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The Impact of Subsidized Health Insurance on the Poor in Colombia: Evaluating the Case of Medellin through Endogenous Dummy Models and Propensity Score Matching for Medical Care Utilization

Andrés Ramírez Hassan · Jhonatan Cardona Jimenez · Ramiro Cadavid Montoya

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Abstract This paper uses count and binary data models with endogenous dummy variable, and propensity score matching to evaluate the effect of the subsidized health care program in Medellin (Colombia). The subsidized program, which primarily covers poor people, is found no to have a significant impact on the use of preventive medical care nor hospitalization. Although, parametric specification of preventive utilization indicates that there are selection and moral hazard, effects that compensated approximately. These facts imply that the program can improve its coverage if creates mechanisms that lower the individual moral hazard effect.

Keywords Program Evaluation · Endogenous Dummy Regression · Count Models · Binary Models · Propensity Score Matching

1 Introduction

Health care utilization and health insurance are intimately related because of moral hazard and self selection. The demand for health care is conditioned by the health insurance status of the user. But, the insurance decision itself depends upon expected future consumption of health services (Cameron et al., 1988). Specifically, the subsidized health insurance program reduces the effective price of medical care; this may lead to "overutilization" by the insured users. And, the future use of health services may induce poor people to enroll in the subsidized health insurance program. This phenomenon is known as simultaneous equation bias or endogeneity bias. The problem is that the error term of the medical care utilization is correlated with a switching variable that determines participation in the program. In order to take into account simultaneous equation bias, we use count and binary models based on full information maximum likelihood that accommodate endogenous switching because of self selection associated to treatment effects (Terza, 1998; Amemiya, 1978). Although, the semistructural models are identified through nonlinear functional forms even if all the variables in the insurance equation are included in the utilization equations, we use traditional exclusion restrictions by specifying a instrumental variable in the subsidized equation that is excluded from utilization equations. Recently, a great effort has been made to provide basic health care insurance to the poor in developing countries. In Colombia, the Philippines and Vietnam, for example, the poor are enrolled in the national social health insurance scheme which is financed by taxpayers. In China and Mexico, by contrast, households not covered by formal sector programs have the option of enrolling in a separate subsidized public health insurance program (Wagstaff et al., 2007). However, the potential gains, because of distributional effects, can be lost due to efficiency losses caused by distortion in users' behavior associated to moral hazard and self selection. As a result, policy makers have to evaluate the programs in order to identify problems with their implementation. Evaluations of subsidized health insurance programs in developing countries are generally based on propensity score matching (Saadah et al., 2001; Trujillo et al., 2005; Urdinola and Jain, 2006; Wagstaff, 2007; Wagstaff et al., 2007; Pita and amd A Sanz, 2008). The empirical evidence based on propensity score matching indicates that subsidized health insurance programs have resulted in a net increase in utilization for the poor beneficiaries. Nevertheless, the level of health care utilization remains low in developing countries. However,

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Andrés Ramírez Hassan
Universidad EAFIT, Carrera 49 7 Sur 50. Bloque 26 oficina 204
Tel.: +00 57 4 29619549
E-mail: aramir21@eafit.edu.co

matching estimators of treatment effects are useful when the process of selection in treatment is based on observable variables, i.e., the key assumption is that unobservable variables play no role in the treatment assignment and outcomes determination. This is known as conditional independence assumption (Cameron and trivedi, 2005). If the conditional independence assumption is no met, the estimated treatment effect is biased and inconsistent. In recent years, instrumental variable methods have been advocated in order to account for unobserved confounding variables, i.e., endogeneity problems. Specifically for the Colombian case, Trujillo et al. (2005) and Gaviria et al. (2006) used instrumental variable methods; they found that the subsidized insurance program greatly increased medical care utilization among the country's poor. However,

> "...Despite the substantial increase in public expenditure on health care and the increase in the proportion of population with health insurance, many problems persist. On the one hand, the implantation of a scheme of subsidies to demand has not been accompanied by a dismantling of subsidies to supply, which has led to a doubling in expenditure and a multiplication of inefficiencies."
>
> *(Gaviria et al., 2006, pp 4)*

These structural problems recently caused the Colombian government to declare a social emergency because of the health care system going bankrupt. This paper evaluates the impact of Colombia's subsidized health insurance program on preventive health care utilization and hospitalization services of Medellin's citizens, and attempts to contribute to the more general literature on the impacts of subsidized health insurance programs implanted in developing countries. The paper is organized as follows. Section II provides a review of the Colombian health care systems. The methodology used to evaluate the impact of the subsidized health insurance on the poor in Colombia is sketched out in section III. Section IV presents the evaluation results of the subsidized health care program in Medellin city, and section V concludes.

