Evaluation of public policies:

An application to health care utilization

Noelia González Prieto

Department of Economics. University of Cantabria (Spain)

Avda. Los Castros, s n 39005 Santander. Cantabria

Email: noelia.gonzalez@unican.es

Tel: 34- 942202275; Fax: 34- 942201603

Marta Pascual Sáez

Department of Economics. University of Cantabria (Spain)

Avda. Los Castros, s n 39005 Santander. Cantabria

Email: pascualm@unican.es

Tel: 34-942 2016208; Fax: 34- 942201603

ABSTRACT

The objective of this paper consists in studying the potential reduction in usage health care associated with the expansion of private insurance. The Spanish Health System establishes that all people, independent of their nationality, have the right to health care. The right for all citizens to enjoy health protection and care is laid down in article 43 of the Spanish Constitution, 1978. However, Spain needs to reduce public health expenditure and waiting lists. Using Spanish micro data from the European Community Household Panel, we study the impact of the type of insurance used on health care. In particular, propensity score methods and matching techniques are used to estimate the treatment given a vector of observed covariates. The empirical results suggest that promoting private medical insurance would reduce waiting lists and increase self-assessed health.

Key Words: Private medical insurance, health care utilization, matching, propensity score. I11, I18.

1. Introduction.

The evaluation of public policies can be defined as the assessment of the actions of public bodies in terms of the results and impact they have in relation to the needs they are intended to satisfy. It is a systematic tool which provides a base for rigorous information centred on clear indications for decision making (European Commission, 2007).

The evaluation is considered an essential part of public policy analysis. First, it provides information on policy performance and provides information about compliance with its objectives and goals. Secondly, it contributes to the clarification and critique of targets and objectives. It appears that some objectives and goals according to certain actions do not generate the expected results. Thirdly, it allows the application of other methods of policy analysis and becomes an input to the restructuring of the problem and recommending policies (Curcio, 2007).

The importance of carrying out the assessment of public policies is based on the fact that a process should be considered (with the use of scientific techniques and the systematic collection of information about a group of variables of different individuals) to evaluate and analyze the conceptualization, design, management and monitoring system and the outcomes and impacts of the implementation of policies and programs with the objective to facilitate and support the decision-making and reconciling the interests of everyone involved (Solís et al., 2009).

The evaluation of public policies emerged primarily to study the effect that years of education had on wages. Although there are different research papers about the evaluation of public policies on many topics such as education, environment and health, there are very few empirical applications because of the problem of computing the data when it is available, which is not usual. In recent years, some studies have focused on the study of public policies related with health because it is important to get health coverage to as many people as possible, while minimizing costs as much as possible.

We are going to study the impact on an individual's use of healthcare when he or she has purchased health insurance. Thus, the problem is to identify the effect of a treatment. In this sense, the causal effect of interest is the difference between the outcome with and without treatment. Obviously, an individual can not be observed in these two situations at the same time, so we are going to focus on the average treatment effect.

In Spain, the National Health Service is almost complete coverage to the entire population. However, there are several problems such as the need to control health spending, waiting lists, etc. It is, therefore, necessary to evaluate policies with respect to the measures taken to address these problems. One of the solutions that arise to reduce costs and reduce waiting lists is to use private healthcare. In this paper we are interested in studying the impact of this private insurance in the use of health services in Spain using microdata from the European Community Household Panel.

The aim of this paper is to apply public policies evaluation techniques to health problems. In particular we are going to study whether having an extra health insurance affects the number of times that health care is required. If having private insurance increases the number of medical visits then we say that there is moral hazard. In this sense, there are two types of moral hazard. When the individual changes his/her behaviour towards risk because it has extra insurance it is called ex-ante moral hazard. The other possibility is that people change their behaviour simply because they have an extra insurance; they seek medical advice in circumstances where if they did not have that extra insurance they would not. To study the influence of private insurance in the number of medical visits we will use matching techniques using the corresponding score propensity.

The structure of this paper is as follows. The next section provides a brief review of the literature on empirical applications of evaluation problems. In section 3, there is a theoretical framework. In section 4, the data that we have used for the public policies evaluation is described. In section 5, we present the empirical results. And finally in section 6, we have the conclusions.

2. Review of the literature.

Research on public policies evaluation is quite actual. We have summarized the literature review in two tables. In table 1 we have the main results on evaluating public policies applied to different applications. In table two we can see the most important results applied to health.

Table 1: Literature Review

Author	Objectives	Methodology	Results
Manski, Sandefur, McLanahan and Powers (1992).	To study the effect of family structure during adolescence on high school graduation.	Parametric models and non-parametric models.	To live in an intact family increases the probability that a child will graduate from high school
Angrist and Imbens (1995).	To estimate the effect of years of schooling on earnings.	Two-least squares estimation and instrumental variables.	Observational data can only be informative about the causal effect of treatment.
Evans and Schwab (1995).	To estimate if studying in Catholic schools has an effect on finishing high school and starting college.	Bivariate probit models.	To study in Catholic high school raises the probability of finishing high school or entering a college.
Angrist (1998).	To study the impact of voluntary military service on the labour market.	Matching estimates with instrumental variables.	When veterans re-entered the civilian labour market, veterans were actually earning less than nonveterans.
Angrist and Lavy (1999).	To estimate the effect of class size on scholastic achievement.	Instrumental variables.	To reduce class size induces an increase in test scores for fourth and fifth graders, although not for third graders.
Casado-Marín, García-Gómez and López-Nicolás (2008).	To study the effects of care giving on labour outcomes.	Matching estimates with propensity score.	Women who were working before becoming a caregiver do not have changes in their chances of being employed.

