PUBLIC VS. PRIVATE HEALTH CARE SERVICES DEMAND IN ITALY*

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Abstract:

In this paper we use data coming from the new Italian Survey on Health Ageing and Wealth (SHAW) to analyse physician services utilization in Italy explicitly acknowledging the existence of two different classes of providers: public and private. We consider visits by a specialist physician as the measure of individual services utilization. In particular we assess the relative importance of variables like income, education, private insurance and supply characteristics as determinants of the utilization of such services, while controlling for individual health and need. We do that by estimating some alternative count data regression models of which we discuss the relative advantages and disadvantages and the entailed different interpretation of the results.

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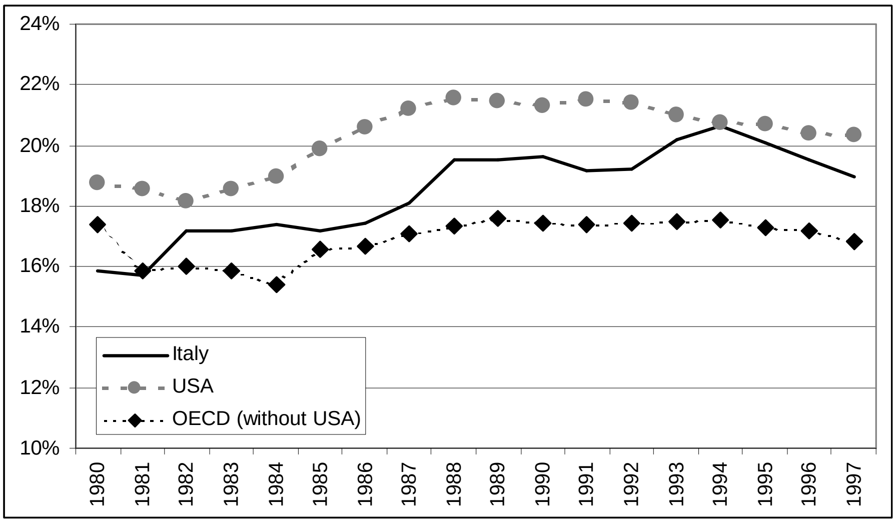
1 INTRODUCTION

Understanding the underlying process of the demand for health services is a key to a better assessment of the forces that increase health care expenditure. Ageing and technological change play a major role in this context with cohorts living longer that consume increasing amounts of intensive, previously unavailable, treatments. Despite attenuating effects due to the lower disability of marginal survivors, health care expenditure is unanimously deemed to increase far beyond existing GDP shares [see Cutler - Sheiner (1998)]. In this turmoil public policies are repeatedly invoked to cap expenditure spiralling and to deal with related equity issues.

Looking at OECD data (see **Figure 1**) it seems that physician services were a victim of this course of events. In all other OECD countries, in particular in Italy, total expenditure on physician services (including both GPs and specialists) stabilised and then started to decrease as a share of total expenditure on health in the last ten years. A possible interpretation of this trend relies on the low technological content of such services compared to others like hospital treatments, pharmaceuticals and instrumental diagnostic checks. Moreover patient time is a basic input in the production of these services. It could be that technological innovation positively affected the organisation of these services reducing the number of visits to obtain, for example, drugs or checks prescriptions. As a matter of fact capping expenditure in this chapter revealed to be relatively easy.

Figure 1: Total per capita expenditure on physician services as a share of total per capita expenditure on health.*



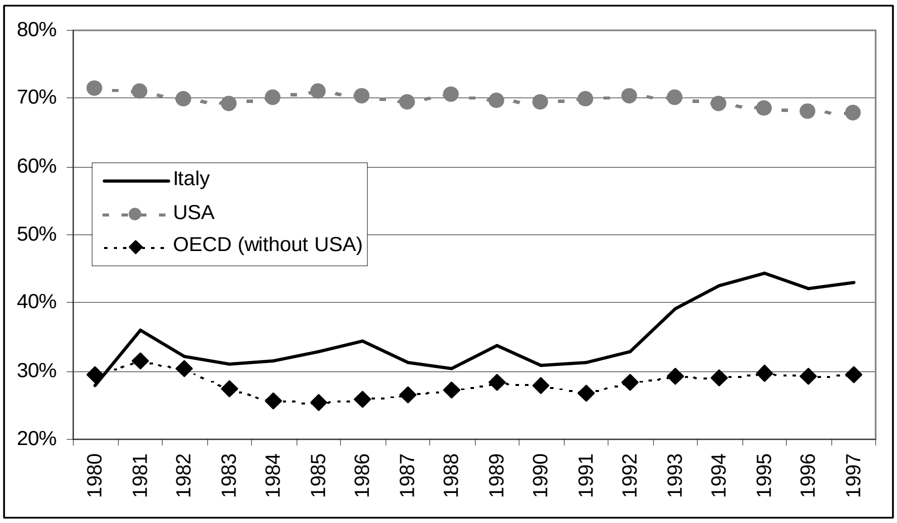
* Expenditure (public and private) on physician services includes expenditure on professional health services provided by general practitioners and specialists. Includes expenditure on services of osteopaths. Original data are denominated in US$/PPP. The OECD average is calculated as a simple mean of the following countries rates: Australia, France, Germany, Iceland, Italy, Netherlands, Switzerland. Source: Our elaboration on OECD Health Data 2000, OECD, Paris, 2000.

In order to motivate our interest for the Italian case study it is relevant to notice how did that happened in terms of public vs. private involvement. According to OECD data (see **Figure 2**) we have no evidence of a shift occurring from public to private expenditure for physician services in the USA and other OECD countries. In the USA we actually observe a slight decrease in the private share. Italy is a relevant exception.[1] The share of private expenditure for physician services remained unchanged, at around 30%, from 1980 to 1992, increasing quite

[1] Similar trends are to be found in France.

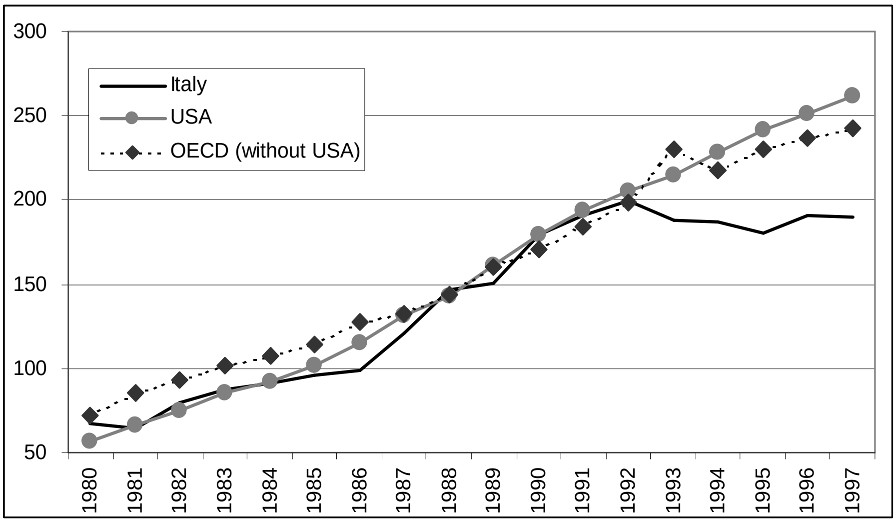
rapidly thereafter and reaching more than 44% by 1995. In the meanwhile public per capita expenditure (see **Figure 3**), constantly increasing since 1980 at the same pace as other OECD countries, from 1992 stabilised at around 200 US$/PPP. This evidence suggests that a dramatic change took place in Italy approximately around 1992. Since then larger shares of expenditure for physician services are financed out-of-pocket as a result of two reinforcing dynamics: first, access to public providers are increasingly subject to significant co-payments (tickets); second, individuals increasingly rely on private professionals.

