Standard Error Estimation for EU-SILC target indicators – First Results of the Net-SILC2 Project

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Abstract

We present the first results of the Net-SILC2 project with regard to standard error estimation in EU-SILC (EU Statistics on Income and Living Conditions). EU-SILC is the main data source for comparative analysis and indicators on income and living conditions in the European Union (EU), covering all the 27 EU countries and a number of other European countries. The growing complexity of EU-SILC, the widening of the user community and the increasing reliance on EU-SILC for policy targeting and evaluation have enhanced the need for comparable, accurate as well as workable solutions to the estimation of standard errors and confidence intervals for the indicators based on the EU-SILC surveys. After presenting the Net-SILC2 project and the recommended variance estimators, we show preliminary estimates of standard error and confidence intervals for cross-sectional measures, longitudinal measures and measures of changes between two waves. The proposed approach is general and can be implemented with multistage surveys. As far as variance of change is concerned, the proposed approach can be used with rotating longitudinal surveys (Kalton 2009) such as Labour Force Surveys.

Keywords: *Variance, Linearisation, Confidence interval*

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1. Introduction – Description of the Work Package

The "EU Statistics on Income and Living Conditions" (EU-SILC) surveys (Eurostat 2012a) cover the 28 EU countries as well as Switzerland, Norway, Iceland and Turkey. It is the main data source for comparative analysis and indicators on income and living conditions in the European Union (EU). Since the launch of the "Europe 2020" Strategy for smart, sustainable and inclusive growth, the importance of EU-SILC has grown even further: one of the five Europe 2020 headline targets is based on EU-SILC data (the social inclusion EU target, which consists of lifting at least 20 million people in the EU from the risk of poverty and exclusion by 2020).

Since EU-SILC was launched in 2003, much attention has been paid to sampling errors, mainly because the EU-SILC data are collected through sample surveys carried out in each participating country. Given that all the indicators based on EU-SILC are sample estimates, they should be reported along with standard errors estimates and confidence intervals, particularly if they are used for policy purposes. The Commission Regulation (EC) n°28/2004 of 5th January 2004 regarding the detailed content of intermediate and final EU-SILC quality reports requires that standard error estimates be provided by countries along with the EU-SILC main target indicators.

EU-SILC methodological work is undertaken in the framework of the "Second Network for the Analysis of EU-SILC" (Net-SILC2), funded by Eurostat (Atkinson and Marlier 2010). Net-SILC2 brings together expertise from 16 European partners: the Luxembourg-based CEPS/INSTEAD Research Institute (Net-SILC2 coordinator), six National Statistical Institutes (from Austria, Finland, France, Luxembourg, Norway and the UK), the Bank of Italy and academics from 8 research bodies (in Belgium, Germany, Sweden and the UK). The two main aims of Net-SILC2 are: a) to carry out in-depth methodological work and socio-economic analysis based on EU-SILC data (covering both the cross-sectional and longitudinal dimensions of the instrument); and b) to develop common tools and approaches regarding various aspects of data production. The activities of the Network are set out in terms of 26 work packages (WP) covering key EU-SILC methodological topics such as, for example, the use of income registers, the measurement of material deprivation in the EU or the implications of the EU-SILC following rules for longitudinal analysis. One of those 26 work packages deals with standard error estimation and other related sampling issues in EU-SILC. The main objective of the WP is to develop a practicable set of recommendations both for data producers (NSIs) and data users regarding standard error estimation. Those recommendations include suggestions concerning the concrete implementation procedures for computing standard errors at NSI's level (production database) and at database users level, i.e. non-NSI's level. It also includes concrete recommendations for better recording of sampling design variables (e.g. suitable documentation and metadata), after reviewing the current practices on micro-data for the sample design variables (Goedemé 2013b).

2. Variance Estimation Approach

The computation of standard errors for estimates based on EU-SILC is confronted with many challenges. Standard error estimation should reflect as much as possible the complexity of the EU-SILC surveys, otherwise estimates may be severely biased. Among others, the complexity of EU-SILC is related to complex sample designs involving stratification, geographical clustering, unequal probabilities of selection and post-survey weighting adjustments (re-weighting for unit non-response and calibration to external data sources) and rotating samples. We also have complex cross-sectional and longitudinal indicators and indicators of net changes. Furthermore, different methods of imputation are used across countries. There are also confidentiality issues and limited resources in terms of budget, staff and time at national and at EU level. Standard errors estimates also depend on the availability of good and well-documented sample design variables (Goedemé 2010, 2013a, 2013b)

Given the growing number of requests for SILC-based statistics, the proposed approach delivers standard error estimates as quickly and accurately as possible for any set of target indicators, including breakdowns. The variance estimation approach makes a trade-off between statistical accuracy and operational efficiency. The proposed approach is general enough to be valid under most of the EU-SILC sampling designs, which is a challenge if we consider the range of sampling designs used in EU-SILC (see Table 1). In addition, the approach is simple to implement with standard statistical software (SAS, SPSS, Stata…) and requires minimal computing power.

