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SAMPLE BIAS, WEIGHTS AND EFFICIENCY OF WEIGHTS IN A CONTINUOUS WEB VOLUNTARY SURVEY

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ABSTRACT

Using micro data from a continuous voluntary web survey, the Wage Indicator, the paper analyses the type of bias that such a sampling method produces and discusses a methodology to weight the data in order to correct such bias and make it possible to run analyses to obtain results and conclusions applicable to the whole population. In order to evaluate the efficiency of the weighting methodology to solve the potential sample bias of web surveys, the results are confronted with those obtained from an alternative standard labour survey dealing with the same issues. Since the Wage Indicator is a survey oriented to labour market issues, we considered that a labour market case study was most appropriate for the evaluation of the results. The method of evaluation followed is to calculate mean salaries, inequality indexes and salary regressions before and after implementing the weights using the Wage Indicator Survey data for Spain. The results are compared with those reached using the Structure of Earnings Survey, a wage survey run by the Spanish Statistical Institute.

Keywords: web surveys, data analysis, labour market

JEL Classification: C42, C81, J01

TABLE OF CONTENTS

1. INTRODUCTION: CONTINUOUS VOLUNTARY WEB SURVEYS AND THE WAGE INICATOR DATASET PROJECT

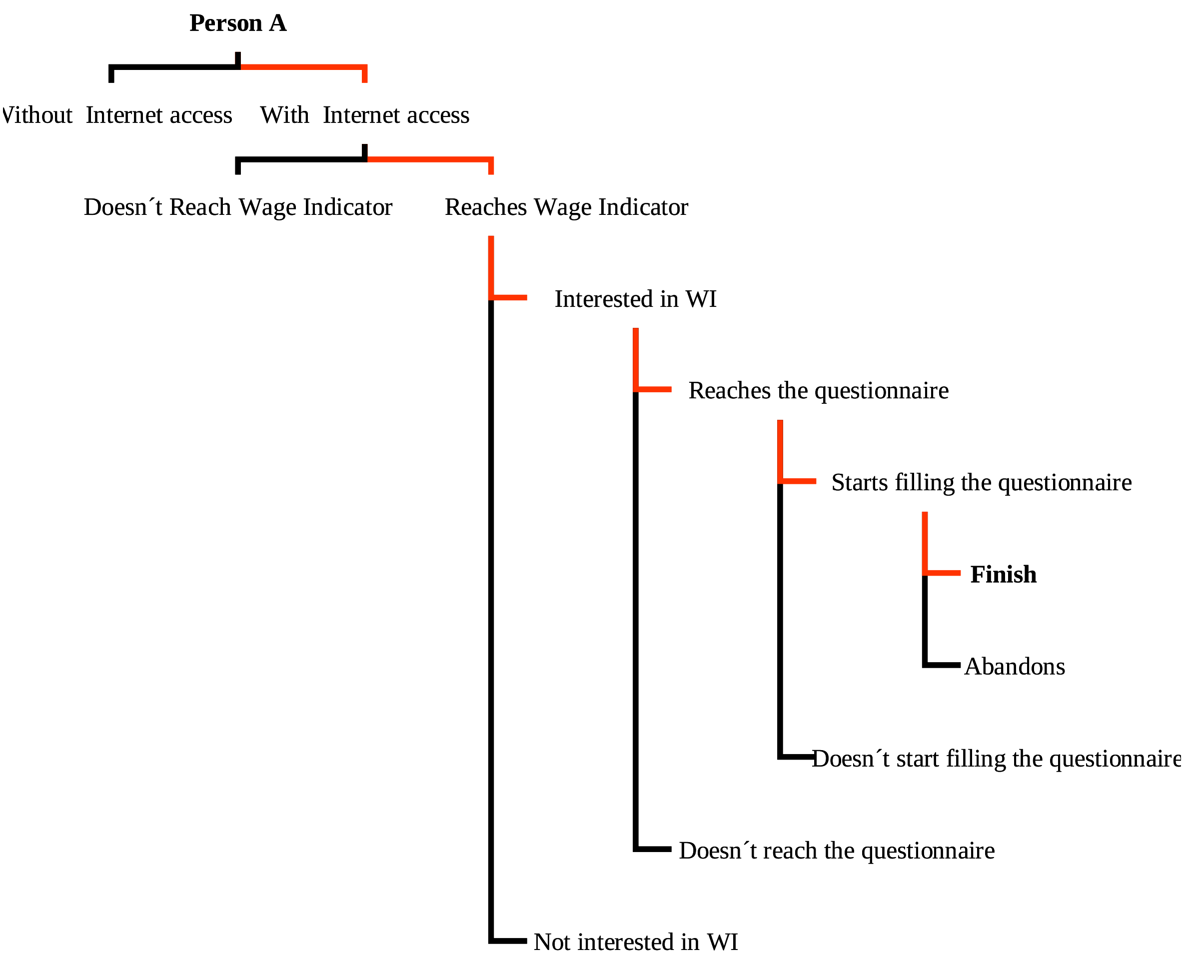
Between 2004 and 2007 the 6th Framework Programme Project *Wage Indicator Dataset* (Work Life Web[1]) was developed in 9 EU countries (Germany, The Netherlands, Belgium, Poland, Finland, Spain, Italy, the United Kingdom and Denmark). Nowadays the project has been expanded to 16 countries, including Brazil, Argentina, South Africa and the USA. The project had two main goals. The first, to increase the transparency of the labour market by developing a reliable tool freely accessible to workers to check wages for different occupations and sectors (the salary checker). The second, to generate data on labour market issues and increase the knowledge of the socioeconomics determinants of citizens' work life attitudes, preferences and perceptions. The major tool for reaching such goals was the development of a continuous Internet web survey, placed on different national web sites[2]. The survey made it possible to collect data on wages (to be used in the development of the salary checkers) as well as other labour related variables not always available on official surveys.

