This module is part of the

Memobust Handbook

on Methodology of Modern Business Statistics

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Method: Generalised Regression Estimator

Contents

General section 3

1. Summary 3
2. General description of the method 3
   - 2.1 Properties of GREG estimator 4
   - 2.2 Particular cases and extensions 5
3. Preparatory phase 5
4. Examples – not tool specific 5
   - 4.1 The Small-Medium Enterprises Survey and the current sampling strategy 5
5. Examples – tool specific 10
6. Glossary 10
7. References 10

Specific section 12

Interconnections with other modules 14

Administrative section 16

General section

1. Summary

The basic estimator (see "Weighting and Estimation – Main Module") of a target parameter expands the observed values on the sample units using direct weights, which are the inverse of the inclusion probabilities. Generalised regression estimator is a model assisted estimator designed to improve the accuracy (see "Quality Aspects – Quality of Statistics") of the estimates by means of auxiliary information. GREG estimator guarantees the coherence between sampling estimates and known totals of the auxiliary variables, as well. In fact, it is a special case of a calibration estimator (see "Weighting and Estimation – Calibration") when the Euclidean distance is used.

2. General description of the method

In the estimation phase, the sample values are weighted to represent also unobserved units. When auxiliary information is available at unit or domain level, a GREG estimator can be used in order to reduce the variance of the estimates by using the relationship between the target variable and the auxiliary variables. At the same time the resulting weights allow calibration to the known totals.

Let y, x be the target variable and the vector of auxiliary variables, respectively.

The GREG estimator (Cassel, Särndal, and Wretman, 1976) can be expressed as a sum of the Horvitz Thompson estimator (HT) (see "Weighting and Estimation – Main Module") and a weighted difference between known totals and their HT estimator:

$$\hat{t}_{GREG} = \sum_{i \in s} d_i y_i + \hat{\beta}' \left(t_X - \sum_{i \in s} d_i x_i \right), \tag{1}$$

where d_i, i=1,…n, is the direct weight equal to the inverse of the inclusion probability, t_X is the vector of known population totals; moreover $\hat{\beta}$ is an estimate of the vector of regression coefficients of y on x, given by

$$\hat{\beta} = \left(\sum_{i \in s} d_i q_i x_i x_i' \right)^{-1} \sum_{i \in s} d_i q_i x_i y_i ,$$

with q_i scale factors chosen properly, e.g., to account for heteroscedasticity. For example, when the variability of the target y depends on enterprises' size, z, the q_i can be chosen as $\sqrt{z_i}$.

In general, z may also be one of the covariates in the regression model.

Alternatively, the GREG estimator can be formulated in terms of predicted values for the target variables calculated on the basis of a linear relationship between y and x. More specifically, these predicted values are used in the estimation together with the residuals from the model, evaluated for sample units, i.e., the GREG estimator can be written as

$$\hat{t}_{GREG} = \sum_{i=1}^{N} \hat{y}_i + \sum_{i \in s} d_i e_i = \sum_{i=1}^{N} \hat{y}_i + \sum_{i \in s} d_i \left(y_i - \hat{y}_i \right), \tag{2}$$

where $\hat{y}_i = x_i'\hat{\beta}$ is the predicted value according to the linear model that relates y and x, e_i is the evaluated residual for a unit in the sample.

Finally, the GREG estimator can be conveniently formulated as a weighted sum of sample values:

$$\hat{t}_{GREG} = \sum_{i \in s} d_i g_{i,s} y_i = \sum_{i \in s} w_{i,s} y_i \tag{3}$$

where the correction factor g_{is} of the direct weights is given by

$$g_{i,s} = 1 + \left(t_X - \sum_{j \in s} d_j x_j \right)' \left(\sum_{j \in s} d_j q_j x_j x_j' \right)^{-1} q_i x_i \tag{4}$$

which does not depend on the target variable *y*.

2.1 Properties of GREG estimator

A fundamental property of the GREG estimator is that it is nearly design unbiased (Särndal et al., 1992).

