

Cross-national Issues in Response Rates¹

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This article was originally published in *The Palgrave Handbook of Survey Research* by Palgrave Macmillan. The publisher's version of this article is available at: <https://link.springer.com/book/10.1007/978-3-319-54395-6>.

Suggested citation: Vehovar, V. in Beullens, K. (2018). Cross-national issues in response rates. V: Vannete, D. L. in Krosnick, J. A. (ur.). *The Palgrave handbook of survey research* (str. 29-42). Cham: Palgrave Macmillan. http://dx.doi.org/10.1007/978-3-319-54395-6_6.

¹ D.L. Vannette, J.A. Krosnick (eds.), *The Palgrave Handbook of Survey Research*, https://doi.org/10.1007/978-3-319-54395-6_6

Introduction

It is commonly agreed that response rates express the ratio between the responding and eligible units in a survey. The American Association for Public Opinion Research (AAPOR) Standard Definitions (2016) set the standards here, including formulas for response rate calculations. In this chapter, we overview contemporary issues concerning response rates. We first illustrate the existing level of response rates in general population surveys. Next, we overview complications with response rate calculations that are emerging due to the expanded use of web surveys and other technological changes. Finally, we address the context of survey costs, which we believe is one of the highest response rate research challenges.

Response rates in the European Social Survey

We illustrate the response rate levels and trends from a European perspective which, however, is very typical of all developed countries. For brevity, we further narrow the focus to general population surveys and the academic context. The European Social Survey (ESS) is perhaps the best case for this purpose given its standardized face-to-face survey mode and that it requires at least four contact attempts. In addition, ambitious methodological targets have been set: non-contacts no greater than 3% and response rates no less than 70% of the sampled persons. Nonresponse issues are studied very closely, including the use of contact forms (e.g. interviewer observations of neighborhood conditions). Response rates are also comprehensively documented² and extensively researched (e.g. Stoop et al., 2010, Billiet & Vehovar, 2009).

Table 1 presents response rates (AAPOR standard RR1) for all countries and for all rounds, from Round 1 in 2002 (R1) to Round 7 in 2014 (R7). We can observe that in some countries the response rates are steadily declining (Germany, Norway, Slovenia, Sweden), but sometimes the opposite trend can also appear (France, Spain, Switzerland), which is mainly due to increased efforts in these countries. When interpreting these figures, we need to be aware that the change (e.g. decline) in respondents' willingness to cooperate can hardly be separated from the year-to-year variations in the level of the survey efforts and fieldwork procedures, such as a change in the survey agency, respondent incentives, interviewer rewards, advanced letters, refusal conversion, etc. However, the overall impression is that response rates converge to between 50%–60%. Alternatively, we could say that the countries make an effort to assure response rates of between 50%–60%. Of course, such a claim might also suggest that further efforts – which could bring the response rates up closer to 70% or higher – are not reasonable since the gains in data quality would be too small given the increase in costs. We address this very intriguing issue in final sections, where we discuss the costs.

² <http://www.europeansocialsurvey.org/>

Table 1: Response rates (%) in the European Social Survey across countries and seven rounds (R1–R7)

COUNTRY	R1 (2002)	R2 (2004)	R3 (2006)	R4 (2008)	R5 (2010)	R6 (2012)	R7 (2014)
Albania	-	-	-	-	-	79	-
Austria	60	62	64	62	-	-	52
Belgium	59	62	62	59	54	59	57
Bulgaria	-	-	66	76	82	75	-
Croatia	-	-	-	64	55	-	-
Cyprus	-	-	67	82	71	77	-
Czech	54	71	-	71	71	69	68
Denmark	68	65	51	54	55	49	52
Estonia	-	79	65	63	56	68	60
Finland	73	71	64	68	60	67	63
France	43	44	47	50	48	53	52
Germany	56	53	55	48	32	34	31
Greece	80	79	-	74	69	-	-
Hungary	70	70	66	62	61	65	53
Iceland	-	51	-	-	-	55	-
Ireland	64	63	57	53	65	68	61
Israel	71	-	-	85	73	78	74
Italy	44	61	-	-	-	37	-
Kosovo	-	-	-	-	-	67	-
Latvia	-	-	71	68	-	-	-
Lithuania	-	-	-	52	45	77	69
Luxembourg	44	52	-	-	-	-	-
Netherlands	68	64	60	50	60	56	59
Norway	65	66	66	60	58	55	54
Poland	73	74	70	71	70	75	66
Portugal	69	71	73	76	67	77	43
Romania	-	-	72	68	-	-	-
Russia	-	-	70	68	67	67	-
Slovakia	-	63	73	73	75	74	-
Slovenia	72	70	65	59	65	58	52
Spain	53	56	66	67	69	71	68
Sweden	69	66	67	63	51	53	51

