

Representativity Indicators for Survey Quality

Theory behind the RISQ package for R

*Vincent de Heij, Reijer Idema, Barry Schouten
Centraal Bureau voor de Statistiek, The Netherlands*

*Natalie Shlomo
University of Manchester, United Kingdom*

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1. Introduction

This document is a manual of the R library RISQ. R code was initially developed within project RISQ (Representativity Indicators for Survey Quality) funded within the EU 7th Framework Programme. Between 2010 and 2024 various updates have been made. In 2026, the RISQ package was uploaded to CRAN including a new feature on the estimation of standard errors of changes in indicators during data collection.

The RISQ suite is developed in SAS and in R and earlier versions and documentation are available at www.risq-project.eu. In this manual, we give basic background to the various indicators, we explain how the suite can be used and adapted to any survey data set, and we illustrate its use for the anonymised data set hlc that comes along with the package. The SAS version of the code is not discussed here.

Detailed background to the concepts and ideas behind representativity indicators can be found in the following documents:

- Schouten, B., Cobben, F., Bethlehem, J. (2009), Indicators for the representativeness of survey response, *Survey Methodology*, 35 (1), 101 – 113.
- Schouten, B., Shlomo, N., Skinner, C. (2011), Indicators for monitoring and improving representativeness of response, *Journal of Official Statistics*, 27(2), 231 – 253.
- Shlomo, N., Skinner, C., Schouten, B. (2012), Estimation of an indicator of the representativeness of survey response, *Journal of Statistical Planning and Inference*, 142, 201 – 211.
- Shlomo, N., Schouten, B. (2013), Theoretical properties for partial indicators for representative response, Technical paper, Southampton, University of Southampton, UK
- Shlomo, N., Schouten, B., De Heij, V. (2013), Designing adaptive survey designs using R-indicators, Paper presented at NTTS conference, March 3 – 7, Brussels, Belgium, Available at: http://www.cros-portal.eu/sites/default/files/NTTS2013fullPaper_63.pdf
- Schouten, B., Shlomo, N. (2014), Selecting adaptive survey design strata with partial R-indicators, Discussion paper 2015xx, Statistics Netherlands, available at www.cbs.nl.

Guidelines and a general overview are contained in the following documents:

- Schouten, B., Morren, M., Bethlehem, J., Shlomo, N., Skinner, C. (2009), How to use R-indicators?, RISQ deliverable 3
- Schouten, B., Bethlehem, J. (2009), Representativeness indicators for measuring and enhancing the composition of survey response, RISQ deliverable 9
- Schouten, B., Bethlehem, J., Beullens, K., Kleven, Ø., Loosveldt, G., Rutar, K., Shlomo, N., Skinner, C. (2012), Evaluating, comparing, monitoring and improving representativeness of survey response through R-indicators and partial R-indicators, *International Statistical Review*, 80 (3), 382 – 399.

Examples of the use of representativity indicators in survey data collection monitoring are given in the following documents:

- Loosveldt, G., Beullens, K. (2009), Fieldwork monitoring, RISQ deliverable 5
- Loosveldt, G., Beullens, K., Luiten, A., Schouten, B. (2010), Improving the fieldwork using R-indicators: applications, RISQ deliverable 6
- Luiten, A., Schouten, B. (2013), Adaptive fieldwork design to increase representative household survey respons. A pilot study in the Survey of Consumer Satisfaction, *Journal of Royal Statistical Society, Series A*, 176 (1), 169 – 190.
- Schouten, B., Calinescu, M. (2013), Paradata as input to monitoring representativeness and measurement profiles. A case study on the Labour Force Survey, In *Improving surveys with paradata* (ed. F. Kreuter).
- Ouwehand, P., Schouten, B. (2014), Measuring representativeness of short term business statistics, *Journal of Official Statistics*, 30, (4).

All documents are available at www.risq-project.eu .

2. The R-indicator

The R-indicator is a transformation of the variance of estimated response propensities to the $[0, 1]$ interval. A value equal to 1 implies representative response. A value equal to 0 implies a maximal deviation from representative response.

Suppose the estimated response probabilities for the n elements in the sample are denoted by $\rho_1, \rho_2, \dots, \rho_n$ and the sample design inclusion weights are denoted by $d_1, d_2, \dots, d_n$. The design weights are the inverse of the probabilities that a population unit is contained in the survey sample. Then the R-indicator is computed as

$$R = 1 - 2S(\rho) = 1 - 2\sqrt{\frac{1}{N-1} \sum_{i=1}^n d_i (\rho_i - \bar{\rho})^2}, \quad (1)$$

with $\bar{\rho} = \frac{1}{N} \sum_{i=1}^n d_i \rho_i$ the weighted sample mean of the estimated response probabilities and N the size of the population.