The linear GREG estimator is motivated via the linear assisting model (Särndal et al., 1992)

$$E(y_i) = \beta' x_i, \; V(y_i) = \sigma_i^2 . \tag{5}$$

However, the knowledge of all *x* values is not necessary to evaluate linear GREG, because the knowledge of totals suffices to calculate the new weights, $w_{i,s}$ (see section 12 below).

The regression coefficient in (5) can be estimated at national level or for a disaggregated level, e.g., NUTS2. This level is referred as model group $\{\mathrm{U(p)}\}$. In case of sub-national model group, the known totals need to be available at this level.

An important feature of the linear GREG is that the weighting system does not depend on the target variable but only on *x* values, as (4) shows.

The GREG estimator is calibrated to the known totals of the assisting model, that is

$$\sum_{i \in s} w_{i,s} x_i = t_X .$$

In fact GREG is a particular case of a calibration estimator (see "Weighting and Estimation – Calibration") when using the Euclidean distance. Moreover, all the calibration estimators can be asymptotically approximated by the GREG (Deville and Särndal, 1992).

Another relevant property of GREG estimator is that the evaluation of its variance (see "Quality Aspects – Quality of Statistics") is based on the variance of the residuals $(y_i - \hat{y}_i)$ (Särndal et al., 1992). As a consequence of this, the higher the fitting of the linear working model the lower the variance of GREG estimator and therefore the higher its accuracy. On the contrary, if the model underlying the GREG is not appropriate for the target variable, a too large variation of weights may increase the variance with respect to the HT estimator. In fact, variability of weights unrelated with the target variable can increase the variance of the estimates, an approximation of this impact is given (Kish, 1995) by

$$1+\mathrm{CV}\left(w_{i,s}\right)^2, \tag{6}$$

where CV stands for the coefficient of variation of final weights.

A possible drawback of the GREG estimator is that it can produce negative weights (cf. section 10 below); on the contrary, in the framework of the calibration estimator, it is possible to obtain weights always positive using different distance functions (see "Weighting and Estimation – Calibration").

2.2 Particular cases and extensions

The ratio estimator is a special case of GREG assisted by a model with only one covariate, obtainable if the variance of the target variable is assumed to be a linear function of the auxiliary variable $V(y_i) = \sigma^2 x_i$ (Deville, Särndal, 1992).

Extended GREG estimators are defined replacing the assisting model (4) with more general (non-linear, generalised, or mixed) models.

The non-linear GREG estimators (e.g., Lehtonen and Veijanen, 1998) require a separate model fitting for every target variable; hence, an important drawback of this kind of model assisted estimators is that they do not produce a unique system of weights uniformly applicable.

On the other side, the nonlinear GREG may give a considerably reduction in variance, as a result of the more refined models that can be considered when there is complete unit level auxiliary information.

3. Preparatory phase

4. Examples – not tool specific

4.1 The Small-Medium Enterprises Survey and the current sampling strategy

Small and Medium-sized Enterprises (SME) sample survey is carried out annually by sending a postal questionnaire with the purpose of investigating profit-and-loss account of enterprises with less than 100 persons employed, as requested by SBS EU Council Regulation n. 58/97 (Eurostat, 2003) and n. 295/2008. The units involved in the survey have also the possibility to fill in an electronic questionnaire and transmit it to Istat via web.

The survey covers enterprises belonging to the following economic activities according to the Nace Rev.1.1 classification:

- Sections C, D, E, F, G, H, I, J (division 67), K;

- Sections M, N and O for the enterprises operating in the private sector.

Main variables of interest asked to the SME sampled enterprises are Turnover, Value added at factor cost, Employment, Total purchases of goods and services, Personnel costs, Wages and salaries, Production value. They are also asked to specify their economic activity sector and geographical location in order to test the correctness of the frame with respect to these information. Totals of variables of interest are estimated with reference to three typologies of domains of study.

4.1.1 Frame of interest

For the reference year 2007, the population of interest for SME sample surveys is about 4.5 millions active enterprises.

