

Variance estimation for sensitivity analysis of poverty and inequality measures in complex surveys

-Supplementary materials-

This document includes appendices B, C, and D. Appendix B covers simulation results on simple random sampling not shown in section 6 and results on stratified sampling. Simulation results for the Gini coefficient and the quintile share ratio are presented in appendix C. In appendix D the problem of weighting for panel attrition is discussed in more depth and different variants of weighting are compared.

B Further simulation results

This section covers additional results of the Monte Carlo simulations presented in section 6. Tables 1 and 2 are based on simulations using $\eta \sim \text{Unif}(0.34, 0.51)$. Table 1 shows results not included in the main text and results on stratified sampling are shown in table 2. The simulation variant using $\eta \sim \text{Unif}(0.32, 0.72)$ is covered by tables 3 (simple random sampling) and 4 (stratified sampling). Tables 5 and 6 include results of the third variant using $\eta \sim \text{Unif}(0, 1)$.

For stratified sampling two regional strata were used, namely West Germany and East Germany. Sample size was split equally between both strata, whereas the CNEF file includes only 24% East German households. This corresponds to oversampling of East German households which is common practice in German surveys. Otherwise simulations were conducted as described in section 6.

All tables show point estimates and standard error estimates. X_{true} denotes the true value of the quantity of interest, $E(X_{\text{sim}})$ is the mean of the sample estimator over all 50000 replications and r.b. is relative bias calculated as $[E(X_{\text{sim}}) - X_{\text{true}}]/X_{\text{true}}$.

In case of stratified sampling relative bias is slightly larger than compared to simple random sampling, but still is small in absolute terms. A notable exception are the results based on $\eta \sim \text{Unif}(0, 1)$ and small sampling fractions, for which relative bias is relatively large (table 6). This can be explained by the violation of the monotonicity assumption for large values of η as described in the main text. Nevertheless, if the assumption is not violated (table 2) or only slightly violated (table 4) results are quite accurate.

Table 1: Simple random sampling, $\eta \sim \text{Unif}(0.34, 0.51)$

Sampling fraction	2.5% ($n = 309$)		5% ($n = 618$)		10% ($n = 1235$)				
	X_{true}	$E(X_{\text{sim}})$	r.b.	X_{true}	$E(X_{\text{sim}})$	r.b.	X_{true}	$E(X_{\text{sim}})$	r.b.
$E(P)$	0.171	0.172	0.001	0.171	0.172	0.002	0.171	0.171	0.000
$SE(E(P))$	0.019	0.019	-0.011	0.013	0.013	-0.015	0.009	0.009	-0.001
$Q_P(0.5)$	0.170	0.171	0.006	0.170	0.171	0.004	0.170	0.171	0.003
$SE(Q_P(0.5))$	0.020	0.020	0.009	0.014	0.014	0.003	0.010	0.009	-0.003
$Q_P(0)$	0.164	0.162	-0.013	0.164	0.163	-0.005	0.164	0.164	-0.002
$SE(Q_P(0))$	0.019	0.019	0.014	0.013	0.014	0.013	0.009	0.009	0.013
$Q_P(1)$	0.180	0.183	0.012	0.180	0.181	0.005	0.180	0.181	0.003
$SE(Q_P(1))$	0.020	0.020	-0.004	0.014	0.014	-0.003	0.010	0.010	-0.003

Table 2: Stratified sampling, $\eta \sim \text{Unif}(0.34, 0.51)$

Sampling fraction	2.5% ($n = 309$)		5% ($n = 618$)		10% ($n = 1235$)				
	X_{true}	$E(X_{\text{sim}})$	r.b.	X_{true}	$E(X_{\text{sim}})$	r.b.	X_{true}	$E(X_{\text{sim}})$	r.b.
$Q_P(0.5)$	0.170	0.172	0.006	0.170	0.171	0.005	0.170	0.171	0.004
$SE(Q_P(0.5))$	0.020	0.020	-0.021	0.014	0.014	-0.026	0.010	0.010	-0.034
$Q_P(0)$	0.164	0.162	-0.014	0.164	0.163	-0.006	0.164	0.164	-0.001
$SE(Q_P(0))$	0.020	0.020	-0.015	0.014	0.014	-0.012	0.010	0.009	-0.016
$Q_P(1)$	0.180	0.183	0.014	0.180	0.182	0.007	0.180	0.181	0.003
$SE(Q_P(1))$	0.021	0.020	-0.038	0.014	0.014	-0.039	0.010	0.010	-0.038

