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Explanation of symbols

.	data not available
*****	provisional figure
******	revised provisional figure (but not definite)
x	publication prohibited (confidential figure)
–	nil
–	(between two figures) inclusive
0 (0.0)	less than half of unit concerned
empty cell	not applicable
2011–2012	2011 to 2012 inclusive
2011/2012	average for 2011 up to and including 2012
2011/'12	crop year, financial year, school year etc. beginning in 2011 and ending in 2012
2009/'10–2011/'12	crop year, financial year, etc. 2009/'10 to 2011/'12 inclusive

Due to rounding, some totals may not correspond with the sum of the separate figures.

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Summary: Recently, survey literature has put forward responsive and adaptive survey designs as means to make efficient tradeoffs between survey quality and survey costs. The designs, however, restrict quality-cost assessments to nonresponse error, while in mixed-mode surveys the measurement or response error plays a dominant role. Furthermore, there is both theoretical and empirical evidence that the two types of error are correlated.In this paper, we investigate adaptive survey designs that minimize both errors simultaneously in the Labour Force Survey. The design features that are selected are self-reporting versus proxy reporting, and the number of contact attempts.

Keywords: Nonresponse bias; Response bias; Total survey error; Markov Decision problem; Adaptive survey design

1. Introduction

Adaptive survey designs (ASDs) have become increasingly interesting as data collection methods. Introduced in Wagner (2008) and Schouten et al. (2011), ASDs borrow the name from the field of clinical trials. In ASDs in clinical trials, treatments are group-specifically set before the start of the trial and changed during the trial according to the responses of the patient groups. ASDs offer two advantages to the field of designing surveys. First, ASDs take into consideration the fact that the impact of various design features varies greatly over persons and households. Therefore, ASDs deliver a higher quality of survey response than traditional survey designs that overlook this aspect. Second, ASDs take care of the cost-effectiveness problem that traditional designs often encounter; they are built to find the optimal balance between costs and quality for any given survey. ASDs start by clustering sample units into subpopulations based on available characteristics (e.g., age, gender and interviewer observations). Then, the effect of the various design features on the willingness to participate in the survey is studied for each subpopulation. The optimal strategy is given by that mix of design features that yields most quality (over all subpopulations) and it is not more expensive than the available budget. When subpopulations are derived from administrative data and sampling frame data, then the ASD is called static. When subpopulations are based on paradata observations or a mix of registry/frame data and paradata observations, then the ASD is called dynamic. Static designs do not adapt to on-going survey data collection, but only to past survey data. In contrast, dynamic designs adapt to data collection as they employ paradata observations on the sampling units. Dynamic ASDs have a close resemblance to responsive designs, see Groves and Heeringa (2006).

Currently, ASDs focus completely on nonresponse error; they maximize response rates and/or representativity of response as measured by some criterion. However, there are other influential errors like measurement error and coverage error. ASDs need yet to make the step from nonresponse errors to multiple survey errors. Quantifying the impact and interaction of multiple survey errors is one of the most difficult tasks. However, in order to obtain effective designs, it is imperative that ASDs widen their scope; especially in surveys that employ multiple survey modes.

In the present paper, we discuss three research questions that arise from including measurement errors (MEs) in the ASD framework: how can we design a suitable optimization model, how can we select appropriate measures to investigate the impact of MEs, and how can we apply the expanded optimization model to realistic survey data? To this end, we study several extensions of the ASD model as given by Calinescu et al. (2011), where each extension treats the addition of MEs to the model in a different manner. As a case study, we use the Labour Force Survey (LFS) data from 2008. We extend the approach in Schouten and Leufkens (2011) where several relevant registers were linked to the LFS 2008. We consider static ASDs only, but extension to dynamic designs is straightforward.

The remainder of the paper is structured as follows. Section 2 gives a broader description of the implications that result from moving towards total survey error in the context of ASDs. Section 3 presents several model instances to investigate measurement errors in the ASD framework and Section 4 provides the results of the case study. Section 5 concludes the paper and gives directions for future research.

2. Adaptive survey designs for nonresponse and measurement

The optimization problem behind ASDs can be formulated as the maximization of a quality objective function given one or multiple cost constraints. A general framework for ASDs in the context of nonresponse is provided by Schouten et al. (2011). In this section, we briefly review the framework and then extend to nonresponse and measurement. We follow the approach taken by Calinescu et al. (2011).

2.1 Adaptive survey designs for nonresponse

Calinescu et al. (2011) consider ASDs for nonresponse in the setting where the survey mode and the contact protocol (timing and number of contact attempts) are the design features of interest. They optimize the response rate subject to constraints on the total number of attempts and on the total budget (in Euro’s). Contact and participation probabilities are allowed to be mode and time slot dependent, but are assumed to be independent of the success or failure of previous contact attempts. The optimization problem can then be formulated as a Markov decision problem.

The time-dependence of the probabilities allows for a flexible fit to historic survey data. The history-independence of contact success is, however, a strong assumption, which needs to be relaxed in future research. Relaxation of the assumption leads to a more complex optimization problem as the solution space is generally large and has relatively little structure. We refer to Durrant, D'Arrigo and Steele (2011) for advanced models for contact. The probabilities estimated from their models could serve as input to more realistic designs. In this paper, we are merely interested in the generalization to nonresponse and measurement error, and avoid the additional complexity of history-dependent contact probabilities. Calinescu et al. (2011) solve the Markov decision problem by dynamic programming, which ensures that the algorithm is computationally feasible and guaranteed to converge to the optimal solution.

Although Calinescu et al. (2011) restrict themselves to survey mode and contact protocol, their approach can be applied directly to other design features. Survey modes can generally be viewed as a set of strategies with different contact and participation probabilities. Interviewers or groups of interviewers, different advance letters and different types of reporting can all be treated in the same way. For instance, if we consider self-reporting and reporting where proxy answers are allowed as two competing strategies, then we can incorporate them in the Markov decision problem in exactly the same way as was done for survey modes. However, instead of mode contact and participation probabilities, one needs the contact and participation probabilities for self-reporting and for self- plus proxy reporting.

ASD optimization amounts to allocation of strategies to population subgroups, where subgroups are formed using administrative data, frame data or paradata observations. Paradata observations are observations made by interviewers or interviewing staff during survey data collection. The allocation probabilities are the decision parameters in the optimization problem. In this paper, and in Calinescu et al. (2011), we let allocation probabilities be either 0 or 1, i.e., each population subgroup is assigned to one strategy. This restriction on the allocation probabilities leads to a finite number of candidate solutions. If relaxed, it generally leads to a more complex optimization problem.

As quality objective function for nonresponse, we choose the expected response rate. Recent literature has debated the use of the response rate as a single measure of response quality. See for example Groves (2006), Groves & Peytcheva (2008) and Schouten, Cobben and Bethlehem (2009). To comply with this conclusion, we add a constraint on the variance of subgroup response rates. Here, the subgroups are taken the same as the subgroups in the allocation of strategies. However, the choice of subgroups could also be different, e.g., aggregated to a less detailed stratification of the population. A constraint on the variance of subgroup response rates corresponds to a constraint on the so-called representativity indicator or R-indicator. Schouten, Cobben and Bethlehem (2009) introduce the R-indicator as a measure to supplement the response rate. It is defined as $R(\rho)=1-2S(\rho)$, where $S(\rho)$ is the standard deviation of subgroup response rates. The constraint requires the expected R-indicator of the ASD to exceed a value α . We will further refer to this constraint as the variability constraint.