Table 1: EU-SILC sampling designs by country (2009)

Sampling unit	Sampling design	Country
Dwellings/ addresses	Simple random sampling	Malta
	Stratified simple random sampling	Luxembourg
	Stratified random sampling from former participants of micro census	Germany
	Stratified multi-stage sampling	Austria, Czech Republic, Spain, Poland, Portugal, Romania
	Stratified multi-stage systematic sampling	France, Latvia, United Kingdom, Netherlands
Households	Stratified random sampling	Cyprus, Slovakia, Switzerland
	Stratified multi-stage sampling	Ireland
	Stratified multi-stage systematic sampling	Belgium, Bulgaria, Greece, Italy
	Stratified sampling according to	Hungary

	different design by rotational group	
Individuals	Simple random sampling	Denmark, Iceland
	Systematic sampling	Sweden
	Stratified random sampling	Lithuania
	Stratified and systematic sampling	Greece, Norway
	Stratified two-phase sampling	Finland
	Stratified two-stage systematic sampling	Slovenia

Source: 2009 Comparative EU Intermediate Quality Report – Version 3 – July 2011 (available on CIRCA)

Re-sampling methods like Bootstrap or Jackknife are flexible enough to be applicable to the sampling designs and the target indicators used in EU-SILC, no matter their complexity (Verma and Betti 2011). However, the computational effort may be considerable, which is not desirable when standard error estimates need to be produced quickly for a large number of target indicators, including breakdowns. That is why we propose to use direct variance estimators (Berger 2004a). The main assumption underlying such estimators is that sample units have been selected with replacement, which considerably simplifies the estimation of variances. Sampling with and without replacement are approximately equal as far as variances are concerned when the sampling fraction is negligible. Note that this is nearly always the case with the EU-SILC sampling designs. Furthermore, those direct estimators can be easily extended to cover multi-stage designs by using the well-known 'ultimate cluster' approximation (e.g. Särndal, Swensson and Wretman 1992).

Consider a population U consisting of N identifiable units such as households or individuals. Let s denote a sample of size n drawn from U using a probabilistic design so that each unit k has a known inclusion probability π_k. Suppose we wish to estimate the total $\theta = \sum_{k \in U} y_k$, where y_k is the value of a study variable y for unit k. The study variable y can be a continuous (e.g.

household income), or a categorical variable (e.g., employment status). If y is a dichotomous variable, then θ is a count. Let $\hat{\theta}$ be an estimator of θ, for which an estimate of the standard error is required. The variance of $\hat{\theta}$ is estimated from the variation between the estimated PSU totals of *y*:

$$\hat{V}\left(\hat{\theta}\right)=\sum_{h=1}^{H}\frac{n_h}{n_h-1}\sum_{i=1}^{n_h}\left(y_{hi\bullet}-\bar{y}_{h\bullet\bullet}\right)^2 \quad ; \tag{1}$$

where $y_{hi\bullet}=\sum_{j=1}^{m_{hi}}\omega_{hij}\cdot y_{hij}$ and $\bar{y}_{h\bullet\bullet}=n_h^{-1}\left(\sum_{i=1}^{n_h}y_{hi\bullet}\right)$

The symbol *h* is the stratum label and *H* the number of strata. If there is no stratification, the whole target population *U* can be regarded as a single stratum (H = 1). The symbol *i* is the label of the primary sampling units (PSU). We have n_h PSUs within the *h*-th stratum. The symbol *j* is the household label within PSU *i* of stratum *h*, with a total of m_{hi} households. For single stage sampling designs, each household can be regarded as a PSU. The quantity ω_{hij} is the sampling weight for household *j* in PSU *i* of stratum *h*. The quantity y_{hij} is the value of the study variable *y* for household *j* in PSU *i* of stratum *h*.

