Weight adjustments after sub-sampling cross-sectional data

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Abstract

To avoid biased results, sample units must be included in the sample in the correct proportion. Sample weights are intended to correct potential disproportions observed in survey sample data. While their use is widely accepted to estimate population descriptive statistics, their role to estimate causal effects is not clear. This paper analyzes when and how to use weights, considering wages in Colombia as an example, providing a procedure for selecting the final weight components based on empirical evidence. Results indicate that weights are required for descriptive statistics to resemble the population ones. However, several coefficients obtained from weighted and unweighted wage equations show no significant differences.

*Keywords***:** sample weights, post-stratification weights, non-response weights.

AMS Classification: 62D05, 62D99, 62D99.

Corrección de los pesos en submuestras de datos de corte transversal

Resumen

A fin de evitar resultados sesgados, las unidades muestrales deben ser incluidas en la muestra en la proporción correcta. Los pesos muestrales se utilizan para corregir posibles desproporciones, frecuentes en datos muestrales. Mientras su uso es ampliamente aceptado para estimar estadísticas descriptivas de la población, su papel en la estimación de efectos causales no es claro. Este trabajo analiza cuándo y cómo utilizar dichos pesos, considerando salarios en Colombia como ejemplo, proporcionando un procedimiento para seleccionar los componentes del peso final basado en la evidencia empírica. Los resultados indican que los pesos muestrales son necesarios para que las estadísticas descriptivas de la muestra se asemejen a las de la población. Sin embargo, varios coeficientes obtenidos a partir de ecuaciones de salarios ponderados y no ponderados no muestran diferencias significativas.

Palabras Claves: Pesos muestrales, pesos de post-estratificación, pesos de no respuesta.

Clasificación AMS: 62D05, 62D99, 62D99.

1. Introduction

In social sciences many studies rely on survey data usually obtained from probability sampling methods intended to provide a given level of precision of the estimates and reduce costs, such as having biased results. Sample weights are estimated to correct disproportions of the sample data with respect to the target population controlling, among others, for differences in the probabilities of being part of the sample or non-response situations.

There are not doubts about the importance of the appropriate estimation of sample weights. Their use, or the lack of it, may affect the results of any study, probably making the difference between a correct diagnose of a situation and the subsequent course of action, and a wrong one. However, the when and how to used them is yet an unsolved problem.

For official survey data, sample weights are regularly provided to resemble the original population. Researchers adapt these data sets to fit the purposes of their study, trimming out individuals that do not satisfy some required conditions. For the resulting subsample, sample weights may not satisfy the original properties so that some adjustments must be introduced for the subsample to be representative. A representative sample is an unbiased representation of the population, showing the same characteristics and holding their proportional distribution among units.

The concept of subsampling has been used in the statistical literature in many different contexts and so, in order to avoid any confusion, we would like to indicate the technical sense in which it is used in this article. The idea of using subsampling is historically attributed to Mahalonobis who, in 1946, proposed it under the name of "interpenetrating network of subsamples" in order to evaluate non sampling errors and estimate standard error in the study of crop yields. Later, the bootstrap research brought a revived interest in the subsampling, which is now used in a wide variety of situations. A combination of interpenetration and repetition was used in a study of response errors in the 1961 Canadian Census of Population. Also, the interpenetration method was used by the U.S. Census Bureau in 1968 to estimate the correlated components of the total response variances. Cochran (1977) gives a detailed account of many other research workers who used the interpenetration method to estimate the correlated response variance.

Even though the interpenetration method is not possible when a complex sampling design is used without being available the details about its construction, necessary to plan the sampling design at priori, we suggest that a post interpenetration method is possible to design based on the distribution of demographic variables, which can be constructed in the same manner as post-stratification is used in order to gain useful information about different types of response errors and estimate its variance in a sampling survey.

We will use subsampling in the sense defined by Kotz, et al. (2006) as a non-parametric technique which can be used to estimate the sampling distribution of a statistic. For this purpose, a subsample of m(n) is taken from the original sample given by $(X_1, X_2, \ldots, X_n)$ such that $m < n$. The procedure to be used in this type of subsampling is very similar to the m out of n bootstrap method.

