response on that day (based on the Bayesian approach) and the “final” predicted probability of response (based on all data from the quarter).

4. We computed the mean difference on that day (as an estimate of bias) and the standard error of the mean difference (as an estimate of variance).

5. We repeated Steps 1 through 4 on each of Day 8, Day 9, …, Day 84 (NSFG quarters generally last 12 weeks), evaluating the mean difference and the standard error of that mean difference on each day.

We proceeded to evaluate trends in the daily differences for each method in each NSFG quarter. We also plotted the distributions across days of these mean differences (i.e., estimated bias only) and the distributions across days of the square roots of the sums of the squared estimates of bias.
and squared standard errors (i.e., estimated RMSE) by quarter, for each of the four approaches.

In these latter plots, we compared the performance of the methods early in each quarter (days 7-30), in the middle period of the quarter (days 31-60), and in the later period of the quarter (days 61-84).

4. Results

4.1 Summaries of Final Response Propensity Models

Table 1 presents summary statistics for the “final” discrete time hazard models fitted in each of the five most recent quarters (using the aforementioned common set of predictor variables; estimates of individual coefficients are available upon request). Recall that these models generated our “final” benchmark predictions of call-level response propensity for each case using all available contact attempt data from each quarter.

<< INSERT TABLE 1 HERE >>

Table 1 suggests that the “final” predictions of daily response propensity computed as benchmarks for each case (using all available data from each quarter) generally arose from discrete time hazard models with reasonable predictive power (Hosmer et al., 2013).

4.2 Trends in Daily Differences across the Quarters

Figure 1 presents trends across the days of one of the five NSFG quarters (Quarter 17) in the mean differences (±/ 1 SE) between the daily predictions of response propensity and the final predictions of response propensity for each case (based on all data collected from the quarter).
This plot demonstrates how earlier on in the data collection, predictions based on the Bayesian approaches using historical data (PWP and LAST) tended to have noticeably lower mean differences compared to the standard method, and converged to zero on these differences more quickly. Figure 2 “zooms in” on the first 10 days during which the predictions were evaluated during this quarter (i.e., Day 7 – Day 16), better demonstrating the differences in performance early on in the quarter. The LIT approach also performs well on selected days, although not as consistently as the other two Bayesian approaches relying on historical data. We observed similar trends in the other four quarters.

4.3 Comparisons of Estimated Bias and RMSE of the Alternative Approaches

Treating the final prediction of response propensity based on all contact attempt data collected from the quarter as the “unbiased” target of the prediction, Figures 3 to 5 present the distributions of the mean differences based on days 7-30, 31-60, and 61-84, for each of the four methods by quarter. Apparent in these three figures is the consistent ability of the Bayesian approaches to shift the central tendencies of the estimated bias measures downward relative to the standard approach, especially during the “middle” periods of each quarter when survey managers applying RSD often consider interventions (Wagner et al., 2012). We also note the general tendency of the predictions to approach the final predictions based on all data accumulated as the days in each quarter proceed, as would be expected.
Figures 6 to 8 present the same comparisons in terms of the estimated RMSE of the mean differences. Similar patterns are evident here, again providing support for the Bayesian approaches when accounting for the estimated variances of the daily mean differences as well (especially in Quarters 17 and 19). These plots also provide consistent evidence in favor of the approaches using historical data to formulate the priors, although the approach based on literature review is certainly competitive.

5. Discussion

5.1 Summary of Findings
We find general evidence of improvements in both the bias and variance of predictions of daily response propensity (at the contact attempt level) in the NSFG via the use of Bayesian methods for estimating the underlying discrete-time logit models. This is especially true in the early to middle periods of a given NSFG data collection quarter, when managers often consider interventions based on estimates of response propensity. When specifically considering the three different methods for eliciting prior evidence on the model coefficients, we find general support for the PWP and LAST methods, where the PWP method is capable of leveraging a large amount of historical data, and the LAST method only requires evidence from a recent data collection. Notably, the method based on the prior literature (LIT) can also be competitive with these other methods leveraging historical data, suggesting that this is a reasonable approach to developing priors when historical data may not be available. All methods are easy to implement using existing statistical software implementing Bayesian computation; we used PROC MCMC in SAS (Version 9.4) in this study.

