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López, Alberto

Universidad Complutense de Madrid

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The effect of microaggregation on regression results: An application to Spanish innovation data*

Alberto López[†]

Universidad Complutense de Madrid

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Abstract

Microaggregation is a technique for masking confidential data by aggregation. The aim of this paper is to analyze the extent to which microaggregated data can be used for rigorous empirical research. In doing this, I adopt an empirical perspective. I use data from the Technological Innovation Panel (PITEC) and compare regression results using both original and anonymized data. PITEC is a new firm-level panel data base for innovative activities of Spanish firms based on CIS data. I find that the microaggregation procedure used has a slight effect on the coefficient estimates and their estimated standard errors, especially when estimating linear models.

Keywords: Microaggregation; Individual ranking; Bias; Innovation data

JEL Classification: C80; O30

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[†]Departamento de Fundamentos del Análisis Económico I. Facultad de Ciencias Económicas y Empresariales. Universidad Complutense de Madrid. E-mail: alberto.lopez@ccee.ucm.es.

1. Introduction

Observing confidentiality is crucial when collecting data and providing individual level information. On the other hand, researchers require access to individual micro data. The main method used to satisfy these two needs is the application of masking or anonymization procedures to data (which are also commonly referred to as disclosure control methods). These masking procedures modify the original data in a way that re-identification of individual respondents (i.e., individuals and firms) is almost impossible (or re-identification may still be possible but would come at great cost). At this point, a trade-off between quality of the data for analysis and confidentiality appears: the higher the degree of anonymization applied to the data, the lower the quality of the data for empirical analysis.

Literature on this topic has focused on two issues. First, a large body of literature has focused on disclosure control¹. These studies evaluate the validity of the different anonymization procedures to avoid disclosure of confidential information. Second, another strand of literature, which is less developed, analyzes the effect of anonymization procedures on estimation. The aim of these studies is to analyze the extent to which anonymized data can be used instead of the original data and how reliable estimates from anonymized data would be.

One of the most commonly used anonymization procedures is microaggregation by individual ranking (IR)². IR is an anonymization procedure by aggregation for continuous data consisting of three steps: sorting, grouping and replacement with average values. As a first step, for each variable to be anonymized, the data records are ranked in decreasing (or increasing) order. Secondly, data records are grouped (usually the group size is 3 or 5). Finally, each original data value is replaced with its respective group mean. This three-step procedure is applied to each variable to be anonymized.

Microaggregation by IR is the anonymization procedure chosen by Eurostat, although

¹See Willenborg and de Waal (2001) for a review.

²See, e.g., Adam and Wortmann (1989) and Winkler (2004) for detailed reviews of the various anonymization procedures, and Schmid and Schneeweiss (2005) for a review of the different microaggregation techniques.

it is used in combination with other disclosure control techniques designed for masking discrete data (see Eurostat 1996, 1999).

Schmid and Schneeweiss (2009) present a theoretical analysis of the effect of the microaggregation by IR on the estimation of linear models. These authors prove the consistency and the asymptotic normality (under weak assumptions) of the empirical moments computed from microaggregated data by IR. Moreover, they provide a simulation study on the theoretical results and an empirical example based on real data.

Evidence on the effect of microaggregation by IR on non-linear model estimation is, to my knowledge, restricted to empirical examples³. Mairesse and Mohnen (2001) compare the estimation results of a generalized tobit model using original and microaggregated data that correspond to the French CIS 2⁴. These authors find that the estimates are “rather similar,” whether they use the original or the microaggregated data.

This paper is an empirical example created to illustrate the effect of microaggregation by IR on estimation results. In doing this, I use data from the Technological Innovation Panel (PITEC) and compare the results from estimating linear and non-linear models using the original data and the anonymized version.

The rest of the paper is organized as follows. Section 2 introduces the data used and describes the anonymization process applied. Section 3 analyzes the effect of the anonymization procedure applied at the PITEC on estimation results, and hence the extent to which anonymized data from PITEC can be used for rigorous empirical research. In doing this, I estimate two linear equations and one non-linear equation, using both the original and the anonymized data from the PITEC. Finally, Section 4 concludes.

³There exists theoretical evidence on the effect of other anonymization procedures in the presence of nonlinear estimation techniques. For example, Ronning (2005) analyzes the effect of randomized response with respect to some binary dependent variable on the estimation of the probit model. Hausman et al. (1998) focus on a more general framework under the heading “misclassification”.