2 Colombian health care systems

Up until the 80s, the Colombian health care system was based on three separate schemes: the private scheme, which provided health services to the wealthiest segment of the population through private health insurance plans; the public scheme, which had the task of providing health services to the poorest part of the population who were not protected by medical insurance; and the social security scheme which aimed to provide basic health services to two different groups of the population, the formal workers belonging to the private sector through the Social Security Institute (Instituto de Seguridad Social) and the public sector workers through the Social Benefit Societies (Cajas de Previsión Social). This health care system had its boom between 1975 and 1984 but fell into decay after that due to the fiscal crisis during 1984 that reduced the contributions assigned to this sector. Despite the aforementioned boom, the system never achieved near acceptable goals, mainly because inequities persisted (both between regions and strata), low levels of insurance coverage and a high inefficiency in the public provision of health services (Gaviria et al., 2006). During the first half of the 1990s, the Colombian government carried out profound reforms to the health care system that reduced its participation in the industry giving space to the rise of a regulated competition among private firms, separated the provision of health insurance from supplying health services, and decentralized subsidized programs to the local governments. The schemes that arose out of these reforms are a contributory social insurance program financed with mandatory taxes, and a subsidized program aimed at covering the lowest income and the most vulnerable population, financed with both local and central government resources, providing basic health services. These reforms were based on five principles, according to the 1993 Law 100: efficiency, universality, solidarity, integrity and participation, which tried to achieve four objectives: increase coverage, increase solidarity through cross subsidies from the contributive to the subsidized program, improve efficiency by allowing competition in the industry and changing the supply side subsidies to demand side subsidies (Congress, 1993). The new health system required people affiliated to the contributive program paid 12% of their income (two thirds paid by the employer and one third by the employee), collected by the insurer that was chosen by the employee. The subsidized program is financed with a constant percentage of the aforementioned contribution, transfers from the central government and resources owned by the local governments and regional entities. The municipalities are responsible for identifying the beneficiaries of the subsidized program, who pay a coinsurance rate in order to rationalize the use of medical services. Additionally, there is still a supply side subsidy paid to ESS (Empresas Solidarias de Salud), nonprofit medical care providers. Compared to the reform's explicit objectives that led to the actual health care system, this has not been successful. It has targeting problems, due to a significant number of low income households which do not receive the benefits from the subsidized program while some high income families do. This happens because of imperfect monitoring, corruption and limitations in administrative capabilities to identify plausible beneficiaries. It also has coverage problems because of the slow growth of people in the contributive program, transfers from the central government and contributions from the regional entities (Gaviria et al., 2006). Additionally, the transition of supply side to demand side subsidies is still incomplete, maintaining inefficiencies due to public hospitals which are not capable of selling services, displaying a structural deficit in their budget. Along with this, the introduction of the subsidized program has led to a growth in the number of public hospitals, which lower the levels of occupation resulting in an underuse of these facilities. The biggest problem of the failure to make the transition between supply side to demand side subsidies is that the first extract resources from the latter.