Next to the variability constraint, we consider another cost constraint: the number of calls or visits. The expected total number of calls is not allowed to be larger than a pre-specified value B . Calinescu et al (2011) consider ASDs with additional cost constraints, including constraints on interviewer occupation rates. Here, we restrict ourselves to a cost function on the number of calls.

2.2 Extending to measurement errors

Schouten and Leufkens (2011) investigate the relationship between nonresponse error and measurement error as a function of several survey design features. The measurement error is decomposed into a measurement profile risk and response errors. Response errors represent the actual differences between the observed and the true values, while the measurement profile risk is the probability that a respondent will show a certain response style that may lead to response errors. Examples of measurement profiles are social desirable answering behaviour, straightlining, acquiescence, primacy and recency effects. Here, we follow the same approach as was used by Schouten and Leufkens, i.e., we abstract from measurement errors on single survey variables and focus on measurement profiles. We will assume that there is only one measurement profile, although the model can easily be extended to include multiple measurement profiles. Occurrence of the measurement profile is conditional on participation, and participation is conditional on contact.

We adopt two approaches:

– Approach 1: The probability for measurement profile is added to the quality objective function. The new objective function is the proportion of sample units that respond without the specified measurement profile. In other words, if the measurement profile is observed, the response thus obtained is treated as a nonresponse. Therefore, the objective in this case is to maximize the response without measurement profile.

– Aprroach 2: The probability for a measurement profile is added as a constraint: the proportion of respondents showing an undesirable measurement profile must be smaller than a specified threshold Θ . For example, if $\Theta = 0.04$, then on average proportion of respondents showing an undesirable measurement profile must be smaller than 4%.

Appendix A translates the two approaches to the notation of Calinescu et al. (2011).

In Schouten and Leufkens (2011), the authors conclude that proxy reporting has the strongest positive impact on the response rate and it is the only feature that mildly increases the risk for a measurement profile. In Thomsen and Villund (2010) however, where the impact of proxy reporting on LFS key statistics in Norway is investigated, the conclusion is that the gain in the response rate outweighs the increase in measurement error.

3. A case study: the Labour Force Survey

In this section we give a brief description of the Dutch LFS and set up the framework to apply the ASD model. Section 4 presents the optimization results.

The LFS targets people with age between 15 and 64 years, therefore undersampling occurs for addresses with households consisting only of persons of 65 years of age and higher. Moreover, households with persons of age between 15 and 26 or from non-western countries are oversampled. The data collection technique is computer assisted personal interviewing (CAPI). The interviewer makes six contact attempts at maximum per household. If the interviewer comes at an inconvenient time, an appointment is scheduled (if possible).

Proxy reporting is allowed by members of the same household (18 years and older) in order to increase the response rate and reduce the travelling costs. Households may refuse participation in the survey since this is not mandatory. These households are not re-approached to gain cooperation.

3.1 Design features of interest in the LFS

In this paper, we focus on the type of reporting (self-reporting vs. proxy reporting) and the number of visits. We explore the impact of the number of contact attempts up to a maximum of ten visits.

For the sake of simplicity, we have to make a number of assumptions. First, we assume that the choice of design features does not impact the travelling distances and travelling times. Second, interviewers handle multiple surveys at the same time and the number and size of running surveys is large. Last, changes in the choice of design features can be subsumed in regular interviewer workloads.

We consider a survey sample of size $N = 10000$. However, the sample size will not be important in the optimization. It merely suggests that standard errors are relatively small. We use age as frame data to define the subgroups since age gives the strongest differential in both nonresponse and response error for the LFS. Based on the age of the sample unit, we distinguish three subgroups, namely $\mathcal{G} = \{15-25, 26-55, 56-65\}$. For illustration purposes we restrict ourselves to a small number of subgroups. Extending to a higher number of groups is trivial. The proportion of each group in the total population is given by

$$w_1 = 0.196, \quad w_2 = 0.624, \text{ and } w_3 = 0.18 .$$

Let $\mathcal{M} = \{0,1,2\}$ be the type of reporting, i.e., 1 denotes self-reporting, 2 proxy-reporting and 0 no visit. Let $\mathcal{T} = \{1,2,...,10\}$ be the time slots at which visits can be made to the sample units.

In case of self-reporting, contact has to be established with the sampled person. In case of proxy-reporting, contact is defined as contact with the household the sampled person belongs to. Obviously, the contact probabilities are larger when proxy-reporting is allowed.

From the 2008 LFS data we estimate contact probabilities, cooperation probabilities and the probabilities for a measurement profile for all groups $g \in \mathcal{G}$ and reporting types $m \in \mathcal{M}$ (see Table 3.1). The probability values for $m = 0$ are omitted since that involves no interaction with the group.

Table 3.1: Estimated probabilities for contact, cooperation and measurement profile (LFS 2008).

Probabilities		*Group* 15-25	26-55	56-65
Contact	$m = 1$	0.261	0.303	0.434
	$m = 2$	0.392	0.367	0.461
Cooperation		0.594	0.651	0.690
Risk	$m = 1$	0.060	0.028	0.041
	$m = 2$	0.078	0.035	0.047

Note that the LFS always allows for proxy-reporting, therefore contact probabilities for self-reporting only were derived from suitable surveys. Moreover, all the input probabilities are independent of the time slot. Thus, the impact of the number of visits is not hindered by the sequence of these visits. However, the optimization problem and strategy can easily be generalized to handle probabilities that depend on the time slot.

3.2 The extended Markov decision problem for the LFS

We study the impact on the strategy allocation by gradually adding constraints to a baseline setting. The baseline setting has a fixed strategy for all age groups, i.e., no optimization is required. It also serves as a benchmark for the other settings where allocation of design features is optimized. The constraints to be added to the baseline setting refer to the maximum allowed number of visits, handling the measurement error, handling the variance in the subgroup rates and the maximum number of switches between reporting types for the same subgroup. Thus, we obtain the following six settings:

- *Setting 1 (baseline)*: The average number of visits for each sample unit is *b* and only one type of reporting is allowed (i.e., 1a self – reporting; 1b – proxy-reporting).
- *Setting 2*: The objective is to maximize the response rate. The reporting type and the number of visits are subject to optimization. A maximum number of $B = bN$ visits are available to handle the entire sample. For example, if $b = 3$, then 30000 visits are available.
- *Setting 3*: The objective is to optimize the response without measurement error using approach 1 (i.e., the probabilities for measurement profile are incorporated in the objective function). The reporting type and the number of visits are subject to optimization. A maximum number of $B = bN$ visits are available to handle the entire sample.

- *Setting 4:* The objective is to optimize the response without measurement error using approach 2 (i.e., constraint on the proportion of respondents showing a measurement profile). The reporting type and the number of visits are subject to optimization. A maximum number of $B = bN$ visits are allowed to handle the entire sample.
- *Setting 5:* To the previous settings (except setting 1) we add the variability constraint. Setting 5a studies the impact of this constraint on the model under setting 2, 5b for the model under setting 3 and 5c for setting 4.
- *Setting 6:* We allow at most one change in the reporting type during data collection for each subgroup for all previous settings.