Web surveys, or more properly Continuous Voluntary Web Surveys, enter uncharted territory in terms of the state of art of sampling and surveying methods. A random sample, the standard procedure followed by surveys, aimed at collecting data from a population in which every individual has the same probability of being selected, can be fairly easily analysed and the conclusion expanded to the whole population using the standard inference procedures. In contrast, open web surveys face several problems that make the proper analysis and interpretation of the results much more difficult [3].

In first place, there is no *ex ante* control of the characteristics of the individual (as in a stratified random sample), nor are individuals randomly selected from a universe, as the survey is answered in a process of non-controlled self-selection, by which some persons complete the questionnaire and others do not bother to complete it. In figure 1 we can see the multiple steps (red line) a person has to take in order to successfully complete the survey. In this respect, the more steps needed to finish the questionnaire, the higher the chances for attrition.

[1] See www.wageindicator.org and www.tusalario.es
[2] For more details see www.wageindicator.org
[3] A good introduction to the specificities of web surveys can be found in Couper (2000) and, from a different, more practical perspecive, Dillman and Bowker (2001)

Figure 1. Stages in the process of filling in a Continuous Voluntary Web Survey such as the Wage indicator, WI.



In first place, all those without access to the Internet (wide band access) are excluded from the survey. Second, the Internet has many attractions, that doubtless will direct many surfers to other sites. Third, of the small fraction of surfers visiting the site hosting the survey, only a few will be interested in participating in the survey (Porter and Whitcomb, 2003). Finally, only a proportion of those originally willing to answer the questionnaire will go through the whole set of questions. In all, only an infinitesimal percentage of those using the Internet, themselves only a percentage of the population, will successfully complete the survey. Therefore, bias in Continuous Voluntary Web Survey may come from self-selection, "non-response", heterogeneity of Internet users and non-users, the technological divide and the lack of Internet access by certain parts of the population. In relation to the technological divide, several factors such as age, level of education, type of work, budget constraints to buy a computer are playing a role, especially in the first phases of Internet penetration in a country and for less IT oriented countries. The same can be said about the profile of those successfully going through the different steps required for the completion of the survey.

Many of the standard tools for dealing with the problems of under-representation in "standard" surveys are not directly applicable in the case of web surveys. To give an example, what is the meaning of the non-response rate when the universe is "universal"? In the terms used by Couper (2000): "For surveys where the frame cannot be identified, the problem of non-response is hard to define" (p. 473). Owing to the inherent difficulties in measuring non-response in open web surveys, many researchers have focused on differences in response rates between mail and e-mail questionnaires in order to know, by approximation, whether the non-response rate problem is greater or smaller in web surveys as compared to other types of surveys. In this respect, the studies summarized by Schaefer and Dillman (1998) and Couper, Blair and Triplett (1999) found lower response rates for e-mail as compared to mail surveys in all but one of the cases studied. Fricker *et al.* (2005) obtained similar results comparing online and telephone surveys. In contrast, Kapowitz, Hadlock and Levine (2004) found that web applications can achieve a similar response rate to standard mail surveys when both are preceded by advance mail notification. As interesting as the differences in response rates is the fact, detected in some of these studies, that the item non-response rate might be different (lower in online surveys) - Fricker *et al.* (2005)- or that the method of survey might affect the type of response. For example, according to Kiesler and Sproull (2001) closed end responses in an electronic survey on health attitudes were less socially desirable and more extreme than those on an alternative paper survey. In the same line, Sparrow (2006) argues that there are sharp differences in the results obtained by online surveys as compared to those obtained by large scale random surveys

Together with the problems relating to sampling, coverage and non-response, web surveys also face problems of measurement errors (differences between the "true" answer and the answer recorded). These measurement errors can be different in web and alternative run surveys with interviewers who, if properly trained, can explain whatever problems the interviewee might have with the questions.

Still, Continuous Voluntary Web Surveys are gaining popularity at the expense of phone, mail and face-to-face surveys. The advantage of Continuous Voluntary Web Surveys is that they give quick and cheap access to a large and growing number of people. Web surveys also allow for quick access to data, something increasingly needed in a fast-changing world, both for firms and academic research.

Some of the bias mentioned can be specifically addressed with the proper resources. Special campaigns can be developed aiming at specific groups under-represented in terms of web access, etc. But many of the problems remain, especially because the type of action needed to solve specific bias will undoubtedly increase the cost of running web surveys, precisely one of their major attractions.

At the same time, computer technology allows us to easily collect vast amounts of data that can be used to get a clear profile about the type of persons filling in the questionnaire. This information in turn can be used to obtain a complete picture of the bias. That is the case with the Wage indicator; the collected data about personal, professional and family life characteristics of surveyed individuals, including data of many of those that abandon the questionnaire before completing it, make it possible to have a quite complete picture of bias in each country.