Switzerland	33	47	52	50	54	52	53
Turkey	-	54	-	67	-	-	-
Ukraine	-	67	66	62	64	59	-
UK	56	51	55	56	56	53	44

- Countries were not included in the corresponding round

Response rate variations across survey types

Let us illustrate the trends and variations in response rates across survey types. We restrict ourselves here only to probability surveys of the general population (we talk about nonprobability surveys in the next section). We further narrow the illustration to the case of Slovenia, which is a typical European Union country with respect to various socio-economic indicators, including survey participation. The directions of the response rate variations presented below are thus very likely to also be found in other countries. Unless stated otherwise, the estimates are for 2015.

Face-to-face surveys of a general population are best illustrated by the Slovenian general social survey (called SJM), one of the longest-running academic surveys in the world. It started in 1968 with a response rate close to 100%, before dropping to 92% (1980) and 86% (1992) (Štebe, 1995). Further declines have more recently led to response rates similar to those for the ESS (Table 1), from 72% (2002) to 53% (2014). The same trend can also be observed with the OECD survey *Programme of the International Assessment of Adult Competencies* (PIAAC³) where the response rate dropped from 70% in 1998 to 62% in 2014. In official statistics⁴, the response rates are slightly higher: 69% for *European Union Statistics on Income and Living Conditions* (EU-SILC) and 68% for the *Labour Force Survey* (LSF), while *Household Budget Surveys* (HBS) have a response rate of 56% for the general part and 49% for the diary part. On the other side, the most elaborated commercial surveys with contact strategies similar to the ESS (e.g. *National Readership Survey*) struggle to achieve 30% response rates (Slavec & Vehovar, 2011).

Let us also provide some expert estimates of response rates for other survey modes in Slovenia:

- The **telephone surveys** in official statistics (e.g. Consumer attitude survey, Tourism travels of the domestic population, Household Energy Consumption) typically obtain a response rate of 40%–50%. In academic surveys, the response rates are around 30%–40%, while for commercial ones they are around 10%. However, due to public telephone directories' low coverage of just 50% of the target population, the overall 'reach' is only less than half of that, i.e. below 25%

³ <http://www.oecd.org/site/piaac/>

⁴ Figures related to official statistical surveys are taken from the website of the Statistical Office of Republic of Slovenia, www.stat.si.

- The **mail surveys** (without incentives) from government statistical offices can obtain response rates of up to about 50%, in academic surveys they range from 20%–40%, while commercial surveys are typically in single digits.
- The **web surveys with mail invitations** in official statistics have response rates of up to 25% (In 2015 the Internet household penetration rate in Slovenia was 78%⁵). Use of mixed-mode data collection (a web questionnaire followed by a mail questionnaire) can move this above 30% and it has been demonstrated that prepaid incentives (5€) can even boost it above 70% (Berzelak et al., 2015).

Response rates and technological evolution

The changes brought by technology, predominantly reflected in the expansion of web surveys, are strongly altering the response rate landscape. On one side, they introduce various problems for response rate calculations:

- With **standard web surveys** (Callegaro et al., 2015) definition problems appear due to the changing nature of breakoffs, as well as with usable, unusable, complete, and partial units. For example, AAPOR (2016, p. 15) still relies on a classification and terminology based on the face-to-face situation in which a break-off has usually meant an unusable interview with the result that completeness statuses are still classified as complete, partial, or breakoff interviews. However, this does not reflect the specific understanding of breakoffs in web surveys, where breakoffs can still have a complete or partial status (e.g. when a respondent leaves the survey one question before the last one). Similarly, web surveys can hardly be called interviews because typically no interviewer is involved.
- In **online probability panels** serious complications appear (DiSogra & Callegaro, 2016) when calculating the response rate due to the increasing complexity of various stages of recruitment (AAPOR, 2016, p. 23).
- Surveys are also conducted with dedicated **mobile survey apps** where respondents answer the questionnaire in off-line mode. This introduces new issues for response rate calculations. For example, a unit may have problems installing the app or a unit might provide all answers, but they were not successfully transmitted, so such cases should be separated from non-cooperation and implicit refusal. Currently, it is unclear exactly how to do this.
- Various **new survey devices** have emerged, from tablets and smart phones to gaming consoles, Web TV and unobtrusive wearable devices. With the “Internet of things”, almost any device linked to the

⁵ Source Eurostat:

<http://ec.europa.eu/eurostat/tgm/table.do?tab=table&init=1&language=en&pcode=tin00134&plugin=1>. Available May 10, 2016.

Internet can also serve as a survey device. However, for any given device, the technical specifics will potentially require adaptations in response rate calculations because of the unique situations that can arise there, similar to those discussed above for mobile apps.

- Technology is also accelerating the introduction of **mixed-mode** surveys, particularly various combinations of inexpensive web surveys and traditional modes (face-to-face, telephone, mail). However, with mixed modes the response rates are becoming complicated to calculate, complex to decompose across the modes, and difficult to compare. They are also becoming less and less informative, as we demonstrate in the next section on survey costs.

On the other side, the changes brought by technology are also closely linked to the prevalent use of nonprobability samples where units are included in a survey with unknown (or zero) probabilities (Vehovar et al., 2016). As a consequence, the initial purpose and meaning of response rates is lost. Namely, without knowing the probabilities of inclusion, the measures developed in probability sampling – including response rates and confidence intervals – cannot and should not be calculated because these calculations rely on the corresponding probabilities. Despite this fact, many practitioners routinely misapply such calculations also in the nonprobability context. However, these response rates, even if calculated, do not represent the response behavior of the target population, but only measure the recruitment efficacy in a specific subset of the target population. Consequently, for some types of nonprobability sampling (e.g. nonprobability online panels, river sampling) the AAPOR Standard Definitions (2016) recommend labelling the ratios between the number of respondents and the number of invited units as “participation rates” and not as response rates. For some other sample types (e.g. quota and convenience samples), we neither count nor care about the nonresponding units so response rate calculations are not possible at all. The new dominance of nonprobability sampling – which is increasingly considered even in official statistics (Cooper & Greenaway, 2015; Rendtel & Amarov, 2015) – is thus radically changing the traditional meaning of the term “response rate”.

Response rates within the context of survey costs

The emerging technological changes and nonprobability samples are not only revolutionizing the survey format and the role of response rate calculations, but they highlight the importance of costs, which have been a somewhat neglected research topic in survey methodology. More specifically, it is very much true that response rates have been extensively discussed in general textbooks, dedicated monographs, papers, book chapters and workshops, such as the Household Survey Nonresponse workshop (1990–2015).⁶

⁶ <http://www.nonresponse.org/>

However, the overall impression is that this research predominantly focuses on isolated aspects related to trends, levels, mediating factors, prevention measures, and post-survey adjustments. On the other side, response rates are rarely observed in relation to nonresponse bias (which is defined as the difference between the true value and expected value of the variable in a sample survey). Namely, when respondents differ from nonrespondents (e.g. respondents may have higher incomes than nonrespondents), this can result in incorrect estimates (e.g. the reported mean income is too high) which produces nonresponse bias. To observe this relationship, we need to run experiments or simulations within single surveys, a research approach we encounter surprisingly rarely (e.g. Fuchs et al., 2013). Meta-analysis of different surveys (e.g. Groves & Peytcheva, 2008) cannot help much here because the uncontrolled variables and selection bias create spurious effects (i.e. ecological fallacies) known in aggregated analyses. For example, surveys with variables, which are vulnerable to nonresponse bias, already make additional efforts to achieve high response rates so as to prevent nonresponse bias, which then contributes to the (false) impression that there is no relationship between response rates and nonresponse bias. To study this relationship, the effect of the increased efforts needs to be observed in a single survey where we can control all the other survey characteristics. For this purpose, we provide the following illustration.