For each of these settings we explore the dependence on the values of b, Θ and α. We let $b \in \{2, 2.5, 3\}$, $\Theta \in \{3\%, 3.5\%, 4\%\}$ and $\alpha \in \{0.8, 0.85, 0.9\}$.

Table 4.1: Overview results settings 1 – 4.

Setting			*Response rate (%)*	*Number of visits*	*R-indicator*	*Average risk (%)*
1a		$b = 2$	43.4	19868	0.548	3.17
		$b = 2.5$	52.6	24979	0.629	3.29
		$b = 3$	60.9	29995	0.851	3.54
1b		$b = 2$	50.5	19960	0.718	4.17
		$b = 2.5$	62.4	24954	0.924	4.50
		$b = 3$	64.2	25689	0.939	4.51
2		$b = 2$	50.5	19960	0.718	4.17
		$b = 2.5$	62.4	24954	0.924	4.50
		$b = 3$	64.2	25689	0.939	4.51
3		$b = 2$	48.5	19989	0.518	3.68
		$b = 2.5$	59.6	24995	0.875	4.38
		$b = 3$	61.5	29199	0.928	3.95
4	$\Theta = 3\%$	$b = 2$	40.0	19488	0.379	2.96
		$b = 2.5$	45.2	21762	0.487	2.99
		$b = 3$	45.2	21762	0.487	2.99
	$\Theta = 3.5\%$	$b = 2$	47.3	19894	0.531	3.49
		$b = 2.5$	55.0	24980	0.609	3.47
		$b = 3$	59.7	29317	0.820	3.49
	$\Theta = 4\%$	$b = 2$	50.4	19805	0.499	3.80
		$b = 2.5$	56.9	24990	0.796	3.99
		$b = 3$	63.5	28809	0.928	3.99

4. Results

The previous sections dealt with designing a suitable framework to address the question on how to investigate the impact of MEs on survey designs. The ASD optimization model is expanded and selected indicators are included to study the impact of MEs. In this section, we present the optimization results obtained from applying the optimization model to realistic survey data (LFS 2008).

Table 4.2: Overview results setting 6 (changes occur only to setting 3).

Setting		*Response rate (%)*	*Number of visits*	*R-indicator*	*Average risk (%)*
6	$b = 2$	48.5	19969	0.518	3.69
	$b = 2.5$	59.6	24938	0.876	4.41
	$b = 3$	61.5	29199	0.928	3.95

Table 4.3: Overview results setting 5.

Setting				*Response rate (%)*	*Number of visits*	*R-indicator*	*Average risk (%)*
5a		$\alpha = 0.8$	$b = 2$	50.0	19738	0.806	4.43
			$b = 2.5$	62.4	24954	0.924	4.50
			$b = 3$	64.2	25689	0.939	4.50
		$\alpha = 0.85$	$b = 2$	48.1	19135	0.872	4.42
			$b = 2.5$	62.4	24954	0.924	4.50
			$b = 3$	64.2	25689	0.939	4.50
		$\alpha = 0.9$	$b = 2$	46.5	18612	0.911	4.41
			$b = 2.5$	62.4	24954	0.924	4.50
			$b = 3$	64.2	25689	0.939	4.50
5b		$\alpha = 0.8$	$b = 2$	47.9	19970	0.806	4.26
			$b = 2.5$	59.6	24995	0.875	4.38
			$b = 3$	61.5	29199	0.928	3.95
		$\alpha = 0.85$	$b = 2$	47.5	19859	0.919	4.51
			$b = 2.5$	59.6	24995	0.875	4.38
			$b = 3$	61.5	29199	0.928	3.95
		$\alpha = 0.9$	$b = 2$	47.5	19859	0.919	4.51
			$b = 2.5$	59.5	24957	0.905	4.44
			$b = 3$	61.5	29199	0.928	3.95
5c	$\Theta = 3.5\%$	$\alpha = 0.8$	$b = 2$	40.6	19847	0.862	3.49
			$b = 2.5$	49.3	24503	0.852	3.47
			$b = 3$	59.7	29317	0.820	3.49
		$\alpha = 0.85$	$b = 2$	40.6	19847	0.862	3.49
			$b = 2.5$	49.3	24503	0.852	3.47
			$b = 3$	49.3	24503	0.852	3.47
	$\Theta = 4\%$	$\alpha = 0.8$	$b = 2$	44.3	19521	0.885	3.99
			$b = 2.5$	55.8	24644	0.816	3.97
			$b = 3$	63.5	28809	0.928	3.99
		$\alpha = 0.85$	$b = 2$	44.3	19521	0.885	3.99
			$b = 2.5$	54.2	24879	0.893	3.97
			$b = 3$	63.5	28809	0.928	3.99
		$\alpha = 0.9$	$b = 2$	42.8	19892	0.935	3.96
			$b = 2.5$	52.6	23853	0.905	3.98
			$b = 3$	63.5	28809	0.928	3.99

The model instances described in Section 3.2 serve to distinguish the impact of various indicators on the optimal strategy allocation to subgroups. Tables 4.1 – 4.3 provide an overview of the results (response rate, number of visits carried out, average risk for measurement profile). In Table 4.3 the results for setting 5c for $\Theta = 3\%$ have been omitted due to infeasibility of the problem. Similarly for setting 5c, $\Theta = 3.5\%$ and $\alpha = 0.9$.

For a clear understanding, we group the results to answer the following questions:

- what setting yields the maximum response rate? (see Section 4.1),
- what is the impact of allowing for proxy reports? (see Section 4.2),
- what are the changes in the group-strategy structure across various model instances? (see Section 4.3),
- what is the impact of measurement error under Approach 1? (see Section 4.4),
- what is the impact of measurement error under Approach 2? (see Section 4.5),
- what is the impact of the variability constraint? (see Section 4.6) and what is the impact of a limited number of reporting type switches (see Section 4.7).

Section 4.8 offers a graphical overview of the results. In Tables 4.4 – 4.10, 1 denotes self-reporting, 2 proxy-reporting and 0 no visit.

4.1 Maximal response rate

Higher response rates are obtained when proxy-reporting is allowed (contact probabilities for proxy-reports are higher than for self-reports) and for large values of b (more visits are allowed). From settings 1b and 2 we get that the maximal response rate given the input data is 64.2% (achieved for $b = 3$).

Table 4.4: Optimal strategy allocation setting 2 (0=no visit, 2=proxy)

		#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	Response (%)
15-25	$b = 2$	2	0	0	0	0	0	0	0	0	0	23.3
	$b = 2.5$	2	2	2	2	2	2	0	0	0	0	56.4
	$b = 3$	2	2	2	2	2	2	2	2	2	2	59.0
26-55	$b = 2$	2	2	2	2	0	0	0	0	0	0	54.7
	$b = 2.5$	2	2	2	2	2	2	2	0	0	0	62.5
	$b = 3$	2	2	2	2	2	2	2	2	2	2	64.4
56-65	$b = 2$	2	2	2	2	2	0	0	0	0	0	65.9
	$b = 2.5$	2	2	2	2	2	2	2	2	2	2	68.9
	$b = 3$	2	2	2	2	2	2	2	2	2	2	68.9

Although resulted from different models, the group strategies in these two settings are identical. There are two reasons that explain why the optimal strategy allocation in setting 2 (see Table 4.4) chooses proxy-reporting at all visits. First, higher contact probabilities lead to higher response rates in the case of proxy-reporting. Second, reporting types cost the same (i.e., 1 visit, since we treat the constraint on the number of visits as a cost constraint) regardless of the visit outcome. Thus, the optimal choice for the reporting type is proxy since it yields higher response.