Table 3: Simple random sampling, $\eta \sim \text{Unif}(0.32, 0.72)$

Sampling fraction	2.5% ($n = 309$)		5% ($n = 618$)		10% ($n = 1235$)				
	X_{true}	$E(X_{\text{sim}})$	r.b.	X_{true}	$E(X_{\text{sim}})$	r.b.	X_{true}	$E(X_{\text{sim}})$	r.b.
P [$\eta = 0.54$]	0.162	0.163	0.007	0.162	0.163	0.006	0.162	0.163	0.006
$SE(P)$ [$\eta = 0.54$]	0.020	0.019	-0.003	0.014	0.014	-0.006	0.009	0.009	-0.009
$E(P)$	0.166	0.166	0.001	0.166	0.166	0.002	0.166	0.166	0.001
$SE(E(P))$	0.018	0.018	-0.012	0.013	0.013	-0.015	0.009	0.009	-0.001
$Q_P(0.5)$	0.163	0.165	0.012	0.163	0.165	0.011	0.163	0.165	0.009
$SE(Q_P(0.5))$	0.019	0.020	0.049	0.013	0.014	0.028	0.009	0.009	0.018
$Q_P(0)$	0.154	0.149	-0.034	0.154	0.152	-0.018	0.154	0.153	-0.009
$SE(Q_P(0))$	0.019	0.019	0.002	0.013	0.013	0.001	0.009	0.009	0.005
$Q_P(1)$	0.183	0.185	0.012	0.183	0.184	0.003	0.183	0.183	0.000
$SE(Q_P(1))$	0.019	0.020	0.020	0.014	0.014	0.007	0.010	0.010	0.001

Table 4: Stratified sampling, $\eta \sim \text{Unif}(0.32, 0.72)$

Sampling fraction	2.5% ($n = 309$)		5% ($n = 618$)		10% ($n = 1235$)				
	X_{true}	$E(X_{\text{sim}})$	r.b.	X_{true}	$E(X_{\text{sim}})$	r.b.	X_{true}	$E(X_{\text{sim}})$	r.b.
$Q_P(0.5)$	0.163	0.165	0.013	0.163	0.165	0.012	0.163	0.165	0.010
$SE(Q_P(0.5))$	0.019	0.020	0.015	0.014	0.014	0.005	0.010	0.009	-0.013
$Q_P(0)$	0.154	0.149	-0.036	0.154	0.151	-0.019	0.154	0.153	-0.010
$SE(Q_P(0))$	0.020	0.019	-0.026	0.014	0.014	-0.017	0.010	0.009	-0.020
$Q_P(1)$	0.183	0.186	0.015	0.183	0.184	0.005	0.183	0.183	0.001
$SE(Q_P(1))$	0.020	0.020	-0.020	0.014	0.014	-0.027	0.010	0.010	-0.033

Table 5: Simple random sampling, $\eta \sim \text{Unif}(0, 1)$

Sampling fraction	2.5% ($n = 309$)		5% ($n = 618$)		10% ($n = 1235$)				
	X_{true}	$E(X_{\text{sim}})$	r.b.	X_{true}	$E(X_{\text{sim}})$	r.b.	X_{true}	$E(X_{\text{sim}})$	r.b.
$E(P)$	0.176	0.176	0.000	0.176	0.176	0.001	0.176	0.176	0.000
$SE(E(P))$	0.016	0.016	-0.016	0.011	0.011	-0.020	0.008	0.008	-0.006
$Q_P(0.5)$	0.165	0.170	0.030	0.165	0.168	0.021	0.165	0.167	0.014
$SE(Q_P(0.5))$	0.018	0.020	0.082	0.013	0.014	0.066	0.009	0.009	0.061
$Q_P(0)$	0.154	0.143	-0.071	0.154	0.148	-0.043	0.154	0.150	-0.025
$SE(Q_P(0))$	0.021	0.019	-0.087	0.014	0.013	-0.061	0.010	0.009	-0.037
$Q_P(1)$	0.229	0.223	0.002	0.229	0.229	0.001	0.229	0.229	0.001
$SE(Q_P(1))$	0.021	0.020	-0.009	0.014	0.014	-0.015	0.010	0.010	-0.018