Very briefly, the Wage Indicator Survey gathers data on labour through the international, continuous web-based *WageIndicator*. The web consists of:

- an attractive website with labour market related information for a large public;
- a crowd-pulling Salary Check providing very detailed salary information related to a set of variables such as education, firm size, supervisory position;
- a *WageIndicator* questionnaire with 67 – 85 questions providing insight into issues related to work and wages and generating the data needed to "feed" the Salary Checker;
- nation-wide promotion, publicity, and answering visitors' emails.

The Wage Indicator Dataset project also has the aim of shedding light on the specific problems (and potential solutions) of web surveys. This aspect is especially important if web surveys are to replace, at least partially, telephone, mail and face-to face surveys. As mentioned above, the principal weaknesses and methodological problems of web surveys are systematic bias, lack of representativeness, and the strong points, the low cost of reaching a potentially large population and obtaining a large number of completed questionnaires. The Wage Indicator Dataset project has been quite successful in gathering large samples; in the case of Spain between 2005 and 2007 more than 14,000 visitors completed the questionnaire. The number of observations goes from 90,000 in The Netherlands, 70,000 in Germany, to 10,000 in Poland. Although in most countries the number of observations of the Wage Indicator is larger than in national LFS, samples fail to be representative of the population (see section 2).

In order to try to solve this problem, two types of measures can be implemented. On the one hand, long term measures targeting large under-represented groups, such as women, unskilled workers, etc., in order to increase the quality of the sample. On the other hand, in the short term, the data can be weighted according to different variables in order to equilibrate the sample artificially. This paper aims at sharing the experience acquired in the Wage Indicator Dataset project regarding the second type of measures, offering a methodology to calculate and implement weights, and testing to what extent such weighting procedure solves the problems derived from working with a large but biased sample.

The paper is divided into three parts. The first one describes the Spanish *Wage Indicator dataset* sample bias, the second one explains the weighting procedure applied to the Spanish data of the *Wage Indicator dataset* and the third one tests for its effectiveness. Apart from the Wage Indicator data the paper also relies on the Spanish national Labour Force Surveys (LFS) to weight the data, and on the Spanish Structure of Earnings Survey (SES). The latter is used to test the efficiency of weights, comparing mean salaries, wage distribution (Gini index) and conventional salary regressions obtained from the *Wage Indicator dataset* before and after weighting with those directly obtained from the Spanish Structure of Earnings Survey.

2. THE WAGE INDICATOR SPANISH SAMPLE: BIAS DESCRIPTION

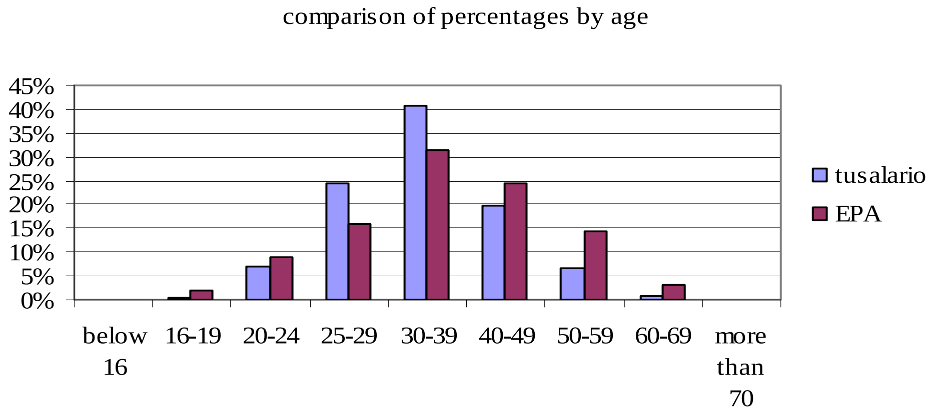
The problem of non-probability samples can be tackled by different and complementary methods. In the Wage Indicator case, the short run solution is to proceed to weight the data on the basis of Labour Force data published by the national offices of statistics. However, in the long run the final goal is to obtain a representative sample of each country's labour force by marketing the under-represented groups.

The Wage Indicator is hugely successful in terms of the number of visits and visitors that it draws, as well as in terms of responses to its questionnaire. Nevertheless, it is clear that important problems remain to be solved with regard to the representativeness of the sample. It seems likely that access to and use of the Internet is biased, especially by level of education and income within and between countries, though one may expect this problem to become progressively less important in the future. For example, the Dutch survey, pioneer of the now large family of wage indicators, launched in 2001, is already accessed by gardeners and other workers in low-wage occupations and under-represented groups have decreased their under-representation over the years. In the meanwhile, weighting the data might solve the problem. We consciously use the verb might as the next step, after weighting, should be to measure the effectiveness of the weighting process by comparing the results obtained with those obtained from alternative standard sources.

In order to analyse the sample bias and select the variables to be used for the calculation of weights, we will compare the structure of the *Wage Indicator* sample with the structure of the LFS sample, assuming that the LFS sample structure is representative of the population.