3 Methodology

Count data models have gained popularity among econometricians; specifically, health care demand has had many contributions. Deb and trivedi (1997) developed a finite mixture Negative Binomial count model that accommodates unobserved heterogeneity; Gurmu (1997) proposed a semi-parametric hurdle model for count data in order to account for an excess of zeros, this model nests Poisson and Negative Binomial as special cases; Mullahy (1997) suggested that a nonlinear instrumental variable strategy offers a reasonably general solution to endogeneity problem; Windmeijer and Santos (1997) built a count data model whose estimation is based on the generalized method of moments for accommodating the same issue. Deb and trivedi (2004) and Deb and Trivedi (2006) developed a specification and estimation framework for a class of nonlinear, non-normal microeconometric models of treatment and outcome with selection that is estimated through a simulated likelihood method. Finally, Munkin and Trivedi (2008) developed a Bayesian analysis that take into account endogenous selection. On the other hand, Amemiya (1978) proposed a class of generalized least squares estimators in the case of a simultaneous equation generalized Probit model; Green (1996) derived the marginal effects for a conditional mean function in the bivariate Probit model, and extends the results to models with sample selection and heteroscedasticity; Monfardini and Radice (2006) conducted a Monte Carlo experiment to examine the finite sample properties of maximum likelihood inference in the bivariate Probit models with endogenous dummy. Waters (1999) used bivariate Probit models to evaluate a publicly-financed health insurance program in Ecuador, this author finds that there is a strong positive association with the use of curative health care, but not a significant effect on the use of preventive care. Finally, Geweke et al. (2003) analyze an endogenous binary Probit model to study the quality of hospitals based on mortality rates in treating pneumonia. The basis for evaluating programs is counterfactual analysis where an outcome is observed for all individuals but in different states. Specifically, we consider a model in which health care utilization is observed for all individuals, but in only one of the two possible states; covered or uncovered by the subsidized program. Individuals self select into a given program, and expected future use of preventive care and hospitalization may affect the decision about enrolling in the scheme, with the potential of causing endogeneity. Roy (1951) considered, informally, this situation in the labor market, but in this case, the outcome variable is continuous; Maddala (1996) called it switching regression model with endogenous switching. Terza (1998) extended the framework to count data models, and Amemiya (1978) suggested bivariate Probit models to correct endogeneity in the case of binary models. This section follows the discussion of Terza (1998) and Miranda (2004). Consider the ith individual from a random sample $I = \{1, 2, \ldots, N\}$ whose dependent variable is the number of preventive visits to the doctor in the last year ($y_i = 0, 1, \ldots$). The conditional probability density function of the count dependent variable is Poisson with mean equals to $Exp\{x_i'\beta + d_i\gamma + e_i\}$. This one depends on a vector of explanatory variables x_i, a random component e_i, and a binary switching variable ($d_i = 0, 1$) which indicates the state of ith individual, covered or uncovered by the subsidized health insurance program. Given a vector of explanatory variables z_i (which may contain some or all the elements of x_i), d_i is characterized by an index process

$$d_i = \begin{cases} 1, & z_i'\alpha + v_i > 0 \\ 0, & z_i'\alpha + v_i \leqslant 0 \end{cases} \tag{1}$$

Suppose that e_i and v_i are jointly Normal,

$$\begin{bmatrix} e_i \\ v_i \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma^2 & \sigma\rho \\ \sigma\rho & 1 \end{bmatrix} \right) \tag{2}$$

After some algebra and given a change of variable $\eta_i = e_i/\sigma\sqrt{2}$, the joint conditional probability density function of y_i and d_i, given x_i and z_i, may be expressed as

$$f(y_i, d_i|z_i, x_i) = \frac{1}{\sqrt{\pi}} \int_{-\infty}^{\infty} f(y_i|z_i, x_i, d_i, \sqrt{2}\sigma\eta_i)[d_i\Phi_i^*(\sqrt{2}\sigma\eta_i) + (1-d_i)(1-\Phi_i^*(\sqrt{2}\sigma\eta_i))]Exp\{-\eta_i^2\}d\eta_i \tag{3}$$

where $f(y_i|z_i,x_i,d_i,\sqrt{2}\sigma\eta_i)$ is the conditional probability density function of y_i given z_i, x_i, d_i and e_i; $\Phi(.)$ is the cumulative distribution function of a Normal standard variable; and $\Phi_i^*(\sqrt{2}\sigma\eta_i) = \Phi[\frac{z_i'\alpha+(\rho\sqrt{2})\eta_i}{\sqrt{1-\rho^2}}]$. Once $f(y_i|z_i,x_i,d_i,\sqrt{2}\sigma\eta_i)$ is specified, the log-likelihood function for a sample of size N can be established. In the Poisson version of the model

$$f(y_i|z_i,x_i,d_i,\sqrt{2}\sigma\eta_i) = \frac{Exp\{x_i'\beta+\gamma d_i+\sqrt{2}\sigma\eta_i\}^{y_i}Exp\{-Exp\{x_i'\beta+\gamma d_i+\sqrt{2}\sigma\eta_i\}\}}{y_i!} \tag{4}$$

Notice that the mean and variance of the count variable are

$$\mu_i = E[y_i|d_i,z_i,x_i] = Exp\{x_i'\beta+\gamma d_i-0.5\sigma\}\left(d_i\frac{\Phi(z_i'\alpha+\sigma\rho)}{\Phi(z_i'\alpha)}+(1-d_i)\frac{1-\Phi(z_i'\alpha+\sigma\rho)}{1-\Phi(z_i'\alpha)}\right) \tag{5}$$

and

$$Var(y_i|d_i,z_i,x_i) = \mu_i + k\mu_i^2 \tag{6}$$

where $k = Exp(2\sigma^2) - Exp(\sigma^2)$. Thus, the model exhibits overdispersion.