Note that in Setting 2 for $b = 3$ there are sufficiently many visits available to completely handle all the groups. Hence, we can also interpret this case as an unconstrained problem (i.e., find the highest response given an unlimited number of visits). Note that also the representativity of this response is maximal, 0.939. This comes as no surprise, given the fact that all groups are approached at all times slots via the same reporting type.

4.2 Impact of proxy-reporting

We analyze the impact of proxy-reporting by comparing settings 1a and 1b. Table 4.5 provides the optimal group strategies for setting 1a.

Setting 1b yields a higher response than 1a for any value of b. The structure of the strategies is, however, different. This is a consequence of the lower probability for contact in the case of self-reporting. Thus, more visits are required, which leads to higher costs (see also the cost function (A8)). This is an important aspect in the case of group *15-25* that receives no visits at all for $b = 2$. In other words, it is preferable to “sacrifice” the response from group *15-25* in order to obtain higher response from the other groups. However, a zero visit-strategy will not be acceptable for the variability constraint.

Table 4.5: Optimal solution setting 1a (0=no visit, 1=self-report)

		#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	Response (%)
15-25	$b = 2$	0	0	0	0	0	0	0	0	0	0	0.0
	$b = 2.5$	1	0	0	0	0	0	0	0	0	0	15.5
	$b = 3$	1	1	1	1	1	0	0	0	0	0	46.3
26-55	$b = 2$	1	1	1	1	0	0	0	0	0	0	49.7
	$b = 2.5$	1	1	1	1	1	1	1	0	0	0	59.9
	$b = 3$	1	1	1	1	1	1	1	1	1	1	63.3
56-65	$b = 2$	1	1	1	1	1	1	1	1	1	1	68.8
	$b = 2.5$	1	1	1	1	1	1	1	0	0	0	67.7
	$b = 3$	1	1	1	1	1	1	1	1	0	0	68.3

The average risk for measurement profile under self-reporting is never higher than 3.6%, while when proxy-reporting is allowed, it can reach 4.5% and higher. Therefore, the settings that account for the measurement risk will have to deal with the trade-off between high response and high risk when using proxy-reporting.

4.3 Group-strategy structure

As seen from Table 4.4, the strategies per group differ significantly when we vary the value of b. For example, for age group *15-25* only one visit is allowed for $b = 2$, whereas for $b = 2.5$ the strategy advises for six visits. This is a big change. On the other hand, the strategy for age group *56-65* does not suffer from any changes between $b = 2.5$ and $b = 3$. Similar patterns can be observed over all settings.

The reason for such strategy structures lies in the input parameters, namely the group size, contact and cooperation probabilities. Age group *56-65* is a rather small group, only 1800 sample units. Therefore, it is cheaper (i.e., small number of visits) to handle this group completely than any other (see (A8) for cost computation). It is also the group with the highest contact and cooperation probabilities. Since our objective is to maximize the overall response rate, this group is preferred.

To explain the sharp change in strategy structure for age group *15-25,* we need to take a look at group *26-55*. This is the largest group in our sample, 6240 sample units, and therefore the costs for this group are the largest. However, it has a higher cooperation probability relatively to that of age group *15-25.* As a consequence, in the optimal strategy more visits are spent on group *26-55* than on group *15-25* since this strategy yields a higher response. Therefore, when a small budget is available, age group *15-25* receives fewer visits than the other groups.

4.4 Optimizing response without measurement errors

Maximizing the response rate corrected for risk of measurement errors (i.e., using Approach 1) does not affect the structure of the original ASD model. Only the objective function is adjusted (see (A5) and (A9)). The resulting strategies are presented in Table 4.6.

Table 4.6: Optimal solution setting 3 (0=no visit, 1=self-report, 2=proxy)

		#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	Response (%)
15-25	$b = 2$	0	0	0	0	0	0	0	0	0	0	0.0
	$b = 2.5$	2	2	2	2	0	0	0	0	0	0	47.3
	$b = 3$	1	1	1	2	2	2	2	2	2	2	54.7
26-55	$b = 2$	2	2	2	2	2	2	0	0	0	0	58.8
	$b = 2.5$	2	2	2	2	2	2	2	2	2	0	61.8
	$b = 3$	1	1	2	2	2	2	2	2	2	2	62.3
56-65	$b = 2$	1	1	2	2	1	1	1	1	1	1	65.9
	$b = 2.5$	2	2	1	1	1	2	2	2	2	2	65.6
	$b = 3$	1	1	1	1	1	1	2	2	2	2	66.0

The group strategies in this setting lead to a mix of reporting types. However, this might seem counterintuitive. Since proxy-reporting presents a high risk for errors, an intuitive optimal strategy would prescribe self-reporting for all visits. On the other hand, such a strategy leads to high costs, as seen from setting 1a. Hence, a mix of reporting types is preferred. This is however not always affordable. For $b < 3$ only age group *56-65* can still afford the reporting type mix, while the other groups are approached only via proxy-reporting.

The prescribed mix, with multiple changes in the reporting type, is unrealistic in practice. For this reason, we have introduced setting 6, where we constrain over the number of switches between reporting types.

4.5 Optimizing response subject to constraints on measurement profile risk

Addressing measurement error under Approach 2 gives the survey researcher a greater control over the model. The detailed strategies are presented in Table 4.7.

Table 4.7: Optimal solution setting 4 (0=no visit, 1=self-report, 2=proxy)

			#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	Response (%)
3%	*15-25*	$b = 2$	0	0	0	0	0	0	0	0	0	0	0.0
		$b = 2.5$	0	0	0	0	0	0	0	0	0	0	0.0
		$b = 3$	0	0	0	0	0	0	0	0	0	0	0.0
	26-55	$b = 2$	1	1	1	2	2	2	2	2	2	2	64.1
		$b = 2.5$	1	1	1	1	1	1	1	2	2	2	63.8
		$b = 3$	1	1	1	1	1	1	1	2	2	2	63.8
	56-65	$b = 2$	0	0	0	0	0	0	0	0	0	0	0.0
		$b = 2.5$	1	0	0	0	0	0	0	0	0	0	30.0
		$b = 3$	1	0	0	0	0	0	0	0	0	0	30.0
3.5%	*15-25*	$b = 2$	0	0	0	0	0	0	0	0	0	0	0.0
		$b = 2.5$	1	0	0	0	0	0	0	0	0	0	15.5
		$b = 3$	1	1	1	1	0	0	0	0	0	0	41.7
	26-55	$b = 2$	1	2	2	2	2	0	0	0	0	0	57.8
		$b = 2.5$	1	1	1	2	2	2	2	2	2	0	63.7
		$b = 3$	1	1	1	1	1	1	1	1	1	1	63.3
	56-65	$b = 2$	1	1	2	2	0	0	0	0	0	0	62.6
		$b = 2.5$	1	1	2	2	2	2	2	0	0	0	68.0
		$b = 3$	1	1	1	1	1	1	0	0	0	0	66.7
4%	*15-25*	$b = 2$	0	0	0	0	0	0	0	0	0	0	0.0
		$b = 2.5$	2	2	0	0	0	0	0	0	0	0	37.4
		$b = 3$	2	2	2	2	2	2	1	0	0	0	57.2
	26-55	$b = 2$	2	2	2	2	2	2	0	0	0	0	60.9
		$b = 2.5$	1	1	1	2	2	0	0	0	0	0	59.5
		$b = 3$	1	1	1	1	1	1	2	2	2	2	63.9
	56-65	$b = 2$	2	2	2	2	2	2	2	2	2	2	68.9
		$b = 2.5$	2	2	2	2	2	2	2	2	2	2	68.9
		$b = 3$	1	1	1	2	2	2	2	2	2	2	68.8