Regarding age, as we can see in table 1, older workers are under-represented in the Spanish sample. This applies particularly to individuals aged 40-49 and over. In comparison, in the Dutch Wage Indicator sample, under-representation of the older worker starts at 55, and went down from 2001 to 2004. This seems to be a matter of the age-technology gap and Internet use by older workers. For that reason, in the absence of marketing measures, age-technology gap implications in web surveys might be solved with the passing of time as workers in the over-represented age intervals - those below 40-49 in Spain- grow older and reach under-represented ages, 50-59 and 60-69. In that case, while in the Netherlands the age-technology gap might be solved within 10 years, it will take more than 15 years in Spain. In addition, table 1 shows that the share of younger workers (16-19) in the Wage Indicator is lower than in the Spanish labour force. In contrast, mid-age workers from 20 to 40 are over-represented.

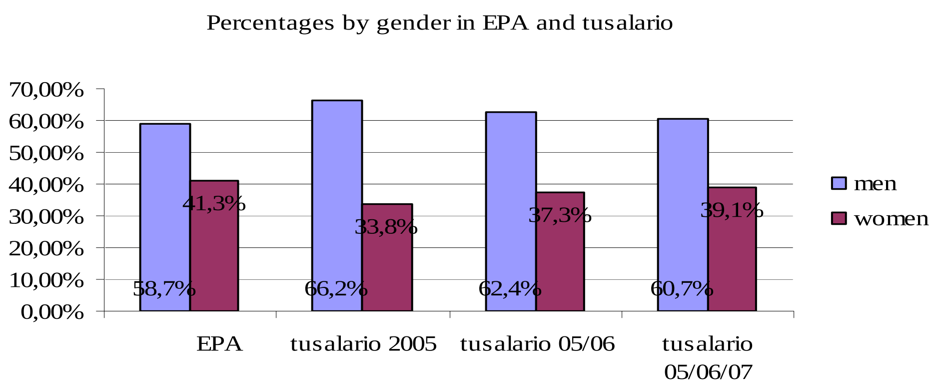
Table1.- Wage Indicator sample and Spanish LFS sample (EPA) by age intervals



Source: Spanish Labour Force Survey (EPA) and Wage Indicator data

Regarding gender, during 2005 and 2006 the female labour force was under-represented in the Wage Indicator. The reason might be that women concentrate more on their job tasks than males, as according to the available information on the times of the day when most questionnaires are filled, most people answer the questionnaire during working hours. Also, owing to the type of occupation most common among women, it is reasonable to assume that women have less opportunity for Internet access in their workplaces. In contrast, in the Dutch sample the male labour force is under-represented, which may be because the survey initially addressed women only. From 2002 to 2004, however, under-representation was reduced. In Spain, marketing measures were taken to reduce the gender bias and by mid 2007 the proportion of women in the sample was closer to the LFS proportion (see table 2).

Table 2.- Gender *Wage Indicator dataset* sample evolution and LFS sample (EPA)[4]

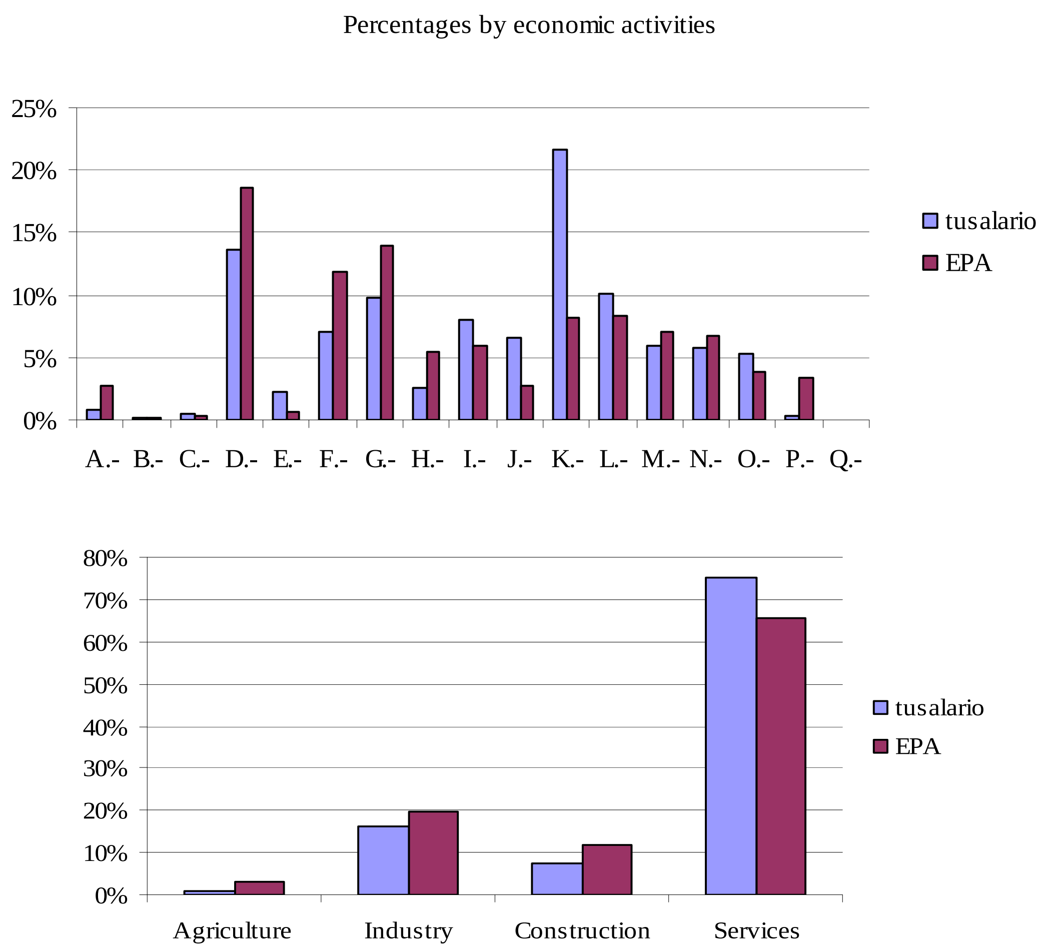


Source: Spanish Labour Force Survey (EPA) and WAGE INDICATOR DATASET.