The frame for SME survey is represented by the Italian Statistical Business Register (SBR). It results from the logical and physical combination of data from both statistical sources (surveys) and administrative sources (Tax Register, Register of Enterprises and Local Units, Social Security Register, Work Accident Insurance Register, Register of the Electric Power Board) treated with statistical methodologies. Variables in the register are both quantitative (Average number of employees in the year *t*-1, Number of employees in date 31/12/year *t*-1, Independent employment in date 31/12/year *t*-1, Number of enterprises) and qualitative (Geographical location, Economic activity according to Nace Rev.1.1- 4 digit). From the Fiscal Register is also provided the VAT Turnover, which represents a good proxy of the variable Turnover asked to the sampled enterprises by questionnaire.

4.1.2 Sampling design (allocation and domain of estimates)

SME is a multi-purpose and multi-domain survey and it produces statistics on several variables (mainly economic and employment variables) for three types of domains, each defining a partition of the population of interest (see Tables 1 and 2).

Table 1: Types of SME Survey domains

Type of domain		Number of Domains
Code	Description	
DOM1	*Class* of economic activity (4-digit Nace Rev.1*)	461
DOM2	*Group* of economic activity (3-digit Nace Rev.1) by size-class of employment	1.047
DOM3	*Division* of economic activity (2-digit Nace Rev.1) by region	984

*Nace Rev.1 = Statistical Classification of Economic Activities in the European Communities

Table 2: Definition of Size-classes of employment for domain DOM3 of SME Survey

Nace Rev.1.1 2-digit level	Size-classes of employment
10-45;	1-9; 10-19; 20-49; 50-99;
50-52;	1; 2-9; 10-19; 20-49; 50-99;
55;60-64;67;70-74;	1; 2-9; 10-19; 20-49; 50-99;
80; 85; 90; 92; 93;	1-9; 10-19; 20-49; 50-99;

Sampling design of the SME survey is a one stage stratified random sampling, with the strata defined by the combination of the modality of the characters Nace Rev.1.1 economic activity, size class and administrative region. A fixed number of enterprises are selected in each stratum without replacement and with equal probabilities. The number of units to be selected in each stratum is defined as a solution of a linear integer problem (Bethel, 1989).

In particular, the minimum sample size is determined in order to ensure that the variance of sampling estimates of the variable of interest in each domain does not exceed a given threshold, in terms of coefficient of variation. The variables of interest used for sample allocation are *Number of persons employed, Turnover, Value added at factor cost*, whose mean and variance are estimated in each stratum by data from the frame and data collected from the previous survey, respectively.

About 103,000 of small and medium-sized enterprises (units) are included in the sample. The sampling units are drawn by applying JALES procedure (Ohlsson, 1995) in order to take under control the total statistical burden, by achieving a negative co-ordination among samples drawn from the same selection register.

4.1.3 The weighting procedure

After calculating the total non-response correcting factors as the ratio of the number of sampled units and the number of responding units belonging to appropriate "weighting adjustment cells", the weight of every single enterprise is further modified in order to match known or alternatively estimated population totals called benchmarks. In particular, known totals of selected auxiliary variables on the Business Register (Average number of employees in the year t-1, Number of enterprises) are currently used to correct for sample-survey nonresponse or for coverage error resulting from frame undercoverage or unit duplication.

Practical aspects in the application of the weighting procedure in the contest of SME survey

The evaluation of final weights for SME survey is usually carried out using the selected auxiliary variables, for the three types of domains described in Table 1. The optimisation problem underlying the GREG estimation process can be therefore formulated in the following way:

- the model group $\{U(p)\}$ is defined as the division of economic activity (2-digit Nace Rev.1.1) of the frame (the updated Business Register);
- the domains of interest are represented by the three typologies of partitions (described in Tables 1 and 2);
- the auxiliary variables are identified by
  - x_1= *Number of enterprises*
  - x_2= *Average number of employees in the year t-1*;
- for each enterprise, the vector $\mathbf{x}_i$ of the auxiliary variables has been defined as follows:

  $\mathbf{x}'_i = (\mathbf{x}'_{1i}, \mathbf{x}'_{2i})$, combination of two vectors $\mathbf{x}'_{1i}$ and $\mathbf{x}'_{2i}$ whose form is, respectively:

  $\mathbf{x}'_{1i} = \{\lambda_i(j_d)\}$,

  $\mathbf{x}'_{2i} = \{\alpha_i \lambda_i(j_d)\}$ with d=1,…,3; j=1,.., J_d ,

  where, according to the updated Business Register information:

  - $\lambda_i(j_d)$ is a dichotomous variable whose value is equal to 1 if the unit i belongs to domain j_d and equal to 0 otherwise;

  - α_i is the number of employed of enterprise i;

- for each model group $\{U(p)\}$, i.e., for each division of economic activity (2-digit Nace Rev.1.1), the known population totals calculated on the updated frame, are expressed by:

$$X_{U(p)} = \Sigma\, U(p)\mathbf{x}'_i = \left(\Sigma U(p)\lambda_i(j_1),\ldots,\Sigma U(p)\lambda_i(j_3),\Sigma U(p)\alpha_i\lambda_i(j_1),\ldots,\Sigma U(p)\alpha_i\lambda_i(j_3)\right).$$

An example

In Table 3A the NACE code of every single domain of interest is listed in each cell; in the input data set of the weighting procedure each of them is replaced by the respective population total, in terms of the auxiliary variable *Average number of employees in the year t-1* (a similar specification is done in terms of the auxiliary variable *Number of enterprises*):

Table 3A: Example of benchmark specification (known totals)

DOMAIN	DOM1: Nace-4 digit (codes)					DOM2: Nace-3 digit * Size class (codes)					DOM3: Nace-2digit *Nuts		
Nace 2 digit	Tx1	Tx2	Tx3	Tx4	Tx_{jd}	Tx15	Tx16	Tx17	Tx18		Tx180	Tx181	Tx182
10	1010	1030	0	0	..	101*1-9	101*10-19	101*20-49	103*1-9	..	north	central	south
11	1111	1112	1113	1120	..	111*1-9	111*10-19	112*10-19	112*20-49	..	north	central	south
13	1310	1320	0	0	..	131*1-9	131*10-19	133*50+	132*1-9	..	north	central	south
14	1411	1412	1413	1421	..	141*1-9	141*10-19	141*20-49	142*50+	..	north	central	south
15	1511	1512	1513	1520	..	151*1-9	151*10-19	151*50+	152*1-9	..	north	central	south
16	1600	0	0	0	..	160*50+	0	0	0	..	north	central	south
17	1711	1712	1713	1715	..	171*1-9	171*10-19	171*20-49	172*1-9	..	north	central	south
…	…	…	…	…		…	…	…	…		…	…	…
93	9301	9302	9303	9304		930*1-9	930*1-9	930*10-19	930*50+		north	central	south

For each responding unit (enterprise), the vector of the auxiliary variable *Average number of employees in the year t-1* can be expressed as in Table 3B, whether or not the unit belongs to the domain represented on the cell:

Table 3B: Example of sample data specification (α_k = number of persons employed of enterprise k)

				DOM1:Nace-4 digit (x_2-values)					DOM2: Nace-3 digit * Size class (x_2--values)					DOM3: Nace-2digit *Nuts		
Unit identifier	Domain Nace2	q_k	Direct weight	x1	x2	x3	x4	xj_d	x15	x16	x17	x18		X180	X181	X182
1	10	α_1	22	α_1	0	0	0	..	α_1	0	0	0	..	0	α_1	0
2	10	α_2	1,4	0	α_2	0	0	..	0	α_2	0	0	..	0	0	α_2
3	93	α_3	10,5	0	0	0	α_3		0	0	0	α_3	..	0	α_3	0
4	14	α_4	3	α_4	0	0	0	..	α_4	0	0	0	..	α_4	0	0
5	17	α_5	6,4	0	α_5	0	0	.	0	0	α_5	0	..	α_5	0	0
…	…	α_k	…	…	…	…	…	..	…	…	…	…	..	…	…	…
n_p	14	α_{np}	18	0	0	α_{np}	0	..	α_{np}	0	0	0	..	α_{np}	0	0

The overall number of benchmarks (constrained estimates) in the optimisation process is equal to 182. In spite of the considerable number of constraints to be satisfied, the weighting process ends with a good convergence between final estimates and know population totals (see Table 4).