Note that if n_h = 1 for some strata, the estimator (1) cannot be used. A solution is to collapse strata to create “pseudo-strata” so that each pseudo-strata has at least two PSUs. A common practice is to collapse strata which are similar which regard to the target variables of the survey (Rust and Kalton 1987, Ardilly and Osier 2007)

The estimator (1) is valid for linear indicators, i.e. means, totals and proportions. However, most of the EU-SILC key indicators are non-linear (e.g. the median income, the persistent risk of poverty or the Gini coefficient). In order to estimate the variance of non-linear indicators, the linearisation approach may be used (Kovacevic and Binder 1997, Deville 1999, Demnati and Rao 2004, Wolter 2007, Osier 2009). The principle is to approximate a non-linear indicator by a linear form by retaining only the first-order term of a Taylor expansion. The variance of the linear approximation can be used as an approximation of the variance of the non-linear indicator considered. The linearisation procedure is justified on the basis of asymptotic properties of large samples and populations (Verma and Betti 2005). Assuming θ is a complex non-linear indicator, the variance of an estimator $\hat{\theta}$ of θ is estimated by:

$$\hat{V}\left(\hat{\theta}\right)=\sum_{h=1}^{H}\frac{n_h}{n_h-1}\sum_{i=1}^{n_h}\left(z_{hi\bullet}-\bar{z}_{h\bullet\bullet}\right)^2 \quad ; \tag{2}$$

where $z_{hi\bullet}=\sum_{j=1}^{m_{hi}}\omega_{hij}\cdot z_{hij}$, $\bar{z}_{h\bullet\bullet}=n_h^{-1}\left(\sum_{i=1}^{n_h}z_{hi\bullet}\right)$ and z_{hij} is the value of a linearised variable.

This is exactly the same formula as (1), except that the study variable y is replaced by the linearised variable z. For example, if $\theta=\left(\sum_k y_k\right)\left(\sum_{k\in U}x_k\right)^{-1}=Y\,X^{-1}$ is the ratio of two population totals, then we have $z_k=X^{-1}\left(y_k-\theta\cdot x_k\right)$ for all *k*.

The differences $\left(y_{hi\bullet}-\bar{y}_{h\bullet\bullet}\right)$ in (1) and $\left(z_{hi\bullet}-\bar{z}_{h\bullet\bullet}\right)$ in (2) can be seen as the residuals of the linear regression of the PSU aggregates $y_{hi\bullet}$ and $z_{hi\bullet}$ on the dummy variables for each stratum category (Berger 2005). This provides a quick and easy way to compute the variance of both cross-sectional and longitudinal measures using basic statistical techniques.

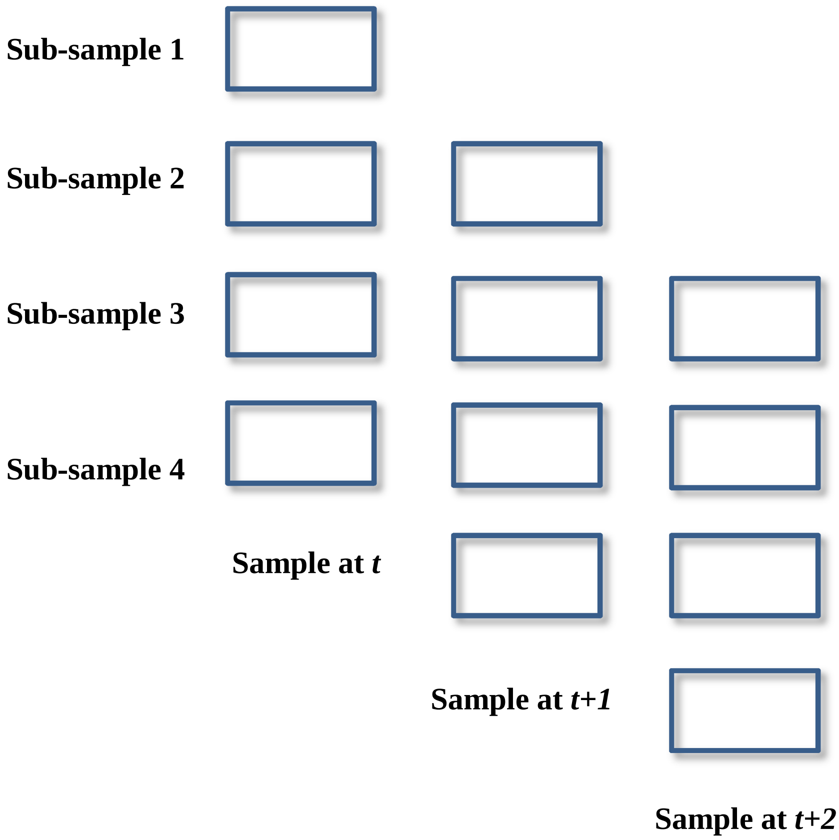
The approach proposed reflects most of the features of the sample design. A specific approach is needed to measure how the calibration weighting (Deville and Särndal 1992) affects the variance. Calibration is expected to have significant effect for the "Nordic" countries like Denmark or Finland which used powerful calibration variables from income registers. As shown by Deville and Särndal (1992), the effect of calibration on variance estimation can be taken into account by replacing the study variable by the residuals of the regression on the calibration variables. This approach is easy to implement as long as the calibration variables are available as well as the initial weights before calibration or, equivalently, the calibration adjustment factors (also called *g-weights*).