Response probabilities can be estimated in the R component of the RISQ library by either a linear or a logistic regression. The default in R is a logistic regression. Let $X = (X_1, X_2, \dots, X_m)'$ be the vector of independent variables. X needs to be provided by the user. Main effect terms as well as interaction effect terms may be included.

The coefficient of variation is a relevant measure whenever a survey produces estimates for population means and totals only. In those cases it may be used instead of the R-indicator. It is defined as

$$CV = \frac{S(\rho)}{\bar{\rho}}. \quad (2)$$

We return to this measure in Sections 7 to 9.

R-indicators have a bias that is due to the estimation of response probabilities. In the RISQ suite the bias is approximated analytically. The standard output contains adjusted R-indicator values.

Suppose the link function h is used in the general linear model for the estimation of the response propensities ρ_i

$$\text{linear regression: } h(x^T \beta) = x^T \beta$$

$$\text{logistic regression: } h(x^T \beta) = \frac{\exp(x^T \beta)}{1 + \exp(x^T \beta)}.$$

Hence, $h(x_i^T \beta)$ is used as a predictor for ρ_i with β a vector that is estimated. Let $\hat{\beta}$ be the estimator and ∇h be the gradient, i.e. the vector with first order derivatives with respect to β .

For simple random samples without replacement, i.e. $d_i = N/n$, the adjusted R-indicator equals

$$R_B = 1 - 2\sqrt{\left(1 + \frac{1}{n} - \frac{1}{N}\right) S^2(\rho) - \frac{1}{n} \sum_{i \in s} z_i^T \left[\sum_{j \in s} z_j x_j^T \right]^{-1} z_i}, \quad (3)$$

with $z_i = \nabla h(x_i^T \hat{\beta}) x_i$.

Since R-indicators are based on weighted sample variances of estimated probabilities, they also have a standard error and precision. The RISQ library provides analytic standard error approximations for the R-

indicator. The standard errors (c.f. the previous sections on output) can be used to construct confidence intervals. We refer to Shlomo, Skinner and Schouten (2012) for details.

The standard error is estimated by

$$\widehat{\text{var}}[\hat{R}_\rho] \approx \hat{S}_\rho^{-2}(S_1 + S_2),$$

where S_1 is a standard design-based estimator of $\text{var}_s[\sum_{i \in s} u_i]$ where u_i is replaced by $d_i(\hat{\rho}_i - \hat{\rho}_U)^2$ in the resulting expression and with

$$S_2 = 4\hat{\mathbf{A}}'\hat{\mathbf{\Sigma}}\hat{\mathbf{A}} + 2\text{tr}[\hat{\mathbf{B}}\hat{\mathbf{\Sigma}}\hat{\mathbf{B}}\hat{\mathbf{\Sigma}}],$$

$$\begin{aligned}\hat{\mathbf{A}} &= N^{-1} \sum_{i \in s} d_i(\hat{\rho}_i - \hat{\rho}_U)(\hat{\mathbf{z}}_i - \hat{\mathbf{z}}_U), \\ \hat{\mathbf{B}} &= N^{-1} \sum_{i \in s} d_i(\hat{\mathbf{z}}_i - \hat{\mathbf{z}}_U)(\hat{\mathbf{z}}_i - \hat{\mathbf{z}}_U)', \\ \hat{\mathbf{z}}_U &= N^{-1} \sum_s d_i \hat{\mathbf{z}}_i,\end{aligned}$$

and $\hat{\mathbf{\Sigma}}$ a standard estimator of the covariance matrix of $\hat{\boldsymbol{\beta}}$ (the expected Fisher information) that is outputted by default by for example glm.

If $\sigma_R = \sqrt{\widehat{\text{var}}[\hat{R}_\rho]}$ is the estimated standard error of the R-indicator, then $[R - \xi_{1-\alpha/2}\sigma_R, R + \xi_{1-\alpha/2}\sigma_R]$ is an $100(1 - \alpha)\%$ confidence interval based on a normal approximation. $\xi_{1-\alpha/2}$ is the $1-\alpha/2$ percentile of the standard normal distribution.

3. Partial R-indicators on the variable level

3.1 The theory behind unconditional partial R-indicators

The unconditional partial R-indicator measures the amount of variation of the response probabilities between the categories of a variable. The larger the between-category variation is, the stronger the relationship is and the stronger the impact of the variable on response.