Figure 2: Private per capita expenditure on physician services as a share of total per capita expenditure on pyhsician services.*



* Expenditure on physician services includes expenditure on professional health services provided by general practitioners and specialists. Includes expenditure on services of osteopaths. Original data are denominated in US$/PPP. The OECD average is calculated as a simple mean of the following countries rates: Australia, France, Germany, Iceland, Italy, Netherlands, Switzerland. Source: Our elaboration on OECD Health Data 2000, OECD, Paris, 2000.

Figure 3: Public per capita expenditure on physician services.*



* Expenditure on physician services includes expenditure on professional health services provided by general practitioners and specialists. Includes expenditure on services of osteopaths. Values denominated in US$/PPP. The OECD average is calculated as a simple mean of the following countries rates: Australia, France, Germany, Iceland, Italy, Netherlands, Switzerland. Source: Our elaboration on OECD Health Data 2000, OECD, Paris, 2000.

In this evolving context some broad policy issues emerge. First of all, how can we figure out the future evolution of the demand and expenditure for physician services in Italy? The observed and foreseeable reduction of public financing to physician services has some impact in terms of equality of access? These kind of questions motivate our interest for a microeconometric analysis of the demand for physician services in Italy.

A remarkable feature of the market for medical professional consultations in Italy is the presence of two broad distinguishable classes of providers: public, highly regulated, specialists, and private, less regulated, ones. We want to account for this peculiarity in our analysis, an issue which has been largely neglected in the literature. Usually the demand for medical consultations is modelled as an aggregate demand irrespective of the type of provider. There are actually good reasons to separately model the counts for public specialists in face of those for private specialists. In our case study we notice that private consultation is typically of higher accuracy, implies lower waiting times at the cost of higher out-of-pocket payment comparing to public ones. Therefore aggregating the two counts would lead to misleading interpretation of the estimated elasticities. On the supply side it is pretty relevant to realise that the role of physician incentives affect utilisation. Indirect evidence of this is provided by **Table 1.** In countries where general practitioners (GPs) are paid fee-for-service, per-capita consultations are slightly more than in countries where they are paid according to capitation, but are almost double than in countries where GPs are salaried. This provides a strong, additional rationale for our analysis of health service utilisation in which we will emphasise the role played by different types of provider.

Table 1: Per-capita general practitioners' consultations across some European countries

	1990-1997	Subgroup mean
	Fee-for-service	
Belgium	7.9	
France	6.2	
Germany	6.0	6.7
	Capitation	
Italy	6.7	
Netherlands	5.7	
United Kingdom	5.8	6.1
	Salary	
Finland	4.0	
Iceland	4.9	
Norway	3.8	
Portugal	3.2	
Sweden	2.9	3.8

Source: Our elaboration on OECD Health Data 1999, OECD, Paris, 1999

Jimenez-Martin - Labeaga - Martinez-Granado (2002), using data from the European Community Household Panel (ECHP), estimate a model of demand for physician services for several European countries, Italy included. However they do not distinguish between public and private providers. We will refer to their results while commenting on ours. On the equity issue Van Doorslaer - Koolman - Puffer (2002), working on an EU sample coming from the ECHP and again disregarding the private vs. public issue, suggest that "the rich appear to receive a higher share of specialist visits than expected on the basis of their need". This result holds for Italy as well. In our viewpoint it is interesting to understand how does this result emerge in terms of access to different types of specialists.

We use the new Italian Survey on Health Ageing and Wealth (SHAW), conducted in the year 2001, to analyse physician services utilisation explicitly acknowledging the existence of two different classes of providers: public and private. We focus on visits by a specialist physician. Actually it is reasonable to presume that the dynamics we described above largely involve this segment and less so GPs visits. In the year before the survey (year 2000), individuals can consume this service going public, private or both. Our aim is to evaluate the determinants of individual utilisation for both classes of providers. In particular we wish to assess the relative importance of variables like income, education, private insurance and supply characteristics as determinants of the utilisation of such services, while controlling for individual health and need.

The paper is organised as follows. In the next section we qualitatively review the existing econometric literature on health-care services utilisation. Section 3 describes the data and some institutional details of our case study. The major empirical results are reported in section 4. Section 5 concludes the paper with suggestions for future research.

2 MODELS FOR HEALTH SERVICE UTILIZATION

It has become generally accepted in the literature on the demand for health care that the demand for certain types of these services depends on two different decision processes. In the Grossman tradition, as far as the demand for health care is essentially seen as the result of patients intertemporal utility maximisation, utilisation is primarily patient determined, though conditioned by the health-care delivery system. In the agency approach, physicians play an active role in assessing the amount of services that patients should consume, up to the point of distorting demand according to their own preferences. These two perspectives lead to two different streams of econometric modelling traditions: one-step models in the Grossman tradition [see Duan et al. (1983) and Cameron et al. (1988)] and two-step models in the agency tradition [see Manning et al. (1981) and Pohlmeier - Ulrich (1995)]. In this paper we model counts of specialist visits by relying on both traditions.

The Grossman model and the agency perspective on patient-physician relationship provide different, despite complementary explanations for the demand for health care. We look at them in sequence.

2.1 THE GROSSMAN MODEL

The Grossman model [see Grossman (1982)] emphasises the role played by patients' choice looking at health and wealth as two interrelated assets the values of which are optimally controlled over time by the individual. In the case of health, the marginal utility of holding a marginal unit of stock has a consumption and an investment component, which together must always be equal to its marginal user cost. This consists of the interest rate, health capital depreciation and a possible change in the value of the health capital over time.

In this context the demand for health care services is a derived demand, in that services are not consumed per se but serve to maintain or improve upon a certain health status. The typical form of the individual demand function for health care services that emerges from the Grossman model is given by:

$$M(t) = f[H(t), w(t), p_m(t), age(t), E(t), X(t)]$$

The demand for health care services (for simplicity we call them medical services) at time t, $M(t)$, is endogenously codetermined[2] with the latent variable "health status", $H(t)$, and it is affected by the wage rate, $w(t)$, a price vector for medical services, $p_m(t)$, individual age, $age(t)$,

[2] The Grossman model is deterministic, so that desidered health stock always equal actual health stock, given constraints. Therefore the demand for health services, which adjust existing health stock net of depreciation, is positively linked, one-to-one, with endogenous health stock.

the level of education, *E(t)*, and a vector of environmental effects, *X(t)*.