High values for the threshold Θ on average risk for measurement profiles might not have any impact on the optimal allocation of strategies. For example, if $\Theta = 5\%$, the resulting group strategies would be just as in setting 2, where the average risk amounted to 4.51% for $b = 3$. Low values on the other hand (e.g., $\Theta = 3\%$) impose a decreased number of visits. Furthermore, for $\Theta < 2.8\%$ the problem becomes infeasible because the risk constraint can no longer be satisfied.

Note that age group *26-55* acts as a risk balancing group due to its low risk for measurement profile. In this sense, a large number of visits for group *26-55* would be necessary to balance the risk for one visit for either of the other groups. For this reason, in the case of low values of b, no visits can be made to the other groups. In other words, there are not enough visits available to cover all the visits to group *26-*

55 necessary to balance the risk for measurement profile at an additional visit to one of the other two groups. Moreover, the structure of the optimal strategy changes to favouring self-reporting, (contrary to the remarks above stating that self-reporting is not acceptable for low values of b) because self-reporting has a lower risk for measurement profiles than proxy.

4.6 Adding the variability constraint

Setting 5 creates the most interesting models. As mentioned in Section 2.1, taking into account the representativity of the response is crucial. Adding the variability constraint will have a strong impact on the structure of the group strategies. This holds particularly in the case of adding the constraint to setting 4. Here, the range of acceptable strategies is significantly reduced, due to the conflicting situation created by combining the variability constraint with the constraint on the average risk for measurement profiles. Thus, a general decrease in the response rates is observed, especially for high values of α . Moreover, infeasibility is often encountered, due to either low values for Θ or high values for α .

Table 4.8: Optimal solution setting 5a for $b = 2$ (0=no visit, 2=proxy)

		#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	Response (%)
$\alpha = 0.8$	*15-25*	2	2	0	0	0	0	0	0	0	0	37.4
	26-55	2	2	2	0	0	0	0	0	0	0	48.6
	56-65	2	2	2	2	2	2	2	2	0	0	68.5
$\alpha = 0.85$	*15-25*	2	2	0	0	0	0	0	0	0	0	37.4
	26-55	2	2	2	0	0	0	0	0	0	0	48.6
	56-65	2	2	2	0	0	0	0	0	0	0	58.2
$\alpha = 0.9$	*15-25*	2	2	0	0	0	0	0	0	0	0	37.4
	26-55	2	2	2	0	0	0	0	0	0	0	48.6
	56-65	2	2	0	0	0	0	0	0	0	0	50

Table 4.9: Optimal solution setting 5b for $b = 2$ and $b = 2.5$ with $\alpha = 0.9$ (0=no visit, 1=self-report, 2=proxy)

		#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	Response (%)
$\alpha = 0.8$	*15-25*	2	2	0	0	0	0	0	0	0	0	34.5
	26-55	2	2	2	0	0	0	0	0	0	0	46.9
	56-65	1	1	1	1	1	1	2	2	2	2	66.0
$\alpha = 0.85$	*15-25*	2	2	2	0	0	0	0	0	0	0	42.5
	26-55	2	2	2	0	0	0	0	0	0	0	46.9
	56-65	2	2	2	0	0	0	0	0	0	0	55.3
$\alpha = 0.9$	*15-25*	2	2	2	0	0	0	0	0	0	0	42.5
	26-55	2	2	2	0	0	0	0	0	0	0	46.9
	56-65	2	2	2	0	0	0	0	0	0	0	55.3
$b = 2.5$ $\alpha = 0.9$	*15-25*	2	2	2	2	2	0	0	0	0	0	50.3
	26-55	2	2	2	2	2	2	2	2	0	0	61.2
	56-65	2	2	2	2	2	2	0	0	0	0	64.0

For settings 5a and 5b we can clearly see the impact of adding this constraint to the model. Tables 4.8 and 4.9 present the optimal group strategies for settings 5a and 5b that differ from the corresponding solutions obtained in settings 2 and 3, respectively.

Infeasibility occurs in setting 5c in the case of $\Theta = 3\%$ and for $\Theta = 3.5\%$ with $\alpha = 0.9$. Tables B.1 and B.2 in appendix B show the group strategies for the remaining cases. A general pattern that can be observed in setting 5 is that age group *15-25* is no longer omitted, as in the solutions in setting 4. In order to reach the given thresholds for the R-indicator, this group has to be approached, which leads to a lower number of visits available to approach the other age groups and thus yielding lower response rates compared to previous settings.

4.7 Limiting the number of reporting type switches

In this section, we consider constraints on the number of switches from self-reporting to proxy reporting or vice versa per subgroup. In practice it would be very inconvenient and error-prone, if interviewers constantly have to check whether proxy reporting is allowed. We assume that at most one switch is allowed.

There are only two cases where this constraint affects the optimal strategies. That is setting 3 for $b = 2$ and $b = 2.5$. Table 4.10 shows the new strategies when the constraint is imposed. A slight decrease in the response rates is observed.

Table 4.10: Optimal solution for setting 6 (0=no visit, 1=self-report, 2=proxy)

		#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	Response (%)
	15-25	0	0	0	0	0	0	0	0	0	0	0.0
$b = 2$	*26-55*	2	2	2	2	2	2	0	0	0	0	58.8
	56-65	1	1	2	2	2	2	2	2	2	2	65.9
	15-25	2	2	2	2	0	0	0	0	0	0	47.3
$b = 2.5$	*26-55*	2	2	2	2	2	2	2	2	2	0	61.8
	56-65	2	2	2	2	2	2	2	2	2	2	65.5

4.8 Visualization of results

Figures 4.1 – 4.3 provide a graphical overview of response rates across the studied settings. The evolution of response rates when measurement error is addressed is visualized in Figure 4.1 by comparing results from settings 2, 3 and 4. The impact of the variability constraint is visualized in Figure 4.2 by comparing results from settings 5a and 5c. Note that in Figures 4.1 and 4.2 the response rate is plotted as a function of b. Dotted lines connect response rate levels resulted from models that differ only in parameter b. Similarity in graphical symbols across figures does not indicate any relation between the plotted values.