As earlier, let X_k be one of the components of the vector $\mathbf{X}$. Suppose X_k is categorical and has H categories. Let n_h denote the weighted sample size in category h , for $h = 1, 2, \dots, H$. That means

$$n_h = \sum_{i=1}^n d_i \Delta_{h,i}, \quad (4)$$

where $\Delta_{h,i}$ is the 0-1 indicator for sample unit i being a member of stratum h . Then $n_1 + n_2 + \dots + n_H = N$.

Let $\bar{\rho}$ again be the weighted mean response probability in the sample. Furthermore, let $\bar{\rho}_h$ the weighted mean of the response probabilities in category h of X_k .

The unconditional partial indicator for variable X_k is measuring the variation between the response categories of the H categories, and is defined as

$$P_U(X_k) = \sqrt{\frac{1}{N} \sum_{h=1}^H n_h (\bar{\rho}_h - \bar{\rho})^2} . \quad (5)$$

It holds that $P_U(X_k) \leq S(\rho) \leq 0.5^1$. i.e. the total variation between categories is always smaller than the total variation. The larger the value of (4), the stronger the impact of the variable on nonresponse. By computing and comparing the unconditional partial indicators for a set of variables it can be established for which variables the relationships are strongest.

Also the unconditional partial R-indicators may be subject to bias and like the overall R-indicator they have a standard error. The bias adjustment for the partial R-indicators at the variable level is based on prorating, see Shlomo and Schouten (2013). Based on extensive simulation studies, it was concluded that the bias approximations work satisfactory for sample sizes up to 15,000. For larger surveys it is recommended to use the unadjusted estimates, although they bias adjusted and bias unadjusted estimates are provided both in the output. The approximated standard error is taken equal to the standard error of the standard deviation of the estimated response propensities as if the response model consists only of the selected variable X_k . We refer to Shlomo, Schouten and De Heij (2013) for details.

3.2 The theory behind conditional partial R-indicators

Conditional partial indicators can only be computed for variables that are included in the response model. These indicators measure the relative importance of a variable, i.e. the impact of a variable conditional on all other variables in the response model. As such conditional partial R-indicators attempt to isolate the part of the deviation of representative response that is attributable to a variable alone.

The conditional partial indicator for a variable X_k is obtained by cross-classification of all model variables, but with the exception of X_k itself. Suppose, this cross-classification results in L cells $U_1, U_2, \dots, U_L$. Let n_l denote the weighted sample size in cell l , for $l = 1, 2, \dots, L$. Then again $n_1 + n_2 + \dots + n_L = N$. Furthermore, let $\bar{\rho}_l$ the mean of the response probabilities in cell l .

The conditional partial indicator for variable X_k is now defined as

$$P_C(X_k) = \sqrt{\frac{1}{N} \sum_{l=1}^L \sum_{i \in U_l} d_i (\rho_i - \bar{\rho}_l)^2} . \quad (8)$$

To say it in words: $P_C(X_k)$ is the remaining within cell variation of the response probabilities if the variable X_k is removed from the cross-classification. If, on the one hand, the remaining variation is large, this can apparently not be accounted for by the other variables. So, there is an important role for X_k . If, on the other hand, the remaining variation is small, the other variables are capable of explaining the variation. It can be concluded that there need not be a role for X_k in reducing the lack of representativity.

Also here it can be remarked that $P_C(X_k) \leq S(\rho) \leq 0.5$, i.e. the total variation within categories is smaller than the total variation, and again a larger value for $P_C(X_k)$ implies a stronger conditional impact.

¹ $S(\rho)$ attains its maximum value when half of the ρ_i 's are 0 and the rest are 1.

The conditional partial R-indicators may also be subject to bias and they have a standard error. The bias adjustment for the partial R-indicators at the variable level is based on prorating, see Shlomo and Schouten (2013). Based on simulation studies, it is again recommended to use the adjusted estimates for sample sizes smaller than 15,000 and the unadjusted estimates for larger sample sizes. Both estimates are, however, provided. The approximated standard error could be taken to be equal to the standard error of the standard deviation of the estimated response propensities, i.e. as if the response model consists only of all other variable X_k^- and not including the selected variable X_k . Based on simulation studies it was concluded that this approximation works satisfactory under most circumstances but may produce invalid results when the R-indicator attains values close to one. For this reason, the R code uses a conservative approximation, namely to take the standard error approximation of the unconditional variable-level partial R-indicator, which is always larger. We refer to Shlomo, Schouten and De Heij (2013) for details.