Source: Own elaboration

Table 2: Literature Review

Author	Objectives	Methodology	Results
Mitra and Indurkhya (2005).	To study the cost-effectiveness of cystectomy versus no cystectomy in elderly patients with muscle invasive bladder cancer in USA.	A linear model with propensity score.	For bladder cancer treatment, propensity score helps make the treatment groups comparable with respect to baseline characteristics.
Dawson, Gravelle, Jacobs, Martín and Smith (2007).	To estimate the impact of the London choice project (LPCP) on ophthalmology waiting times in UK.	Differences in differences models.	PLPC produced a small decrease in waiting time.
Basu, Heckman, Navarro-Lozano and Urzua (2007).	To estimate the average treatment effect and the effect on those treated on 5-year direct costs of breast- conserving surgery and radiation therapy (BCSRT) compared with mastectomy in breast cancer patients in USA.	Instrumental variable methods.	The treatment effect on 5-year medical cost for patients whose unobserved characteristics make them most likely to receive BCSRT is significantly positive.
Barros, Machado and Sanz-de-Galdeano (2008).	To study moral hazard and demand for health services in Portugal.	Matching techniques.	They conclude that the impact of insurance is large and positive.
Goodman, Kachur, Abdulla, Bloland and Mills (2009)	To study the influence of market structure on the care of malaria in Tanzania	Log-linear regressions.	The retail sector is an important source of treatment, but antimalarial coverage is low.
Stillman, McKenzie, and Gibson (2009).	To study the effect of migration on mental health applied to Tongans who migrate to New Zealand.	Matching techniques.	Migration from Tonga to New Zealand produces improvements in mental health.

Source: Own elaboration.

Table 2 (Continue): Literature Review

Author	Objectives	Methodology	Results
Wagstaff, Lindelow, Jun and Juncheng (2009).	To study the impact of a subsidized voluntary health insurance program for rural residents in China.	Differences in differences and matching techniques.	Health insurance has increased the volume of care provided.
Sosa, Galárraga, and Harris (2009).	To estimate the impact of “Seguro popular” to finance health care for the poor in Mexico.	Multinomial choice model with a discrete endogenous variable.	*Seguro popular* program has had a significantly positive effect on the access of poor women to obstetrical care.
Lindeboom, Llena-Nozal, and Klaauw (2009).	To study the effect of parental education on child health outcomes in UK.	Instrumental variable methods.	There is a strong positive associaition between parental socioeconomic status and child health.
Fabbri, and Monfardini (2009).	To study the effectiveness of using charges and waiting lists to rationing public health care in Italy.	Multivariate count data model.	The demand for public healthcare does not depend on household income. The demand for private healthcare increases with income.
Bago d’Uva and Jones (2009).	To analyze health care utilisation in Europe using ECHP.	Latent class and latent class hurdle models.	There are differences between the different types of users according to their income.
Wang, Yip, Zhang and Hsiao (2009).	To study whether the increase in insurance involves improving people's health.	Difference in deference combined propensity score matching.	It is possible to improve the health of the population through the expansion of health insurance.
Wagstaff (2009).	To study the impact of Vietnam’s health care fund for the poor. This is a government program to finance health care for poor households.	Mixture of high-level differencing and regression analysis.	About 60% of those eligible for coverage were covered in 2006, and nearly 80% of those covered were eligible.
Böckerman, and Ilmakunnas (2009).	To study the relationship between unemployment and self-assessed health (SAH) using ECHP for Finland.	Difference in deference models and propensity score matching.	Unemployment does not matter as such for the level of SAH.

Source: Own elaboration.

3. Theoretical framework.

3.1 Basic definitions.

We are going to define the causal effect in terms of potential outcomes or counterfactuals (Angrist and Imbens, 1991). We consider an individual *i*. He or she can receive the tratment and his/her outcome is y_1. If he/she do not receive the treatment, then his/her outcomes is y_0. Obviously, an individual can not be in the two states, therefore we can not observe both.

Let the variable w be a binary treatment indicator, where $w = 1$ denotes treatment and $w = 0$ otherwise. We have a random vector (y_0, y_1, w) from an individual of the population of interest. Rosenbaum and Rubin (1983) gave the next definitions:

Definition 1: We call average treatment effect (ATE) to:

$$ATE \equiv E(y_1 - y_0)\,. \qquad (1)$$

Definition 2: The average treatment effect on treated (ATE_1) is:

$$ATE_1 \equiv E(y_1 - y_0 \mid w = 1)\,. \qquad (2)$$

ATE_1 is the average effect on participants in the program. In general, ATE and ATE_1 are different.

Let x be a set of covariates of individual characteristics, for example income, education. Then we can define both previous treatments conditioning on x. The ATE conditional on x is $E(y_1 - y_0 \mid x)$ and the ATE_1 conditional on x is $E(y_1 - y_0 \mid x, w = 1)$.