A higher wage lowers the marginal incentive to hold health as an asset for consumption use, thus depressing the demand for medical care. By way of contrast it increases the opportunity cost of sick time, hence reinforcing the incentive to hold health as an asset. Assessing the impact of wage on medical service demand is therefore an empirical matter. The impact of prices is negative like that of better education. This last one should lower the demand for investment in health because it contributes to lower health stock depreciation[3]. Demand for medical care should increase with ageing, because it is not optimal to let health stock decline in step with depreciation.

2.2 THE AGENCY APPROACH

In the agency approach, physicians play an active role in assessing the amount of services that patients should consume as far as they typically act a double role: performing checks on the status of patient's health stock and, conditional on checks, supplying treatments aimed at restoring health stock to a desired level. Significant information asymmetry may provide physicians the opportunity to influence demand through their role as health evaluators. This informational advantage is exploited provided that physician's objective function differs from patient's. In this respect it is common to assume that physicians do not only follow Hippocratic oath (for example maximising individual health), but derive utility also from income and leisure. Therefore, when income or leisure are tailored to specific procedures and/or services, physicians will distort demand to perform more remunerative, or less time consuming, procedures/services, if the marginal benefits of a specific procedure outweighs the associated marginal costs.

In this framework a large body of empirical research is devoted to test the so called supplier induced demand (SID) hypothesis. The SID hypothesis states that [McGuire - Pauly (1991)] in the face of negative income shocks, physicians may exploit their agency relationship with patients by providing excessive care. Income shocks examined in the literature arise from three different sources. A first source is variation in the physician/population density across areas: increased density lowers the income of existing stock of physicians, and it will lead to increased utilisation of medical procedures in an inducement-type model. Income shocks may also emerge as the consequence of an exogenous change in demand due to epidemiological shifts, evolution of needs, variation in tastes. However, the most common source is variation in fees paid to physicians, generally by government payers. The inducement model has traditionally been tested by assessing how these three alternative changes in the environment facing physicians affect the utilisation of medical procedures[4]. Despite each of these testing strategies face important problems they are quite convergent in suggesting that physicians, to some extent, do actually manage demand according to economic incentives.

2.3 THE BASIC FRAMEWORK FOR MODELS OF VISITS' COUNTS

2.3.1 Econometric models for count data

The class of econometric models of health service demand we consider here is that concerned with discrete counts of medical visits. In this case excess zeroes is the most relevant

[3] In a more general model, Ehrlich - Chuma (1990) show that the impact of education may go in both directions.

[4] Representative studies that use physician density changes to proxy for income shocks are Fuchs (1978) and Cromwell - Mitchell (1986). Gruber - Owings (1996) use exogenous demand changes, while Yip (1998) examines fee changes.

modelling issue[5]. From a purely statistical viewpoint, the problem basically consists in building enough flexibility into the econometric model to account for the excess probability mass concentrated in the zero counts. Tackling this problem has major econometric and economic implications. In general terms the problem of built-in-flexibility can be addressed in either a single process perspective (determining both null and positive counts), or in a double process perspective (one generating the zeroes vs. the positives and one determining the positives provided that a positive has been already generated). In the context of our study, this amounts to say that in a single process approach all the visits counts, zeroes included, are driven by the same process. On the other hand, when a double process is envisaged, contact process (to access to medical treatment or not?) is distinguished from utilisation (given that the first answer is YES, how much to consume?). From an economic viewpoint, the double process perspective has a natural appeal in the health economics literature as far as it distinguishes the two-part character of the decision-making process in health care demand [Stoddart - Barer (1981)]. While at the first stage it is the patient who decides whether or not she needs medical attention and therefore to access a physician (contact analysis), in the second stage the health care providers together with the patient determine the intensity of the treatment (frequency analysis). This modelling approach has, given certain conditions, a sound structural interpretation [see Santos Silva - Windmeijer (2001)] which motivated its broad adoption in empirical studies. Moreover it provides a unifying empirical framework for the two above-mentioned theories of health care demand. A Grossman-like interpretation might be called for explaining the contact decision, while an agency perspective could be invoked for the interpretation of the frequency decision.

In the single process approach, the simplest econometric model for count data is based on the Poisson distribution, which is characterised by the property of equidispersion. This imply that, conditionally to the covariates introduced in the model, the mean of the count variable is equal to its variance and makes the Poisson model unsuitable in most empirical application, where the above-mentioned excess zeroes displayed by the count variable makes the conditional variance to exceed the conditional mean. The most popular parametric model accounting for overdispersion is based on the Negative Binomial distribution, which can be seen as a generalisation of a Poisson process. The alternative way of dealing with the excess zeros lies in the second modelling approach, represented by the hurdle model. This modification of the basic model was firstly introduced by Mullahy (1986) and thereafter received a great deal of attention in the empirical analysis of the usage of medical services. The hurdle model can be interpreted as a two part model, in which a binary model for the decision of use, determining the probability of crossing a zero threshold, is combined with a truncated count data model on positive counts, explaining the extent of use conditionally to some use.[6]

We present in the Appendix the econometric details of the Negative Binomial (NB) and the Double Hurdle (H) model we use later in the paper for our empirical application, where the demand for physician services is measured by counts of utilisation, i.e. number of public and private visits consumed by the individuals in our sample.

[5] Similar methodological problems arise while considering continuous demand measures like expenditure [see Newhouse and The Insurance Experiment Study Group (1993)].

[6] For the sake of completeness it has to be noticed that, on a purely statistical ground, there is no clear evidence that econometric models based on the two process approach should be preferred to those relying on a single process approach. Actually it has been shown [Deb - Trivedi (1997, 2002)] that sufficiently flexible specification, based on latent class analysis, let single process models better fit the empirical distribution of visits' counts.

2.3.2 Overview of empirical evidence on the determinants of specialist visits

A common feature in the literature on models for visit counts is the lack of control for medical services' prices. This is due to unavailability of detailed data on single visits outlays. As far as surveys are designed to gather total number of visits per time period, no data are available on each visit payment[7]. Therefore, monetary opportunity costs are typically captured by private insurance status variables [like in Pohlmeier and Ulrich (1995) and Deb - Trivedi (1997)] or, more precisely, by individual coinsurance rates [like in Deb - Trivedi (2002)].[8] Usually the availability of private insurance is found to positively affect contact choice but not frequency choice [Pohlmeier - Ulrich (1995)]. Similar effects are found for co-payment rates: higher co-payment rates result in a lower probability of contact while frequency is unaffected [Deb - Trivedi (2002)]. These results are coherent with a Grossman interpretation but less so with an agency perspective.