⁴Eurostat (1999) details the microaggregation process adopted by Eurostat for CIS 2.

2. Data and anonymization procedure

The data used correspond to the Technological Innovation Panel (PITEC). PITEC is a data base for studying the innovation activities of Spanish firms over time. The data come from the Spanish Community Innovation Survey (CIS) and the survey is being carried out by the INE (The National Statistics Institute).

The PITEC has two main advantages. First, it is designed as a panel survey and contains a huge amount of information related to the innovation activities of Spanish firms. This data base includes information for more than 450 variables and 12,000 firms, and from 2003 to 2008, for the moment. Second, it is a free available data set. The data base is placed at the disposal of researchers on the FECYT⁵ web site. Except for the anonymization of a set of variables, the files available on the web site correspond with the “original” files in the hands of the INE.

Anonymization procedure applied at the PITEC

The anonymization procedure applied at the PITEC consists mainly of a microaggregation by IR. This method is applied to five quantitative variables (turnover, investment, number of employees, innovation expenditures and number of R&D employees) using two different ways for forming groups of observations. First, the data records are divided into groups according to the firm’s industry (56 industries corresponding to 2-digit or 3-digit NACE codes). For each variable and industry, the value of the five highest observations are replaced with its group (of size 5) mean. Second, the rest of the original data values are ranked in decreasing order and replaced with the respective group (of size 3) mean.

Moreover, the firm-level observations of the rest of the quantitative variables are replaced with the percentage value with respect to microaggregated variables. For example, intramural R&D expenditure is replaced by the percentage of intramural R&D expenditure on total innovation expenditure. Appendix A gives a detailed description of the anonymization procedure.

⁵[http://icono.fecyt.es/contenido.asp?dir=05\)Publi/AA\)panel](http://icono.fecyt.es/contenido.asp?dir=05)Publi/AA)panel).

3. The effect of the anonymization procedure applied at the PITEC

The aim of this section is to analyze the effect of the anonymization procedure applied at the PITEC on estimation results. In view of the procedure applied (consisting mainly of a microaggregation by IR) and the literature reviewed in the introduction, the expected estimation bias is small.

I present the estimation of two linear equations (a sales equation and a labour productivity equation) and one non-linear equation (an innovation cooperation equation), using both the original and the anonymized data from the PITEC. I present three simple empirical examples and, thus, this paper does not aim to be an in-depth analysis of these issues.

In the first equation, sales are assumed to be a linear function of size, exports, investment in equipment and innovation expenditures. Hence, the sales equation can be expressed as follows:

$$\begin{aligned} \log(\textit{sales}) = & \alpha_1 \log(\textit{size}) + \alpha_2 \log(\textit{exports}) + \alpha_3 \log(\textit{investment}) + \\ & \alpha_4 \log(\textit{innovation expenditures}) + u_1 \end{aligned} \quad (1)$$

The second equation specifies labour productivity as a linear function of export intensity and technological innovation. I express the labour productivity equation as follows:

$$\log(\textit{labour productivity}) = \beta_1 \log(\textit{export intensity}) + \beta_2 \textit{technological innovation} + u_2 \quad (2)$$

Finally, I estimate the determinants of innovation cooperation by using the standard probit model. The third equation models the probability of innovation cooperation as a non-linear function depending on size, R&D intensity and a measure of cost as a hampering factor for innovation. The innovation cooperation equation can be expressed as follows:

$$\begin{aligned} P(\textit{innovation cooperation} = 1) = & \Phi(\gamma_1 \log(\textit{size}) + \gamma_2 \log(\textit{R\&D intensity}) + \\ & \gamma_3 \textit{cost} + u_3) \end{aligned} \quad (3)$$

where Φ is the standard normal cdf.

In estimating equations (1), (2) and (3), I also include industry dummies⁶ and a constant. Moreover, equations (1) and (2) include a dummy for belonging to a group. Appendix B gives details on the variables employed.

In this empirical exercise, I use data from the PITEC for the year 2005 and for manufacturing and service sectors. This gives a total sample of 11,241 firms (6,305 manufacturing firms and 4,936 service firms). The final sample employed to estimate each equation depends on the data available (i.e., for the estimation of each equation, I drop all the observations for which the data needed are not available). Moreover, when analyzing cooperation in innovative activities, I restrict my attention to a subsample of innovating firms⁷.