3.3 Bias and standard errors

As for the R-indicators, partial R-indicators have a bias and standard error.

In the RISQ library the bias of the variable-level partial R-indicators is adjusted by prorating the overall R-indicator bias over the partial R-indicators. That means that the estimated bias of the variance of response probabilities $B(S^2(\rho))$ is multiplied by the ratio between the square of the partial R-indicator and $S^2(\rho)$. This approximation is motivated by the fact that the partial R-indicators are between and within variances which are components of the total variance of response probabilities $S^2(\rho)$. The resulting, prorated bias is then subtracted from the between variance (unconditional partial R-indicators) or the within variance (conditional partial R-indicators). And the partial R-indicators are computed by taking the square root of the adjusted between or within variance.

Let $S_{W,unadj}^2(\rho)$ and $S_{B,unadj}^2(\rho)$ denote, respectively, the unadjusted within variance and the unadjusted between variance of the estimated response propensities. Both variance terms are adjusted for bias in the following way

$$S_W^2(\rho) = S_{W,unadj}^2(\rho) - B(S^2(\rho)) \frac{S_{W,unadj}^2(\rho)}{S^2(\rho)} \quad (11)$$

$$S_B^2(\rho) = S_{B,unadj}^2(\rho) - B(S^2(\rho)) \frac{S_{B,unadj}^2(\rho)}{S^2(\rho)} \quad (12)$$

and the adjusted partial R-indicators at the variable level are computed by taking square roots.

The category-level partial R-indicators are not adjusted for bias following recommendations in Shlomo and Schouten (2013).

For details about the standard error approximations for both variable-level and category-level partial R-indicators we refer to Shlomo, Schouten and De Heij (2013). Here, we restrict ourselves to a summary

- The standard error for the variable-level unconditional partial R-indicator is approximated by the standard error for the standard deviation of the estimated response propensities restricted to a model with only the selected variable. See Shlomo, Skinner and Schouten (2012) for details.
- The standard error for the variable-level conditional partial R-indicator approximated by the standard error for the standard deviation of the estimated response propensities restricted to a model with all variables except the selected variable. See Shlomo, Skinner and Schouten (2012) for details. This approximation does not behave well under all circumstances. For this reason in R the conservative choice is made to use the standard error approximation for the unconditional partial R-indicator at the variable-level.
- The standard error for the category-level unconditional partial R-indicator follows the approximation in Shlomo, Schouten and De Heij (2013).
- The standard error for the category-level conditional partial R-indicator follows the approximation in Shlomo, Schouten and De Heij (2013).

4. Partial R-indicators within categories

4.1 The theory behind unconditional category-level partial R-indicators

The unconditional partial R-indicator can give more information about the relationship of a variable X_k and response behaviour if this indicator is computed for each category of X_k separately. It is clear from (4) that each category h contributes an amount

$$\frac{n_h}{n} (\bar{\rho}_h - \bar{\rho})^2 \quad (6)$$

to $P_U(X_k)$. The unconditional partial indicators within categories are obtained by taking the square root of the quantities in (6), giving

$$P_U(X_k, h) = \sqrt{\frac{n_h}{N}} (\bar{\rho}_h - \bar{\rho}). \quad (7)$$

$P_U(X_k, h)$ can assume positive and negative values. A positive value means that the particular category is over-represented. A negative value means that the particular category is under-represented.

Based on a simulation study, Shlomo and Schouten (2013) recommend to not perform any bias adjustment at the category level.

4.2 The theory behind conditional category-level partial R-indicators

The conditional partial indicators can give even more insight when they are computed for each category of a variable separately. The remaining within cell variation of the response probabilities after removing a variable X_k from the cross-classification, is computed for each category of X_k separately. Let again X_k

have H categories, labelled $h=1,2,\dots,H$, and $\Delta_{h,i}$ be the 0-1 indicator for category h . From (7) it can be seen that each category h contributes an amount

$$\frac{1}{N} \sum_{l=1}^L \sum_{i \in U_l} d_i \Delta_{h,i} (\rho_i - \bar{\rho}_l)^2 \quad (9)$$

to $P_C(X_k)$. The conditional partial indicators within categories are then obtained by taking the square root of (9)

$$P_C(X_k, h) = \sqrt{\frac{1}{N} \sum_{l=1}^L \sum_{i \in U_l} d_i \Delta_{h,i} (\rho_i - \bar{\rho}_l)^2}. \quad (10)$$

The category-level conditional partial R-indicators are always larger than or equal to zero. A large value of (10) does not correspond to either under- or over-representation. Such an interpretation cannot be given as within some cells l the category may be over-represented while in other cells it may be under-represented. Hence, the subpopulation corresponding to a category may be overrepresented in some cells and underrepresented in others. The conditional partial indicator within a category $P_C(X_k, h)$ must be interpreted as the impact of that category on the deviation from representative response after conditioning on the other variables. The larger the indicator the larger the impact of that category and the more interesting the corresponding subpopulation becomes in nonresponse reduction methods.