Our problem is that we want to estimate the previous effects ATE and ATE_1 and we can only observe:

$$y = (1 - w)y_0 + wy_1 = y_0 + w(y_1 - y_0)\,. \qquad (3)$$

To solve our problem we need to suppose that w is statistically independent of (y_0, y_1). This implies that ATE and ATE_1 are equal and using equation (3):

$E(y \mid w=1) = E(y_1 \mid w=1) = E(y_1)$ and $E(y \mid w=0) = E(y_0 \mid w=0) = E(y_0)$.

Then, we have:

$$ATE = ATE_1 = E(y \mid w=1) - E(y \mid w=0). \qquad (4)$$

If we assume that w is independent of y_0, we can estimate ATE_1 consistently:

$$\begin{aligned} &E(y \mid w=1) - E(y \mid w=0) = E(y_0 \mid w=1) - E(y_0 \mid w=0) + \\ &+ E(y_1 - y_0 \mid w=1) = [E(y_0 \mid w=1) - E(y_0 \mid w=0)] + ATE_1 \end{aligned}. \qquad (5)$$

If it holds that

$$E(y_0 \mid w) = E(y_0), \qquad (6)$$

substituting in equation (5) we have an unbiased estimator of ATE_1.

We are going to work now with a vector x of observed covariates. Now we have a vector (y_0, y_1, w, x) that describe the population.

When w and (y_0, y_1) are allowed to be correlated we need the assumption that Rosenbaum y Rubin proposed in 1983 and which was called ignorability of treatment:

Assumption 1: Conditional on x, w and (y_0, y_1) are independent.

Often it is enough to assume:

Assumption 2: a) $E(y_0 \mid x, w) = E(y_0 \mid x)$ and b) $E(y_1 \mid x, w) = E(y_1 \mid x)$.

Under *Assumption 2* the average treatment effect conditional on x ($ATE(x)$) and the average treatment effect of the treated conditional on x ($ATE_1(x)$), are identical (Wooldridge, 2002).

3.2 Matching techniques

Matching methods are based on comparing two groups. On one hand, in the first group are individuals who have received treatment and in the second group, called the control group, are the individuals who have not received treatment but they have similar characteristics to those who received treatment. In particular, each individual of the first group is paired with one or more individuals in the control group. With this method different outcomes are due to treatment. To use these methods we need to accept A*ssumption 1*, which is a particular case of a balancing score.

Definition 3: A balancing score is a function $b(x)$ of the observed covariates such that $(y_0, y_1 \perp w) \mid b(x)$ (Rosenbaum and Rubin, 1983).

As we said, the simplest case of balancing score is $b(x) = x$. To ensure compliance of the *Assumption 1*, the vector of covariates x should contain all information affecting the participation in the program and the variable that is being studied. One of the balancing score most used is the propensity score (Rosenbaum and Rubin, 1983).

Definition 4: Let x be a set of covariates. The propensity score is the conditional probability of assignment to treatment one, given the covariates. We denote it:

$$p(x) \equiv P(w = 1 \mid x). \qquad (7)$$

We can use the propensity score to calculate the average treatment effect and the averge treatment effect on the treated. The propensity score is useful because reduces the size of the problem.

Proposition 2 (Wooldridge, 2002): Under Assumption 2 and suppose that

$$0 < p(x) < 1, \quad \text{all } x. \qquad (8)$$

Then

$$ATE = E([w - p(x)]y / \{p(x)[1 - p(x)]\}) \qquad (9)$$

and

$$ATE_1 = E\{[w - p(x)]y/[1 - p(x)]\}/P(w=1). \qquad (10)$$

The initial bias in x is

$$B = E(x \mid w=1) - E(x \mid w=0). \qquad (11)$$

If we use matching methods and suppose that each treated individual is matched with a control individual, then the expected bias in matched samples is:

$$B_m = E(x \mid w=1) - E_m(x \mid w=0), \qquad (12)$$

where *m* indicates the distribution in matched samples. Rosenbaum and Rubin (1983) showed that B_m is the zero vector if we have done exact matches on a balancing score. Therefore, if we do matches using propensity score, the expected bias will be zero.

Once we have calculated the propensity score we have several methods to make matching. In particular, we are going to use nearest-neighbour matching:

- Nearest-neighbour matching: This will match the individuals whose propensity score with the smaller difference. Nearest-neighbour matching sets (Becker and Ichino, 2002):

  $$C(i) = \min_j \|p_i - p_j\|, \qquad (21)$$

  where $C(i)$ is the set of control individuals matched to the treated individual i with an estimated value of the propensity of p_i and p_j is the propensity score of each individual of the control group.

4. Data description: the European Community Household Panel.

The data used in this paper are obtained from the European Community Household Panel Survey (ECHP). This survey contains data on individuals and households for the European Union countries with eight waves available (1994 to 2001). The main advantage is that information is homogeneous among countries since the questionnaire is similar across them. This source of data is coordinated by the Statistical Office of the European Communities (EUROSTAT). Also, this survey includes rich new information about income, education, employment, health, etc.

This representative survey of households of different European Union countries was carried out for the first time in 1994 and 60500 households were interviewed (approximately 170000 individuals). The income measure is disposable (after tax) individual income. However the reference period of income is the year prior to interview. The interviews corresponding to the first eight waves of the ECHP were performed from 1994 to 2001, meaning that the corresponding incomes refer, respectively, from 1993 to 2000 (eight years). All monetary amounts in the data are expressed in national currency units. However, comparisons among countries can be made in equivalent units taking into account differences in the national currency purchasing power.