Coming to the results concerning other typical regressors in models for visits' counts it must be noticed that some predictions of the Grossman model are frequently contradicted by empirical evidence[9]. In particular, good health status is found to be negatively related to the number of visits. This results is coherently consistent across all the papers we reviewed despite differences in econometric specification. Education, typically measured as years of schooling, is usually found to increase visits counts [see Deb - Trivedi (1997, 2002)]. Pohlmeier - Ulrich (1995) show that higher education reduces contact decision for GPs visits while increases it for specialists, in both cases not affecting frequency. Santos Silva - Windmeijer (2001) find that education positively affects contacts and negatively affects frequency for specialist visits. Evidence concerning the impact of income and age tends to be more coherent with the theory.

The theoretical partition between the two processes in the two-part approach underpins the choice and interpretation of typical regressors' coefficients introduced in each of the two-part components. Take for instance the paper by Pohlmeier - Ulrich (1995). They estimate two distinct two-part models for general practitioners visits and for specialist visits on a sample of 5.000 employed Germans. They control for sex, income, age, education, chronic conditions, physician density in place of residence, plus a set of other covariates. It is interesting here to notice the results on physician density. The two-part model estimates show that physician density does not affect the contact choice while it has a positive impact on the frequency decision. The authors note that "while physician density proxies an availability effect for the patient at the first stage, it captures both demand and supplier response at the second stage. … we are inclined to interpret this finding as some evidence of supplier-induced demand". Likewise also other common covariates to the two parts are given different interpretation in the contact and frequency analysis.

3 DATA AND INSTITUTIONAL SETTING

Our data source is the new Survey on Health Ageing and Wealth (SHAW) collected in 2001. The data are described in Brugiavini, Jappelli and Weber (2002) and are downloadable at the following address: http://www.dise.unisa.it/WP/shaw_public_file.dta. The survey focuses on individuals aged 50 or more. The dataset includes a wide range of micro-level information on socio-economic characteristics of individuals and households, including specific variables on

[7] Pohlmeier - Ulrich (1995) argue that the impact of prices may be neglected given that for many western health care systems the direct price of medical services is close to zero.

[8] Introducing insurance status variables raises endogeneity problems. See Cameron et al. (1988), Windemeijer - Santos Silva (1997), Vera Hernandez (1999).

[9] Wagstaff concludes that "the majority of the model's structural parameters are in fact of the 'wrong sign'" [Wagstaff (1986), p. 216].

working and living conditions as well as variables on health condition and health care utilisation. We include in our sample householders and their spouse when the latter is aged 50 or more. Accordingly, the total sample consists of 1664 individuals.

We model as a dependent variable the number of visits to a specialist physician. These include opticians, dentists and any other physician specialised in a certain field. In performing our analysis of visit counts separately for public and private specialists we dropped observations displaying missing values or unrealistic counts (greater than 20) for the dependent variables. As a result, we work on a sample of 1598 individuals for the analysis of private specialist visits and a sample of 1608 observations for public specialist visits. **Table 2** shows the tabulations for the two counts in our dependent variables. Zero counts are about 60% for private specialist consultations, and about 3 point percent higher in the distribution of public ones. Alternative, private visits' participation rates is around 40%, while the corresponding figure for public visits is 37%. 647 and 597 individuals are observed with at least one visit to a public and a private specialist respectively. Private consultations are more frequent on our sample due to larger incidence of higher counts - 3.7 vs. 2.9 on positive counts -. Contact decision process leads to similar sample means participation rates across providers' types, while the second stage process differentiates conditional frequencies of visits across types. This provides a first evidence that the process underlying the contact decision is different from the second stage process.

Table 2: Tabulations of specialist visits in our sample

		PUBLIC			PRIVATE		
	Count	Freq.	Percent	Cum.	Freq.	Percent	Cum.
	0	1011	62.87	62.87	951	59.51	59.51
	1	213	13.25	76.12	180	11.26	70.78
	2	147	9.14	85.26	138	8.64	79.41
	3	81	5.04	90.3	99	6.2	85.61
	4	50	3.11	93.41	60	3.75	89.36
	5	31	1.93	95.34	51	3.19	92.55
	6	28	1.74	97.08	28	1.75	94.31
	7	10	0.62	97.7	20	1.25	95.56
	8	6	0.37	98.07	17	1.06	96.62
	9	2	0.12	98.2	2	0.13	96.75
	10	11	0.68	98.88	18	1.13	97.87
	+10	18	1.12	100	34	2.14	100
Total		1608	100	100	1598	100	100
Positives		597			647		
		Mean	Variance	St. dev.	Mean	Variance	St. dev.
Full Sample		1.088	4.554	2.134	1.501	8.318	2.884
Positive counts		2.930	6.869	2.621	3.708	12.361	3.516
Participation rate		0.371	0.147	0.383	0.405	0.143	0.379

A first indication of overdispersion in the data is obtained when the sample variance of the dependent count variable is found to be greater than its sample mean. After inclusion of regressors, the Poisson model sample conditional variance will decrease with respect to the sample variance, while the sample average of the conditional mean will be equal to the sample mean if a constant is included among the regressors. Cameron and Trivedi point out that if the sample variance is more than twice the sample mean - this is true in our data for both public and private visits - the data are likely to exhibit overdispersion even after inclusion of regressors, as in cross-section data regressions usually explain less than half of the variation of the dependent variable.

Explanatory variables are conventional predisposing variables and variables capturing the access to medical services. **Table 3** contains a description of the variables used in this piece of empirical work (see **Table A1** in Appendix 1 for some descriptive statistics of these variables).

We tried to keep our specification as parsimonious as possible, while mimicking similar specification in the literature. In this respect our specification is very close to Deb - Trivedi (1997) and quite similar to Pohlmeier - Ulrich (1995) thus allowing us to make useful comparisons.

It should be noticed that public specialists are paid according to administered prices, while private ones are free to set prices according to competitive pressures coming from close substitutes. This feature would suggest that controlling for out-of-pocket payments would be quite relevant in our case study. SHAW collects information on total amount paid out-of-pocket for the cumulative count of visits, both specialist and generic, in each type of provider. However no-response rate was quite large (23% for public and 17% for private visits). Moreover averaging outlays across multiple visits could severely distort results. We preferred, at this stage, not to use payments information in the modelling exercise.