Tables 1, 2 and 3 present the results for the estimation of equations (1), (2) and (3), respectively. In each table, estimate (column) *a* presents the results using the original data, while estimate (column) *b* shows the estimations using the anonymized data. All estimates have been rounded to three decimal places. Columns *c* and *d* present aggregation biases in coefficients and standard errors, respectively.

First, I focus on comparing the results using original and anonymized data. I find that the anonymization procedure used has a slight effect on the coefficient estimates of equations (1), (2) and (3) and their estimated standard errors.

Maximum aggregation bias for estimated coefficients and standard errors arises in estimating a non-linear model (see Table 3), in particular, in the estimation of the effect of R&D intensity on innovation cooperation. Aggregation bias becomes smaller when estimating linear models (see Tables 1 and 2), consistently with results from Schmid and Schneeweiss (2009). The main lesson that can be drawn from this exercise is that the use of anonymized data from the PITEC produces reliable results.

Second, I briefly comment on the results obtained for the estimation of equations (1), (2) and (3). I estimate three simple equations explaining sales, labour productivity and

⁶I include 52 industry dummies. Industry breakdown is defined by 2-digit or 3-digit NACE codes.

⁷Innovating firms are defined as those which report having introduced product or process innovations, having ongoing innovation activities, or having abandoned innovation activities, and, at the same time, present a positive amount spent on innovation.

innovation cooperation. However, results are consistent with the existing literature. Firstly, innovation expenditure has a positive effect on sales. Moreover, firm size, exports and investment have the expected positive effect. Secondly, technological innovation and firm export intensity are associated with higher labour productivity (see, for example, Crepon et al. (1998) and Bernard and Jensen (1999), respectively). Thirdly, absorptive capacity of the firm (measured by firm size and R&D intensity) and the importance of cost as a hampering factor for innovation are significant and positive determinants of innovation cooperation (see, for example, López (2008) for evidence from Spanish manufacturing firms).

4. Conclusions

There exist different techniques for masking confidential data. These masking procedures modify the original data in a way that re-identification of individual respondents is almost impossible and, thus, anonymized data can be used by researchers. At this point, a question arises as to whether the use of anonymized data produces reliable results.

One of the most commonly used anonymization procedures is microaggregation, and in particular microaggregation by individual ranking (IR). This paper is an empirical exercise performed to analyze the extent to which microaggregated data can be used for rigorous empirical research. In doing this, I use data from the Technological Innovation Panel (PITEC) and compare regression results using both original and anonymized data. In particular, I present the estimation of two linear equations (a sales equation and a labour productivity equation) and one non-linear equation (an innovation cooperation equation).

The PITEC is a new firm-level panel data base for innovative activities of Spanish firms based on CIS data. It contains a huge amount of information related to innovation activities. Moreover, an important feature of this data base is that it is placed at the disposal of researchers in a microaggregated form. The anonymization procedure applied at the PITEC consists mainly of a microaggregation by IR.

Results show that the microaggregation procedure used has a slight effect on the coefficient estimates and their estimated standard errors, especially when estimating linear

models. Hence, the use of anonymized data from PITEC produces reliable results.

Appendix A: Anonymization procedure

The anonymization procedure used involves four modifications:

1. Microaggregation by individual ranking (IR) of five quantitative variables (turnover, investment, number of employees, innovation expenditures and number of R&D employees). IR procedure used slightly departs from that described in the introduction. In this sense, IR is applied using two different procedures for forming groups of observations.

Firstly, the data records are divided into groups according to the firm's industry. For each of the continuous variables mentioned above (and for each industry), the data records are ranked in decreasing order. Then, the arithmetic mean of the five highest observations is calculated. Finally, the value of each "top five" observation is replaced with its cluster mean. Note that this procedure is applied for each of the variables in question in each industry. If there are fewer than three firms with a positive value for the variable in question in a given industry, this procedure is not applied.

Secondly, for each of the variables in question, the data records are ranked in decreasing order (without considering the records replaced in the previous procedure). Then, the observations are grouped by three and the value of each one is replaced with the cluster arithmetic mean. The last group or the last two groups may have four observations.

In summary, applying IR implies that the available variables are (i) the mean of the five highest observations after ranking the data in decreasing order and according to the firm's sector, or (ii) the mean of three or four consecutive observations after ranking the data in decreasing order.