3. Extension to estimators of changes between two time points

The regression-based approach described in the previous section can be easily extended to cope with estimators of changes between two time points (Berger and Priam 2013, Berger and Oguz Alper 2013). Monitoring changes or trends in indicators over time is of key importance in many areas of economic and social sciences.

In order to monitor trends towards agreed policy goals, we compare two cross-sectional estimates for the same study variable taken on two different waves or occasions. The aim is to judge whether the observed change is statistically significant. Therefore, interpreting differences between point estimates may be misleading if temporal correlations between indicators is not be taken into account properly. This would be relatively straightforward if estimates were based upon independent samples. However, nearly all the EU-SILC countries have adopted a four-year rotating structure (see Figure 1) as recommended by Eurostat, where individuals are interviewed for a maximum of four years and 25% of the sample is refreshed every year with new individuals.

Figure 1: The EU-SILC four-year rotating structure



Berger and Priam (2013) proposed to use the residual variance matrix of a multivariate regression model. The residual correlation matrix is used to produce estimates of correlation which are used in the variance of the net change between indicators. The multivariate model includes covariates which specify the stratification and interactions terms which specify the rotation of the sampling designs. The estimator proposed by Berger and Priam (2013) is simpler to implement than the estimators proposed by Munnich and Zins (2011), Nordberg (2000), Qualité (2009), Qualité and Tillé (2008), Tam (1984) and Wood (2008). In particular cases, the proposed estimator reduces to these estimators.

4. Preliminary results

We implemented the proposed regression-based approach to compute standard error estimates for key EU-SILC cross-sectional measures, longitudinal measures and measures of changes. The first indicator considered is the at-risk-of-poverty or social exclusion indicator (AROPE) and its three sub-indicators: the at-risk-of-poverty rate (POV), the severe material deprivation rate (DEP) and the share of individuals aged less than 60 living in households with very low work intensity (LWI) (Eurostat 2012b). The at-risk-of-poverty or social exclusion (AROPE) is the "Europe 2020" headline indicator on poverty and social exclusion. It counts the number of individuals living in households which are at-risk-of-poverty, severely materially deprived or with very low work intensity; the individuals present in several sub-indicators being counted only once (Eurostat 2013). The change in the AROPE between two years is also considered. We also consider the persistent at-risk-of-poverty rate, which is the key EU-SILC longitudinal indicator. The persistent risk of poverty is defined as having an equivalised disposable income below the at-risk-of-poverty threshold in the current year and in at least two of the preceding three years.

The estimates are based upon anonymised EU-SILC micro-data files that are provided by Eurostat for statistical/research purposes only. Since research files do not include any stratum identification number nor calibration variables, we had to use NUTS2 region as a proxy for stratification and ignore the impact of calibration on the variance estimates.

4.1. Cross-sectional measures

In table 2, we have the estimator of the standard error for the at-risk-of-poverty rate (POV), the severe material deprivation rate (DEP), the share of individuals aged less than 60 living in households with very low work intensity (LWI) and the AROPE.

The standard error estimates for the AROPE lies between 0.5 and 1 percentage point in most of the countries, which means that the absolute margin of error for the indicators (based on normality assumption) lies between ±1 and ±2 percentage points. The standard errors are greater than 1 point in Bulgaria, Lithuania and Romania; while they are lower than 0.5 point in Germany and Sweden.

As far as the AROPE's three sub-indicators are concerned (POV, DEP, LWI), the standard error estimates appear lower than those calculated for the AROPE because, by definition, the AROPE indicator reaches higher values than its three components. For example, the estimated standard errors for the severe material deprivation rates are relatively low for some countries (e.g. 0.1 percentage point for Sweden and 0.2 point for Luxembourg).

Table 2: Standard error estimates for the at-risk-of-poverty or social exclusion indicator (AROPE) and its three sub-indicators, 2011