Table 3: Description of variables

Variable	Description
Dependent	
Public specialist visits	Number of visits to a public specialist in the year before survey (2000)
Private specialist visits	Number of visits to a private specialist in the year before survey (2000)
Explanatory	
Family income	Monthly family income, net of income taxes and social insurance rates
Education	Number of year of education
Unemployed	=1 if the person is unemployed
Female	=1 if the person is female
Single	=1 if the person is unmarried or widow
Age	Age in years
Chronic conditions	=1 if the person suffers from chronic conditions
Physical limitations	=1 if the person has a condition that limits activities of daily life
Poor self-perceived health	=1 if self-perceived health is poor
Excellent self-perceived health	=1 if self-perceived health is excellent
Hearing troubles	=1 if the person suffers from hearing troubles
Eyesight troubles	=1 if the person suffers from eye troubles
Never smoked	=1 if the person never smoked in his life
Alcohol consumption	=1 if the person consumes alcohol regularly
Private health insurance	=1 if the person is covered by private health insurance
Central region	=1 if the person lives in central regions
Southern region	=1 if the person lives in southern regions
Public exp. per-capita	Public expenditure per capita in the residing Local Health Authority
Availability of private hospitals	=1 if private hospitals are present in the residing Local Health Authority area
Physicians per bed in private	Ratio of physician per bed in private hospitals operating in the residing Local Health Authority area
Physicians per bed in public	Ratio of physician per bed in public hospitals operating in the residing Local Health Authority area
Physician density	Authorised physician per 1000 inhabitants in place of residence
Population	Total population in place of residence (in thousands of inhabitants)

4 RESULTS

4.1 THE NEGATIVE BINOMIAL ESTIMATES

We start our empirical analysis by estimating NB models on the number of public and private specialist consultations respectively. The Maximum Likelihood estimation results[10] reported in **Table 4** reveal that the Poisson distribution is indeed rejected by the data, as the "nesting" parameter f is found to be significantly different from zero. This confirms the stylised facts on overdispersion of the data emerged by the descriptive analysis.

[10] The estimation has been obtained using STATA 7.

The main findings concerning the role of the inserted explanatory variables are the following. Family income appears to be an important determinant of the number of private consultations, with higher income families increasing their utilisation of private services. On the contrary, the demand of public specialist visits is not affected by the family income variable.

The level of schooling has a significant positive impact on both private and public counts. This education effect result agrees with the conventional reason that education makes individuals more informed consumers and signals that more educated people are oriented towards a more frequent use of medical care services.

Table 4: Estimates of the negative binomial model

	PUBLIC				PRIVATE			
	Coef.	Std. Err.	z		Coef.	Std. Err.	z	
Family income	-0.0123	0.0499	-0.2500		0.1282	0.0427	3.0000	***
Family income_sq	0.0028	0.0021	1.3000		-0.0054	0.0019	-2.8700	***
Education	0.1087	0.0361	3.0100	***	0.0851	0.0361	2.3600	**
Education_sq	-0.0058	0.0020	-2.8600	***	-0.0016	0.0018	-0.9100	
Unemployed	0.2178	0.1369	1.5900		-0.0756	0.1254	-0.6000	
Female	0.1778	0.1074	1.6600	*	0.3897	0.1073	3.6300	***
Single	-0.0270	0.1328	-0.2000		0.0675	0.1229	0.5500	
Age	-0.0984	0.0695	-1.4200		0.0707	0.0722	0.9800	
Age_sq	0.0007	0.0005	1.4300		-0.0006	0.0006	-1.0400	
Chronic conditions	0.5299	0.1097	4.8300	***	0.3312	0.1223	2.7100	***
Physical limitations	0.4695	0.1315	3.5700	***	-0.1615	0.1443	-1.1200	
Poor self-perceived health	0.1596	0.1472	1.0800		0.3649	0.1693	2.1500	**
Excellent self-perceived health	-0.5103	0.1163	-4.3900	***	-0.0368	0.1255	-0.2900	
Hearing troubles	0.2435	0.1677	1.4500		0.1115	0.2058	0.5400	
Eyesight troubles	0.2600	0.1419	1.8300		0.3506	0.1540	2.2800	**
Never smoked	-0.2273	0.1069	-2.1300	**	-0.3823	0.1038	-3.6800	***
Alcohol consumption	0.5514	0.4578	1.2000		-0.9225	0.4584	-2.0100	**
Private health insurance	-0.0258	0.2320	-0.1100		0.5300	0.1954	2.7100	***
Central region	-0.4911	0.1505	-3.2600	***	0.0248	0.1507	0.1600	
Southern region	-0.2974	0.1146	-2.5900	***	0.0356	0.1179	0.3000	
Public expenditure per-capita	0.1411	0.1136	1.2400		-0.0184	0.1202	-0.1500	
Availability of private hospitals	0.5966	0.1877	3.1800	***	-0.1051	0.1891	-0.5600	
Physicians per bed in private	-1.8275	0.5158	-3.5400	***	0.3111	0.5418	0.5700	
Physicians per bed in public	-0.7078	0.6174	-1.1500		-1.1649	0.5726	-2.0300	**
Physician density	0.1873	0.0386	4.8500	***	0.0526	0.0415	1.2700	
Population/100	0.0444	0.0314	1.4200		-0.0185	0.0292	-0.6300	
Population/100_sq	-1.9050	1.2610	-1.5100		-0.1420	1.1800	-0.1200	
Constant	1.5368	2.3347	0.6600		-2.5140	2.3555	-1.0700	
Ln(alpha)	0.7402	0.0792			1.0697	0.0623		
Alpha	2.0965	0.1660			2.9145	0.1815		
Number of obs.	1608				1598			
Wald chi2(27)	310.54				157.02			
Prob > chi^2	0.000				0.000			
Pseudo R^2	0.0556				0.0221			
Log likelihood	-2061.76				-2426.88			

Holding a private health insurance increases the consultations of private specialists. This is a common result in the applied literature which is coherent with fours stories. The first one relates to price elasticities (being double insured allows to access private health care at lower out-of-pocket payments). According to the second explanation, this could also be the effect of an adverse selection process making the frequent health services users to look for supplementary coverage and cost reimbursement.[11] A third key of interpretation is represented by moral hazard where incentives by the patient and the physicians for over-treatment align against the insurer. The last possible explanation has to do with supplier induced demand in a wide sense. Pohlmeier - Ulrich (1995) find no evidence of such behaviour as the private insurance dummy is only significant in the firs stage - i.e. contact decision - of their hurdle model.

Turning to the demographic variables, we find that individual's age play no role in both equations. The effect of this variable is usually found to be negative until some age (which varies from 33 to 52 in different studies), and increasing thereafter. We observe coherent coefficient signs in the public visit equation, but these parameters are not enough precisely estimated.[12] Women appear to seek more medical care than men, as usually evidenced in empirical studies. In our context, this is true both for private and public specialist consultations.

The health status measures display the usual empirical link with the degree of utilisation of medical care. This increases when chronic conditions or physical limitations are present, the level of self-perceived health is poor and in presence of eyesight troubles (private visits), and decreases with excellent self-assessed health (public visits). Individuals who never smoked seek less both public and private medical consultations. Customary consumers of super-alcoholic drinks use less private doctor visits.

Regional-specific unobservable factors make public specialists less accessible in central and southern Italy than in northern Italy. This evidence has been already noticed by Van Doorslaer - Koolman - Puffer (2002) for the aggregate utilisation of specialist visits. We show however that it does not hold for the private providers. We could infer that this effect has to do with local government "failures", being private consultation purchased on competitive local markets. The effect of the size of the community of residence, aimed at proxying the opportunity costs of visiting a physician, turns out not to be significant. The variables which proxy the accessibility to the two kind of medical services show the expected sign, with the ratio of physicians per bed in private (public) hospitals exhibiting a negative effect on the number of visits demanded from public (private) physicians. Finally a higher physician density increases the number of public specialists consultations.