5. Empirical results.

The rapid growth of expenditure in European Union countries has been largely the result of structural factors in the health care system. Nowadays, the increase in health expenditure is in part due to a manifestation of a richer society whom looks for more health care. Part of this increase is because of population aging and technological improvements. In general, access to some level of health care services in European countries is universal for all individuals however individuals may opt to private health are systems by contracting a supplementary coverage. Obviously, health care systems in European countries differ in the source of financing, coverage and means of delivering benefits. This fact justifies the differences between public and private health expenditure.

Health care systems in the European Union are mainly financed through taxation or contributions from employers and employees. However, there exists an important increase in supplementary voluntary health insurance (double coverage) because individuals look for faster access to treatment (avoiding long waiting lists) or superior accommodation.

In recent years, developed countries have maintained or increased public spending on health. Particularly in Spain, public health expenditure has increased from 2000 to 2005 by 0.7% of the gross domestic product. But also in those countries, there has been an increased of private spending on health. In the case of Spain, private spending on health has increased between 2000 and 2005 by 0.4% of the gross domestic product.

In Table 3 we have the number of visits by the Spanish in the population to the general practitioner.

Table 3: Adults by age and number of times they have gone to consult a general practitioner

Both sexes	Number of people (in thousands)	No time	1-2 Times	3-5Times	6-9 Times	More than 10 times
De 16 a 29 años	8316.6	40.1	34.5	17.5	3.8	3.1
De 30 a 44 años	9163.9	37.1	33.7	16.3	6.8	6
De 45 a 64 años	8714.2	28.8	28.3	20	7.7	15.1
65 años o más	6672.4	14.7	20.9	20.3	12.4	31.6

Source ECHP (INE)

In Table 4 we can see the number of people who had a private health insurance in Spain in 2001.

Table 4: People who had a private health insurance in Spain

	Frequency	Percentage
Not known	61	0.51
Have private health insurance	1377	11.51
Heve not private health insurance	10526	87.98
Overall	11964	100.00

Source ECHP (2001)

In order to establish the main socio-demographic characteristics of people who have a private health insurance, we have classified them into five groups of variables: personal and household characteristics: education level, marital status, income, occupational status, and variables related to individuals' health. Table 7 shows explanatory variables used in estimations and their corresponding definitions. Firstly, as personal characteristics we have included two variables: individual's age (in years) and gender (building a dummy variable which takes value of 1 if individual is female and 0 otherwise). To allow for a flexible relationship between the probability of having a private health insurance and AGE, a quadratic polynomial function of this variable is included (AGE2=Age2). The second group of variables is referred to the maximum level of education completed. In the ECHP, education is classified into three categories based on ISCED classification: less than secondary level

(ISCED 0-2), second stage of secondary level (ISCED 3) and third level (ISCED 5-7). Thus, two dummies variables have been included: less than secondary level (EDUC1) and third level education (EDUC2). Thirdly, representing marital status, we have considered four variables (SINGLE, SEPARATED, DIVORCED and WIDOWED) with married as the reference category. On the other hand, we are concerned with the influence of income on having a private health insurance. Our income variable is natural logarithm of the individual's wage (Logwage). Other variables included in the analysis related to occupational status are status in employment. We have considered a dummy variable that takes value one if the individual is unemployed and zero otherwise (UNEMPLOYMENT). Also, we have considered other variables related to health status. For example, we have taken into account if an individual has any chronic condition (CHRONIC), a dummy variable (HOSPITAL) that indicate if the individual has been in the hospital the previous year, the number of visits to the doctor (NUMBER_VISITS) and finally we have considered the self assessed health (SAH) and we have defined two dummies variable: FAIR_HEALTH (1 if individual's SAH is fair, 0 otherwise) and BAD_HEALTH (1 if individual's SAH is bad or very bad, 0 otherwise). As well, we have incorporated another dummy variable which takes value 1 if individual smokes daily or occasionally (SMOKER). Moreover we have defined another dummy variable that indicates if the individual has a private health insurance (PRIVATE_INSURANCE). The definition of each variable used in the estimates is given in Table 5.

The results obtained are based on the ECHP. We are going to comment the results for 2001. Table 6 shows the descriptive statistics (mean and standard deviation) of our variables.

Table 5: Variable definitions

Name	Definition
Income	
LOGWAGE	Natural logarithm of the individual's earnings
Personal Characteristics	
FEMALE	1 if female, 0 otherwise
AGE	Individual's age
AGE^2	Square of the individual's age
Marital Status	
SINGLE	1 if single, 0 otherwise
SEPARATED	1 if separated, 0 otherwise
DIVORCED	1 if divorced, 0 otherwise
WIDOW	1 if widowed, 0 otherwise
MARRIED	1 if married, 0 otherwise
Employment	
UNEMPLOYMENT	1 if unemployed, 0 otherwise
Health Status	
SMOKE	1 if individual is a smoker, 0 otherwise
NUMBER_VISITS1	Number of visits to general practitioner
NUMBER_VISITS2	Number of visits to specialist doctors in the previous year
HOSPITAL	1 if individual has been hospitalized in the previous year, 0 otherwise
FAIR_HEALTH	1 if individual's self assessed health is fair, 0 otherwise
BAD_HEALTH	1 if individual's self assessed health is bad or very bad, 0 otherwise
CHRONIC	1 if individual is an chronic sick, 0 otherwise
PRIVATE_INSURANCE	1 if individual has private insurance, 0 otherwise