5.2 Directions for Future Research

We explicitly did not consider one alternative to prior elicitation that has also received attention in the health sciences literature: consultation with subject-matter experts to elicit their beliefs about the parameters of interest in these models (e.g., Boulet et al., 2019). Such an approach would require developing a simple questionnaire for survey managers and data collection managers (e.g., interviewer supervisors) that explicitly collects information about expected call-level response rates in subgroups defined by the predictors of interest. The results from a fairly large number of completed questionnaires could then be aggregated and translated to the coefficients of a logistic regression model (on the log-odds scale) to ultimately generate prior
distributions for each of the coefficients of interest. One could also use the variance among the questionnaire responses for a given predictor to approximate uncertainty about each of the coefficients in the assumed prior distributions. This approach would require pre-testing of the questionnaire and careful discussion with the subject-matter experts to ensure that they understand the questions and the objective of the data collection. We view this as a worthwhile alternative to eliciting prior information that future research could contrast with the approaches studied here.

Finally, replications of the approaches used here to confirm our general findings would also be welcome in other survey contexts, where the gains from the Bayesian approach may be larger if the prior distributions are more informative or daily response propensity models have a stronger fit than was found here. Replications of this work in studies with historical data readily available should be straightforward, but the literature review required for a different survey context may be more time-consuming. Researchers are welcome to examine and utilize the results of our literature review, available in the supplementary Excel file for this article.

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Table 1: Model fit statistics for the “final” response propensity models fitted to all call-level data from each of the five most recent NSFG quarters.

|                      | Quarter 16 | Quarter 17 | Quarter 18 | Quarter 19 | Quarter 20 |
|----------------------|------------|------------|------------|------------|------------|
| **Number of Calls**  | 15,521 (3,431 interviews; 12,090 non-interviews) | 15,646 (3,668; 11,978) | 15,455 (3,431; 12,024) | 13,652 (3,426; 10,226) | 14,175 (3,373; 10,802) |
| Nagelkerke Pseudo R-Squared | 0.095 | 0.116 | 0.089 | 0.130 | 0.088 |
| Hosmer-Lemeshow GOF test: p-value | 0.163 | 0.895 | <0.01 | <0.01 | 0.448 |
| AUC                  | 0.712 | 0.683 | 0.661 | 0.690 | 0.656 |
Figure 1. Trends in mean differences between daily predictions and final predictions across the 84 days in Quarter 17.
Figure 2. Trends in mean differences between daily predictions and final predictions across the first 10 evaluation days in Quarter 17.
Figure 3. Distributions of mean differences (estimated bias) across days by prediction approach for each of the five quarters (days 7 – 30 only).
Figure 4. Distributions of mean differences (estimated bias) across days by prediction approach for each of the five quarters (days 31 – 60 only).
Figure 5. Distributions of mean differences (estimated bias) across days by prediction approach for each of the five quarters (days 61 – 84 only).
Figure 6. Distributions of estimated RMSE across days by prediction approach for each of the five quarters (days 7 – 30 only).
Figure 7. Distributions of estimated RMSE across days by prediction approach for each of the five quarters (days 31 – 60 only).
Figure 8. Distributions of estimated RMSE across days by prediction approach for each of the five quarters (days 61 – 84 only).
ONLINE APPENDIX

Table A1: Significant predictors of screener response propensity in the final discrete time logit model for call-level data from the eight most recent quarters, after applying backward selection 

\(n = 119,981\) calls; Nagelkerke pseudo R-squared = 0.09; Residual chi-square test \(p > 0.10\); AUC = 0.66).