4.2 THE HURDLE MODEL ESTIMATES

The Maximum Likelihood estimation results of the two parts of the model (probit at the first stage, truncated negative binomial at the second one) are contained in **Tables 5** and **6**[13].

A first look at both tables reveals that the first stage model exhibits a better fit than the second one. Some of the variables which were non significant in the NB specification turned out as being important determinants of the contact decision. It may be tempting to interpret this finding as an evidence in favour of the Grossman model for the explanation of the contact decision. However, as Pohlmeier - Ulrich (1995) point out, household data are better suited to quantify the determinants of the contact decision, while the frequency of use also depends on supply-side factors on which observable information is limited. Also, the number of observations is considerably reduced in the second part of the model. Despite this, there is a number of relevant comments concerning differences between the parameters across the two stages and with the NB model, which does not distinguish between the two parts.

[11] Following this interpretation, a problem of endogeneity of the private insurance variable can be envisaged.

[12] This result might be due to the substitution of hospital admissions for specialists' visits. We are grateful to Tullio Jappelli for suggesting this interpretation of the age coefficient.

[13] In order to implement estimation with the truncated negative binomial distribution we resorted to the STATA ado file provided by Hilbe (1999) on the Stata Technical Bulletin.

The regressors mostly exert on the modelled probability of contacting a public/private specialist a similar effect to what was found in the NB model. To higher family income corresponds higher probability of contacting a private specialist. The income variable is now significant also in determining a less probable contact with a public specialist. This result marks a clear distance between our analysis and that conducted by Jimenez-Martin - Labeaga - Martinez-Granado (2002). According to them the contact decision for specialist visits in Italy is positively, despite decreasingly, affected by income.[14] We show that this holds for private specialists only. We report no significant impact of income on the frequency decision.

Consistently with our previous findings, more educated individual tend to have higher probability of contacting a public physician. It has to be noticed that this set of variables turns out not to be relevant in the second stage model. Pohlmeier and Ulrich (1995) find the same result on both the counts of general practitioner and specialist visits. This means that once the kind of provider is chosen, income and education do not affect the frequency behaviour.

Table 5: Estimates of the double hurdle model: first stage

	PUBLIC				PRIVATE			
	Coef.	Std. Err.	z		Coef.	Std. Err.	z	
Family income	-0.0470	0.0203	-2.3100	**	0.0694	0.0233	2.9800	***
Family income_sq	0.0039	0.0013	2.9900	***	-0.0024	0.0013	-1.8800	*
Education	0.0407	0.0132	3.0700	***	0.0131	0.0147	0.8900	
Education_sq	-0.0021	0.0006	-3.2700	***	0.0004	0.0008	0.4900	
Unemployed	0.0860	0.0464	1.8500	*	-0.0643	0.0617	-1.0400	
Female	0.0546	0.0407	1.3400		0.1564	0.0474	3.3000	***
Single	-0.0403	0.0511	-0.7900		0.0543	0.0572	0.9500	
Age	-0.0565	0.0295	-1.9200	*	0.0247	0.0293	0.8400	
Age_sq	0.0005	0.0002	1.9900	**	-0.0002	0.0002	-0.9200	
Chronic conditions	0.2242	0.0579	3.8700	***	0.1517	0.0556	2.7300	***
Physical limitations	0.2343	0.0871	2.6900	***	-0.0049	0.0733	-0.0700	
Poor self-perceived health	0.0220	0.0987	0.2200		0.0553	0.0867	0.6400	
Excellent self-perceived health	-0.1796	0.0530	-3.3900	***	-0.0287	0.0523	-0.5500	
Hearing troubles	0.0157	0.1040	0.1500		0.1131	0.0958	1.1800	
Eyesight troubles	0.0713	0.0777	0.9200		0.1698	0.0826	2.0600	**
Never smoked	-0.0702	0.0396	-1.7800	*	-0.1160	0.0472	-2.4600	**
Alcohol consumption	-0.0484	0.1434	-0.3400		-0.2508	0.1402	-1.7900	*
Private health insurance	-0.0833	0.0728	-1.1400		0.1759	0.1234	1.4300	
Central region	-0.1852	0.0538	-3.4400	***	-0.0542	0.0629	-0.8600	
Southern region	-0.1519	0.0490	-3.1000	***	-0.0422	0.0542	-0.7800	
Public expenditure per-capita	0.1323	0.0569	2.3200	**	-0.0530	0.0574	-0.9200	
Availability of private hospitals	0.3367	0.0778	4.3300	***	-0.0817	0.0818	-1.0000	
Physicians per bed in private	-0.9976	0.2178	-4.5800	***	0.1428	0.2407	0.5900	
Physicians per bed in public	-0.4148	0.2307	-1.8000	*	0.0442	0.2626	0.1700	
Physician density	0.0747	0.0194	3.8500	***	0.0301	0.0194	1.5500	
Population/100	0.0310	0.0136	2.2900	**	-0.0060	0.0145	-0.4200	
Population/100_sq	-1.3310	0.5220	-2.5500	**	-0.2880	0.5510	-0.5200	
Constant	1.6293	0.9528	1.7100	*	-0.5659	0.9744	-0.5800	
Number of obs	1608				1598			
Wald chi2(27)	229.62				112.12			
Prob > chi^2	0.000				0.000			
Pseudo R^2	0.0305				0.015			
Log likelihood	-1435.06				-1422.85			

[14] Within a different framework Van Doorslaer - Koolman - Puffer (2002) reach a similar conclusion.

Age has significant negative, despite decreasing, impact on the propensity to contact a public specialist. Age, however, does not seem to affect the frequency decision. This result was concealed in the NB model specification. Women do not show to contact and to visit more frequently public specialists. On the contrary the female dummy have a significant impact on both steps for private consultations. Health status variables tend to play a major role in the contact decision and for the public specialists. According to our evidence it seems that, once a patient choose a private specialist, the frequency of visits does not depend on his health.

Differently from the NB model, the size of the community of residence positively affects the decision of contacting a public specialist: individuals living in a bigger town reveal to face a lower opportunity cost of contacting a public specialist. On the same line of reasoning, regional effects, which, according to the NB model, proved to be relevant for the public consultations, not for the private, show to be mainly relevant for the contact decision and less so for the frequency decision. These two results might reflect government inefficiencies, compared to the performance of competitive markets for private consultations, in providing equal access to specialist visits.