Table 6: Stratified sampling, $\eta \sim \text{Unif}(0, 1)$

Sampling fraction	2.5% ($n = 309$)		5% ($n = 618$)		10% ($n = 1235$)				
	X_{true}	$E(X_{\text{sim}})$	r.b.	X_{true}	$E(X_{\text{sim}})$	r.b.	X_{true}	$E(X_{\text{sim}})$	r.b.
$Q_P(0.5)$	0.165	0.170	0.031	0.165	0.168	0.023	0.165	0.167	0.015
$SE(Q_P(0.5))$	0.019	0.020	0.055	0.013	0.014	0.039	0.009	0.010	0.028
$Q_P(0)$	0.154	0.143	-0.076	0.154	0.147	-0.047	0.154	0.150	-0.027
$SE(Q_P(0))$	0.022	0.019	-0.112	0.015	0.014	-0.084	0.010	0.009	-0.064
$Q_P(1)$	0.229	0.229	0.004	0.229	0.229	0.001	0.229	0.229	0.001
$SE(Q_P(1))$	0.021	0.020	-0.044	0.015	0.014	-0.054	0.010	0.010	-0.051

C Gini coefficient and quintile share ratio

C.1 Definitions and influence functions

In what follows, the Gini coefficient and the quintile share ratio are defined for finite populations and their influence functions are given. For detailed discussions and derivations see Langel and Tillé (2013) in case of the Gini coefficient and Osier (2009) and Langel and Tillé (2011) for the quintile share ratio.

Let G denote the Gini coefficient. In case of a finite population it can be defined as

$$G = \frac{2}{NY_{tot}^*} \sum_{k \in \mathcal{U}} N_k y_k^* - \frac{N+1}{N}, \quad (1)$$

where $Y_{tot}^* = \sum_{k \in \mathcal{U}} y_k$ and N_k is the rank of unit k with respect to equivalent income. The influence function of the Gini coefficient, I_G , is given by

$$I_G(M; k) = \frac{1}{NY_{tot}^*} [2N_k(y_k^* - \bar{Y}_k^*) + Y_{tot}^* - Ny_k^* - G(Y_{tot}^* + y_k^*N)], \quad (2)$$

where \bar{Y}_k^* is defined as

$$\bar{Y}_k^* = \frac{\sum_{l \in \mathcal{U}} y_l \mathbb{1}(N_l \leq N_k)}{N_k}. \quad (3)$$

The quintile share ratio S is given by

$$S = \frac{Y_{tot}^* - L(0.8)}{L(0.2)}, \quad (4)$$

where $L(\beta) = Y_\beta^*/Y_{tot}^*$ and $Y_\beta^* = \sum_{k \in \mathcal{U}} y_k^* \mathbb{1}(y_k^* \leq Q_{Y^*}(\beta))$. The influence function of the quintile share ratio, I_S , is given by

$$I_S(M; k) = \frac{y_k^* - 0.8Q_{Y^*}(0.8) + \mathbb{1}(y_k^* \leq Q_{Y^*}(0.8)) [Q_{Y^*}(0.8) - y_k^*]}{Y_{0.2}^*} - \frac{[Y_{tot}^* - Y_{0.8}^*][0.2Q_{Y^*}(0.2) - \mathbb{1}(y_k^* \leq Q_{Y^*}(0.2)) [Q_{Y^*}(0.2) - y_k^*]]}{Y_{0.2}^{*2}} \quad (5)$$

C.2 Simulation setup and results

Running simulations as described in section 6 in case of small samples leads to biased variance estimates for the Gini coefficient and the quintile share ratio. This can be seen in table 7 which shows relative bias of the standard error of the Gini coefficient and the standard error of the quintile share ratio using $\eta = 0.54$. Results for standard error

Table 7: Relative bias of the standard errors for the Gini coefficient and the quintile share ratio; simple random sampling; $\eta \sim \text{Unif}(0.32, 0.72)$

Sampling fraction	2.5% ($n = 309$)	5% ($n = 618$)	10% ($n = 1235$)
SE(G) [$\eta = 0.54$]	-0.209	-0.153	-0.098
SE(S) [$\eta = 0.54$]	-0.144	-0.108	-0.066

estimates of the quantiles of the induced distribution are not shown, but bias is of the same magnitude.