	At-risk-of-poverty rate (POV)		Severe material deprivation rate (DEP)		Share of individuals living aged < 60 living in households with very low work intensity (LWI)		At-risk-of-poverty or social exclusion (AROPE)	
	Indicator value (%)	*Estimated standard error (% points)*	*Indicator value (%)*	*Estimated standard error (% points)*	*Indicator value (%)*	*Estimated standard error (% points)*	*Indicator value (%)*	*Estimated standard error (% points)*
Austria	12,6	0,58	3,9	0,35	8,0	0,51	16,9	0,63
Belgium	15,3	0,86	5,7	0,53	13,7	0,87	21,0	0,98
Bulgaria	22,2	0,97	43,5	1,07	11,0	0,75	49,0	1,07
Switzerland	15,0	0,57	1,0	0,26	4,7	0,41	17,2	0,61
Cyprus	14,5	0,66	10,7	0,70	4,5	0,36	23,5	0,85
Czech Republic	9,8	0,49	6,1	0,41	6,6	0,43	15,3	0,57
Germany	15,8	0,38	5,3	0,23	11,1	0,38	19,9	0,41
Denmark	13,0	0,71	2,6	0,35	11,4	0,76	18,9	0,77
Estonia	17,5	0,65	8,7	0,48	9,9	0,57	23,1	0,73
Greece	21,4	0,78	15,2	0,77	11,8	0,69	31,0	0,94
Spain	21,8	0,55	3,9	0,27	12,2	0,45	27,0	0,58
Finland	13,7	0,45	3,2	0,24	9,8	0,45	17,9	0,50

France	14,0	0,49	5,2	0,32	9,3	0,41	19,3	0,54
Hungary	13,8	0,61	23,1	0,75	12,1	0,58	31,0	0,79
Iceland	9,2	0,60	2,1	0,27	6,2	0,56	13,7	0,70
Italy	19,6	0,73	11,2	0,59	10,4	0,51	28,2	0,89
Lithuania	20,0	1,07	18,5	0,93	12,3	0,93	33,4	1,22
Luxembourg	13,6	0,81	1,2	0,22	5,8	0,41	16,8	0,83
Latvia	19,3	0,71	30,9	0,89	12,2	0,58	40,1	0,91
Malta	15,4	0,69	6,3	0,46	8,1	0,51	21,4	0,77
Netherlands	11,0	0,81	2,5	0,47	8,7	0,71	15,7	0,89
Norway	10,6	0,53	2,3	0,29	7,1	0,50	14,6	0,61
Poland	17,7	0,52	13,0	0,46	6,9	0,27	27,2	0,63
Portugal	18,0	0,84	8,3	0,64	8,2	0,62	24,4	0,94
Romania	22,1	1,08	29,2	1,19	6,7	0,57	40,1	1,24
Sweden	14,0	0,47	1,2	0,14	6,8	0,40	16,1	0,49
Slovenia	13,6	0,44	6,1	0,30	7,6	0,38	19,3	0,50
Slovakia	13,0	0,62	10,6	0,56	7,6	0,52	20,6	0,70
United Kingdom	16,2	0,58	5,1	0,38	11,5	0,56	22,7	0,68

Source: Authors' calculations based on anonymised EU-SILC micro-data files provided by Eurostat for statistical/research purposes only (Version 01-03-13)

4.2. Longitudinal measures

In table 3, we have standard error estimates for the persistent risk of poverty. The relative margin of error of the persistent at-risk-of-poverty rate ranges from 14% in France to more than 50% in the Netherlands and Iceland. The precision of the persistent at-risk-of-poverty rate appears to be lower than the precision of the AROPE. There are several possible reasons for this. For the longitudinal component of EU-SILC, the achieved sample size is lower than for the cross-sectional component: the longitudinal sample sizes range from about 1000 individuals in Iceland to 11000 in France. This is caused mainly by the rotating design used in most of the countries (25% of the sample is refreshed every year with new individuals), but also by losses to follow-up and attrition. Another explanation is that the persistent at-risk-of-poverty rate generally takes lower value than the cross-sectional at-risk-of poverty rate (POV) or the AROPE indicator. Finally, the higher dispersion of the longitudinal sampling weights, which are adjusted at each wave for attrition and calibration to external data sources, is likely to reduce the precision of the persistent risk of poverty.

Table 3 – Standard error estimates and confidence intervals for the persistent at-risk-of-poverty rate, 2006-2009

	Persistent at-risk-of-poverty rate (%)	**Confidence interval (Empirical Likelihood - EL)**		**Confidence interval (Central Limit Theorem - CLT)**	
		Lower	Upper	Lower	Upper
Austria	5.93	4.59	7.73	4.38	7.47
Belgium	8.94	7.10	11.31	6.89	10.98
Bulgaria	10.67	8.20	13.87	7.92	13.42
Cyprus	10.95	9.13	13.10	8.88	13.02
Czech Republic	3.55	2.53	5.13	2.33	4.77
Denmark	6.27	4.58	8.43	4.39	8.15
Estonia	12.97	11.13	15.13	10.91	15.04
Spain	11.1	9.49	12.95	9.40	12.80
Finland	6.91	5.55	8.59	5.37	8.45
France	6.92	6.04	7.92	6.00	7.84
Greece	14.5	11.76	17.84	11.76	17.25
Hungary	8.28	6.60	10.41	6.46	10.10
Ireland	6.34	4.34	9.54	3.74	8.94
Iceland	4.17	2.36	6.89	1.97	6.38
Italy	13.38	11.16	16.04	11.28	15.48
Lithuania	11.73	9.18	15.19	8.91	14.54
Luxembourg	8.82	6.88	11.47	6.66	10.98
Latvia	17.74	13.96	23.94	13.48	22.01
Malta	6.21	4.62	8.21	4.40	8.03
Netherlands	6.36	4.10	9.78	3.73	9.00
Norway	5.36	4.15	6.93	4.03	6.70
Poland	10.16	7.54	13.43	8.62	11.71
Portugal	9.98	7.81	12.67	7.60	12.36
Sweden	5.66	4.38	7.24	4.24	7.07
Slovakia	5.01	3.54	7.11	3.30	6.72
United Kingdom	8.36	6.66	10.48	6.51	10.21