2. To replace the firm-level observations of the rest of the quantitative variables with the percentage value with respect to the microaggregated value. The variables related to exports, innovation expenditures and R&D personnel are expressed in percentage values. Specifically, variables related to exports are given as a percentage of sales; intramural R&D expenditures according to the nature of the spending, the source of funding and spending by region, R&D expenditures in biotechnology and the amount of research grants are given as a percentage of the intramural R&D expenditures; the external R&D expenditure by

supplier is given as a percentage of external R&D expenditure; the expenditure for each innovation activity and the innovation expenditures by region are given as a percentage of the total innovation expenditure; R&D personnel by activity, by education and by region, and the number of research scholars are given as a percentage of total R&D personnel.

3. The firm's activity (4-digit NACE Code) is replaced with a 56-industry breakdown until 2008 and with a 44-industry breakdown from 2008.

4. In order to avoid the disclosure problem, and considering the sample stratification, the data of a given number of firms has been censored: those firms belonging to an industry in which the number of firms is less than or equal to three, both in the sample and in the population. Once a firm is censored in a given year, it will be censored in previous and subsequent years.

Appendix B: Definitions of Variables

Cost: Sum of the scores of importance of the following obstacles to innovation process (number between 1 (high) and 4 (not relevant)): Lack of funds within the firm or group; Lack of finance from sources outside the firm; Innovation costs too high. Rescaled between 0 (not relevant) and 1 (high).

Exports: Firm's total exports.

Export intensity: Ratio between exports and number of employees.

Group: Dummy variable that takes the value 1 if the firm belongs to a group.

Innovation cooperation: Variable which takes the value 1 if the firm cooperates on innovation activities with suppliers, customers, competitors, commercial laboratories/R&D enterprises, universities, or government or private non-profit research institutes.

Innovation expenditures: Total amount of expenditure in innovation activities.

Investment: Physical investment.

Labour productivity: Ratio between sales and number of employees.

R&D intensity: Ratio between intramural R&D expenditure and number of employees.

Sales: Firm's total turnover.

Size: Total number of employees.

Technological innovation: Dummy variable that takes the value 1 if the firm reports having introduced product or process innovations.

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Table 1. Sales equation^{a,b}
 Dependent variable: Sales (in logs)

	(a) Original Data	(b) Anonymized data	(c) Bias in coeff. (%)	(d) Bias in std. error (%)
Size (in logs)	0.963 (0.009)	0.959 (0.009)	-0.42	0.00
Exports (in logs)	0.033 (0.001)	0.032 (0.001)	-3.03	0.00
Investment (in logs)	0.009 (0.002)	0.010 (0.002)	11.11	0.00
Innovation expenditures (in logs)	0.011 (0.002)	0.011 (0.002)	0.00	0.00
Group	0.434 (0.022)	0.442 (0.022)	1.84	0.00
R ²	0.809	0.808		
Number of firms	11,156	11,156		

^aRobust standard errors in brackets.

^bIndustry dummies included.

Table 2. Labour productivity equation^{a,b}
 Dependent variable: Sales/Employees (in logs)

	(a) Original Data	(b) Anonymized data	(c) Bias in coeff. (%)	(d) Bias in std. error (%)
Export intensity (in logs)	0.052 (0.002)	0.051 (0.002)	-1.92	0.00
Technological innovation	0.040 (0.023)	0.041 (0.023)	2.50	0.00
Group	0.427 (0.019)	0.429 (0.019)	0.47	0.00
R ²	0.326	0.324		
Number of firms	11,160	11,160		

^aRobust standard errors in brackets.

^bIndustry dummies included.

Table 3. Innovation cooperation equation^{a,b}
 Dependent variable: Innovation cooperation (dummy variable)

	(a) Original Data	(b) Anonymized data	(c) Bias in coeff. (%)	(d) Bias in std. error (%)
Size (in logs)	0.054 (0.004)	0.050 (0.004)	-7.41	0.00
R&D intensity (in logs)	0.032 (0.003)	0.022 (0.002)	-31.25	-33.33
Cost	0.114 (0.019)	0.114 (0.019)	0.00	0.00
pseudo-R ²	0.046	0.043		
Number of firms	7,969	7,969		

^aRobust standard errors in brackets. The coefficients are the marginal effect of the independent variable on the probability of cooperation.

^bIndustry dummies included.