| Predictor                                             | Coefficient | Standard Error |
|-------------------------------------------------------|-------------|----------------|
| Intercept                                             | -1.59       | 0.48           |
| Mail Delivery Point Type: Missing                     | -0.54       | 0.36           |
| Mail Delivery Point Type: A                           | -0.58       | 0.36           |
| Mail Delivery Point Type: B                           | -0.65       | 0.36           |
| Mail Delivery Point Type: C                           | -0.70       | 0.36           |
| Mail Delivery Point Type: D                           | -0.62       | 0.36           |
| Interviewer-Judged Eligibility: Missing              | 2.46        | 0.10           |
| Interviewer-Judged Eligibility: No                   | 0.63        | 0.07           |
| Segment Listed: Car Alone                             | 0.05        | 0.02           |
| Segment Listed: Car with Driver                       | 0.14        | 0.04           |
| PSU Type: Non Self-Representing                       | 0.05        | 0.03           |
| PSU Type: Self-Representing (Not Largest 3 MSAs)      | 0.03        | 0.03           |
| Previous Call: Contact                                | 3.96        | 0.28           |
| Previous Call: Different Window                       | -0.12       | 0.02           |
| Previous Call: Building Ever Locked                   | 0.32        | 0.05           |
| Previous Call: Building Locked                        | 2.15        | 0.14           |
| Previous Call: Max Resistance                         | 0.26        | 0.04           |
| Previous Call: No Contact                             | 2.25        | 0.13           |
| Previous Call: Other Contact, No Resistance           | -1.35       | 0.25           |
| Previous Call: Resistance                             | -1.57       | 0.26           |
| Previous Call: Soft Appointment                       | -1.04       | 0.30           |
| Previous Call: Call Window Sun.-Thurs. 6pm-10pm       | 0.07        | 0.03           |
| Previous Call: Call Window Fri.-Sat. 6pm-10pm         | 0.08        | 0.02           |
| No Access Problems in Segment                         | -0.04       | 0.02           |
| Evidence of Other Languages (not Spanish)             | -0.09       | 0.03           |
| Census Division: G                                    | -0.14       | 0.03           |
| Census Division: B                                    | -0.32       | 0.03           |
| Census Division: D                                    | -0.23       | 0.03           |
| Census Division: H                                    | -0.25       | 0.03           |
| Census Division: C                                    | -0.21       | 0.03           |
| Census Division: F                                    | -0.27       | 0.04           |
| Category                                                                 | Value 1 | Value 2 |
|-------------------------------------------------------------------------|---------|---------|
| Census Division: E                                                      | -0.21   | 0.03    |
| Census Division: A                                                      | -0.20   | 0.04    |
| Contacts: None                                                          | -0.68   | 0.24    |
| Contacts: 1                                                             | -0.54   | 0.22    |
| Contacts: 2 to 4                                                        | -0.42   | 0.19    |
| Segment Domain: <10% Black, <10% Hispanic                               | -0.04   | 0.02    |
| Segment Domain: >10% Black, <10% Hispanic                               | -0.05   | 0.02    |
| Segment Domain: <10% Black, >10% Hispanic                               | 0.01    | 0.03    |
| Percentage of Segment Non-Eligible (Census Data)                        | -0.01   | <0.01   |
| IWER Estimated Segment Eligibility Rate                                  | -0.54   | 0.12    |
| IWER Estimates Household Eligible                                       | -0.07   | 0.02    |
| Segment Type: All Residential                                           | -0.08   | 0.05    |
| Segment Type: Mixed Residential / Commercial                            | -0.13   | 0.05    |
| Log(Number of Calls Made)                                               | -0.60   | 0.03    |
| Log(Number of Calls Made) x No. Prev. Contacts                          | -0.04   | 0.01    |
| MSG* HoH Age: Missing                                                   | -0.29   | 0.03    |
| MSG HoH Age: 18-44                                                      | -0.30   | 0.03    |
| MSG HoH Age: 45-59                                                      | -0.18   | 0.03    |
| MSG Adult Count: Missing                                                | -0.14   | 0.04    |
| MSG Adult Count: 1                                                      | -0.09   | 0.03    |
| MSG Adult Count: 2                                                      | 0.01    | 0.03    |
| MSG Asian in HH: Missing                                                | 0.21    | 0.04    |
| MSG Asian in HH: No                                                     | 0.20    | 0.05    |
| MSG HoH Gender: Missing                                                 | -0.03   | 0.02    |
| MSG HoH Gender: Female                                                  | -0.01   | 0.02    |
| MSG HoH Income: $35k-$70k                                               | 0.12    | 0.02    |
| MSG HoH Income: less than $35k                                          | 0.14    | 0.02    |
| MSG HH Own/Rent: Missing                                                | -0.06   | 0.03    |
| MSG HH Own/Rent: Owned                                                  | -0.02   | 0.02    |
| MSG Age of 2nd Person: Missing                                          | -0.13   | 0.03    |
| MSG Age of 2nd Person: 18-44                                            | -0.15   | 0.03    |
| No Respondent Comments                                                  | 0.08    | 0.04    |
| Non-Contacts: None                                                      | -0.51   | 0.08    |
| Non-Contacts: 1                                                         | -0.25   | 0.05    |
| Non-Contacts: 2-4                                                       | -0.03   | 0.03    |
| Occupancy Rate of PSU                                                   | -0.26   | 0.10    |
| Respondent Other Concerns                                               | 0.18    | 0.06    |
| Physical Impediment to Housing Unit: Locked                             | -0.35   | 0.03    |
| Day of Quarter                                                          | 0.01    | <0.01   |
| Resistance: None                                                        | -1.26   | 0.15    |
| Resistance: Once                                                        | 0.15    | 0.09    |
| Single Family Home / Townhome                                           | -0.21   | 0.03    |
| Structure with 2-9 Units                                                 | -0.28   | 0.04    |
| Category                                      | Value 1 | Value 2 |
|----------------------------------------------|---------|---------|
| Structure with 10+ Units                     | -0.20   | 0.04    |
| Respondent Concern: Survey Voluntary?        | -0.47   | 0.14    |
| Respondent Concern: Too Old                  | 0.60    | 0.15    |

*MSG denotes Marketing Systems Group ([https://www.m-s-g.com/Pages/](https://www.m-s-g.com/Pages/))