Source: Own elaboration from ECHP

Table 6: Descriptive statistics

Variable	Mean	Std. Dev.
number_visits1	4.0828	6.9875
number_visits2	1.7091	4.0508
age	46.2874	19.6670
widowed	0.0893	0.2851
separated	0.0144	0.1190
divorced	0.0097	0.0980
single	0.3001	0.4583
married	0.5866	0.4925
smoke	0.3208	0.4668
hospital	0.0868	0.2815
chronic	0.2293	0.4204
bad_health	0.1052	0.3069
fair_health	0.2170	0.4122
educ2	0.1317	0.3382
educ1	0.4269	0.4946
logwage	8.5737	1.5832
unemployment	0.0605	0.2384
female	0.5202	0.4996
private_insurance	0.1151	0.3192

Source: Own elaboration from ECHP (2001)

We define a dummy variable representing whether ($y=1$) or not ($y=0$) an individual has a private health insurance. A set of factors, such us age, gender, etc…gathered in a vector *x* explain this fact so the probability model is a regression:

$$E(y \mid x) = F(x, \beta).$$

The set of parameters β reflects the impact of changes in *x* on the probability. In order to estimate this equation, a nonlinear specification of $F(.)$ can avoid logical inconsistency and the possibility of predicted probabilities outside the range $[0,1]$. The most common nonlinear parametric specifications are logit and probit models which have been analysed. So, we are going to use a latent variable interpretation (Jones, 2000; Greene, 2003). Let

$$\begin{array}{l} y = 1, \ \text{if} \quad y_i^* > 0 \\ y = 0, \ \text{if} \quad y_i^* \leq 0 \end{array},$$

Where $y^* = x'\beta + \varepsilon$.

If we assume that ε has a standard normal distribution, we obtain the probit model, while assuming a standard logistic distribution, we obtain the logit model. These models are usually estimated by maximum likelihood (Pascual and Cantarero, 2008).

Table 7 shows the results of the probit equation. The aim is to model the probability of an individual to have a private health insurance as a function of socioeconomic characteristics, such as age, gender, marital status, educational qualifications, work status, earnings, and self assessed health. For example, the coefficient of unemployment is negative, then an unemployed is less likely to have a private health insurance than a worker. On the other hand the coefficient of educ2 is positive, and then university graduates are more likely to have a private health insurance.

To interpret the quantitave implications of the results, we compute partial effects. Table 8 shows the cuantitative effects of this probit equation. Women are 1.33% less likely to have a private health insurance than a man. And university graduates are 5.11% more likely to have a private health insurance.

Table 7: Probit regression

Probit regression						
Number of obs = 11964						
LR chi2(12) = 755.56						
Prob > chi2 = 0.0000						
Log likelihood = -2707.0081						
Pseudo R2 = 0.1225						

private_in~e	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
age	.0068184	.001445	4.72	0.000	.0039862	.0096506
female	-.1218735	.0397602	-3.07	0.002	-.199802	-.043945
unemployment	-.3456613	.1055718	-3.27	0.001	-.5525782	-.1387443
wage	.0000224	1.88e-06	11.94	0.000	.0000187	.0000261
educ1	-.543041	.0564289	-9.62	0.000	-.6536396	-.4324424
educ2	.3764303	.0486453	7.74	0.000	.2810873	.4717734
fair_health	-.0452678	.0540882	-0.84	0.403	-.1512788	.0607432
bad_health	-.2907629	.0958129	-3.03	0.002	-.4785527	-.102973
chronic	-.0092829	.0585887	-0.16	0.874	-.1241147	.1055489
hospital	.1499782	.0678568	2.21	0.027	.0169812	.2829751
smoke	-.0855927	.0409362	-2.09	0.037	-.1658262	-.0053592
married	.0513936	.0400972	1.28	0.200	-.0271953	.1299826
_cons	-1.805005	.064746	-27.88	0.000	-1.931905	-1.678105

Now, we are going to estimate the average treatment effect and the average treatment effect on treated. To calculate the average treatment effect on the treated we have used two different matching models: single match and four matches.

Table 8: Partial effects for probit model

Probit regression, reporting marginal effects

Number of obs = 11964

LR chi2(12) = 755.56

Prob > chi2 = 0.0000

Log likelihood = -2707.0081

Pseudo R2 = 0.1225

privat~e	dF/dx	Std. Err.	z	P>|z|	x-bar	[95% C.I.	]
age	.0007421	.0001564	4.72	0.000	46.2874	.000436	.001049
female*	-.0133309	.0043542	-3.07	0.002	.520227	-.021865	-.004797
unempl~t*	-.0294186	.0067336	-3.27	0.001	.060515	-.042616	-.016221
wage	2.44e-06	2.13e-07	11.94	0.000	7625.52	2.0e-06	2.9e-06
educ1*	-.0565584	.0055794	-9.62	0.000	.426864	-.067494	-.045623
educ2*	.0510876	.0080468	7.74	0.000	.131729	.035316	.066859
fair_h~h*	-.0048267	.0056472	-0.84	0.403	.216984	-.015895	.006242
bad_he~h*	-.0263112	.0070387	-3.03	0.002	.105232	-.040107	-.012516
chronic*	-.0010063	.0063255	-0.16	0.874	.229271	-.013404	.011391
hospital*	.0180279	.0089466	2.21	0.027	.08676	.000493	.035563
smoke*	-.0090921	.0042471	-2.09	0.037	.320796	-.017416	-.000768
married*	.0055548	.004306	1.28	0.200	.586593	-.002885	.013994
obs. P	.0716316						
pred. P	.0535052	(at x-bar)					