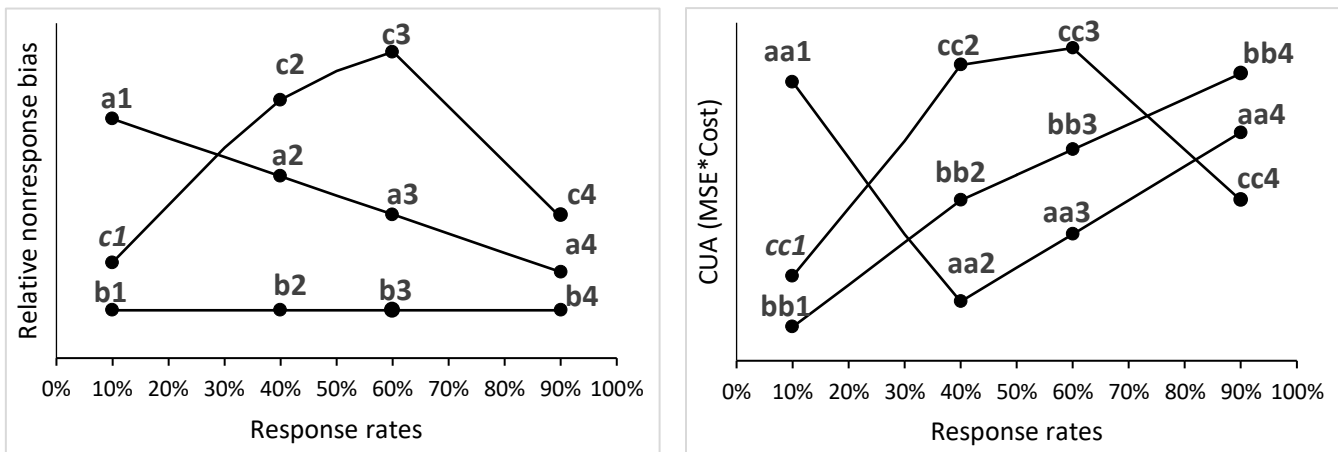
Three hypothetical but plausible situations are illustrated for a single variable, where – all else equal – we observe the effects of increased efforts to obtain high response rates (e.g. more contacts, higher incentives, refusal conversions) on the nonresponse bias. We can assume that initial response rates of 10% would be obtained, say, with a single contact attempt, 40% with three contacts, 60% with five and 90% with 10 contacts. In Figure 1 (left panel), we present three potential patterns showing the relationship between response rates and nonresponse bias:

- **Line a** shows the most commonly expected situation where increased efforts actually improve the bias; the corresponding points a1 (response rate 10%), a2 (40%), a3 (60%) and a4 (90%) show a linearly declining bias.
- However, it is often true, particularly for variables in marketing research, that response rates have little effect on the bias. Fuchs et al. (2013) also demonstrated for many variables in the ESS that increased response rates (due to more contact attempts) do not change the estimates, so little relation was found with the bias. **Line b** shows this very clearly because efforts to move response rates from 10% → 40% → 60% → 90% have no effect on the bias ($b_1 = b_2 = b_3 = b_4$).
- Intriguingly, situations also exist where increased response rate efforts attract even more of the unrepresentative population (Vehovar et al., 2010), so the initial increase in the response rate is counterproductive. We have this situation with **line c** where the rise in the response rate from 10%

to 40% and then to 60% further increases the bias ($c1 \rightarrow c2 \rightarrow c3$). It is only when efforts push the response rate beyond 60% ($c3$) and towards 90% ($c4$) that the bias starts to decrease.

These hypothetical examples reveal that a high response rate is not always desirable. Still, this is often an implicit assumption, although there is no empirical evidence showing this is generally true. Instead, as we demonstrated above, the relationship can be very complex. The situation further changes when we observe the entire context of the total survey error, which is often reduced to **accuracy** (Vehovar et al., 2010). The latter is measured with the inverse of the mean squared error (MSE), which typically integrates bias and sampling variance ($MSE = Bias^2 + Var$).