In Figure 4.1, setting 4 brings great differences in the response rate levels. For $\Theta = 4\%$ the highest difference occurs for $b = 2.5$, although for both $b = 2.5$ and $b = 3$ the average risk in setting 2 was around 4.5%. The relatively small drop in the response rate for $b = 3$ is due to the higher value of b. The higher number of available visits created a larger solution space, which lead to a solution that simultaneously restrains the level of allowed risk to the given value and yields a relatively high response rate. Decreasing Θ from 3.5% to 3% brings a more significant decrease in the response rate than moving from 4% to 3.5%. This decrease is amplified at larger values of b. This behaviour is a consequence of the changes in size of the solution space for various values of Θ and b.

Figure 4.1: Impact of measurement error on the response rate

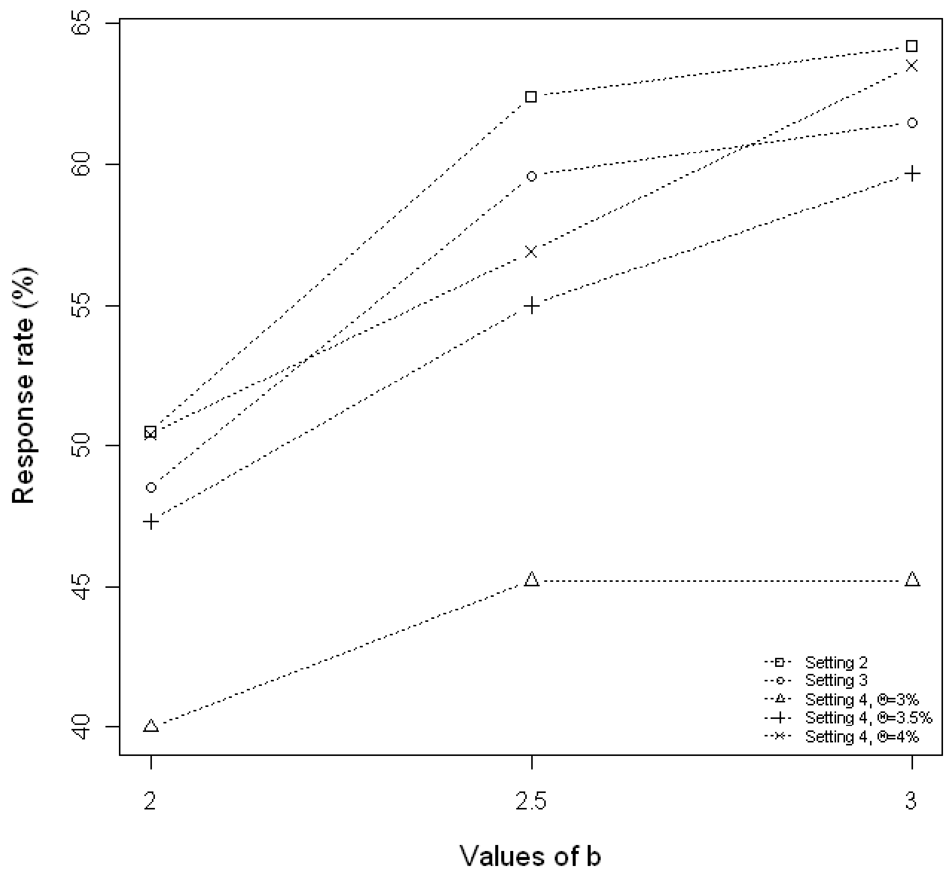

Figure 4.2: Impact of variability constraint on the response rate

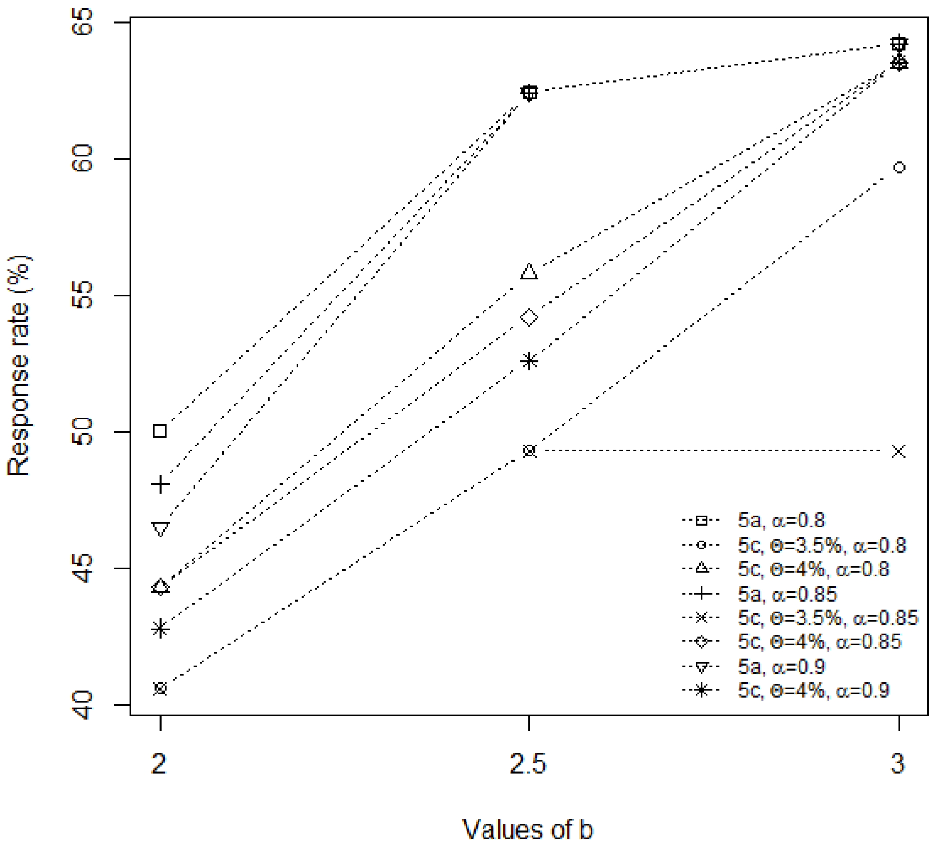

Figure 4.3: Evolution of response rate for various levels of minimum R-indicator

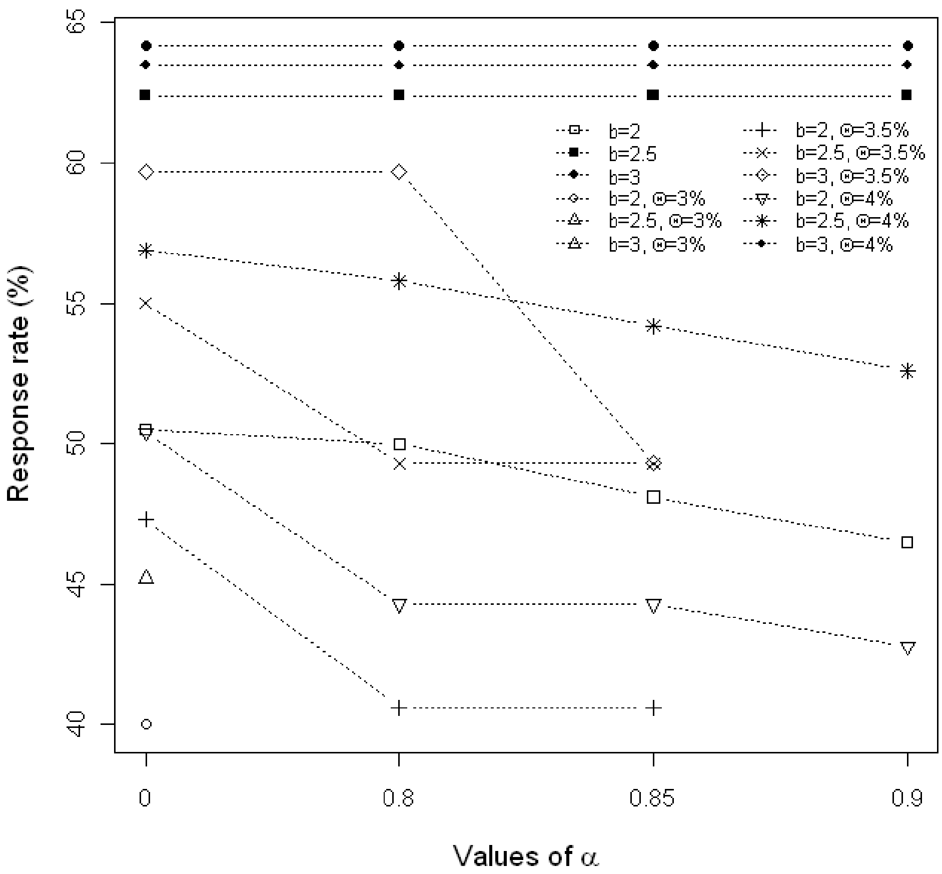

Figure 4.2 depicts the decrease in the response rate levels due to additional restrictions imposed by the variability constraint. In some cases (setting 5c, $\Theta = 3\%$) the solution space is reduced to an empty set, which leads to infeasibility. Figure 4.3 differs greatly from the previous ones by visualizing the response rate as a function of α. Settings 2 (i.e., $\alpha = 0$), 5a and 5c are compared. Here, the dotted lines connect response rate levels resulted from models that differ only in parameter α (i.e., b and Θ do not change across the lines). As noted before, similarity in graphical symbols across figures does not indicate any relation between the plotted values. The trend of most solutions is decreasing for increasing values of α, reaching infeasibility in the more extreme cases (e.g., for $\Theta = 3\%$). Moreover, high values of α (e.g., $\alpha = 0.9$) pose stricter conditions on the size of the solution space than Θ. Thus, the solution space can be reduced to an empty set even in the case of $\Theta = 3.5\%$.

5. Discussion

Survey research has tried to improve designs of surveys such that the quality of the estimates is high. To this end, multiple issues have to be taken into account, such as presence of nonresponse, measurement errors, lack of representativity in responses and budget overruns. To our best knowledge, this paper is the first that handles these issues simultaneously. In this paper, we present an optimization model that extends the framework of adaptive designs to specifically address measurement errors and response representativity. Thus, we hope to build a modelling basis for addressing measurement error and nonresponse error in adaptive designs.

We focus in our investigation on the difference between self- and proxy-reporting in the case of the Labour Force Survey. Proxy-reporting reduces the costs by less travelling and increases the response rates by higher contact probabilities. However, there are also disadvantages, namely the increase in the measurement error. It is not clear whether the disadvantages outweigh the benefits. Given the results in Section 4, we can conclude that it is not possible to run a full self-reporting survey, unless a very large budget is available. On the other hand, a full proxy-reporting survey does not lead to dangerously high levels of measurement profile risk. Also, it provides a high level of representativity of response.