Based on the simulation study described in Shlomo and Schouten (2013) no bias adjustment is performed for category-level partial R-indicators. Approximations for standard errors are provided.

5. The coefficient of variation and partial coefficients of variation

5.1 Coefficients of variation

In all RISQ deliverables, the R-indicators are interpreted in terms of the impact of nonresponse on survey estimation by considering the standardized bias of the design-weighted response mean $\hat{y}_r$ of a survey variable y

$$\frac{|B(\hat{y}_r)|}{S(y)} = \frac{|Cov(y, \rho_Y)|}{\bar{\rho}S(y)} = \frac{|Cov(y, \rho_{\mathbb{X}})|}{\bar{\rho}S(y)} \leq \frac{S(\rho_{\mathbb{X}})}{\bar{\rho}} = \frac{1-R(\mathbb{X})}{2\bar{\rho}}, \quad (13)$$

with $\bar{\rho}$ the average response propensity and $\mathbb{X}$ the vector of auxiliary variables explaining response behaviour. The vector $\mathbb{X}$ is unknown and, as a consequence, we do not know $\rho_{\mathbb{X}}$. Since we are interested in the general representativeness of a survey, i.e. not the representativeness with respect to single survey items, we use as an approximation for (13)

$$CV(X) = \frac{1-R(X)}{2\bar{\rho}}. \quad (14)$$

CV is the coefficient of variation of the estimated response propensities and represents the maximal absolute standardized bias under the scenario that non-response correlates maximally to the selected auxiliary variables. ρ_X are the response propensities with a response model based on X . The coefficient of variation (14) is estimated by

$$CV(X) = \frac{S(\hat{\rho}_X)}{\hat{\rho}}. \quad (15)$$

The standard error of (15) is derived using the approximation

$$Var(CV(X)) \cong \frac{S^2(\hat{\rho}_X)}{\hat{\rho}^2} \left[\frac{Var(\hat{\rho})}{\hat{\rho}^2} + \frac{Var(S(\hat{\rho}_X))}{S(\hat{\rho}_X)^2} - 2 \frac{Cov(\hat{\rho}, S(\hat{\rho}_X))}{\hat{\rho} S(\hat{\rho}_X)} \right]. \quad (16)$$

Let the variance of the standard deviation of response propensities be denoted by S^2 . It can be reasoned that the covariance between the mean and standard deviation of the response propensities in (16), $Cov(\hat{\rho}, S(\hat{\rho}_X))$, is negligible as long as $\hat{\rho}$ is roughly in the range $[0.2, 0.8]$. In the extreme case where all response propensities are either zero or one, $S(\hat{\rho}_X)$ is approximately equal to $S(\hat{\rho}_X) = \sqrt{\hat{\rho}(1-\hat{\rho})}$. For $\hat{\rho} \in [0.2, 0.8]$ this function is very flat and covariances must be small. For values of $\hat{\rho} \leq 0.2$, there is a positive covariance, and for $\hat{\rho} \geq 0.8$ there is a negative covariance. Since it can be expected that response propensities will not all be zero or one, even for values outside the range $[0.2, 0.8]$, the covariance is expected to be small. The variance of the average response propensity, $Var(\hat{\rho})$, is also small. It can be approximated by $S^2(\hat{\rho}_X)/n$, with n the sample size.

Given these considerations, the approximation (15) is rewritten to

$$Var(CV(X)) \cong \frac{S^2(\hat{\rho}_X)}{\hat{\rho}^2} \left[\frac{S^2(\hat{\rho}_X)}{n\hat{\rho}^2} + \frac{S^2}{S(\hat{\rho}_X)^2} \right] = \frac{S^2}{\hat{\rho}^2} + \frac{S^4(\hat{\rho}_X)}{n\hat{\rho}^4}. \quad (17)$$

5.2 Partial coefficients of variation

Analogous to the partial R-indicators, there is an unconditional and a conditional version, and there are variable-level and category-level coefficients. In all cases, they are defined as the corresponding partial R-indicator divided by the estimated mean of the response propensities.