Figure 1: Response rates in relation to nonresponse bias (left) and costs per unit of accuracy (right)



Even more differences appear when we integrate not only nonresponse bias and accuracy, but also the survey costs, e.g. Vehovar et al. (2010), Vannieuwenhuyze (2014), Tourangeau et al. (2016), and Roberts et al. (2014). This also puts the problem in a real setting the practitioner faces: which survey design and nonresponse strategy provides the “best buy”, i.e. the best information (highest data quality) for my costs (efforts)? For this purpose, we observe the **costs per unit of accuracy (CUA)**, which can be calculated as the product of total survey costs and MSE. Based on the CUA, Figure 1 (right panel) further expands the three examples:

- With **line a**, where an increasing response rate reduces the bias, the decreased bias ($a1 \rightarrow a3$) initially (10% \rightarrow 40%) outweighs the increased costs. As a consequence, the CUA first decrease ($aa1 \rightarrow aa2$), too. However, later (at 60% and 90%) the costs of achieving higher response rates outweigh the gains ($a2 \rightarrow a4$) of the reduced bias. The best buy (i.e. the lowest CUA) thus remains at 40% ($aa2$).

- With **line b**, where increased response rates are of no help in reducing the bias, this same effect also manifests in a steady increase of the corresponding CUA ($bb1 \rightarrow bb2 \rightarrow bb3 \rightarrow bb4$), so $bb1$ at response rate of 10% remains the optimal decision.
- With **line c**, the initial efforts to increase the response rates (10% \rightarrow 40% \rightarrow 60%) are counterproductive, because – besides increasing the costs – they further increase the bias ($c1 \rightarrow c2 \rightarrow c3$). As expected, this also increases the CUA ($cc1 \rightarrow cc2 \rightarrow cc3$). Only after 60% do the efforts to increase the response rates (towards 90%) finally become beneficial and they decrease the CUA ($cc4$). However, the best buy still remains at 10% ($cc1$).

These hypothetical, yet realistic, illustrations show how risky it is to focus only on response rates because in surveys we wish to obtain (accurate) information with given resources, and we do not necessarily focus on high response rates or low nonresponse bias. Adding the context of costs can thus radically change the conclusion from an analysis based on the isolated treatment of response rates. For example, when Lozar Manfreda et al. (2008) observed in their meta-analysis of response rates that web surveys have 10% lower response rates compared to mail surveys, this is a very limited and partial insight because the results would likely change if the key metric was the CUA. In this case, the cost savings from using a web survey could be invested, say, in incentives, which would further increase the corresponding response rate, thereby dramatically changing the response rate comparisons.

The decreased informative value of response rates can already be observed in the context of mixed-mode surveys, where the response rates are usually lower than in an alternative surveys based only on a single traditional mode. This is typically true when web is combined with face-to-face mode (Ainsaar et al., 2013) or when web is combined with mail (Dillman, 2013). However, despite the lower response rates, researchers (and clients) still prefer mixed-mode designs because of their better cost-error performance.

Conclusions

We can summarize that with probability samples the response rates for academic face-to-face surveys of the general population have roughly stabilized (at least in Europe) in the range of 50%–60%. Of course, this is achieved – and continuously preserved – only at the cost of increased efforts. In addition, there are considerable variations in response rates depending on type of survey and other circumstances. On the other hand, we can observe that technological changes, emerging nonprobability samples and mixed-mode surveys are creating serious problems for response rate calculations and also for their perceptions.

We also demonstrated in this chapter that an extremely important issue for future response rate research relates to the context of costs, which is a much neglected research area. The explicit modelling of the relationships between response rates, response bias, accuracy, and survey costs can thus bring about important insights here, which can help practitioners in deciding whether to increase the efforts to achieve high response rates or not.

Directions that are also challenging for future response rate research are the efforts to provide improved definitions and calculations, as well as strategies for observing and comparing response rates. With respect to the latter, a very important challenge stems from international surveys and comparative research.

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