[4] Sample sizes are the following: in tusalario 2005 the number of observations were 6000, in tusalario 05/06 9666 observations and in tusalario 05/06/07 14556.

Regarding NACE classification (table 3), agriculture, hunting and forestry (A); manufacturing (D); construction (F); wholesale, retail trade, repair of vehicles and household goods (G); hotels and restaurants(H); education (M), health and social work (N) and extra-territorial organizations and bodies(Q) are all under-represented. On the contrary, electricity, gas and water supply (E); transport, storage and communication (I); financial intermediation (J) and other community, social and personal service activities (O) are over-represented. Table 3 also shows NACE classification of economic activities recoded into agriculture, industry, construction and services (AICS) showing that while services is over-represented, agriculture, industry and construction are under-represented.

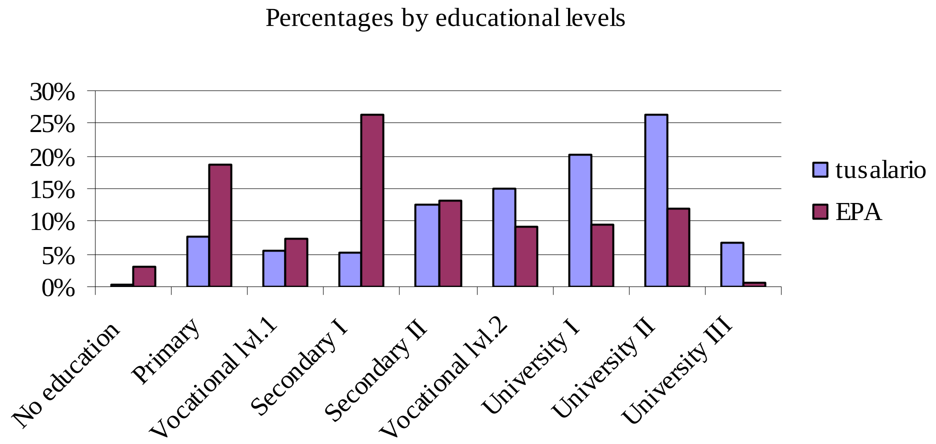
Table 3.- *Wage Indicator dataset* sample and Spanish LFS sample (EPA) by NACE classification and by Agriculture, Industry, Construction and Services (AICS).



Source: Spanish Labour Force Survey (EPA) and WAGE INDICATOR DATASET data

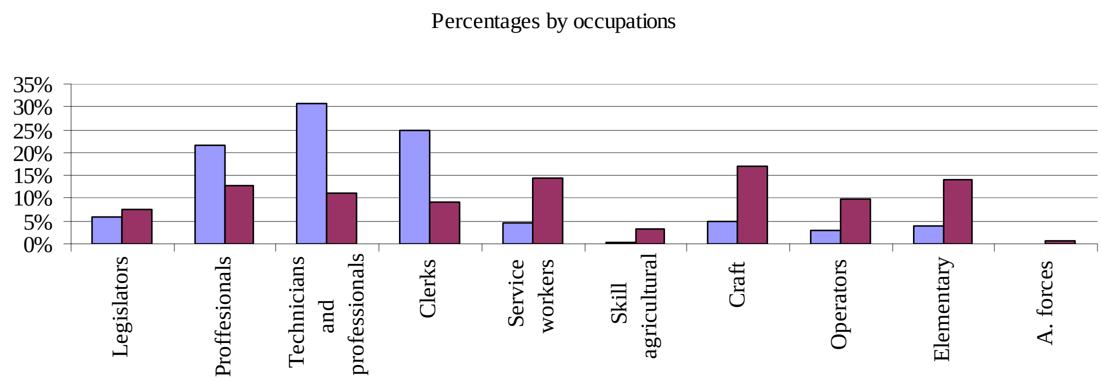
Another source of bias is education (see table 4), as it is reasonable to assume that those with higher education will have a higher probability of reaching and filling in the survey. As a result, low educated labour force is under-represented. Regarding occupation (table 5), as expected, owing to the close relation between Internet use and skill level, low skilled labour force and elementary occupations are under-represented in the sample. Although occupation and education attainment are clearly related, we have included both sources of bias as due to the existence of over-qualification in the Spanish labour market, especially among young workers; it is common to find people with an educational level higher than the level required for the performance of their jobs.

Table 4.- *Wage Indicator dataset* sample and Spanish LFS sample (EPA) by educational levels.