Source: Authors' calculations based on anonymised EU-SILC micro-data files provided by Eurostat for statistical/research purposes only (Version 01-03-13)

In table 3, we also have the empirical likelihood (EL) confidence intervals based on a novel approach proposed by Berger and De la Riva Torres (2012). These intervals have better coverage than the intervals based upon the Central limit theorem (CLT). The difference between the CLT confidence intervals and the EL confidence intervals are due to the lack of normality of the sampling distribution.

4.3. Standard errors of measures of changes

In table 4, we have the standard error estimates and confidence intervals (based on normality assumption) for changes in the AROPE between 2010 and 2011. The computations were made within Eurostat premises using the EU-SILC Production Data Base (EU-SILC PDB). In this case, we use the right stratification variable. If a confidence interval does not include 0, we can say the difference between 2010 and 2011 is statistically significant (at a given level of confidence).

Table 4 – Estimated standard errors for estimators of net change in the AROPE between 2010 and 2011

	AROPE (%) - 2010	AROPE (%) - 2011	(2011) - (2010) (% points)	Estimated standard error (% points)	Confidence interval at 95% - Lower bound	Confidence interval at 95% - Upper bound	Is the difference significant (Y/N)?
Austria	16,6	16,9	0,34	0,47	-0,58	1,26	N
Belgium	20,8	21,0	0,14	0,70	-1,23	1,51	N
Bulgaria	49,2	49,1	-0,04	0,76	-1,53	1,44	N
Switzerland	17,2	17,2	0,02	0,37	-0,71	0,74	N
Cyprus	23,5	23,7	0,24	0,65	-1,05	1,52	N

Czech republic	14,4	15,3	0,94	0,26	0,44	1,45	Y
Germany	19,7	19,9	0,14	0,22	-0,29	0,57	N
Denmark	18,3	18,9	0,51	0,45	-0,37	1,38	N
Estonia	21,7	23,1	1,34	0,54	0,27	2,40	Y
Greece	27,7	31,0	3,29	0,50	2,30	4,27	Y
Spain	25,5	27,0	1,44	0,42	0,61	2,26	Y
Finland	16,9	17,9	1,05	0,33	0,41	1,68	Y
France	19,2	19,3	0,12	0,39	-0,65	0,89	N
Hungary	29,9	31,0	1,09	0,50	0,10	2,08	Y
Iceland	13,7	13,7	-0,03	0,38	-0,79	0,72	N
Italy	24,5	28,2	3,68	0,81	2,10	5,26	Y
Lithuania	33,4	33,4	-0,01	0,96	-1,88	1,87	N
Luxembourg	17,1	16,8	-0,29	0,35	-0,98	0,40	N
Latvia	38,1	40,4	2,37	0,39	1,61	3,13	Y
Malta	20,3	21,4	1,13	0,43	0,29	1,97	Y
Netherlands	15,1	15,7	0,64	0,64	-0,62	1,91	N
Norway	14,9	14,6	-0,28	0,32	-0,90	0,34	N
Poland	27,8	27,2	-0,57	0,28	-1,12	-0,02	Y
Portugal	25,3	24,4	-0,86	0,09	-1,05	-0,68	Y
Romania	41,4	40,3	-1,12	0,08	-1,28	-0,96	Y
Sweden	15,0	16,1	1,10	0,26	0,60	1,60	Y
Slovenia	18,3	19,3	0,96	0,26	0,46	1,46	Y
Slovakia	20,6	20,6	0,02	0,51	-0,97	1,01	N
United Kingdom	23,1	22,7	-0,41	0,48	-1,36	0,53	N

Source: EU-SILC Production Database (PDB)

Note: (i) Results still provisional (ii) No data for Ireland yet (iii) For Luxembourg: the effect of stratification is not taken into account

5. Conclusion

The proposed variance estimator is simple and flexible, yet theoretically sound. It can accommodate a wide class of sampling designs and estimators using standard statistical techniques. It is not necessary to develop a specialised computer package for the implementation of the proposed approach as it can be implemented with standard statistical procedures in SAS, SPSS or Stata. It can also be extended to complex estimators through linearisation. However, as the linearisation procedure is justified on the basis of asymptotic properties, variance estimates may not be reliable if the sample size is not sufficiently large.