The program effect can be measured by the Average Treatment Effect (ATE). This is $ATE = E[y_i|z_i,x_i,d_i = 1] - E[y_i|z_i,x_i,d_i = 0]$. Given that the mean of the process is exponential, we choose to measure the ATE as

$$\frac{E[y_i|z_i,x_i,d_i = 1]}{E[y_i|z_i,x_i,d_i = 0]} = Exp\{\gamma\}\left(\frac{\Phi(z_i'\alpha+\sigma\rho)}{\Phi(z_i'\alpha)}\right)\left(\frac{1-\Phi(z_i'\alpha)}{1-\Phi(z_i'\alpha+\sigma\rho)}\right) \tag{7}$$

where $Exp\{\gamma\}$ measures the moral hazard effect and $\left(\frac{\Phi(z_i'\alpha+\sigma\rho)}{\Phi(z_i'\alpha)}\right)\left(\frac{1-\Phi(z_i'\alpha)}{1-\Phi(z_i'\alpha+\sigma\rho)}\right)$ is the selection effect based on unobservable factors.

If $\rho = 0$, e_i and v_i are independent, then d_i is an exogenous process, i.e., there is not self selection under this formulation. Thus, the parameters estimated in a exogenous count model are unbiased and consistent. Note that in this case, the selection effect is equal to one. The model is identified through nonlinear functional form even if all the variables in the insurance equation are included in the utilization equation. However, we use exclusion restrictions by specifying instrumental variables in the subsidized regimen equation. In the case of hospitalization, we follow the discussion of Green (2003) and Miranda and Rabe-Hesketch (2006), where $y_i = \{0,1\}$ is a dichotomous variable which is equal to 1 if individual i was hospitalized in the last year. The model can be formulated as a system of equations for two latent variables (y_i^* and d_i^*). The process for d_i is characterized by equation (1) where $d_i^* = z_i'\alpha + v_i$ and y_i is generated by

$$y_i = \begin{cases} 1, & y_i^* = x_i'\beta + d_i\gamma + e_i > 0 \\ 0, & y_i^* = x_i'\beta + d_i\gamma + e_i \leqslant 0 \end{cases} \tag{8}$$

A bivariate Normal distribution is assumed for v_i and e_i, i.e.,

$$\begin{bmatrix} e_i \\ v_i \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}\right) \tag{9}$$

Again, the semistructural model is identified, but we introduce exclusion restrictions in order to get more robust results. If $\rho = 0$ there is not self selection under this formulation, and the parameters estimated in a univariate Probit model are unbiased and consistent. To construct the log-likelihood, let $q_{i1} = 2y_i - 1$, $q_{i2} = 2d_i - 1$, $y_{1i} = x_i'\beta + d_i\gamma$, $y_{2i} = z_i'\alpha$, $w_{ij} = q_{ij}y_{ij}$ for $j = 1,2$ and $\rho_{i^*} = q_{i1}q_{i2}\rho$.

The probabilities that enter the likelihood function are

$$P(Y = y_i, D = d_i|z_i,x_i) = \Phi_2(w_{i1},w_{i2},\rho_{i^*}) \tag{10}$$

where Φ_2 is the bivariate Normal cumulative distribution function. This expression accounts for all the necessary sign changes needed to compute probabilities for y_i and d_i equal to zero and one.

Additionally, we use propensity score matching for evaluating the subsidized health insurance program. In this case, counterfactual analysis is based on a set of potential comparison units (controls) for whom the observable variables, x, match those of the treated units. The concept of propensity score is useful when treatment participation is targeted to a population defined by some observable characteristics. The propensity score is defined by Rosenbaum and Rubin (1983) as the conditional probability of receiving a treatment given pre-treatment characteristics:

$$p(x_i) \equiv Pr\{d_i = 1|x_i\} = E\{d_i|x_i\} \tag{11}$$

There are two assumptions that play an important role in treatment evaluation; first, the balancing condition, which states that $d_i \perp x_i | p(x_i)$, and means that for individuals with the same propensity score the assignment to treatment is random and should look identical in terms of their x_i vector. And second, the conditional independence condition, $y_i \perp d_i | x_i$, which means that participation in the treatment program does not depend on the outcomes, after controlling for the variation in outcomes induced by differences in x_i. Rosenbaum and Rubin (1983) stated that $y_i \perp d_i | x_i \Rightarrow y_i \perp d_i | p(x_i)$. The propensity score reduces the dimensionality problem of matching treated and control units on the basis of the multidimensional vector x_i. In implementing propensity score matching three issues are relevant: (1) whether to match with or without replacement, (2) the number of units to use in the control set, and (3) the choice of the matching method (Cameron and trivedi, 2005). Technically, the issue is a trade-off of bias for efficiency. Various methods have been proposed in the literature to overcome this problem, and four of the most widely used are Nearest Neighbor Matching, Radius Matching, Kernel Matching and Stratification Matching (Becker and Ichino, 2002). Once the propensity score is estimated, the matching Average Treatment Effect on Treated (ATET) can be calculated.