Source: Spanish Labour Force Survey (EPA) and Wage Indicator data

Table 5.- *Wage Indicator dataset* sample and Spanish LFS sample (EPA) by occupation (ISCO classification)



Source: Spanish Labour Force Survey (EPA) and Wage Indicator data

Summing up, according to the above comparisons between EPA and *Wage Indicator* data, gender, educational levels and sector of economic activity and occupation are adequate variables for calculating weights. However, as occupation is closely correlated with education, we decided to consider education together with sector of activity, gender and age, excluding occupation in the final analysis. Otherwise, sample divisions would have been too small. We leave for future research the calculation of weights using more variables such as geographical units, an alternative that could be interesting in the case of large countries, like Spain or Germany, that are composed of very heterogeneous regions in terms of economic structure.

3. WEIGHTING THE SPANISH DATA SET BY GENDER, AGE, SECTOR OF ACTIVITY AND EDUCATIONAL LEVEL

The following method has been developed to weight, by a number above 1, groups of age, gender, sector of activity and educational level, whose representation in the *Wage Indicator* sample is below their proportion in the population and, to weight by a number below 1, groups of age, gender, sector of activity and educational level, whose representation in the *Wage Indicator dataset* SET sample is above their proportion in the population.

The first step to obtain the weights is to calculate the proportion of each group in the labour force. We used eleven age intervals (15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, and over 65); four categories of economic activities: Agriculture, Construction, Industry and Services; three educational categories: low, medium and high; and gender. Therefore, we worked with over three hundred groups. As explaining our methodology in detail using all these categories would involve a lot of space, table 5 reproduces the simple version used in this paper as an example of how weights were calculated. To reduce the number of groups we excluded educational levels from the analysis and took only four age intervals: from 16 to 19, from 20 to 24, from 25 to 54 and over 55, the aforementioned four categories of economic activities, and gender. Table 6 reproduces the number of people in each example-group in the Spanish labour force. The analysis was performed using data from the Spanish Labour Force Survey (EPA) downloadable from the INE web site (www.ine.es).

The second step was to replicate the process with the Wage Indicator sample. Table 7 shows the number of people in each of the example-groups in the wage indicator sample. Several groups with very few cases had to be merged together, forcing us to go back to the EPA in order to merge the same groups. For example, there is only one man aged between 16 and 19 years old working in agriculture.

Table 6: number of people in each group, EPA (thousands).

Age	Sector	EPA (LFS)	
		Men	Women
16-19	Agriculture	19,1492075	6,061955
16-19	Industry	54,72684	12,134255
16-19	Construction	73,4662675	1,832115
16-19	Services	99,28094	115,18999
20-24	Agriculture	52,158985	19,320915
20-24	Industry	209,9928375	76,2368675
20-24	Construction	234,4665975	11,1650525
20-24	Services	424,5239425	594,78315
25-39	Agriculture	255,9042425	90,5890325
25-39	Industry	1067,497505	409,55226
25-39	Construction	1036,983235	78,86818
25-39	Services	2541,729965	2965,487443
> 40	Agriculture	405,3425925	153,52236
> 40	Industry	1134,749513	315,059695
> 40	Construction	885,1543025	35,2802825
> 40	Services	2895,006125	2701,822205
Gender total		11390,1331	7586,905758
Total		18977,0389	

Source: Spanish Labour Force Survey (EPA).

Table 7: number of people in each group, Wage Indicator sample.

Age	Sector	Wage Indicator	
		Men	Women
16-19	Agriculture	1	0
16-19	Industry	4	2
16-19	Construction	3	0
16-19	Services	28	33
20-24	Agriculture	5	5
20-24	Industry	73	48
20-24	Construction	52	34
20-24	Services	382	409
25-39	Agriculture	62	39
25-39	Industry	1028	493
25-39	Construction	482	304
25-39	Services	3871	3225
> 40	Agriculture	30	16
> 40	Industry	619	106
> 40	Construction	197	37
> 40	Services	2021	947
Gender total		8858	5693
Total			14556

Source: Wage Indicator data set.

We followed several merging principles. Firstly, men and women were never merged together. Secondly, we never merged more than three-four age intervals together, especially when dealing with age intervals between 25 and 50. Both principles are justified because we are working with data regarding wages and gender is an important source of wage discrimination, and because wages increase faster between 25 and 50. Thirdly, although we have not considered educational levels in the example, with very few exceptions, the three educational levels were never merged together. For example, we merged people between 16 and 19 regardless of their sector of activity and educational level because most people entering the labour force at those ages have similar characteristics such as low educational level. Finally, we merged groups whenever the sample was below fifteen and we never accepted a weight value above 10.

The third step was to calculate the proportion of each group in the Wage Indicator and in the EPA. Finally a *weight variable* was obtained dividing the population proportion by the sample proportion:

$$weight = \frac{n_{population}}{n_{sample}}$$

Table 8. Weights (EPA proportion/wage indicator dataset proportion).