This study uses information from the Colombia's Integrated Household Sample Survey (IHSS) corresponding to August 2014 to show the need for and the methodology used to restore the sample weight properties for representativeness purposes, once some units are excluded. The sample weights of the 60,337 individuals included in the original data set add up to 35,626,316, pretty close to the population size of 35,626,302 individuals reported by the Colombia's Administrative Department of National Statistic (DANE) for year 2014.

Particularly, to analyze the wage distribution of workers, we limit our sample to employed individuals aged between 15 and 80 years. The generated subsample just includes 27,407 observations whose combined weights go down to 18,719,563. We show that, once original weights are rescaled and post-stratification and non-response weights are computed, the main statistics for the original sample and the weighted subsample show no significant difference. We also examine the effect of sample weights on the estimated parameters of wage equation models. Our findings show that the impact of some variables on wages may be overestimated when using the wrong weights, but are inconclusive when compared to the unweighted coefficients.

2. Post-stratification and non-response adjustments

Weights allow making inference about the population from a sample, by adjusting for either unequal probabilities of selection, non-response, or both. When taken into account, these weights are generally used in descriptive statistics. However, many studies neglect the fact that changes in the original sample may affect the properties of the sample weights, jeopardizing the randomness or the representativeness of the resulting data set.

Brewer and Mellor (1973) suggest that the decision about whether to use sample weights in a regression analysis depends on the structure of the model used. A similar conclusion is reached by DuMouchel and Duncan (1983) comparing different models. A general recommendation is to recalculate the weights so that its sum in a sample or within groups is equal to the population size. Wooldridge (1999) develops the properties of the estimator in the presence of weights, and describes how these properties can be affected in either direction, depending on whether the sampling probabilities vary exogenously or endogenously.

Pfefferman (1993) compares the use of sampling weights for either ex -post corrections or as part of a regression model, in an attempt to determine if their use is justified and draws some guidelines about their use. His remarks about different approaches leading to similar estimators speak by themselves. Solon et al. (2013) highlight the lack of clarity on the sampling weights issue, through a collection of cases in which the use of sample weights helps or not to correct problems. Based on that, they conclude that knowledge about the reasons for weighting spreads light on the need of using sampling weights.

In order to reduce survey costs, most of the household surveys use complex sampling designs which involve stratification, multi-stage sampling and unequal sampling rates. A complete sampling frame listing all possible sampling units is not always available or known. Consequently, different techniques such as post-stratification and non-response adjustments are required to be used in order to increase the efficiency of the estimates.

Since it is impossible to collect all the expected information from all the surveyed units, non-response adjustments have attracted a great deal of attention. Gelman and Carlin (2000) lay out the main assumptions required when using sample weights to correct for non-response. Similarly, Yansaneh (2003) summarizes the stages to construct sample weights to be used in the analysis of survey data, emphasizing the need for adjustments to compensate for non-coverage and non-response.

Schouten et al. (2009) suggest that controlling for high non-response rates do not necessarily reduces the non-response bias, which we will show is not the case in the example included ahead. According to them, the propensity to non-response should be considered. Vives et al. (2009) use both, field substitution and response propensity weights to adjust for non-response, concluding that both techniques show similar results.

2.1 Post-stratification

Responses on sampling units in a survey will vary according to the different variables included in the sample. For example, in the case of a sample on persons, often data on demographic variables such as age, race, education level, sex, etc. are collected. For some of these variables, it can be constructed the sample distribution frequency and compared it to the population frequency distribution obtained in a recent census; if a recent census data is not available, data on a major national survey with variables similar as in the research being conducted may be used as an approximation. If a discrepancy exists between the distribution frequencies of the survey data under investigation and the census data, the representativeness of the sample obtained in the survey sample is not assured and correctional measures should be taken using post-stratification methods to restore the representativeness of such a sample.

The post-stratification is very similar to stratification but it cannot be applied before obtaining the sample in the survey. However the post-stratification is considered potentially more efficient than stratification itself, since it is possible to select factors in such a way as to maximize the gain in precision of the estimates.