(*) dF/dx is for discrete change of dummy variable from 0 to 1

z and P>|z| correspond to the test of the underlying coefficient being 0

Table 9 shows the results of the estimation of the average treatment effect of having private health insurance on the number of consultations with specialists using four matches. This output implies that for the individuals of our sample, the average effect of having a private health insurance is an increase of the number of consultations with specialists by 0.77.

Table 9: *ATE* on the visits to specialists

```
Matching estimator:  Average Treatment Effect

Weighting matrix: inverse variance          Number of obs          =      9558

                                            Number of matches  (m) =         4

------------------------------------------------------------------------------

number_vis~2 |      Coef.   Std. Err.      Z    P>|z|     [95% Conf. Interval]

-------------+----------------------------------------------------------------

        SATE |   .7684034   .1760355     4.37   0.000     .4233801    1.113427

------------------------------------------------------------------------------

Matching variables:  logwage educ2 bad_health hospital chronic smoke married age
```

Table 10 shows the results of the estimation of the average treatment effect of having private health insurance on the number of visits to the general practitioner using four matches. We can see in this output that for the individuals of our sample, the average effect of having a private health insurance is a decrease of the number of visits to the general practitioner by 0.53.

Table 10: *ATE* on visits to the general practitioner

```
Matching estimator:  Average Treatment Effect

Weighting matrix: inverse variance          Number of obs          =      9557

                                            Number of matches  (m) =         4

------------------------------------------------------------------------------

number_vis~1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]

-------------+----------------------------------------------------------------

        SATE |  -.5326462   .2682606    -1.99   0.047    -1.058427   -.0068651

------------------------------------------------------------------------------

Matching variables:  logwage educ2 bad_health hospital chronic smoke married age
```

Tables 11 and 12 show the results of the estimation of the average treatment effect on the treated on the number of consultations with specialists and the number of visits to the general practitioner using four matches. The effect of having a private health insurance on the consultations with specialists on those who have private health insurance is an increase of the number of consultations by 0.77. On the other hand, the effect of having a private health insurance on the number of visits to the general practitioner is a decrease by 0.31.

Table 11: ATE_1 on the visits to specialists using 4 matches

```
Matching estimator:  Average Treatment Effect for the Treated

Weighting matrix: inverse variance          Number of obs          =      9558

                                            Number of matches  (m) =         4

------------------------------------------------------------------------------

number_vis~2 |      Coef.   Std. Err.      Z    P>|z|     [95% Conf. Interval]

-------------+----------------------------------------------------------------

        SATT |   .7710293   .1569122     4.91   0.000     .4634869    1.078572

------------------------------------------------------------------------------

Matching variables:  logwage educ2 bad_health chronic hospital smoke married age
```

Table 12: ATE_1 on visits to the general practitioner using 4 matches

```
Matching estimator:  Average Treatment Effect for the Treated

Weighting matrix: inverse variance          Number of obs          =      9557

                                            Number of matches  (m) =         4

------------------------------------------------------------------------------

number_vis~1 |      Coef.   Std. Err.      Z    P>|z|     [95% Conf. Interval]

-------------+----------------------------------------------------------------

        SATT |  -.3132209   .1668378    -1.88   0.060    -.6402169     .013775

------------------------------------------------------------------------------

Matching variables:  logwage educ2 bad_health chronic hospital smoke married age
```

Table 13 shows the results of the average treatment effect on the treated on the number of consultations with specialists using single match. The effect of having a private health insurance on the consultations with specialists on those who have private health insurance is an increase of the number of consultations by 0.79. This conclusion is similar to the previous results.

Table 13: ATE_1 on the visits to specialists using single match

```
Matching estimator:  Average Treatment Effect for the Treated

Weighting matrix: inverse variance          Number of obs          =      9558

                                            Number of matches  (m) =         1

------------------------------------------------------------------------------

number_vis~2 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]

-------------+----------------------------------------------------------------

        SATT |   .7932564   .2070232     3.83   0.000     .3874984    1.199014

------------------------------------------------------------------------------

Matching variables:  logwage educ2 bad_health chronic hospital smoke married age
```

Table 14 shows the results of the average treatment effect on the treated on the number of visits to the general practitioner. The effect of having a private health insurance on the number of visits to the general practitioner is a decrease by 0.28.

Table 14: ATE_1 on visits to the general practitioner using single match

```
Matching estimator:  Average Treatment Effect for the Treated


Weighting matrix: inverse variance          Number of obs          =      9557

                                            Number of matches  (m) =         1


------------------------------------------------------------------------------

number_vis~1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]

-------------+----------------------------------------------------------------

        SATT |  -.2778764   .2279139    -1.22   0.223    -.7245795    .1688267

------------------------------------------------------------------------------

Matching variables:  logwage educ2 bad_health chronic hospital smoke married age
```

6. Conclusions.

The evaluation must be considered as an essential part of public policy analysis. It contributes to the clarification and critique of objectives and goals. In Spain, there exists an important problem referred to "long waiting lists" for non-urgent medical care, in diagnostic or therapeutic procedures. In this sense, it is important to study if promoting private medical insurance would reduce waiting lists and increase self assessed health.