Gender	Age Interval	Sector of Activity*	WI sample	EPA Sample	WI Proportion	EPA Proportion	**WEIGHTS**
Men	16-19	all	36	246,623255	0.00247321	0.01299588	5.2546661
	20-24	Agr. & Ind.	78	262,151823	0.00535862	0.01381416	2.5779345
	20-24	Construction	52	234,466598	0.00357241	0.01235528	3.45852753
	20-24	Services	382	424,523943	0.02624347	0.0223704	0.85241764
	25-39	Agriculture	62	255,904243	0.00425941	0.01348494	3.16591606
	25-39	Industry	1028	1067,49751	0.0706238	0.05625206	0.79650289
	25-39	Construction	482	1036,98324	0.03311349	0.0546441	1.65020651
	25-39	Services	3871	2541,72997	0.26593844	0.13393712	0.50363956
	>40	Agriculture	30	405,342593	0.00206101	0.02135963	10.3636941
	>40	Industry	619	1134,74951	0.04252542	0.05979592	1.40612185
	>40	Construction	197	885,154303	0.01353394	0.04664344	3.44640537
	>40	Services	2021	2895,00613	0.13884309	0.1525531	1.09874465
Women	16-19	all	35	135,218315	0.00240451	0.00712536	2.96333722
	20-24	Agr. & Ind.	53	95,5577825	0.00364111	0.00503544	1.38294145
	20-24	Construction	34	11,1650525	0.00233581	0.00058835	0.25188103
	20-24	Services	409	594,78315	0.02809838	0.03134225	1.11544702
	25-39	Agriculture	39	90,5890325	0.00267931	0.00477361	1.78165912
	25-39	Industry	493	409,55226	0.03386919	0.02158146	0.63720035
	25-39	Construction	304	78,86818	0.02088486	0.00415598	0.19899485
	25-39	Services	3225	2965,48744	0.22155812	0.15626713	0.70530988
	>40	Agriculture	16	153,52236	0.0010992	0.0080899	7.35978717
	>40	Industry	106	315,059695	0.00728222	0.01660215	2.27982013
	>40	Construction	37	35,2802825	0.00254191	0.0018591	0.73138143
	>40	Services	947	2701,82221	0.06505908	0.14237322	2.18836816
Total			14556	18977,0389	1	1	1

Source: Spanish Labour Force Survey (EPA) and Wage Indicator.

4. DOES WEIGHTING WORK?

As mentioned in the introduction, the methodology proposed for testing the efficiency of the weighting strategy for overcoming some of the problems derived from the existence of sample bias is to compare the results obtained in terms of wage, wage distribution and wage determinants using the Wage Indicator data with and without weighting, with the same indicators as derived from an alternative standard statistical source, the SES.

4.1 MEAN SALARIES AND GINI INDEXES

Table 8 reproduces the mean salaries and Gini indexes that were calculated using the Wage Indicator data, the weighted Wage Indicator data, and the Spanish Structure of Earning Survey. As the SES only takes into account firms with 10 employees or more[5], in order to make comparison more reliable, we deleted from the Wage Indicator sample those employees working in firms with less than ten employees and calculated again mean salaries and Gini index.

Table 9. Mean salaries and wage distribution.

	Wage Indicator Data		Wage Indicator Data : Only firms > 9 employees		Spanish SES
	Unweighted	Weighted	Unweighted	Weighted	
Mean annual gross salary	23,112 €	22 807 €	25,106 €	24,593 €	18,182 €
Gini index of annual gross salaries	0.36283	0.37888	0.35581	0.36580	0,36911

Source: Spanish SES and Wage Indicator data

Regarding mean salaries, at first glance we can see that the SES mean salary is much lower than that calculated using the Wage Indicator; this is due to the over-representation of highly educated workers in the Wage Indicator. After weighting the data, Wage Indicator mean salary is lower and, therefore closer to SES. However, after deleting workers in firms with fewer than ten employees from the sample, Wage Indicator mean salaries are even higher. This is because, in general, working in a big company has a positive effect on salary (see salary regressions in table 8).

Regarding the Gini index, inequality in the SES is higher than in the Wage Indicator. The Gini Wage Indicator index is biased downwards because of low paid labour infra-representation in the Wage Indicator sample. Weighting the data is successful in reducing the differences in the inequality index; however, the new index is biased upwards and its difference with the SES is higher. Dropping small firms from the sample again reduces the Gini index. Finally, the Gini index is very close to the SES once weights are implemented to the sample without small firms.

Therefore, our weighting methodology only partly solves the problem: mean salaries are closer to SES salaries, but only in the full sample and even so the difference is still quite large; the Gini indexes are quite similar. It is clear that to calculate mean salaries, alternative approaches are needed, mainly targeting measures.

Table 9 reproduces the results of running conventional salary regressions using Wage Indicator data, unweighted and weighted, and SES data. Regarding variables such as age, gender, firm size, years with current employer and educational levels the sign of the impact on salary is the same in the three regressions. Therefore, reliable conclusions can be obtained from the Wage Indicator sample, even without implementing weights. Very often the impact of living in a specific region is not significant in both Wage Indicator regressions but it is significant when using SES. R squared and t-values are always higher when using SES because it is a much larger sample (215,000 employees).

[5] The methodology of the SES can be found at http://europa.eu.int/estatref/info/sdds/en/earn/earn_ses_sm.htm

5. CONCLUSIONS AND FURTHER RESEARCH

As we have seen, weighting the data has been proven to be a good method to partly overcome problems coming from a biased sample obtained using a Continuous Voluntary Web Survey. The weighting was tackled on the basis of the Labour Force Survey (LFS) published by the Spanish National Statistics Office (Instituto Nacional de Estadística). The Wage Indicator Dataset sample proportions was compared with LFS proportions for variables that were assumed to be subject to bias, notably gender, age, sector of activity and educational level (section 2). These variables are assumed to matter in every country but different types of weights can be calculated depending on the sample characteristics. In the implementation of this methodology there are country specific variables that should be included in country specific weights. For example, working hours (part-time or full-time) is important in the Netherlands but not in Spain, the kind of contract (temporary or permanent) is relevant in Spain but not in most of the countries. Geographical variables such as east-west in Germany or Autonomous Regions in Spain could also be included in large countries. Because of that, before weighting, it is important to make the simple bias description as above, which compares the sample with the population (LFS) in order to choose the right variables to weight.