The numerical results obtained using this approach seem plausible, although they have to be interpreted with caution given the lack of sampling design information in the EU-SILC user data files and potential quality problems with the current design variables. Eurostat is currently working with Net-SILC2 to improve the situation. Concrete recommendations have already been made for better recording of sampling design variables in EU-SILC (Goedemé 2013b).

A major shortcoming of the proposed approach is that it does not take the imputation variance into account. However, the income variables have been heavily imputed, with different imputation methods used across countries. For simplicity, imputed values have been treated as true values. However, this assumption may lead to severely under-estimating the variance, particularly when the proportion of imputed values is important (Rao and Shao 1992). Variance estimation under imputation is not an easy task. Direct variance formulas are usually very complex (Deville and Särndal 1994) and method-specific. For example, for hot-deck imputation, Berger and Escobar (2012) proposed an approach to estimate the variance of change in the presence of imputed values. Thus, it does not seem realistic to try to estimate the imputation variance on a streamline basis, especially when the imputation methods vary greatly from one country to another. Nevertheless, the imputation variance may be estimated occasionally using for instance the SAS software SEVANI developed by Statistics Canada (Beaumont and Bissonnette 2011). It would be useful to develop a "rule of the thumb" approach which would take into account of the effect of imputation.

The proposed approach can be implemented with any rotating longitudinal survey as long as the sampling fraction is negligible. Berger (2004b) proposed a variance estimator for change which is more complex and can be used with large sampling fractions. With small sampling fraction, Berger and Priam (2013) showed that the estimator proposed in this paper is asymptotically equal to Berger (2004b) estimator. In a series of simulation based on the Swedish Labour Force Survey, Andersson et al. (2011) showed that for estimation of strata domains the variance estimator proposed by Berger (2004a) gives accurate variance estimates.

Empirical likelihood confidence intervals (Berger and De la Riva Torres 2012) are an alternative way to measure the accuracy of indicators. This approach does not require analytic derivation of variances, linearisation or resampling. Its implementation is relatively simple, but requires a specialised computer package (currently developed in R at the University of Southampton).

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References

- Andersson, C., Andersson, K. and Lundquist, P. (2011) Variansskattningar avseende forandringsskattningar i panelundersokningar (variance estimation of change in panel surveys). Methodology reports from Statistics Sweden (Statistiska centralbyran).
- Ardilly, P. and Osier, G. (2007). Cross-sectional variance estimation for the French “Labour Force Survey”. Survey Research Methods, 1, 2, pp. 75-83. Available at: URL = http://w4.ub.uni-konstanz.de/srm/article/viewPDFInterstitial/77/55
- Atkinson, A. B. and Marlier, E. (2010) Income and living conditions in Europe. Luxembourg: Office for Official Publications. Available at: URL = http://epp.eurostat.ec.europa.eu/cache/ITY_OFFPUB/KS-31-10-555/EN/KS-31-10-555-EN.PDF

- Beaumont, J.-F. and Bissonnette, J. (2011). Variance Estimation under Composite Imputation: The Methodology Behind SEVANI. Survey Methodology, vol. 37, pp. 171-179.
- Berger, Y. G. (2004a). A Simple Variance Estimator for Unequal Probability Sampling Without Replacement. Journal of Applied Statistics, 3, 305-315.
- Berger, Y. G. (2004b) Variance estimation for measures of change in probability sampling. Canadian Journal of Statistics, 32, 451–467.
- Berger, Y. G. (2005) Variance estimation with highly stratified sampling designs with unequal probabilities. Australian and New Zealand Journal of Statistics, 47, 365–373.
- Berger, Y. G. and De La Riva Torres, O. (2012) A unified theory of empirical like- lihood ratio confidence intervals for survey data with unequal probabilities and non negligible sampling fractions,Working paper. http://eprints.soton.ac.uk/337688/
- Berger, Y. G. and Escobar, E. L. (2012). Variance estimation of imputed estimators of change over time from repeated surveys. In Journées de Méthodologie Statistiques 2012, Paris, FR, 24-26 Jan 2012. 8pp.
- Berger, Y. G. and Oguz Alper, M. (2013). Variance estimation of change of poverty based upon the Turkish EU-SILC survey. Paper presented at the NTTS (New Techniques and Technologies for Statistics) Conference, Brussels, 5-7 March 2013.
- Berger, Y. G. and Priam, R. (2013). A simple variance estimator of change for rotating repeated surveys: an application to the EU-SILC household surveys. University of Southampton, Statistical Sciences Research Institute. Available at: URL = http://eprints.soton.ac.uk/347142