Evaluation of public policies is important because it provides feedback on the efficiency, effectiveness and performance of public policies and can be critical to policy improvement and innovation. In essence, it contributes to accountable governance.

Using the European Community Household Panel and public evaluation policies techniques, we have studies if there exist differences in the number of visits to specialist doctors between individuals with public healthcare coverage only and the population with double healthcare coverage through additional affiliation to mutual or private health insurance companies. In this sense, there is no empirical evidence of an overuse of health care by the population with double health insurance coverage. We have used matching techniques to estimate the average treatment effect and the average treatment effect on the treated of having a private health insurance on the number of medical visits.

In this paper, we have also analysed the characteristics of those individuals who have private health insurance. The results of the probit model show that most of the coefficients are significant and have the expected signs. For example, UNEMPLOYMENT has a negative coefficient. Also, those with less education (and fewer years of education) are less likely to have a private health insurance. The education coefficients maintain statistical significance showing that more education leads to an increase in the probability of having a private health insurance.

For the individuals of our sample, the average effect of having a private health insurance is an increase of the number of consultations with specialists by 0.77. On the other hand, the average effect of having a private health insurance is a decrease of the number of visits to the general practitioner by 0.53. To calculate the average treatment effect on the treated we have used two different matching models: single match and four matches. The results of all models are similar. The effect of having a private health insurance on the consultations with specialists on those who have private health insurance is an increase of the number of consultations by 0.77-0.79. On the other hand, the effect of having a private health insurance on the number of visits to the general practitioner is a decrease by 0.28-0.31.

7. References

Angrist, J. (1998): "Estimating the Labor Market Impact of Voluntary Military Service UsingSocial Security Data on Military Applicants". *Econometrica*, Vol. 66, No. 2, pp. 249-288.

Abadie, A., Drukker, D., Leber Herr, J. and Imbens, G. (2001): "Implementing Matching Estimators for Average Treatment Effects in Stata". *The Stata Journal*, Vol. 1, No. 1, pp. 1-18.

Angrist, J. and Imbens, G. (1991): "Sources of Identifying Information in Evaluation Models". NBER Technical Working Papers.

Angrist, J. and Imbens, G. (1995): "Two-Stage Least Squares Estimation of Average Causal Effects in Models with Variable Treatment Intensity". *Journal of the Statistical Association*, Vol. 90, No. 430, pp. 431-442.

Angrist, J. and Krueger, A. (1991): "Does Compulsory School Attendance Affect Schooling and Earnings?" *Quarterly Journal of Economics*, Vol. 106, No. 4, pp. 979-1014.

Angrist, J. and Lavy, V. (1999): "Using Maimonides'Rule to Estimate the Effect of Class Size on Scholastic Achievement". *Quarterly Journal of Economics*, Vol. 114, No. 2, pp. 533-575.

Arellano, A. (2006): "Una Revisión Sobre los Métodos de Estudio y Evaluación en las Políticas Activas de Empleo". Instituto Valenciano de Investigaciones Económicas, WP-EC 2006-06.

Bago d'Uva T. and Jones, A. (2009): "Health Care Utilisation in Europe: New Evidence from the ECPH". *Journal of Health Economics*, Vol. 28, No. 2, pp. 265-279.

Barros, P., Machado, M. and Sanz-de-Galdeano, A. (2008): "Moral Hazard and the Demand for Health Services: A Matching Estimator Approach". *Journal of Health Economics,* Vol. 27, No. 4, pp. 1006-1025.

Basu, A., Heckman, J., Navarro-Lozano, S. and Urzua, S. (2007): "Use of Instrumental Variables in the Presence of Heterogeneity and Self-selection: An Application to Treatment of Breast Cancer Patients". *Health Economics*, Vol. 16, No. 11, pp. 1133-1157.

Becker, S. and Ichino, A. (2002): "Estimation of Average Treatment Effects Based on Propensity Scores". *The Stata Journal*, Vol. 2, No. 4, pp. 358-377.

Böckerman, P. and Ilmakunnas, P. (2009): “Unemployment and Self-assessed Health: Evidence from Panel Data”. *Health Economics*, Vol. 18, No. 2, pp. 161-179.

Casado-Marín, D., García-Gómez, P. And López-Nicolás, A. (2008): “Labour and income effects of caregiving across Europe: an evaluation using matching techniques”. HEDG Working Paper 08/23.

Curcio, P. (2007): “Metodología para la Evaluación de Políticas Públicas de Salud”. *Politeia*, vol.30, No.38, pp.59-85.

Dawson, D., Gravelle, H., Jacobs, R., Martín, S. and Smith, P. (2007): “The Effects of Expanding Patient Choice of Provider on Waiting Times: Evidence from a Policy Experiment”. *Health Economics*, Vol. 16, No. 2, pp. 113-128.

Echebarría, C. (2000): “La Evaluación de Políticas públicas**”.** *Congreso de Economía Regional de Castilla y León.*

Evans, W. and Schwab, R. (1995): “Finishing High School and starting College: Do Catholic Schools Make a Difference?” *The Quarterly Journal of Economics*. Vol. 110, No. 4, pp. 941-974.