Table 10: Salary regressions

	Wage Indicator		Wage Indicator Weighted		SES	
	β	t	β	t	β	t
Age	.04335*	10.86	.0332808*	3.60	.037667*	45.37
Age squared	-.00036*	-7.09	-.0002452*	-2.18	-.000375*	36.75
< than 1 year with employment	-.036487*	-2.72	-.0936939*	-3.61	-.280862*	69.64
From 3 to 6 years with employment	-.020159	-1.41	-.008034	-0.29	.038751*	8.17
More than 6 years with employment	.0821439*	5.55	.1051752*	3.82	.235311*	57.99
Gender (women)	-.208845*	21.86	-.2539696*	-15.21	-.372975*	-135.67
Firm size >10(19) & <100	.104867*	9.68	.0919604*	5.01	.087998*	23.56
Firm size > than 100	.2213648*	17.87	.1939787*	8.34	.221467*	60.10
Regions						
Aragon	-.055056	-1.81	-.080805	-1.59	-.030524*	-4.4
Asturias	-.08959*	-2.44	-.087934	-1.93	-.003594	0.48
Balearic Islands	.0683798	1.50	.0743968	1.39	.036577*	4.69
Canary Islands	-.068921*	-2.42	-.0936349	-1.82	-.008874	-1.28
Cantabria	-.050165	-0.98	-.014827	-0.23	-.02915*	-3.33
Castile and León	-.044649	-1.50	-.014102	-0.32	-.086191*	-12.33
Castile La Mancha	-.113228*	-5.20	-.1158148*	-3.77	-.073468*	-11.24
Catalonia	.0617363*	4.35	.0691996*	2.60	.055092*	10.43
Valencian community	-.073603*	-4.05	-.0900766*	-2.69	-.040562*	-7.01
Extremadura	-.138182*	-3.10	-.101009	-1.35	-.138948*	-16.05
Galicia	-.124757*	-5.51	-.1413551*	-4.85	-.058563*	-9.08
Madrid	.0437746*	3.28	.0802064*	2.93	.063373*	11.71
Murcia	-.098742*	-2.48	-.1045829*	-2.07	-.118417*	-15.99
Navarre	.030113	0.59	-.0840515	-1.25	.059217*	7.45
Basque Country	-.000082	-0.00	.009716	0.21	.100487*	15.77
La Rioja	-.196893*	-3.43	-.2715782*	-4.39	-.073695*	7.81
Ceuta and Melilla	.0430976	0.27	.1520525	1.32	.062522*	3.18
Education						
Incomplete primary	-.496126*	-6.67	-.2965652	-1.03	-.896327*	-77.05
Primary	-.447118*	-23.63	-.4764619*	-19.13	-.710959*	-150.66
Secondary	-.337777*	-15.46	-.3738901*	-13.33	-.656288*	-144.66
Upper secondary	-.308548*	-19.75	-.3423322*	-17.11	-.417461*	-76.71
Vocational level 1	-.365734*	-17.14	-.4045522*	-11.45	-.475556*	-78.83
Vocational level 2	-.261349*	-17.80	-.3013454*	-16.41	-.3901*	-68.24
University level 1	-.106145*	-8.02	-.1217529*	-7.39	-.136864*	-23.77
University level 3	.1114298 *	5.63	.0983281*	3.61	.284037*	13.49
Temporary contract	-.19244*	-16.16	-.1445474*	-6.29	-.340047*	-94.00
Sector						
Agriculture	.0125602	0.27	.011524	0.15	-	-
Industry	.0855605*	6.67	.093594*	4.76	.171289*	61.33
Construction	.1354911*	7.65	.1359085*	4.42	.296738*	57.56
Constant	8.918569 *	116.24	9.157862*	51.78	9.20427*	523.43
R squared	0.2973		0.2972		0.4808	
Observations	14 556		14 556		203486	

Source: Spanish SES and Wage Indicator data

After weighting, estimated mean salaries and Gini index moved in the right direction. Therefore, it is worthwhile to make an in-depth review of this method, the different ways in which it can be implemented, the different variables that can be used and its application to other Wage indicator samples. Nevertheless, weighting is far from being a full solution to the problem. Therefore other correction techniques are needed in order to bring the volunteer sample closer to a probability sample. One option is the so-called Propensity Score Adjustment (PSA), a statistical approach for self-selection. There is a large bibliography (see Deaton 1997) dealing with different ways to tackle the analysis of non-random samples that needs further empirical research to be adapted to continuous Internet web surveys. We also leave for future research the implementation of a priori measures aimed at obtaining a more representative sample. As we showed above regarding gender bias, certain types of bias can be solved using marketing and targeting measures. Wage Indicator structure is an opportunity to explore new methods addressed to obtaining a representative sample of the population such as collaboration with trade unions, NGOs and social agents that can give access to under-represented groups such as the lower educated.

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