These results are at odds with simulations described in the literature, which show that influence functions generally work well for both the Gini coefficient and the quintile share ratio (Langel and Tillé, 2011, 2013). The reason for this difference is a peculiarity of the SOEP data. As will be described in more depth in the next subsection, the SOEP is comprised of several subsamples. Subsample G is a sample of high income households, which are oversampled. Both the Gini coefficient and the quintile share ratio are strongly influenced by observations in the tail of the income distribution. The number of extreme outliers is still small in absolute terms but these strongly affect simulation results for small sample size and because of oversampling their inclusion probabilities are unrealistically high.

To deal with this problem, 29 households with income above 250000 Euro were excluded from the analysis. This reduces the number of extreme estimates considerably while still including most households from subsample G. Otherwise simulations were run as described in section 6. Also note that results for the low income proportion are not sensitive to these outliers and results do not change much if they are not included.

Figures 1 and 2 show the Gini coefficient and the quintile share ratio as a function of η . Simulations were conducted assuming $\eta \sim \text{Unif}(0.32, 0.72)$. As can be seen from the figures the monotonicity assumption does hold approximately for both cases. More specifically, the Gini coefficient is a monotonic function of η on the interval $[0, 0.69]$ and for the quintile share ratio the monotonicity assumption approximately holds on the interval $[0, 0.73]$.

Simulation results based on the slightly restricted data set are given in tables 8 (Gini coefficient) and 9 (quintile share ratio). X_{true} denotes the true value of the quantity of interest, $E(X_{\text{sim}})$ is the mean of the sample estimator over all 50000 replications and r.b. is relative bias calculated as $[E(X_{\text{sim}}) - X_{\text{true}}]/X_{\text{true}}$. Both tables include results for standard error estimates of the induced distribution. In all cases bias is negligible and results prove again that variance estimates are reliable.

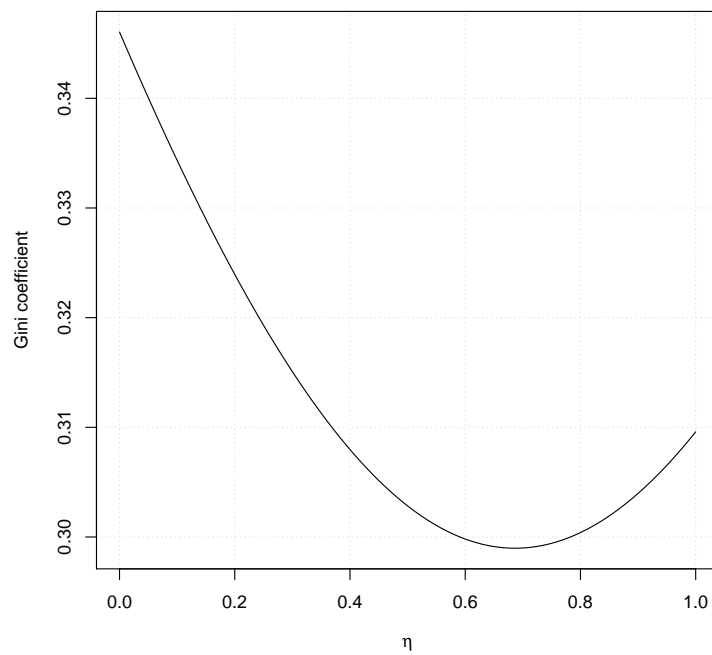


Figure 1: Gini coefficient as a function of η for the 2012 CNEF-file of the German Socio-Economic Panel using $\eta \sim \text{Unif}(0, 1)$