We consider a population denoted by Π which is partitioned in strata for which we denote its strata size equal to N_h such that $\sum_h^H N_h$= N. We also consider a sample of size n for which y_{hi} is the value of an observed variable for the i-th observation obtained that belongs to the h-th stratum such that h=1 …, H; i = 1, …, n_h and $\sum_h^H n_h = n$. The values of n_h are known only after the sample is obtained. We can calculate the population strata means and variances and the whole population means and variances based on

$$\bar{Y} = \sum_{h=1}^{H} \sum_{i=1}^{N_h} y_{hi} /N \qquad [1]$$

$$S^2 = \sum_{h=1}^{H} \sum_{i=1}^{N_h} (y_{hi} - \bar{Y})^2 /(N-1) \qquad [2]$$

Similar formulas may be used for estimators which are given below. The h-th stratum sample mean is

$$\bar{y}_h = \frac{\sum_{i\in s}^{n_h} y_{hi}}{n_h} \qquad [3]$$

where $i \in s$ indicates the set of i in the sample such that the units belong to the h-th stratum. The variance of the h-th stratum is then given by

$$s_h^2 = \sum_{i\in s}^{n_h} (y_{hi} - \bar{y}_h)^2/(n_h - 1) \qquad [4]$$

2.2 Non-response adjustments

Non sampling error is any type of error which is different than a sampling error. Biemer and Lyberg (2003) decompose the non-sampling errors into their components. The non-sampling error is the cumulative effect of the errors that have been made during data collection, data processing and estimation of parameters of interest in the study. Some of the errors which may frequently occur in a study are due to different sources given below:

a. Respondents may not wish to reveal information, for example their true incomes or parts of their incomes coming from different sources.

b. The interviewer may make mistakes in entering data.

c. The respondent may refuse to participate in the interview.

d. There may be errors in data entry from the survey questionnaire that will be used to obtain the estimation of parameters.

A non-sampling error is inevitable in a large survey and may not be controlled easily, whereas a sampling error can be controlled just by using an optimum sample size.

A non-response error is a type of non-sampling error that can be caused by the lack of cooperation to respond questionnaire by not revealing the true information required by the interviewer. Such an error can be of different types whether it is due to providing information which affects the whole sampling unit, or within unit or item. Non-response errors can introduce bias in the survey results especially in situations in which the non-responding units are not representative of those who responded the questionnaire. Non-response increases non-sampling errors as well as the sampling error, by decreasing the sample size.

Different methods exist that can help reduce the non-response bias in a survey:

a. Non-response adjustments using the sample weights.

b. Obtaining a large sample containing replacements that can be used in the case of non response.

c. Using a substitution to replace a non-responding unit in the sample by another unit not included in the sample but very similar to the sampled unit which did not respond.

However non-response adjustment of the sample weight appears to be the method preferred by most of the research workers and will be explained in the next section, along with the procedure for calculating sample weights.

3. A procedure for selecting components for final weight

Once a subsample is generated, the next step is to re-estimate sample weights. In addition of rescaling the original ones (base), we compute the post-stratification weights based on some characteristic variables, considering the proportion of observations in the subsample with respect to those in the original sample. We also estimate the non-response weight based on the number of units who did not report their wage. These weights are the components of the final ones.

The number of components that will be used in calculating the final weights should be decided based on a test of significance for the difference $\widehat{\Lambda} = \hat{\theta}_w - \hat{\theta}$, where θ is some parameter of interest. For example, if we are considering the household income, then θ can be taken as the population mean μ and the test of significance of the difference $\widehat{\Lambda} = \hat{\mu}_w - \hat{\mu}$ between the household weighted income mean ($\hat{\mu}_w$) and unweighted mean ($\hat{\mu}$) should be used to make the decision. Since the final weights are composed by 3 types of weights, namely base, post-stratification and non-response, we decide which one works better based the results of different significant tests, following the steps outlined below.

Table 1

Steps and tests of significance for the selection of components of the final weight

Step	*Difference to test*	*Comparison*
1	$\widehat{\Lambda} = \hat{\theta}_w - \hat{\theta}$	Base weighted vs. unweighted
2	$\widehat{\Lambda}_2 = \hat{\theta}_{w(b+po)} - \hat{\theta}_{w(b)}$	Base and poststratification weighted vs. base weighted

3	$\widehat{\Lambda}_3 = \widehat{\theta}_{w(b+po+ns)} - \widehat{\theta}_{w(b+po)}$	Base, poststratification and non-response weighted vs. base and poststratification weighted

Source: created by the authors

The selection of the final weight and its components should be done only after the results of all 3 steps are obtained. For example if the difference in step 1 is not significant, implying that there is no apparent advantage in using base weight, it does not indicate that such a base weight is not required as a component in the final one, since the results obtained in this step do not take into account further information, only available after performing steps 2 and 3.