The variable-level unconditional CV, $CV_U(X_k)$, is defined as

$$CV_U(X_k) = \frac{P_U(X_k)}{\hat{\rho}}, \quad (18)$$

the variable-level conditional CV, $CV_C(X_k)$, is defined as

$$CV_C(X_k) = \frac{P_C(X_k)}{\hat{\rho}}, \quad (19)$$

and analogously for the category-level versions.

Standard errors for the partials coefficients are derived analogously to (16), and are approximated by

$$Var(CV_U(X_k)) \cong \frac{S^2}{\hat{\rho}^2} + \frac{P_U^2(X_k)S^2(\hat{\rho}_X)}{n\hat{\rho}^4}, \quad (20)$$

$$\text{Var}(CV_C(X_k)) \cong \frac{S^2}{\hat{\rho}^2} + \frac{P_C^2(X_k)S^2(\hat{\rho}_X)}{n\hat{\rho}^4}, \quad (21)$$

where the S^2 is the estimated variance of the unconditional partial R-indicator in (20) and the conditional partial R-indicator in (21).

6. General guidelines to R-indicators and partial R-indicators

The following, general recommendations must be kept in mind when using the (partial) R-indicators and (partial) coefficients of variation:

- None of the indicators can be evaluated or presented separately from the variables X that were used in the response model and all indicators should always be presented together with X .
- When comparing different surveys, one should use the same model for nonresponse, where the variables X , have the same categories.
- All indicators should be adjoined by a confidence interval in order to indicate the uncertainty due to the estimation based on a sample.
- The inclusion of response-unrelated variables into the response model leads to an increase of the standard errors of the indicators. It is recommendable to restrict analysis to variables X for which it is known from the literature or strongly conjectured that they relate to response behaviour and to the key survey variables. If there is a wide range of survey variables, or the objective is to compare different surveys, then they should, generally, relate to response behaviour.
- R-indicators measure the distance to a fully representative response; they do not reflect the impact of non-response on the bias of (weighted) means or the contrast of survey variables, and nor does the response rate. The coefficient of variation combines the response rate and the R-indicator and is designed to make comparisons of non-response bias under worst case scenarios.

The various indicators may be used to compare different surveys or a single survey in time. When comparing different surveys, we recommend to fix a number of sets of auxiliary variables beforehand (including interactions) and to add all variables to the models. One should restrict to demographic and socio-economic characteristics that are generally available in many surveys. When comparing a survey in time, we recommend to fix a number of sets of auxiliary variables. However, now the sets may also include variables that correlate to the main survey items, and variables that relate to the data collection (paradata). When many variables are available, parsimonious models may be favoured.

Partial R-indicators provide insight that is helpful in the reduction of nonresponse. We provide the following simple guidelines:

- In the comparison of different surveys, partial R-indicators are supplementary to R-indicators. Response models are simple and employ general auxiliary variables only.
- In the comparison of a survey in time, partial R-indicators are again supplementary to R-indicators. Response models may be more complex, e.g. define multiple model equations or levels, and may employ paradata additionally to auxiliary variables.

- Conditional partial R-indicators should be used in conjunction with unconditional partial R-indicators. They are always smaller than the unconditional partial R-indicators and comparing the two shows to what extent the apparent impact of a single variable is taken away by the others.
- When many variables are added to models for response, then conditional partial R-indicators naturally are smaller. When two or more variables are included that correlate strongly, then the conditional partial R-indicators will be small for both variables. It is recommendable not to include many related variables.

R-indicators and the more detailed partial R-indicators measure the distance to a fully representative response; they do not reflect the impact of non-response on the bias of (weighted) means or the contrast of survey variables, and nor does the response rate. The coefficient of variation combines the response rate and the R-indicator and is designed to make comparisons of non-response bias under worst case scenarios. When a survey or multiple surveys have (mostly) population means or totals as the parameters of interest, then (partial) coefficients of variation are more suitable than (partial) R-indicators. A solution is to use so-called response-representativity plots (e.g. Schouten, Cobben, Bethlehem 2009 and Ouwehand and Schouten 2014) in which iso-bias lines reflect a constant coefficient of variation. Another solution is to use the (partial) coefficient of variation directly for evaluating and monitoring response.

As a general guideline, we conclude with the remark that in improving representativity of response it must always be the objective to increase the response rate and to improve the R-indicators simultaneously.