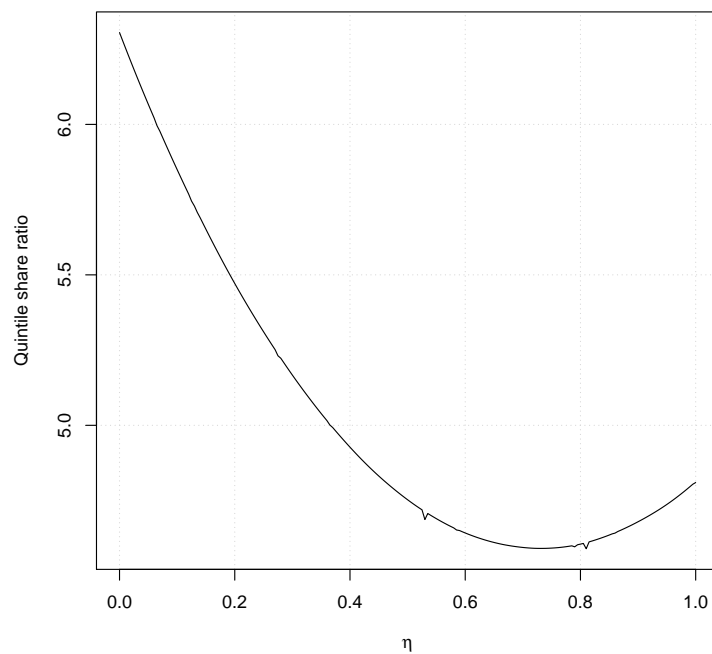


Figure 2: Quintile share ratio as a function of η for the 2012 CNEF-file of the German Socio-Economic Panel using $\eta \sim \text{Unif}(0, 1)$

Table 8: Simulation results for the induced distribution of the Gini coefficient; simple random sampling; $\eta \sim \text{Unif}(0.32, 0.72)$

Sampling fraction	2.5% ($n = 308$)			5% ($n = 616$)			10% ($n = 1232$)		
	X_{true}	$E(X_{\text{sim}})$	r.b.	X_{true}	$E(X_{\text{sim}})$	r.b.	X_{true}	$E(X_{\text{sim}})$	r.b.
G ($\eta = 0.54$)	0.301	0.303	0.007	0.301	0.302	0.003	0.301	0.302	0.001
$SE(G)$	0.014	0.014	-0.028	0.010	0.010	-0.015	0.007	0.007	-0.007
$Q_G(0.5)$	0.302	0.304	0.007	0.302	0.303	0.003	0.302	0.302	0.001
$SE(Q_G(0.5))$	0.014	0.014	-0.021	0.010	0.010	-0.009	0.007	0.007	-0.008
$Q_G(0)$	0.299	0.300	0.005	0.299	0.300	0.002	0.299	0.299	0.001
$SE(Q_G(0))$	0.014	0.014	-0.023	0.010	0.010	-0.011	0.007	0.007	-0.009
$Q_G(1)$	0.314	0.316	0.006	0.314	0.314	0.003	0.314	0.314	0.001
$SE(Q_G(1))$	0.014	0.014	-0.020	0.001	0.001	-0.009	0.007	0.007	-0.008

Table 9: Simulation results for the induced distribution of the quintile share ratio; simple random sampling; $\eta \sim \text{Unif}(0.32, 0.72)$

Sampling fraction	2.5% ($n = 308$)			5% ($n = 616$)			10% ($n = 1232$)		
	X_{true}	$E(X_{\text{sim}})$	r.b.	X_{true}	$E(X_{\text{sim}})$	r.b.	X_{true}	$E(X_{\text{sim}})$	r.b.
S ($\eta = 0.54$)	4.701	4.667	-0.007	4.701	4.647	-0.012	4.701	4.689	-0.003
$SE(S)$	0.346	0.340	-0.016	0.244	0.237	-0.029	0.167	0.165	-0.014
$Q_S(0.5)$	4.726	4.691	-0.007	4.726	4.671	-0.012	4 - 726	4.714	-0.002
$SE(Q_S(0.5))$	0.346	0.342	-0.010	0.246	0.239	-0.030	0.167	0.166	-0.008
$Q_S(0)$	4.591	4.549	-0.009	4.591	4.534	-0.013	4.591	4.578	-0.003
$SE(Q_S(0))$	0.334	0.329	-0.017	0.239	0.230	-0.037	0.162	0.160	-0.010
$Q_S(1)$	5.114	5.075	-0.008	5.114	5.054	-0.012	5.144	5.102	-0.002
$SE(Q_S(1))$	0.382	0.377	-0.012	0.271	0.263	-0.031	0.185	0.183	-0.009

D Accounting for sample design and panel attrition

As noted in section 7 the sampling design of the SOEP is complex. To deal with this complexity, the data include design weights, cross-sectional raking weights and weights to account for panel attrition. For a general overview see Haisken-DeNew and Frick (2005). A description of the derivation of design weights can be found in Spieß (2005) and Spieß and Kroh (2007). Cross-sectional weighting is discussed in Pischner (2007) and Kroh (2009). Weights to account for panel attrition are calculated as the inverse probability of a successful re-interview (see e.g. Kroh, 2014).