$$\widehat{ATET} = \frac{1}{N_T} \sum_{i \in \{d=1\}} \{y_i - \sum_j w(i,j) y_j\} \tag{12}$$

where N_T is the number of treated units ($d = 1$), and $w(i,j)$ ($0 < w(i,j) \leq 1$) denote the weight given to the jth control case in making a comparison with the ith treated case. Different matching estimators are generated by varying the choice of $w(i,j)$.

4 Econometric Results

The models are estimated using data from Medellin Living Standards Survey (ECV/2007). ECV is a cross-section representative survey of the non-institutionalized population in Medellin with excellent information on demographic and socioeconomic characteristics and health status. A sample of 14,145 individuals that freely can choose to be on subsidized program, 10,074 of them are in the program, is used. As can be seen in Table (1), there is not statistical difference in the unconditional mean of the number of preventive medical care utilization and hospitalization between covered and uncovered individuals. On the other hand, 1.8% and 13.5% of agents in the program have bad and regular self denominated health status, respectively. The program is focused on older and female individuals. As can be seen, the program is concentrated on low strata people, i.e., poor population. The relative frequency distribution by program of preventive medical care utilization, given in percentages, is shown in Table (2). As can be seen, there is not much difference between individuals covered and uncovered by the subsidized program. As can be seen in Table (3), 14.8% of the observations are equal to zero, and the cumulative relative frequency until four visits is 98.3%. Probably, there is unconditional overdispersion in data because of the long right tail (the maximum number of preventive care visits is 64) and the unconditional variance is 3.71, which is greater than the mean that is 2.51. Sorting by subsidized program, the mean of preventive health utilization for covered and uncovered users are 2.52 and 2.49, respectively.

Table 1: Descriptive statistics: Medellin 2007.

Variable	Subsidized Regimen	No Subsidized Regimen
Nvisit	2.52	2.49
	(1.82)	(2.15)
Hosp	0.034	0.023
	(0.18)	(0.15)
Age	35.1	28.5
	(20.69)	(17.72)
Gender	0.59	0.46
	(0.49)	(0.49)
Hstatus1	0.018	0.005
	(0.13)	(0.07)
Hstatus2	0.135	0.071
	(0.34)	(0.25)
Hstatus3	0.76	0.82
	(0.42)	(0.38)
Hstatus4	0.082	0.10
	(0.27)	(0.30)
Stratum1	0.24	0.16
	(0.42)	(0.37)
Stratum2	0.62	0.38
	(0.48)	(0.48)
Stratum3	0.12	0.36
	(0.33)	(0.48)
Stratum4	0	0.046
	(0.00)	(0.21)
Stratum5	0	0.025
	(0.00)	(0.15)
Stratum6	0	0.008
	(0.00)	(0.089)
Ylive	0.53	0.51
	(0.40)	(0.42)

Nvisit: Medical appointments per year, Hosp: Hospitalization in the last year, Stratum1: Under-Lower stratum, Stratum2:Lower stratum, Stratum3:Medium-Low strata, Stratum4: Average strata, Stratum5: Medium-High strata, Stratum6: High, Hstatus1: Poor health status,Hstatus2: Near poor health status, Hstatus3: Good health status, Hstatus4: Very good health status, Gender: 1-Female, 0-Male, SP: 1-Covered Subsidized Regimen, 0-Uncovered Subsidized Regimen, Ylive: Years living in the neighborhood/Age.

Source: Authors' estimations

Table 2: Preventive Health Care Visits: Observed Frequencies by Program, Medellin 2007.