- Demnati, A. and Rao, J. N. K. (2004). Linearization variance estimators for survey data. Survey Methodology, 30, 17-26.
- Deville, J-C. (1999). Variance estimation for complex statistics and estimators: linearization and residual techniques. Survey Methodology, December 1999, 25, 2, 193-203.
- Deville, J-C. and Särndal, C-E. (1992). Calibration estimators in survey sampling. Journal of the American Statistical Association, 87, 418, 376-382.
- Deville, J-C. and Särndal, C-E. (1994). Variance Estimation for the Regression Imputed Horvitz-Thompson Estimator. Journal of Official Statistics, 10, 4, 381–394.
- Eurostat (2012a) European Union statistics on income and living conditions (EU-SILC). http://epp.eurostat.ec.europa.eu/portal/page/portal/microdata/eu_silc. [Online; accessed 7 Jan. 2013].
- Eurostat (2012b) People at risk of poverty or social exclusion (EU-SILC). http://epp.eurostat.ec.europa.eu/portal/page/portal/product_details/dataset?p_product_code=T2020_50. [Online; accessed 7 Jan. 2013]].
- Goedemé, T. (2010). The construction and use of sample design variables in EU-SILC. A user's perspective. Report prepared for Eurostat. Available at: URL = http://www.centrumvoorsociaalbeleid.be/index.php?q=node/2157/en
- Goedemé, T. (2013a). 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*, vol. 110, no. 1, pp. 89-110
- Goedemé, T. (2013b). *The EU-SILC sample design variables: critical review and recommendations*. CSB Working paper 13/02, Antwerp: Herman Deleeck Centre for

Social Policy – University of Antwerp. Available at: http://www.centrumvoorsociaalbeleid.be/index.php?q=node/3891

- Kalton G. (2009). *Design for surveys over time*. Handbook of Statistics: Design, Method and Applications: D. Pfeffermann and C.R. Rao. (editors). Elsevier.
- Kovacevic, M. and Binder, D.A. (1997). Variance Estimation for Measures of Income Inequality and Polarization – The Estimating Equations Approach. Journal of Official Statistics, 13, 1, 41-58.
- Muennich, R. and Zins, S. (2011). Variance estimation for indicators of poverty and social exclusion. Work-package of the European project on Advanced Methodology for European Laeken Indicators (AMELI).

  Available at URL = http://www.uni-trier.de/index.php?id=24676. [Online; accessed 4 Jan. 2013].
- Nordberg, L. (2000). On variance estimation for measures of change when samples are coordinated by the use of permanent random numbers. Journal of Official Statistics, 16, 363–378.
- Osier, G. (2009). Variance estimation for complex indicators of poverty and inequality using linearization techniques. Survey Research Methods, 3, 3, 167-195. Available at: URL = http://w4.ub.uni-konstanz.de/srm/article/view/369
- Qualité, L. (2009). Unequal probability sampling and repeated surveys. PhD Thesis, University of Neuchatel, Switzerland.
- Qualité, L. and Tillé, Y. (2008). Variance estimation of changes in repeated surveys and its application to the Swiss survey of value added. Survey Methodology, 34, 173–181.

- Rao, J. N. K. and Shao, A. J. (1992). Jackknife variance estimation with survey data under hotdeck imputation. Biometrika, 79, 811-822.
- Rust, K. and Kalton, G. (1987). Strategies for collapsing strata for variance estimation. Journal of Official Statistics, 3, 1, 69-81.
- Särndal, C-E., Swensson, B. and Wretman, J. (1992). Model Assisted Survey Sampling. Springer Series in Statistics.
- Tam, S. M. (1984). On covariances from overlapping samples. American Statistician, 38, 288–289.
- Verma, V. and Betti, G. (2005). Sampling errors and design effects for poverty measures and other complex statistics. University of Siena, working paper n°53. Available at: URL = http://www.econ-pol.unisi.it/dmq/pdf/DMQ_WP_53.pdf
- Verma, V. and Betti, G. (2011). Taylor linearization sampling errors and design effects for poverty measures and other complex statistics. Journal of Applied Statistics, 38, 8, 1549-1576.
- Wolter, K. M. (2007). *Introduction to Variance Estimation.* 2nd ed. New York: Springer.
- Wood, J. (2008). On the covariance between related Horvitz-Thompson estimators. Journal of Official Statistics, 24, 53–78.