Different combinations of these weights can be used for analysis. Ideally, one would use all weights. This would require a combination of inclusion probabilities (inverse of design weights) and probabilities of successful re-interview (inverse attrition weights) to arrive at some kind of longitudinal inclusion probability from which d_k could be calculated. As will be discussed below such a combination is not without problems, which is why only design weights and cross-sectional weights were used in the main text. This will be demonstrated by calculations based on SOEP CNEF data for the years 2000 to 2012. More specifically, four variants will be compared. The first variant treats the data as a simple random sample. Cross-sectional weights are employed in the second variant. Design weights and cross-sectional weights are combined for the third variant. The fourth variant, finally, makes use of all weights and thus also covers panel attrition. Before the latter variant will be discussed in more detail, a short description of the sample design of the SOEP will be given.

The SOEP consists of 11 subsamples, called sample A, sample B, and so on up to sample K. The samples were all taken at different times and do not cover the same universe. For example, sample A was taken 1984 and covers West-German households. Sample B was also taken 1984 and covers households with household head either from Turkey, Italy, Spain, Greece or former Yugoslavia. Sample C was taken 1990 after German unification and includes East German households, while sample K is a refreshment sample taken 2012. Furthermore, some of the samples comprise several strata. For instance, sample B is stratified according to household size and nationality of household head (see Spieß and Kroh, 2007). Design weights provided with the SOEP data are derived from estimated inclusion probabilities for the year each sample was taken.

Starting from the first year a household is included, annual re-interviews are conducted. Panel attrition is quite large and should be accounted for. The fourth variant mentioned above will achieve this by using design weights corrected for panel attrition (corrected design weights). Corrected design weights are calculated as the inverse of the product of inclusion probability and probability of re-observation. Weights have been rescaled such that they sum to N for each year.

This approach has several drawbacks, though. Consider the case of a household of a couple living with their child. Suppose this household has been included in all waves from 2000 up to 2012. The child moves out of the parental household at the end of 2003. In the SOEP all household members are followed and thus the new household of the child will be included in 2004. What is the inclusion probability of this new household for 2004? On the one hand, a requirement for observation is that the parental household is included and followed up to 2003, so the inclusion and attrition probabilities of the parental household should be acknowledged. On the other hand, the resulting weight is influenced by characteristics of the parental household (i.e. its first-wave inclusion probability depending on sample design) and the response behavior of the parents and will probably be different from a weight which would result if the household of the child was included by way of a refreshment sample. This would be especially odd if weights differ considerably.

The latter is closely connected to another problem: Corrected weights for households which have been included for a long time can become quite large. The SOEP started 1984. Some households have been included in the SOEP since then. Their probability of re-observation in 2012 is small, though. Multiplying this small probability with the first-wave inclusion probability and calculating the inverse leads to corrected design weights which are considerably larger than those of households of subsample K. Looking at other years and subsamples, this problem may not be as severe, but results presented below are heavily influenced by it.

Moreover, another possible issue is that the approach for accounting for cross-sectional weighting as described in section 7 depends on the assumption that cross-sectional weights are derived from design weights (Deville, 1999). This is the case for the SOEP, where cross-sectional weights are calculated based on design weights. An additional correction for panel attrition may thus prove problematic.

Results in table 10 allow to compare the effect of accounting for sample design and cross-sectional weighting and cover all four variants introduced above. For each year from 2000 to 2012 standard errors of the low income proportion and the median of the induced distribution of the low income proportion are shown, the latter in two variants: one using $\eta \sim \text{Unif}(0.32, 0.72)$ and the other $\eta \sim \text{Unif}(0.34, 0.51)$. All variants using cross-sectional weights have been corrected using the approach of Deville (1999) as described in section 7. Results on the minimum and maximum of the induced distribution can be found in tables 11 and 12. The main conclusions for median, minimum, and maximum are the same and only results for the median as shown in table 10 will be discussed.