We also evaluated whether measurement profile risk should be modelled as a correction in the objective function or as a constraint. Handling new objective functions in the ASD model is complex due to the non-linearity of those functions. Therefore, there is a preference for the second option (i.e., adding a constraint). The ASD model is flexible and guarantees optimality with short computational times. Developing more complex settings (adding various constraints) was successfully carried out.

A few remarks are in place. The choice of survey design features and the number of subgroups that enter the adaptive design should be modest and backed up by historical survey data. Certain combinations might not have enough support in the historical survey data to accurately estimate the input parameters. The accurate estimation of the input parameters is paramount to obtaining effective survey designs. In this paper, we have not performed sensitivity and robustness analyses, which would be necessary in order to implement them in practice. Furthermore, we simplified the model by assuming history-independent probability of contact. This is a crucial feature of the Markov decision problem, but may not be realistic in practical survey settings. Theoretically, the assumption can also be relaxed, leading to a more complex optimization problem. Future research should aim at addressing these issues in order to develop a model that provides robust and effective designs.

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Appendix A: Expansion of the ASD notation to measurement

In Calinescu et al. (2011), the ASD optimization for nonresponse is formulated as a Markov Decision Problem. We extend the notation of that paper to the ASD optimization for nonresponse and measurement error, as adopted by this paper. We again allow for time-dependent contact and participation probabilities, but assume independence on the history of contacts.

Sample units are clustered into $\mathcal{G} = \{1,..., G\}$ homogeneous groups. The relative sizes are w_g, i.e. $\sum_g w_g = 1$. The set of available strategies is represented by $\mathcal{M} = \{1,..., M\}$, and the data collection period is divided into $\mathcal{T} = \{1,..., T\}$ time slots. At each time slot $t \in \mathcal{T}$, a survey unit from group $g \in \mathcal{G}$ can be approached for the survey using strategy $m \in \mathcal{M}$. Group-dependent contact probabilities $p_g(t,m)$ and mode participation probabilities $r_g(t,m)$ are assumed to be known from historic survey data. The response probability is given by the product of the two probabilities, i.e., $p_g(t,m) r_g(t,m)$. Nonresponse occurs with probability $p_g(t,m)(1 - r_g(t,m))$ and non-contact with probability $1 - p_g(t,m)$. In case of noncontact, the unit can be considered for a future contact. An additional contact attempt at time t' via strategy m' brings response with probability $(1 - p_g(t,m)) p_g(t',m') r_g(t',m')$. Additional attempts to gain cooperation after refusal of an initial survey request are not included, but they could be added in a straightforward way.

Let $x_g(t,m) \in \{0,1\}$ be the decision variable that indicates whether units in subgroup g are approached for survey at time t using mode m. For simplicity, we assume that at time t only one mode can be employed to approach a group. This yields the following constraint

$$\sum_{m \in \mathrm{M}} x_g(t,m) \leq 1, \forall g \in \mathrm{G}, \ \forall t \in \mathrm{T} \ . \qquad \text{(A1)}$$

The probability that a contact would fail at time t', denoted by $f_g(t')$ is given by

$$f_g(t') = \prod_{t=1}^{t'} \prod_{m \in \mathrm{M}} \left[x_g(t,m)\left(1 - p_g(t,m)\right) + \left(1 - x_g(t,m)\right)\right] . \qquad \text{(A2)}$$

In other words, $f_g(t')$ represents the proportion of subgroup g that will be handled after time t'.