Table 6: Estimates of the double hurdle model: second stage

	PUBLIC				PRIVATE			
	Coef.	Std. Err.	z		Coef.	Std. Err.	z	
Family income	0.0742	0.0536	1.3800		0.0168	0.0480	0.3500	
Family income_sq	-0.0036	0.0026	-1.3900		-0.0012	0.0023	-0.5300	
Education	0.0375	0.0425	0.8800		0.0499	0.0406	1.2300	
Education_sq	-0.0017	0.0024	-0.7300		-0.0009	0.0020	-0.4600	
Unemployed	-0.0250	0.1672	-0.1500		-0.0245	0.1337	-0.1800	
Female	0.0660	0.1294	0.5100		0.2286	0.1137	2.0100	**
Single	-0.0445	0.1453	-0.3100		-0.0741	0.1362	-0.5400	
Age	-0.0235	0.0788	-0.3000		0.0153	0.0821	0.1900	
Age_sq	0.0001	0.0006	0.2100		-0.0001	0.0006	-0.2300	
Chronic conditions	0.2675	0.1201	2.2300	**	0.0938	0.1236	0.7600	
Physical limitations	0.2945	0.1398	2.1100	**	-0.1508	0.1565	-0.9600	
Poor self-perceived health	0.2770	0.1539	1.8000	*	0.2568	0.1772	1.4500	
Excellent self-perceived health	-0.2815	0.1366	-2.0600	**	0.0285	0.1268	0.2200	
Hearing troubles	0.3027	0.1914	1.5800		-0.0212	0.2114	-0.1000	
Eyesight troubles	0.2555	0.1479	1.7300	*	0.1946	0.1589	1.2200	
Never smoked	-0.0807	0.1223	-0.6600		-0.2694	0.1109	-2.4300	**
Alcohol consumption	0.8001	0.4373	1.8300	*	-0.4247	0.5754	-0.7400	
Private health insurance	0.2474	0.2630	0.9400		0.4172	0.1989	2.1000	**
Central region	-0.3341	0.1653	-2.0200	**	0.1029	0.1492	0.6900	
Southern region	-0.0157	0.1297	-0.1200		0.1288	0.1292	1.0000	
Public expenditure per-capita	-0.0796	0.1284	-0.6200		-0.0063	0.1387	-0.0500	
Availability of private hospitals	0.3633	0.1964	1.8500	*	-0.0157	0.1943	-0.0800	
Physicians per bed in private	-0.7005	0.5892	-1.1900		0.2921	0.5824	0.5000	
Physicians per bed in public	-0.4842	0.6547	-0.7400		-2.1332	0.6224	-3.4300	***
Physician density	0.1056	0.0414	2.5500	**	0.0394	0.0432	0.9100	
Population/100	0.0029	0.0329	0.0900		-0.0042	0.0342	-0.1200	
Population/100_sq	-0.0818	1.3280	-0.0600		0.5180	1.3700	0.3800	
Constant	0.7328	2.6225	0.2800		0.6960	2.6495	0.2600	
Constant	-0.1894	0.2006	-0.9400		0.0281	0.1652	0.1700	
Alpha	0.8275				1.0285			
LR test against Poisson, $chi^2(1)$	349.647				586.659			
Number of obs	597				647			
Model $chi^2(27)$	89.03				56.04			
Prob > chi^2	0.000				0.0009			
Pseudo R^2	0.0397				0.0201			
Log Likelihood	-1075.4595				-1368.0918			

It is interesting to remark the impact of holding a private health insurance. This has no importance in the contact of either kind of specialists, but positively affects the frequency of private specialist visits. Following a line of reasoning suggested by Pohlmeier - Ulrich (1995) this last evidence is plausibly due to a supplier induced demand effect since only the frequency equation describes the outcome of the joint decisions of the physician and the patient, while the contact equation reflect patients' decisions only.

Coming to the supply-side variables, their coefficients display different significance and magnitude in the two stages, as the hurdle model allows to disentangle their effect on the contact decision and the number of visits respectively. Public per-capita expenditure affects positively the decision to contact a public specialist, but not the number of referrals. The second measure of accessibility, represented by the number of doctors per bed in public hospitals is significant in the second part of the model and negatively related to the number of visits provided by private specialists. A higher physician density increases both the contact and frequency of use of public specialists.

5 DISCUSSION AND CONCLUSIONS

Since 1992 larger shares of expenditure for physician services in Italy are financed out-of-pocket. This is a result of two reinforcing dynamics: first, access to public providers are increasingly subject to significant co-payments (tickets); second, individuals increasingly rely on private professionals. These evolving patterns motivate our interest for a microeconometric analysis of the demand for physician services in Italy.

Existing econometric models perform aggregate demand analysis, i.e. model the overall counts of physician visits or specialist visits consumed by individuals as explained by covariates like income, out-of-pocket payments, coinsurance rates, health conditions. In case patients, within an health-care delivery system like the Italian, could receive the same service by two different classes of providers, say public vs. private, major problems of interpretation arise in performing aggregate demand estimation.

We used the new Italian Survey on Health Ageing and Wealth (SHAW) to analyse physician services utilisation explicitly acknowledging the existence of two different classes of providers: public and private. We considered visits by a specialist physician as the measure of individual services utilisation. Our aim was to evaluate the determinants of individual utilisation for both classes of providers. The econometric evidence we found confirmed that the private and public counts are driven by different processes. Therefore, examining the two services separately allowed us to make some inference and to gain some hints on the specific determinants for each class of providers.

Generally speaking, our analysis confirmed that the kind of observational data on visits counts typically used in the literature are better suited to quantify the determinants of the contact decision, while the frequency of use also depends on supply-side factors on which observable information is limited. It is rash to say that this evidence is in favour of a Grossman-like explanation of the demand for health care services. Actually, it is hard to believe that physicians play no role in determining visits counts. However, in the health economics literature, it is common to notice that individual conditions generally play a major role in explaining behavioural and medical outcome variation [see Silber - Rosenbaum - Ross (1995)].

According to our results age does not play any strong role in determining the utilisation of medical consultations. We only found a very small negative effect on the decision to contact a public physician. Putting this result on a policy perspective we might be tempted to observe that ageing does not seem to be a major problem for the public financing of such expenditures.

We also found that holding a private health insurance has no importance in determining the contact of either kind of specialists, but positively affects the frequency of private specialist visits. We interpreted this last evidence as due to a supplier induced demand effect. A deeper analysis of such an effect is needed than the one we conducted here. We believe that this will be a major issue in the next future, given the foreseeable reduction of public direct provision of specialist consultations and the enlargement of the doubly-insured segment of the population. A predictable effect is an increasing tendency towards the integration of insurance companies and medical providers aimed at reducing ex-post moral hazard behaviour of physicians.

Coming to the equity of access issue our separate analysis for public and private specialists proved to be quite fruitful. Van Doorslaer - Koolman - Puffer (2002) show that looking at aggregate demand for medical services might conceal redistributing effects in the constituent components of this demand, namely GPs and specialists, as far as one may offset the other. In their context they show that, in Italy, GPs access is slightly pro-poor, while access to specialist is clearly pro-rich. Our analysis extends this results to the constituent part of the demand for specialist visits. Namely we find that being richer increases the propensity to contact a private specialist and consistently decreases the propensity to contact a public specialist. It is common to retain that private specialist are of higher quality. Therefore we conclude that in the Italian national health service access to better specialist consultation is pro-rich, with public provision mainly guaranteeing access to specialists consultation for the poorer. Moreover we found some indirect evidence of government failures to guarantee equal access opportunity to medical consultation across the country. Central and southern regions seem to suffer some rationing compared to the northern regions. We found no evidence of this differential effect for private consultation. Incidentally it must be noticed the doubly-insured segment of the population is mainly concentrated in the northern regions.