4. An example

This study relies on data from the Colombia's IHSS corresponding to August 2014, for which the sum of sample weights equals the country's 2014 population size of 35,626,316[1] citizens. For the purpose of the study, only employed individuals between 15 and 80 years of age are considered, so that the original sample size of 60,337 goes down to 27,407 observations, while the original sample weights add up only 18,719,563.

The post-stratification weight (w2) is estimated nesting each level of education within each age group by gender[2]. For each group, we calculated the proportion of weighted units in the original sample (b_j) and the proportion of observations in the sample (d_j), so that $w2_j = b_j/d_j$ as shown in table A1 in appendix.

Next, the non-response weight (w3) is calculated to correct for individuals who did not report their wages. To do that, for each strata of the original sample weight we estimated the number of non-response (k_j) and the number of observations (n_j), so that the non-response weight was obtained as given by $w3_j = n_j/(n_j - k_j)$.

Finally, all weights (including the original sampling weight, w1) are rescaled using the ratio between the population size and the sum of the corresponding weights, and multiplied between them to obtain w12=w1*w2 as well as w123=w1*w2*w3. All the computations were done using Stata/SE 14.0 and Excel. Table 2 provides the main statistics for wages from the original sample as well as for the weighted and unweighted subsample.

Table 2

Descriptive statistics (August 2014)

Wages	*Mean*	*Median*	*Standard deviation*	*Skewedness*
IHSS weighted original sample (y_0)	962,900.80	640,000	1,424,324	9.02
Unweighted subsample (y)	909,336.90	616,027	1,714,030	8.80
w1 weighted subsample (y_1)	1,008,358.90	680,000	1,512,753	9.06

[1] This number differs from the DANE's estimates by only 14 individuals.

[2] Education includes four levels: Basic (1); high school (2); technology (3) and university (4). In the original data set there are six age groups: less than 15 (1); 15-25 years (2); 26-45 (3); 46-60 (4); 61-80 (5) and above 80 (6).

w12 weighted subsample (y_{12})	1,003,075.80	680,000	1,508,209	9.31
w123 weighted subsample (y_{123})	950,609.30	680,000	1,082,838	6.43

Source: estimated by the authors with data from IHSS 2014

As observed in this case, once a subsample is extracted from the original sample, the average wage may be underestimated if the sample weights are ignored, or overestimated if the researcher insists in using the original base weights provided along with the data set. Post-stratification weights do seem to correct the problem at the light of the similarities between the y_1 and y_{12} main statistics. These differences however, appeared to be solved once all wages are corrected by their corresponding total combined weights. The significance of such differences is shown in table 3. Following table 1, all possible combinations are considered, so that the equality between the original average wage (y_0) and the weighted and unweighted wages are tested, assuming unequal variances. As expected only the difference between μ_{y0} and μ_{y123} proved not to be statistically significant, meaning that the weight adjustments restored the representativeness of the subsample[3].

Table 3

Mean-comparison tests

Hypothesis	*Z – value*	*p-value*	*Confidence interval (95%)*
$m_{y0} = m_y$	4.30	0.00002	(2.94E4 ; 7.86E4)
$m_{y0} = m_{y1}$	-3.97	0.00007	(-6.78E4 ; -2.3E4)
$m_{y0} = m_{y12}$	75.4	0.00000	(8.38E5 ; 8.82E5)
$m_{y0} = m_{y123}$	1.32	0.18800	(-5.85E3 ; 2.99E4)
$m_y = m_{y1}$	-6.78	1.17E-11	(-1.3E5 ; -7.18E4)
$m_y = m_{y12}$	-6.33	2.44E-10	(-1.23E5 ; -6.5E4)
$m_y = m_{y123}$	-5.78	7.78E-09	(-5.53E4 ; -2.73E4)