	Subsidized Regimen		No Subsidized Regimen	
Medical appointments per year	Percent	Frequency	Percent	Frequency
0	13.67	1,377	17.69	720
1	22.27	2,247	17.78	724
2	8.67	873	11.67	475
3	16.10	1,622	15.48	630
4	37.98	3,826	34.73	1,414
More than 4	1.28	129	2.65	108

Source: Authors' estimations

We estimate a count data model with endogenous switching where the count variable is the number of preventive medical care visits in the last year and the switching variable is belonging to subsidized program. Also, we control by age, gender, own perceived health status and strata. In general, all estimated coefficients have the expected sign and an intuitive statistical significance, for both count and switching variables (See Table (4)). We use the ratio between time living in the neighborhood and age as identifying instrument in order to get more robust outcomes, although the model is identified through the functional form. Gaviria et al. (2006) used this variable as instrument in their article, and demonstrate that is a valid instrument in a linear context. Because there is not formal test for the validity of exclusion restrictions in a nonlinear setting such as ours, our checks of instrument relevance and exogeneity are informal. As can be seen, a high fraction on time living in the neighborhood implies a bigger probability of being in the subsidized program, an intuitive result because people with high fraction would increase the probability that the municipality identifies them as beneficiaries of the subsidized program. We conduct a likelihood ratio test for significance of the instrument, the test statistic is 137.68 which is large relative to conventional 95% critical value for $\chi_c^2(1)$. In order to test endogeneity a preliminary z statistic can be used to test $\rho = 0$, as can be seen in the second column of Table (4), ρ is statistically significant at 5%. We estimate a model with the restriction $\rho = 0$ and perform a likelihood ratio test, $\chi_c^2(1) = -2*(-35055.472-(-34986.633)) = 116$. Thus, the adequacy of the endogenous switching specification is supported by the rejection of the null hypothesis $\rho = 0$ at any standard confidence level ($Pr \geq \chi_c^2(1) = 0$).[1] Using equation (7), we calculate the Average Treatment Effect (ATE). The result indicates that there is a mean Ex-post moral hazard of 211.11%, but a favourable selection effect of 47.11%, i.e., the unobservable factors that increase the probability of being enrolled in the subsidized program also led to lower utilization relative to that of the randomly assigned into the subsidized regimen. These effects compensate them approximately.

Table 3: Preventive Health Care Visits: Observed and Fitted Frequencies, Medellin 2007.

	Observed Percent		Expected Percent Poisson model		Expected Percent Negative binomial model	
Medical appointments per year	Percent	Frequency	Mean %	Std. Dev	Mean %	Std. Dev
0	14.83	2,097	8.51	0.012	11.39	0.013
1	20.98	2,967	20.33	0.019	21.50	0.015
2	9.53	1,348	25.46	0.008	22.96	0.005
3	15.92	2,252	21.34	0.006	18.27	0.004
4	37.07	5,240	13.46	0.012	12.05	0.008
More than 4	1.70	241	11.23	0.021	13.80	0.021

Source: Authors' estimations

As can be seen in Table (4), there is simultaneous equation bias in exogenous Poisson and Binomial Negative models that causes the variable subsidized regimen not to be statistically significant at 5% level. According to results in the second column in Table (4), σ is positive and significantly different from zero. Therefore, there is evidence that overdispersion and unobserved heterogeneity are present. This evidence is supported by the Binomial Negative model. As is well known, the excess of zeros cannot be handled by a Poisson model, an outcome that is supported in Table (3), where we compare the actual and fitted frequencies for a different number of preventive doctor visits. We observe that the Poisson regression seriously underpredicts the proportion of zero visits and overestimates the proportion of positive visits. As can be seen in Table (3), fitted frequencies of Negative Binomial model are nearer to actual frequencies than fitted frequencies of Poisson model.

[1] Note that under the null hypothesis ρ lies in the boundary of the set of its admissible values. Thus, the likelihood-ratio statistic is distributed as a 50:50 mixture of a mass point at zero and a chi-squared variable with one degree of freedom.

Table 4: Estimated Models: Preventive Health Care Utilization, Medellin 2007.