Fabbri, D. and Monfardini, C. (2009): “Rationing the Public Provision of Healthcare in the Presence of Private Supplements: Evidence from the Italian NHS”. *Journal of Health Economics*, Vol. 28, No. 2, pp. 290-304.

González-Álvarez, L. and Clavero, A. (2009): “Inequalities in Health Care Utilization in Spain Due to Double Insurance Coverage: An Oaxaca-Ransom Decomposition”. *Social Science & Medicine*, Vol. 69, No. 5, pp. 793-801.

Goodman, C., Kachur, P., Abdulla, S., Bloland, P. and Mills, A. (2009): “Concentration and Drug Prices in the Retail Market for Malaria Treatment in Rural Tanzania”. *Health Economics*, Vol. 18, No. 6, pp. 727-742.

Greene, W.H. (2003): “Econometric Analysis”. 5th Edition, Prentice Hall, New York.

Hahn, J. (1998): “On the Role of the Propensity Score in Efficiente Semiparametric Estimation of Average Treatment Effects”. *Econometrica*, Vol. 66, No. 2, pp. 315-331.

Hárdle, W. and Linton, O. (1994): “Applied Nonparametric Methods”. R. F. Engle & D. McFadden (ed.), Handbook of Econometrics, edition 1, Vol. 4, chapter 38, pp. 2295-2339.

Heckman, J. (1997): “Instrumental Variables: A Study of Implicit Behavioral Assumptions Used in Making Program Evaluations”. *The Journal of Human Resources*, Vol. 32, No. 3, pp. 441-462.

Heckman, J., Ichimura, H. and Todd, P. (1998): “Matching as an Econometric Evaluation Estimator”. *The Review of Economic Studies*, Vol. 65, No. 2, pp. 261-294.

Imbens, G. and Angrist, J. (1994): “Identification and Estimation of Local Average Treatment Effects”. *Econometrica*, Vol. 62, No. 2, pp. 467-475.

Jones, A.M. (2000): “Health Econometrics” in Culyer, A.J. and Newhouse, J.P. (eds.) H*andbook of Health Economics*, Elsevier, Amsterdan.

Jones, A. (2007): “Applied Econometrics for health Economists”. Radcliffe Publishing.

Lindeboom, M., Llena-Nozal, A. and Klaauw, B. (2009): “Parental Education and Child Health: Evidence from a Schooling Reform”. *Journal of Health Economics*, Vol. 28, No. 1, pp. 109-131.

Manski, C., Sandefur, G., McLanahan, S. and Powers, D. (1992): “Alternative Estimates of the Effect of Family Structure During Adolescence on High School Graduation”. *Journal of American Statistical Association*, Vol. 87, No. 417, pp. 25-37.

Mitra, N. and Indurkhya, A. (2005): “A Propensity Score Approach to Estimate the Cost-effectiveness of Medical Therapies from Observational Data”. *Health Economics*, Vol. 14, No. 8, pp. 805-815.

Moreno-Serra, R. (2007): “Matching Estimators of Average Treatment effects: A Review Applied to the Evaluation of Health Care Programmes.” HEDG Working Paper 07/02.

Rosenbaum, P. and Rubin, D. (1983): “The central role of the propensity score in observational studies for causal effects”. *Biometrika*, Vol. 70, No. 1, pp. 41-55.

Pablos-Solís, G., Ortiz-Rojas, G. and Pons-Duartes, H. (2009): “Investigación monográfica. La Evaluación de Políticas Públicas”, en Contribuciones a las Ciencias Sociales, www.eumed.net/rev/cccss/04/srd.htm.

Pascual, M. and Cantarero, D. (2008): “Analysing Health Limitations in Spain: An Empirical Approach Based o the European Community Household Panel”. *Fundación de las Cajas de Ahorro*. Documento de trabajo No. 422/2008.

Sosa, S., Galárraga, O. and Harris, J. (2009): “Heterogeneous Impact of the “Seguro Popular” Program on the Utilization of Obstetrical Services in Mexico, 2001–2006: A Multinomial Probit Model with a Discrete Endogenous Variable”. *Journal of Health Economics*, Vol, 28, No. 1, pp. 20-34.

Stillman, S., McKenzie, D. and Gibson, J. (2008): “Migration and Mental Health: Evidence from a Natural Experiment”. *Journal of Health Economics*, doi: 10.1016/j.jhealeco.2009.02.007.

Wagstaff, A. (2009): “Estimating Health Insurance Impact Under Unobserved Heterogeneity: The Case of Vietnam’s Health Care Fund for the Poor”. *Health Economics*, doi: 10.1002/hec.1466.

Wagstaff, A., Lindelow, M., Jun, G. and Juncheng, Q. (2009): “Extending Health Insurance to the Rural Population: An Impact Evaluation of China’s New Cooperative Medical Scheme”. *Journal of Health Economics*, Vol. 28, No. 1, pp. 1-19.

Wang, H., Yip, W., Zhang, L. and Hsiao, W. (2009): “The Impact of Rural Mutual Health Care on Health Status: Evaluation of a Social Experiement in Rural China”. *Health Economics*, Vol. 18, No. 2, pp. 65-82.

Wooldridge, J.M. (2002): “Econometric Analysis of Cross Section and Panel Data”. The MIT Press. Cambridge, Massachusetts, London, England