Source: estimated by the authors with data from IHSS 2014

These findings point out not only that non-response for the variable of interest must be considered, but also that the researcher should analyze the reasons for the high incidence of such non-response situations. In the case considered here, several reasons can be blamed for it. Colombia's 32 Departments are divided into five natural geographical regions, based on their location and physical and climatic characteristics, although some Departments may be part of more than one region. The Andean region is the most densely populated, showing a very low non-response incidence, exception made by Norte de Santander. The Departments belonging to the Caribbean region tend to show very large non-response rates, although the largest rate (68%) is observed in Chocó in the Pacific region. The sparsely populated Llanos is barely represented in the IHSS by just one of its four Departments. Finally, the Amazon region is larger and less populated than the previous one, which may explain the fact that only Caquetá is considered in the sample. A look at a Colombia's map indicates two facts: first, the IHSS excludes the less populated Departments, most of them located in the western regions and second, central

[3] These tests assume that *ly* follows a normal distribution, based on the results of the Shapiro-France test (Z=0.147, pvalue=0.44138). The Kolmogorov-Smirnov test corroborates the results shown in the table.

Departments show the lowest non-response rates. As for the other factors, there exists a relatively higher level on non-response among women and people with low level of education. However, it seems that the non-response is mostly attributable to regional location (see table 4).

Table 4

Non-response possible sources

Variable	*Region / Departments*		*Response*	*Non-response*
Geographic area	Andean:	Antioquia	90.35	9.65
		Bogotá	90.41	9.54
		Boyacá	90.69	9.31
		Caldas	93.88	6.12
		Huila	88.33	11.67
		N. de Santander	76.32	23.68
		Quindío	88.50	11.50
		Risaralda	92.97	7.03
		Santander	92.60	7.40
		Tolima	89.87	10.13
	Caribbean:	Atlántico	58.76	41.24
		Bolívar	44.60	55.40
		Cesar	72.21	27.79
		Córdoba	90.48	9.52
		La Guajira	83.68	16.32
		Magdalena	81.48	18.52
		Sucre	86.75	13.25
	Pacific:	Cauca	71.09	28.91
		Chocó	32.28	67.72
		Nariño	79.44	20.56
		Valle del Cauca	86.34	13.66
	Amazon:	Caquetá	90.91	9.09
	Llanos:	Meta	86.59	13.41
Gender	Male		84.19	15.81
	Female		79.07	20.93
Education	Elementary		79.63	20.37
	High School		82.82	17.18
	Superior		83.43	16.57

Source: estimated by the authors with data from IHSS 2014

For descriptive analysis, sample weights are widely accepted as a way to restore the proportions observed in the target population. However, their role and need when trying to estimate parameters when modeling survey data is yet a matter of controversy. In order to determine whether our findings apply only to main statistics, we estimate traditional wage equations always correcting for potential selection bias, so that our model may be represented as given by

$$Ly = f(gender, age, education, informal, sector, tenure, union, \lambda) + \varepsilon \qquad [5]$$

where *Ly* stays for the logarithm of wages and λ accounts for the probability of being employed. The results, assuming different scenarios regarding sample weights, are summarized in table 5. As shown, the estimates exhibit similar patterns as those observed in table 2; that is, compared to the estimates obtained when considering the total combined weight (w123), the parameters tend to be underestimated when sample weights are ignored, and overestimated when non-response weights are not considered (w1 and w12).