First note that standard errors of the low income proportion and the median are quite similar and differ only marginally. Treating the SOEP as a simple random sample gives

Table 10: Standard error estimates of P and $Q_P(0.5)$ accounting for different aspects of the sampling process

Year	SE(P)				SE($Q_P(0.5)$)				SE($Q_P(0.5)$)			
	$\eta \sim \text{Unif}(0.32, 0.72)$				$\eta \sim \text{Unif}(0.34, 0.51)$							
	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]
2000	0.0028	0.0028	0.0039	0.0047	0.0028	0.0028	0.0039	0.0047	0.0028	0.0028	0.0039	0.0047
2001	0.0029	0.0029	0.0042	0.0050	0.0030	0.0029	0.0042	0.0050	0.0030	0.0029	0.0042	0.0050
2002	0.0030	0.0027	0.0042	0.0051	0.0030	0.0027	0.0042	0.0051	0.0031	0.0027	0.0042	0.0051
2003	0.0030	0.0029	0.0044	0.0054	0.0032	0.0029	0.0044	0.0055	0.0032	0.0029	0.0044	0.0055
2004	0.0029	0.0029	0.0044	0.0055	0.0033	0.0029	0.0044	0.0055	0.0033	0.0029	0.0044	0.0055
2005	0.0031	0.0031	0.0047	0.0060	0.0032	0.0031	0.0047	0.0061	0.0032	0.0030	0.0047	0.0060
2006	0.0032	0.0032	0.0045	0.0059	0.0032	0.0032	0.0045	0.0059	0.0032	0.0032	0.0045	0.0059
2007	0.0031	0.0030	0.0044	0.0067	0.0032	0.0030	0.0044	0.0066	0.0032	0.0030	0.0044	0.0066
2008	0.0032	0.0031	0.0045	0.0075	0.0033	0.0031	0.0045	0.0069	0.0033	0.0031	0.0045	0.0069
2009	0.0031	0.0030	0.0040	0.0084	0.0032	0.0030	0.0041	0.0081	0.0032	0.0030	0.0041	0.0082
2010	0.0033	0.0032	0.0044	0.0092	0.0035	0.0032	0.0045	0.0084	0.0034	0.0032	0.0045	0.0084
2011	0.0033	0.0031	0.0041	0.0083	0.0033	0.0031	0.0041	0.0084	0.0033	0.0031	0.0041	0.0084
2012	0.0030	0.0030	0.0038	0.0080	0.0031	0.0030	0.0038	0.0082	0.0031	0.0030	0.0038	0.0081

Note: [1]=Random sampling; [2]=Accounting for raking; [3]=Accounting for raking and using design weights; [4]=Accounting for raking and using design/attrition weights

Table 11: Standard error estimates of $Q_P(0)$ accounting for different aspects of the sampling process

Year	SE($Q_P(0)$) $\eta \sim \text{Unif}(0.32, 0.72)$				SE($Q_P(0)$) $\eta \sim \text{Unif}(0.34, 0.51)$			
	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]
2000	0.0028	0.0028	0.0039	0.0047	0.0028	0.0028	0.0039	0.0047
2001	0.0029	0.0029	0.0042	0.0050	0.0029	0.0029	0.0042	0.0050
2002	0.0030	0.0027	0.0042	0.0051	0.0030	0.0028	0.0042	0.0052
2003	0.0031	0.0029	0.0044	0.0055	0.0031	0.0029	0.0043	0.0054
2004	0.0030	0.0029	0.0044	0.0055	0.0030	0.0029	0.0044	0.0055
2005	0.0032	0.0031	0.0047	0.0060	0.0032	0.0031	0.0047	0.0060
2006	0.0032	0.0028	0.0039	0.0054	0.0032	0.0032	0.0045	0.0059
2007	0.0032	0.0030	0.0044	0.0066	0.0032	0.0030	0.0044	0.0066
2008	0.0033	0.0031	0.0045	0.0075	0.0033	0.0031	0.0045	0.0075
2009	0.0033	0.0030	0.0041	0.0085	0.0032	0.0031	0.0041	0.0085
2010	0.0034	0.0032	0.0045	0.0089	0.0034	0.0033	0.0045	0.0089
2011	0.0033	0.0031	0.0041	0.0083	0.0033	0.0031	0.0041	0.0083
2012	0.0031	0.0030	0.0038	0.0080	0.0031	0.0030	0.0038	0.0080

Note: [1]=Random sampling; [2]=Accounting for raking; [3]=Accounting for raking and using design weights; [4]=Accounting for raking and using design/attrition weights

slightly higher results compared to those based on cross-sectional weighting. In both cases standard errors are relatively stable over time. Including design weights yields standard errors which are markedly higher, even more so if in addition panel attrition is accounted for. Moreover, in the latter case standard errors increase considerably over time. This is due to the fact that corrected design weights may get quite large for some observations, as noted above.