Table 4A: Example of output of the weighting procedure for a domain of interest (2 digit NACE): Check on the auxiliary variables

Domain code =14						
Constraint code	Known Totals (1)	Final Estimates of X variables (2)	Direct Estimates of the X variables (3)	(2)-(1)	(3)-(1)	Sampling units
1	83081	83081	62133	0	-20948	57
2	249069	249069	227430	0	-21639	17397
3	33099	33099	23961	0	-9138	426
4	27339	27339	22323	0	-5016	12
5	451	451	294	0	-157	63
….	…	…	…	…	…	…
182	4676	4676	3375	0	-1301	6

Table 4B: Example of output of the weighting procedure for a domain of interest (2 digit NACE): Final weights

Unit identifier	Domain Nace2	q_k	**Direct weight**	**Final weight**
1	10	α_1	**22**	**18,2**
2	10	α_2	**1,4**	**2**
3	93	α_3	**10,5**	**12**
4	14	α_4	**3**	**5**
5	17	α_5	**6,4**	**4,2**
…	…	α_k	**…**	**…**
n_p	14	α_{np}	**18**	**15**

The estimator effect for the final weights has been calculated on the sample of responding enterprises with less than 100 persons employed at division of activity level (NACE Rev.1.1-2 digit), for the following subset of target variables:

1. Turnover (code 12 11 0)

2. Value added at factor cost (code 12 15 0)
3. Personnel costs (code 13 31 0)
4. Gross investment in tangible goods (code 15 11 0)
5. Number of employees(code 16 13 0)
6. Wages and salaries (code 13 32 0).

The estimator effect values confirm the higher efficiency gained by using the GREG estimator instead of the direct estimation for most of the considered divisions of activities and target variables; the main exception concerns the variable "Gross investment in tangible goods", which is hardly predictable by a model. Moreover, the variables "Turnover" and "Value added at factor cost" have an estimator effect higher than 1 for some divisions, i.e., 73-"Research and development" and 74-"Other business activities", that are characterised by specialised activities where the high amounts invoiced by the enterprises can be attained by a relatively small number of skilled employees.

In conclusion, apart from a small group of economic activity classes, the variable "average number of employees" has shown a good correlation with the following target variables of interest: "turnover", "production value", whereas it is not enough correlated with "Gross investment in tangible goods".

5. Examples – tool specific

6. Glossary

For definitions of terms used in this module, please refer to the separate "Glossary" provided as part of the handbook.

7. References

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Specific section

8. Purpose of the method

The method is used for estimation, when auxiliary information is available at unit or domain level. It can be used to reduce the variance of the estimates if a strong correlation between the target variable and the auxiliary variables exists. At the same time, GREG allows to calibrate to the known population totals of the auxiliary variables *x*. This means that GREG is a particular case of a calibration estimator when the distance function is linear, i.e., the final weights that satisfy the calibration equations *w* are chosen to minimise the following distance with the initial weights *d*:

$$\sum_s \frac{(w-d)^2}{2d}.$$

9. Recommended use of the method

1. GREG is recommended when a linear relationship between target y and covariate variables x is present, $y = \beta x + \varepsilon$.

10. Possible disadvantages of the method

1. GREG can introduce a large variation in weights that can cause an increase in variance, see formula (6) to quantify the impact.
2. Possibly correction weights *g* too far from unity or negative final weights as the correction factors (see formula (4)) can be in some cases a negative quantity.
3. Even being asymptotically unbiased, bias can be introduced if sample size is too small (see also section 14).
4. GREG can be very sensitive to presence of outliers (see "Weighting and Estimation – Outlier Treatment"); an illustrative example with discussion can be found in Hedlin et al. (2001). This issue is very relevant to business survey where target variables are typically non-normal and very skewed.

11. Variants of the method

1. Specific case: Ratio regression.
2. Non-linear GREG estimators. Expression (2) can be applied on general models. In fact, the prediction $\hat{y}_i$, that for GREG is based on linear model can be based on more complex models if the target variable for example is not normal. An example of non-linear GREG is logistic GREG which is based on logistic model when the target variable is a binary variable. The use of more complex models, however, requires more detailed information on the x variable w.r.t. the knowledge of population total that is needed by (linear) GREG.