	Endogenous Poisson Model ($\rho \neq 0$)	Exogenous Poisson Model	Negative binomial model	Probit model
	Coef (s.d)	Coef (s.d)	Coef (s.d)	Coef (s.d)
Variables	Nvisit	Nvisit	Nvisit	
Age	0.0044231* (0.0012791)	0.0060889*(0.0012542)	0.0060902*(0.0012615)	
Gender	-0.0959222*(0.0139889)	-0.0184223(0.0127698)	-0.0181572(0.0127978)	
Age2	-0.0000961*(0.0000159)	-0.0000855*(0.0000167)	-0.0000856*(0.0000168)	
Hstatus2	-0.124752(0.0907661)	-0.1261603(0.0908463)	-0.124752(0.0907661)	
Hstatus3	0.02332(0.0567404)	-0.1116166(0.0885423)	-0.111017(0.0883978)	
Hstatus4	0.1671627*(0.0605137)	0.015652(0.0893371)	0.0159575(0.0891615)	
Stratum2	-0.0156933(0.0167357)	0.0479041*(0.0158439)	0.0473426*(0.0158743)	
Stratum3	0.1901979*(0.0226834)	-0.0055951(0.0213796)	-0.0061661(0.0214525)	
SR	0.7474637*(0.0331389)	0.008389(0.0171163)	0.0078736(0.0171893)	
Intercept	0.3171489*(0.0664424)	0.9276507*(0.0914805)	0.9276467*(0.091397)	
	SR			SR
Age	0.007016*(0.0022526)			0.0066102*(0.0023808)
Gender	0.3209827*(0.023273)			0.3187319*(0.0235869)
Age2	0.0000599*(0.0000286)			0.0000605*(0.0000312)
Hstatus2	-0.4033499*(0.1311738)			-0.3063945*(0.1286992)
Hstatus3	-0.6690486*(0.1274869)			-0.5328867*(0.1246742)
Hstatus4	-0.7475981*(0.1324188)			-0.5732186*(0.1300383)
Stratum2	0.2295052*(0.0279194)			0.2661917*(0.0285102)
Stratum3	-0.7486271*(0.0337093)			-0.7404144*(0.033759)
Ylive	0.3206878*(0.0263201)			0.1514044*(0.0292171)
Intercept	0.5891571*(0.1344295)			0.5485757*(0.1316716)
σ	0.490351*(0.013541)			
ρ	-0.9111115*(0.0174774)			

Nvisit: Medical appointments per year, Stratum1: Under-Lower stratum, Stratum2: Lower stratum, Stratum3: Medium-Low strata, Hstatus2: Near poor health status, Hstatus3: Good health status, Hstatus4: Very good health status, Gender: 1-Female, 0-Male,SR: 1-Covered Subsidized Regimen, 0-Uncovered Subsidized Regimen and Ylive: Years living in city/Age.
Significance code: 0.05 *.
Source: Authors' estimations

Table 5: Estimated Models: Hospitalization, Medellin 2007.

	Endogenous Logit Model	Endogenous Probit Model	Exogenous Logit Model	Exogenous Probit Model
	Coef (s.d)	Coef (s.d)	Coef (s.d)	Coef (s.d)
Variables	Hosp	Hosp	Hosp	Hosp
Age	0.0062595(0.0050941)	0.0042924(0.0040698)	0.0100162(0.0084776)	0.003896(0.0038174)
Gender	0.180569*(0.0631951)	0.1462849*(0.0583317)	0.286769*(0.1052192)	0.1336824*(0.0458008)
Age2	4.99e-06(0.0000535)	0.0000152(0.0000434)	8.14e-06(0.0000916)	0.000015(0.0000433)
Hstatus2	-0.5503371*(0.2382918)	-0.5118204*(0.1083958)	-0.9373642*(0.1882427)	-0.50403*(.1059638)
Hstatus3	-1.36244*(0.5948511)	-1.157111*(0.1117277)	-2.337213*(0.1947166)	-1.141863*(.1048308)
Hstatus4	-1.27147*(0.5481311)	-1.094512*(0.1361939)	-2.174313*(0.2673378)	-1.077679*(0.1291573)
Stratum2	-0.0942849(0.120276)	-0.0795144(0.0607999)	-0.1859579(0.1179057)	-0.0899033(0.052568)
Stratum3	-0.0850463(0.1799313)	-0.0677954(0.1268729)	-0.0695915(0.1490282)	-0.0315762(0.0664058)
SR	-0.1577207(0.8068887)	-0.1210576(0.4540764)	0.0622984(0.128048)	0.0270077(0.0544089)
Intercept	-1.025535(1.095032)	-1.00992*(0.3534277)	-2.012909*(0.2856227)	-1.114131*(0.1363613)
	SR	SR		
Age	0.0065899*(0.002295)	0.0042924*(0.0040698)		
Gender	0.3187753*(0.0235331)	0.3188191*(0.0235342)		
Age2	0.0000608*(0.0000294)	0.0000608*(0.0000294)		
Hstatus2	-0.3113119*(0.1292009)	-0.3106422*(0.1281708)		
Hstatus3	-0.5357402*(0.1237821)	-0.5353118*(0.1235183)		
Hstatus4	-0.5759692*(0.1290383)	-0.5755491*(0.1288173)		
Stratum2	0.2665001*(0.0283089)	0.2664507*(0.0282806)		
Stratum3	-0.7401238*(0.0339165)	-0.7401441*(0.0339013)		
Ylive	0.151619 *(0.0291288)	0.1516672*(0.0291267)		
Intercept	0.5513493*(0.1308431)	0.5508877*(0.1305971)		
ρ	0.1063796(0.4723848)	0.0859076(0.2583989)		