The ASD objective is to maximize quality in terms of the response rate. That is,

$$\max_{x_g(t,m)} \rho = \sum_{g \in \mathrm{G},\, t \in \mathrm{T},\, m \in \mathrm{M}} w_g\, f_g(t-1) x_g(t,m)\, p_g(t,m) r_g(t,m) . \qquad \text{(A3)}$$

The variance of the subgroup response rates can be written as

$$S^2 = \sum_{g \in G} w_g \left(\sum_{t \in T, m \in M} f_g(t-1) x_g(t,m)\, p_g(t,m) r_g(t,m) - \rho \right)^2 .$$

(A4)

The constraint on the R-indicator is given by

$$1 - 2S \geq \alpha \ , \qquad \text{(A5)}$$

where α is a pre-specified lower limit.

Let $b^s(m)$ be the costs incurred by a successful outcome via mode m, $b^{f_r}(m)$ be the costs at failure due to nonresponse, $b^{f_c}(m)$ be the costs at failure due to non-contact and B be the total available budget. The cost constraint is as follows

$$\sum_{g \in \mathcal{G},\, t \in \mathcal{T},\, m \in \mathcal{M}} N_g b_g(t,m) \leq B \ , \qquad \text{(A6)}$$

with

$$b_g(t,m) = x_g(t,m) f_g(t-1) \left[p_g(t,m) \left[r_g(t,m) b^s(m) + \left(1 - r_g(t,m)\right) b^{f_r}(m) \right] + \left(1 - p_g(t,m)\right) b^{f_c}(m) \right], \qquad \text{(A7)}$$

and N_g the sample size of group g.

Quality objective function (A3) and constraints (A1), (A4), (A5) and (A6) form the Markov decision problem (MDP) for nonresponse. The configuration $\left(x_g(t,m)\right)_{t \in \mathcal{T},\, m \in \mathcal{M},\, g \in \mathcal{G}}$, at optimality, forms the optimal strategy (i.e., the sequence of contact attempts that yields the highest response rate within the budget bounds).

We, now, add the two approaches to include the risk of measurement profiles. Let $\theta_g(t,m)$ be the probability for finding a measurement profile given cooperation at time slot $t \in \mathcal{T}$, survey mode $m \in \mathcal{M}$ and population group $g \in \mathcal{G}$.

Under approach 1, the probability for measurement profile is added to the quality objective function, and (A3) is adjusted to

$$\max \sum_{g\in G, t\in T, m\in M} w_g f_g(t-1) x_g(t,m) p_g(t,m) r_g(t,m)(1-\theta_g(t,m)) . \quad \text{(A8)}$$

Under approach 2, the probability for a measurement profile is added as a constraint:

$$\frac{\sum_{g\in G, t\in T, m\in M} w_g f_g(t-1) x_g(t,m) p_g(t,m) r_g(t,m)\theta_g(t,m)}{\sum_{g\in G, t\in T, m\in M} w_g f_g(t-1) x_g(t,m) p_g(t,m) r_g(t,m)} \le \Theta , \quad \text{(A9)}$$

i.e., the proportion of respondents showing an undesirable measurement profile is constrained to be smaller than a threshold Θ .

Appendix B: Optimal strategies for settings 5c

Table B.1: Optimal solution setting 5c with $\Theta = 3.5\%$ *(0=no visit, 1=self-report, 2=proxy)*

			#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	Response (%)
0.8	*15-25*	$b = 2$	1	1	0	0	0	0	0	0	0	0	27
		$b = 2.5$	1	1	1	0	0	0	0	0	0	0	35.4
		$b = 3$	1	1	1	1	0	0	0	0	0	0	41.7
	26-55	$b = 2$	1	1	1	0	0	0	0	0	0	0	43.1
		$b = 2.5$	1	1	1	1	1	0	0	0	0	0	54.4
		$b = 3$	1	1	1	1	1	1	1	1	1	1	63.3
	56-65	$b = 2$	1	1	0	0	0	0	0	0	0	0	46.9
		$b = 2.5$	1	1	0	0	0	0	0	0	0	0	46.9
		$b = 3$	1	1	1	1	1	1	0	0	0	0	66.7
0.85	*15-25*	$b = 2$	1	1	0	0	0	0	0	0	0	0	27
		$b = 2.5$	1	1	1	0	0	0	0	0	0	0	35.4
		$b = 3$	1	1	1	0	0	0	0	0	0	0	35.4
	26-55	$b = 2$	1	1	1	0	0	0	0	0	0	0	43.1
		$b = 2.5$	1	1	1	1	1	0	0	0	0	0	54.4
		$b = 3$	1	1	1	1	1	0	0	0	0	0	54.4
	56-65	$b = 2$	1	1	0	0	0	0	0	0	0	0	46.9
		$b = 2.5$	1	1	0	0	0	0	0	0	0	0	46.9
		$b = 3$	1	1	0	0	0	0	0	0	0	0	46.9

Table B.2: Optimal solution setting 5c with $\Theta = 4\%$ *(0=no visit, 1=self-report, 2=proxy)*

			#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	Response (%)
0.8	*15-25*	$b = 2$	1	2	0	0	0	0	0	0	0	0	32.7
		$b = 2.5$	2	2	0	0	0	0	0	0	0	0	37.4
		$b = 3$	2	2	2	2	2	2	1	0	0	0	57.2
	26-55	$b = 2$	1	2	2	0	0	0	0	0	0	0	46.9
		$b = 2.5$	1	1	1	2	2	2	0	0	0	0	59.5
		$b = 3$	1	1	1	1	1	1	2	2	2	2	63.9
	56-65	$b = 2$	2	1	0	0	0	0	0	0	0	0	48
		$b = 2.5$	2	2	2	2	0	0	0	0	0	0	63.2
		$b = 3$	1	1	1	2	2	2	2	2	2	2	68.8
0.85	*15-25*	$b = 2$	1	2	0	0	0	0	0	0	0	0	32.7
		$b = 2.5$	2	2	2	0	0	0	0	0	0	0	46.1
		$b = 3$	2	2	2	2	2	2	1	0	0	0	57.2
	26-55	$b = 2$	1	2	2	0	0	0	0	0	0	0	46.9
		$b = 2.5$	1	1	1	1	1	2	0	0	0	0	58.3
		$b = 3$	1	1	1	1	1	1	2	2	2	2	63.9
	56-65	$b = 2$	2	1	0	0	0	0	0	0	0	0	48
		$b = 2.5$	2	2	0	0	0	0	0	0	0	0	49
		$b = 3$	1	1	1	2	2	2	2	2	2	2	68.8
0.9	*15-25*	$b = 2$	2	2	0	0	0	0	0	0	0	0	37.4
		$b = 2.5$	2	2	2	0	0	0	0	0	0	0	46.1
		$b = 3$	2	2	2	2	2	2	1	0	0	0	57.2
	26-55	$b = 2$	1	1	1	0	0	0	0	0	0	0	43.1
		$b = 2.5$	1	1	1	2	2	0	0	0	0	0	56.3
		$b = 3$	1	1	1	1	1	1	2	2	2	2	63.9
	56-65	$b = 2$	1	2	0	0	0	0	0	0	0	0	48
		$b = 2.5$	2	2	0	0	0	0	0	0	0	0	46.9
		$b = 3$	1	1	1	2	2	2	2	2	2	2	68.8