All in all, accounting for sample design has strong effects on standard error estimates (see also Howes and Lanjouw, 1998; Goedeme, 2013). Combining design weights and weights for attrition yields implausible results, though. On the other hand, not considering sample design seems also unsatisfactory. Because of this, standard errors accounting for raking and using design weights but no attrition weights were used as a middle ground.

Table 12: Standard error estimates of $Q_P(1)$ accounting for different aspects of the sampling process

Year	SE($Q_P(1)$) $\eta \sim \text{Unif}(0.32, 0.72)$				SE($Q_P(1)$) $\eta \sim \text{Unif}(0.34, 0.51)$			
	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]
2000	0.0029	0.0028	0.0040	0.0048	0.0029	0.0028	0.004	0.0048
2001	0.0030	0.0029	0.0043	0.0051	0.0030	0.0029	0.0043	0.0051
2002	0.0031	0.0027	0.0043	0.0053	0.0031	0.0027	0.0043	0.0053
2003	0.0032	0.0029	0.0044	0.0055	0.0032	0.0029	0.0044	0.0055
2004	0.0033	0.0029	0.0045	0.0056	0.0033	0.0029	0.0045	0.0056
2005	0.0033	0.0031	0.0047	0.0060	0.0033	0.0031	0.0047	0.0060
2006	0.0032	0.0031	0.0045	0.0059	0.0032	0.0031	0.0045	0.0059
2007	0.0033	0.0030	0.0044	0.0067	0.0033	0.0030	0.0044	0.0067
2008	0.0033	0.0031	0.0045	0.0068	0.0033	0.0031	0.0045	0.0068
2009	0.0033	0.0030	0.0042	0.0077	0.0033	0.0030	0.0042	0.0076
2010	0.0035	0.0032	0.0045	0.0083	0.0035	0.0032	0.0045	0.0083
2011	0.0033	0.0031	0.0042	0.0079	0.0033	0.0031	0.0042	0.0079
2012	0.0031	0.0031	0.0038	0.0084	0.0031	0.0031	0.0038	0.0084

Note: [1]=Random sampling; [2]=Accounting for raking; [3]=Accounting for raking and using design weights; [4]=Accounting for raking and using design/attrition weights

References

- Deville JC (1999) Variance estimation for complex statistics and estimators: Linearization and residual techniques. *Survey Methodology* 25:193–203
- Goedeme T (2013) How much confidence can we have in EU-SILC? Complex sample designs and the standard error of the Europe 2020 poverty indicators. *Social Indicators Research* 110:89–110
- Haisken-DeNew JP, Frick JR (eds) (2005) *Desktop Companion to the German Socio-Economic Panel (SOEP)*. DIW Berlin
- Howes S, Lanjouw JO (1998) Does sample design matter for poverty rate comparisons? *Review of Income and Wealth* 44:99–109
- Kroh M (2009) Short documentation of the update of the SOEP-Weights, 1984-2008, DIW Berlin
- Kroh M (2014) Documentation of sample sizes and panel attrition in the German Socio-Economic Panel (SOEP) (1984 until 2012), *SOEP Survey Papers* 177
- Langel M, Tillé Y (2011) Statistical inference for the quintile share ratio. *Journal of Statistical Planning and Inference* 141:2976–2985
- Langel M, Tillé Y (2013) Variance estimation of the gini index: revisiting a result several times published. *Journal of the Royal Statistical Society, Series A* 176:521–540
- Osier G (2009) Variance estimation for complex indicators of poverty and inequality using linearization techniques. *Survey Research Methods* 3:167–195
- Pischner R (2007) Die Querschnittsgewichtung und die Hochrechnungsfaktoren des Sozio-oekonomischen Panels (SOEP) ab Release 2007 (Welle W), *SOEP Data Dokumentation* 22
- Spieß M (2005) Derivation of design weights: The case of the German Socio-Economic Panel (SOEP), *SOEP Data Dokumentation* 8, DIW Berlin
- Spieß M, Kroh M (2007) Documentation of the data design of the Socio-Economic Panel Study (SOEP), DIW Berlin