Hosp: Hospitalization in the last year, Stratum1: Under-Lower stratum, Stratum2: Lower stratum, Stratum3: Medium-Low strata, Hstatus2: Near poor health status, Hstatus3: Good health status, Hstatus4: Very good health status, Gender: 1-Female, 0-Male,SP: 1-Covered Subsidized Regimen, 0-Uncovered Subsidized Regimen, Ylive: Years living in city/Age.
Significance code: 0.05 *.
Source: Authors' estimations

In order to evaluate Average Treatment Effects on hospitalization, we estimate bivariate Logit and Probit models. Again, we use as instrument the ratio of time living in neighborhood over age. The likelihood ratio test for testing statistical significance of this variable in Logit and Probit models are 24.03 and 27.12, these values are large relative to conventional 95% critical value for $\chi^2_c(1)$. As can be seen in Table (5), after controlling for selection bias, the subsidized health care program does not affect the probability that an individual is hospitalized. Given that the null hypothesis $\rho = 0$ cannot be rejected with a z statistic in Logit and Probit endogenous switching models, we perform likelihood ratio tests in both models; the null hypothesis $\rho = 0$ cannot be rejected. Thus, there is neither selection bias nor moral hazard, and parameters estimated under univariate specification are unbiased and consistent. We estimate univariate Logit and Probit models and find that the subsidized health care program is no associated with hospitalization (See Table (5)). On the other hand, the significance of the health status variables in the subsidized regimen equations indicates that there is evidence of selection on the basis of observed health status (See Tables (5) and (4)). Users with worst health status have a bigger probability of being in the subsidized program.

Table 6: Average Treatment Effect on the Treated: Medical care utilization, Medellin 2007.

	Method			
	Stratification	Kernel Matching	Radius Matching	Nearest Neighbor
Preventive	$\widehat{ATET} = -0.024$	$\widehat{ATET} = -0.01$	$\widehat{ATET} = -0.039$	$\widehat{ATET} = -0.083$
	$ee = 0.053$	$ee = NA$	$ee = 0.049$	$ee = 0.054$
	$ee_{boostrap} = 0.056$	$ee_{boostrap} = 0.048$	$ee_{boostrap} = 0.058$	$ee_{boostrap} = 0.053$
Hospitalization	$\widehat{ATET} = 0.005$	$\widehat{ATET} = 0.007$	$\widehat{ATET} = 0.010$	$\widehat{ATET} = 0.010$
	$ee = 0.004$	$ee = NA$	$ee = 0.004$	$ee = 0.005$
	$ee_{boostrap} = 0.004$	$ee_{boostrap} = 0.003$	$ee_{boostrap} = 0.004$	$ee_{boostrap} = 0.006$

Source: Authors' estimations

We use propensity score matching to calculate the effect on preventive health care utilization and hospitalization. We formulate a Logit model that satisfied the balancing condition in order to calculate propensity scores. We use equation (12) to estimate the Average Treatment Effect on Treated ($\widehat{ATET}$) with different methods. Specifically, we use Nearest Neighbor, Radius Matching, Kernel Matching and Stratification Matching. As can be seen in Table (6), the outcomes for preventive care utilization are not statistically significant at 5%. On the other hand, there is not a clear answer about ($\widehat{ATET}$) for hospitalization. Nearest Neighbor and Stratification Matching do not find statistically significant effects, but Radius and Kernel Matching do it.

5 Conclusions

Although the results are not directly comparable, the parametric and non-parametric methodologies provide evidence in the same direction. Both methodologies indicate that there is no statistically significant difference in utilization between covered and uncovered individuals of the subsidized health care program in Medellin. However, the endogenous count model indicates that there are moral hazard and self selection in preventive medical care utilization. Specifically, the significance of the health status variables in the subsidized regimen equations indicates that there is evidence of selection on the basis of observed health status. People with self perceived poor health status have a bigger probability of being covered by the program. This fact joined with moral hazard suggest that there are agents which imply high costs for the program. Although, favourable selection based on unobservables relaxes the aggregate financial constrain of the program. Therefore, the subsidized health program in Medellin would improve its coverage if creates mechanisms that lower the individual moral hazard.

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