From the analysis performed in this paper we received a strong indication of the importance of modelling the two counts, corresponding to private and public specialist visits, as driven by different processes. Next step in this direction consists in considering the two processes as jointly dependent, describing their interrelation in an analogous way as the seemingly unrelated regression model. The resulting bivariate framework is indeed the appropriate one to take into account and evaluate substitution/complementarity relationships which are likely to exists between the two classes of providers.

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APPENDIX 1

Table A1: Descriptive statistics for the regressors

Variable	Mean	Std. Dev.	Min	Max
Family income	3.260	2.426	0.300	25
Family income_sq	16.511	41.272	0.09	625
Education	7.662	4.578	0	21
Education_sq	79.647	87.006	0	441
Unemployed	0.753	0.431	0	1
Female	0.533	0.499	0	1
Single	0.195	0.397	0	1
Age	63.108	9.010	50	92
Age_sq	4063.768	1181.410	2500	8464
Chronic conditions	0.338	0.473	0	1
Physical limitations	0.186	0.389	0	1
Poor self-perceived health	0.138	0.345	0	1
Excellent self-perceived health	0.598	0.490	0	1
Hearing troubles	0.057	0.232	0	1
Eyesight troubles	0.111	0.314	0	1
Never smoked	0.594	0.491	0	1
Alcohol consumption	0.014	0.117	0	1
Private health insurance	0.049	0.217	0	1
Central region	0.209	0.407	0	1
Southern region	0.362	0.481	0	1
Public exp. per-capita	1.932	0.421	0.922	3.377
Availability of private hospitals	0.826	0.379	0	1
Physicians per bed in private	0.209	0.132	0	0.494
Physicians per bed in public	0.429	0.102	0.182	0.649
Physician density	5.624	1.377	3.513	8.782
Population	240.978	592.576	0.337	2653.245
Population_sq	409.005	1482.840	0.000	7039.709

APPENDIX 2: THE NEGATIVE BINOMIAL AND DOUBLE HURDLE MODELS

Having available a sample of N independent observations (y_i, x_i), where y_i denote the count variable of interest and x_i a set of covariates, the starting point for count data analysis is the Poisson regression model, defined by the conditional density:

$$f^{P}(y_i \mid x_i; b) = \frac{e^{-m_i} m_i^{y_i}}{y_i!} \quad y_i = 0,1,2,..... \tag{1}$$

where: $m_i = \exp(x_i^{'} b)$, $m_i > 0$. The property of equidispersion implied by the Poisson distribution means that:

$$E(y_i \mid x_i) = V(y_i \mid x_i) = m_i$$

To tackle with overdispersion we resort to the Negative Binomial (NB) distribution. This can be derived as a compound Poisson process where the parameter of the Poisson distribution includes a gamma distributed random variable reflecting individual heterogeneity: $y_i \sim Poisson(m_i n_i)$ with $n_i \sim Gamma(a, l)$ [15], with $a = l$, and the negative binomial distribution is obtained by integrating over n_i:

$$\begin{aligned} f^{NB}(y_i \mid x_i; a, b) &= \int_0^{\infty} \frac{e^{-(m_i n_i)} (m_i n_i)^{y_i}}{y_i!} g(n_i) dn_i \\ &= \frac{\Gamma(y_i + a)}{\Gamma(a)\Gamma(y_i + 1)} \left(\frac{a}{m_i + a} \right)^{a} \left(\frac{m_i}{m_i + a} \right)^{y_i} \end{aligned} \tag{2}$$

where $m_i = \exp(x_i^{'} b)$ as above, and the conditional mean and variance are given by:

$$E(y_i \mid x_i) = m_i$$

$$V(y_i \mid x_i) = m_i + f m_i^2$$

where $f = a^{-1} > 0$ is an overdispersion parameter, making the variance greater than the mean, as observed in many data sets. The parameters (a, b) can be estimated by the maximizing numerically the log-likelihood function corresponding to the density above (estimation is automatically implemented in some statistical packages, like STATA). This is the most common implementation of the Negative Binomial Model, NB2 in the terminology of Cameron - Trivedi (1998). The additional parameter characterizing the NB distribution makes it more flexible than the Poisson, to which it reduces when $f = 0$. In most applications, NB regression models are likely to provide more efficient estimators than those based on Poisson distribution, as failure of the assumption of equidispersion has similar consequences to failure of the homoskedasticity assumption in the linear regression model [Cameron - Trivedi, 1998].

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[15] The density function for the positive continuous variable n_i is given by: $g(n_i) = \frac{n_i^{a-1} l^{a}}{\Gamma(a)} \exp(-l n_i)$, where $l > 0, a > 0$ and $\Gamma(a) = \int_0^{\infty} e^{-t} t^{a-1} dt = (a-1)!$, $a > 0$.

The alternative way of dealing with the "excess zeros" we follow in the paper is represented by the hurdle model. To illustrate the hurdle model, define a dummy variable describing the non use of a doctor in a given period: i.e. $d_i = 1$ if $y_i = 0$. The probability function is then given by:

$$f^H(y_i \mid x_i; J_1, J_2) = f_1(0 \mid x_i; J_1)^{d_i} \left[(1 - f_1(0 \mid x_i; J_1)) f_{trunc}(y_i \mid x_i, y_i > 0; J_2)\right]^{(1-d_i)} \qquad (3)$$

where:

$$f_1(0 \mid x_i; J_1) = pr(y_i = 0 \mid x_i; J_1)$$

$$f_{trunc}(y_i \mid x_i, y_i > 0; J_2) = \frac{f_2(y_i \mid x_i; J_2)}{1 - f_2(0 \mid x_i; J_2)}$$

The model specifies a binary probability determining whether the count has a zero realization. If the realization is positive, the hurdle is crossed and the conditional distribution is described by a truncated count model. The two processes can be driven by the same explanatory variables, but the interpretation of parameters will be different depending on the considered stage.

The log-likelihood functions corresponding to (3) factors in two components, which can be separately maximized on the whole sample and on the positive observations respectively:

$$\ln L(J_1, J_2) = \sum_i d_i \ln f_{1i}(J_1) + (1 - d_i) \ln(1 - f_{1i}(J_1)) + \sum_{i \mid d_i = 0} \ln f_{2i}(J_2) - \ln(1 - f_{2i}(0))$$

Estimation of the parameters requires some choice for the two density functions. In our application we use a probit model for the binary outcome, and a truncated negative binomial density for the intensity of use part of the model.