Table 5

Wage equations estimates

Covariate / *Weight*	*None*	*w1*	*w12*	*w123*
Gender (Male)	-0.0701**	-0.2305*	-0.2188*	0.2161*
	-0.0343	-0.0613	-0.0648	-0.063
Age	0.0027	-0.0443*	0.0353*	0.0300**
	-0.0076	-0.0119	-0.0119	-0.0153
Age^2	-0.0001	0.0003*	0.0002***	-0.0002
	-0.0001	-0.0001	-0.0001	-0.0001
Education (High School)	0.0501***	0.1685*	0.1407*	0.0529***
	-0.0299	-0.0339	-0.014	-0.0299
Education (Superior)	0.5173*	0.6463*	0.6161*	0.5177*
	-0.0404	-0.0388	-0.017	-0.0405
Informal (Yes)	-0.1797*	-0.1981*	-0.1944*	-0.1857*
	-0.0125	-0.0393	-0.0398	-0.0526
Sector (Public)	0.2337*	0.3461*	0.3222*	0.2395*
	-0.401	-0.0527	-0.0187	-0.0406
Tenure (No)	-0.0450*	-0.1075*	-0.1076*	-0.045
	-0.0119	-0.0223	-0.0224	-0.0307
Union (Yes)	0.0861**	0.1497*	0.13305***	0.0898**
	-0.0439	-0.0239	-0.0718	-0.0446
Lambda	3.6600*	10.8085*	10.8578*	-5.883
	-0.8343	-1.4115	-1.4702	-6.2914
Constant	10.3198	4.7726	4.5125	18.8321
R^2	0.3601	0.3596	0.357	0.3147

Source: estimated by the authors with data from IHSS 2014

For example, the bargaining power of unions may go down from near 15% to less than 9% once non-response weights are "also" considered. Similarly, the returns to human capital may not be as large as 0.6 for highly educated workers, nor averaging 0.15 for unskilled workers, while tenure seems to be non-significant after all. Another important result is that, once sample weights are included, there are not sample selection problems, as indicated by the fact that λ becomes non-significant too. However, as some modelers argue, sample weights may be irrelevant especially if we consider the similarities between the estimated parameters shown in the first and last columns of table 5 for variables such as education, union, tenure and sector of employment.

5 Conclusions

This paper studies the convenience of using sample weights when analyzing survey sample data considering, as an example, a subsample of employed individuals aged 15-80 years obtained from the Integrated Household Sample Survey in Colombia in August 2014. For this data set, sample weights were obtained both rescaling the original weights and computing post-stratification and non-response weights based on wages. The product of these three forms the combined final sample weights.

The results indicate that basic descriptive statistics obtained using the final sample weights resemble the population values, but can be wrongfully estimated if sample weights are ignored, especially non-response weights. However, there is no clear indication about the convenience of using sample weights when estimating the relationship between variables as in wage equations models corrected by sample selection bias. In fact, some results obtained with weighted data are similar to those obtained ignoring the weights.

In line with other studies, our first conclusion is that no generalization is possible when trying to decide about whether or not to consider sample weights, since it is not possible to identify a pattern of behavior at this regard. The decision, therefore, relies on the empirical evidence and the researcher's experience. However, since computing sample weights may be cumbersome, a few words can be said about the conditions under which the researcher should consider to undertake this task.

As said before, representativeness is required in order to avoid bias results. If the researcher has information about the lack of representativeness of the sample or has doubts about it, sample weights are likely to be required. On the other hand, a large and unequal incidence of non-response in the target variable across regions or groups is another reason for sample weights to be computed and included in the analysis, a problem that is very common is our region due to geographical or cultural factors.

Finally, just rescaling the original sample weights once a subsample is tailored to the purposes of the study is not enough and the results, even basic statistics, are likely to be biased.