12. Input data

1. Ds-input1 = elementary sample data containing covariates, direct weights and scale coefficients q_i, model group (i.e., level for which the model is specified).

2. Ds-input2 = known totals on the covariates for each model group.

13. Logical preconditions

1. Missing values
    1. GREG is calculated on sample values on DS-input1 after imputation – anyway, variance estimation is affected by the imputation.
    2. Ds-input2 cannot contain missing values.
2. Erroneous values
    1.
3. Other quality related preconditions
    1.
4. Other types of preconditions
    1. If the auxiliary variables are categorical, the known totals for different partitions should not be in conflict.

14. Tuning parameters

1. Choice of the auxiliary covariates in the model, a rule of thumb for the choice of categorical variable is to define categories so that the sample totals are greater than 30.
2. Choice of the model group level.
3. Choice of q_i.

15. Recommended use of the individual variants of the method

1. Non-linear GREG can be used when auxiliary variables are available for each unit in the population and the relationship with the target variable is markedly non-linear.

16. Output data

1. Ds-output1 = elementary sample data set containing the new final weights.

17. Properties of the output data

1. The final weights allows to satisfy the implicit constraints given by the known totals of the auxiliary variables.

18. Unit of input data suitable for the method

Sample units, also separately by model group.

19. User interaction - not tool specific

1. Choice of auxiliary covariates.
2. Choice of the group level.

3. Choice of q_i.

20. Logging indicators

1. The run time of the application.
2. Iterations to attain convergence in the estimation process.
3. Characteristics of the input data, for instance problem size.

21. Quality indicators of the output data

1. The coefficient of variation of the final weights in comparison with the basic weights.
2. Presence of negative weights, in this case it may be appropriate to consider a different underlying model or to use a calibration estimator with a function that allows to restrict the range of final weights (see the module "Weighting and Estimation – Calibration").
3. Variance, coefficient of variation of produced estimates.
4. Check of equality of sample estimates of x and known population totals.

22. Actual use of the method

1.

Interconnections with other modules

23. Themes that refer explicitly to this module

1. Weighting and Estimation – Main Module
2. Quality Aspects – Quality of Statistics

24. Related methods described in other modules

1. Weighting and Estimation – Calibration
2. Weighting and Estimation – Outlier Treatment

25. Mathematical techniques used by the method described in this module

1. Matrix algebra

26. GSBPM phases where the method described in this module is used

1. 5.6 "Calculate weights"
2. 5.7 "Calculate aggregates"

27. Tools that implement the method described in this module

1. CALMAR (Deville, Särndal and Sautory 1993)
2. CLAN (Statistics Sweden)
3. BASCULA (The Netherlands)

4. GES (StatCan)
5. GENESEES (ISTAT)
6. Survey, an R package downloadable from the CRAN
7. Sampling, an R package downloadable from the CRAN
8. REgenesees (ISTAT), an R package downloadable from the JoinUP: https://joinup.ec.europa.eu/software/regenesees/release/release150#download-links

28. Process step performed by the method

Estimation

Administrative section

29. Module code

Weighting and Estimation-M-Generalised Regression Estimator

30. Version history

Version	Date	Description of changes	Author	Institute
0.1	06-02-2012	first version	Loredana Di Consiglio, Claudia De Vitiis, Cristina Casciano	ISTAT
0.2	03-05-2012	second version	Loredana Di Consiglio, Claudia De Vitiis, Cristina Casciano	ISTAT
0.2.1	22-06-2012	second version – with corrections	Loredana Di Consiglio, Claudia De Vitiis, Cristina Casciano	ISTAT
0.2.2	11-11-2013	second version – after EB review	Loredana Di Consiglio, Claudia De Vitiis, Cristina Casciano	ISTAT
0.2.3	13-11-2013	preliminary release		
1.0	26-03-2014	final version within the Memobust project		

31. Template version and print date

Template version used	1.0 p 4 d.d. 22-11-2012
Print date	26-3-2014 13:32