Appendix

Table A1

Post-stratification weights

Variables			Original sample			Sub Sample		B/D
Gender	Age group	Educ	Obs	A Weight	B Proportion	C Obs	D Proportion	W2
Male	0	1	7,555	4,635,051	0.130102	0	0.000000	-
		2	1	96	0.000003	0	0.000000	-
	1	1	2,556	1,613,441	0.045288	2,533	0.056956	0.79514
		2	2,739	1,462,708	0.041057	2,730	0.061386	0.66884
		3	466	327,214	0.009185	464	0.010433	0.88032
		4	136	53,027	0.001488	136	0.003058	0.48672
	2	1	3,307	2,278,335	0.063951	3,294	0.074067	0.86341
		2	3,406	2,040,401	0.057272	3,400	0.076451	0.74914
		3	1,128	705,845	0.019812	1,125	0.025296	0.78322
		4	1,297	825,976	0.023184	1,295	0.029119	0.79620
	3	1	2,931	1,786,148	0.050136	2,923	0.065725	0.76281
		2	885	522,859	0.014676	883	0.019855	0.73918
		3	239	138,742	0.003894	239	0.005374	0.72466
		4	666	375,925	0.010552	666	0.014975	0.70462
	4	1	311	186,857	0.005245	310	0.006971	0.75244
		2	34	27,622	0.000775	34	0.000765	1.01416
		3	5	7,688	0.000216	5	0.000112	1.91937
		4	16	13,085	0.000367	16	0.000360	1.02092
	5	1	297	174,959	0.004911	0	0.000000	-
		2	24	8,780	0.000246	0	0.000000	-
		3	3	3,235	0.000091	0	0.000000	-
		4	18	8,679	0.000244	0	0.000000	-
Female	0	1	7,322	4,362,959	0.122464	0	0.000000	-
		2	1	107	0.000003	0	0.000000	-
	1	1	2,415	1,357,939	0.038116	2,398	0.053920	0.70690
		2	3,108	1,562,278	0.043852	3,098	0.069660	0.62951
		3	771	457,783	0.01285	768	0.017269	0.74409
		4	258	127,403	0.003576	258	0.005801	0.61643
	2	1	3,785	2,244,693	0.063007	3,780	0.084995	0.74129
		2	3,875	2,305,183	0.064704	3,871	0.087042	0.74337
		3	1,831	1,021,049	0.028660	1,830	0.041149	0.6965
		4	1,881	1,014,323	0.028471	1,881	0.042295	0.67315
	3	1	4,064	2,329,171	0.065378	4,061	0.091314	0.71597
		2	1,019	519,313	0.014577	1,019	0.022913	0.63618
		3	333	203,729	0.005719	333	0.007488	0.76372
		4	644	367,670	0.010320	644	0.014481	0.71268
	4	1	428	255,117	0.007161	427	0.009601	0.74582
		2	38	18,057	0.000507	38	0.000854	0.59320
		3	4	768	0.000022	4	0.000090	0.23967
		4	10	4,868	0.000137	10	0.000225	0.60765
	5	1	488	250,020	0.007018	0	0.000000	-
		2	30	20,132	0.000565	0	0.000000	-
		3	7	2,501	0.000070	0	0.000000	-
		4	5	4,583	0.000129	0	0.000000	-
TOTAL			60,337	35,626,316	1.000000	44,473	1.000000	24.22728

References

BIEMER, P. AND LYBERG, L. E. (2003), «Introduction to survey quality», New Jersey, Wiley & sons, Inc.

BREWER, K. R. AND MELLOR, R. (1973), «The effect of sample structure on analytical surveys», *Australian Journal of Statistics*, 15, 145–152.

COCHRAN, W. (1977), «Sampling techniques», New York, John Wiley, 3rd ed.

DUMOUCHEL, M. AND DUNCAN, G. (1983), «Using sample survey weights in multiple regression analysis of stratified samples», *American Statistical Association*, 78, 535–543.

GELMAN, A. AND CARLIN, J. B. (2001), «Post stratification and weigting adjustments». In *Survey Nonresponse*, Wiley Series in Probability and Statistics.

KOTZ, S., BALAKRISHNAN, N., READ, C., AND VIDACOVIC, B. (2006), «Encyclopedia of statistical sciences». New York, John Wiley.

PFEFFERMAN, D. (1993), «The role of sampling weights when modeling survey data», *International Statistical Review,* 61(2), 317–337.

SCHOUTEN, B., COBBEN, F. AND BETHLEHEM, J. (2009), «Indicators for the representativeness of survey response», *Survey Methodology*, 35(1), 101–113.

Solon, G., Haider, S. J., and Wooldridge, J. M. (2013), «What Are We Weighting For?», Journal of Human Resources, 50(2), 301–316. http://doi.org/10.3368/jhr.50.2.301

VIVES, A.; FERRECCIO, C. AND MARSHALL, G. (2009), «Comparación de dos métodos para corregir el sesgo de no respuesta a una encuesta: sustitución muestral y ajuste según propensión a responder», *Gaceta Sanitaria*, 23(4), 266–271.

WOOLDRIDGE, J. (1999), «Asymptotic properties of weighted M-estimators for variable probability samples», *Econometrica*, 67(6), 1385–1406.

YANSANEH, I. S. (2003), «Construction and use of sample weights», in S. D. United Nations Secretariat (Ed.), *Draft handbook on designing household samples surveys* (pp. 1–14). United Nations.