The Demand for Medical Visits in Italy: a Two-Part Model

Recent Developments in INFORUM-type Modeling

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THE DEMAND FOR MEDICAL VISITS IN ITALY: A TWO-PART MODEL

1. The Scientific Problem and the Modelling Approach: an Introduction

Health care services have peculiar characteristics which make difficult to build a model explaining how the consumer formulates his demand. From an economic viewpoint, in this market the consumer is the vulnerable side: in a moment of extreme need, he is forced to express a demand of health care without the complete necessary information hence he must rely upon other agents with better information but sometimes different preferences.

Health can be considered as a durable good that depreciates. By means of net investments, the stock of health capital can be accumulated by combining medical services and other inputs, such as time, to produce new health which counters the effects of aging. However, there is no certain relation between health and medical services: thus, in the literature on demand for health services, medical care is used as an input in the household production function of health. The demand for medical services is therefore a derived demand, since services are not consumed per se but to maintain or improve upon a given health status. This approach has been described in the seminal work by Grossman (1972) where the demand for medical services is essentially seen as the result of patients intertemporal utility maximization, utilization is primarily patient determined, though conditioned by the health-care delivery system. The typical demand is thus determined by the latent variable 'health status', the individual wage rate, a price vector for medical services, a time trend, a vector of environmental effects and the level of education. A higher wage leads to a substitution of time for medical services, because time becomes relatively more expensive; by way of contrast it increases the opportunity cost of sick time, hence increasing the incentive to hold health as an asset. The impact of prices is negative, although for many western countries the direct price of medical services is close to zero so that the impact of prices can be neglected. The rate of depreciation for the health capital stock increases with ageing and if environmental factors are damaging to health, their impact on demand should be positive. Finally, theory predicts a negative coefficient for education if it more educated people are more efficient producers of health. However, the estimation of these type of equations has usually provided results counter to theoretical predictions[1].

One possible explanation for these results is that the process that drives the demand for medical services is more complicated. As stated at the beginning, it involves two agents, the patient and the physician, with asymmetric information about the illness and the possible treatments. If this is the case – as the recent literature on the demand of health care has generally acknowledged – the demand of health services depends on two different decision processes and thus can be broken down into two stages. While at the first stage, it is the patient who decides whether to visit the physician (contact decision), it is essentially up to the physician to determine the duration of the treatment (frequency decision). The patient/consumer (the principal) is not able to translate his needs into a demand of a specific treatment thus he explains his symptoms to a physician (the agent) who can use his professional knowledge to formulate the demand for the appropriate treatment.[2] The message behind the agency approach of the second stage is that a significant information asymmetry may provide physicians the opportunity to influence demand as they may determine treatment not only according to medical criteria but also reacting to economic incentives. In this framework the physician may decide a level of consumption which is different from what a consumer with perfect information would have chosen (supplier induced demand)[3]. This concept is very important in health care systems where doctors are paid on the basis of services provided, while in countries such as Italy with a capitation system is probably less relevant.[4] This two-stage modelling approach has been widely applied in empirical studies. It provides a unifying empirical framework for the two above-mentioned theories of health care demand: a traditional Grossman-like interpretation may be called for explaining the contact decision, while an agency perspective could be referred to interpret the frequency decision. Besides the theoretical connection with a two-step decision-making process, the appeal of the hurdle model is partly driven by an important feature of the demand for medical care, which is the high incidence of zero usage. For instance, approximately 72% of cross-sectional sample of Italian individuals reports no outpatient visits in the year 2000[5].

In this work we aim to compare a one-step decision-making process model with a two-part approach to estimate the demand of medical visits in Italy. The ultimate goal is to select the most appropriate framework to improve modelling and forecasting of health care demand in an Inforum-type long-term multisectoral model for Italy. The paper is organized as follows. Section 2 describes the main characteristics of the Italian National Health System. Alternative available data sources for estimating health care demand are presented in Section 3. The econometric models – a binomial negative model and a two-part model – are presented and compared in Section 4. Then in Section 5 some descriptive statistics of the dependent variables and of the covariates used in the models are shown. Finally results and comments conclude the paper.

2. The Market for Physician Care in the Italian NHS

The Italian National Health Service (NHS) was founded in 1978[6]. It provides universal coverage and uniform health care to the entire population. It is mainly financed through compulsory worker contributions and general taxation. However, depending on a citizens income, age and health condition, patient co-

[1] See Wagstaff (1986), Cameron and Trivedi (1986). These studies along with many others are reviewed and commented by Grossman (2000).

[2] In health economics asymmetric information and uncertainty are the main factors influencing physician behaviour. Sources of uncertainty are the following: 1) the classification of the patient in terms of disease condition; 2) uncertainty about the effects of treatment for a given condition; 3) patient preferences may not be known to the physician (McGuire (2000)).

[3] A review of the theory and empirical literature of physician agency is given by McGuire (2000). Physician – induced demand is "when the physician influences a patient's demand for care against the physician's interpretation of the best interest of the patient" (p.504). This demand inducement must be distinguished from useful agency: inducement is a prescription of care that a fully-informed consumer would not want to use.

[4] However supply may induce its own demand also where a third party practically guarantees reimbursement of usage. Empirical analysis usually shows that per-capita consumption of medical services is positively correlated with the physician/population density across areas as summarized by the Roemer law "a bed built is a bed filled".

[5] A similar issue arises also when considering continuous demand measures like expenditure. Bardazzi and Barnabani (1998) show that this percentage of zero expenditures for medical visits amounts to 86.2% in the year 1993. However, zero expenditures may also arise because of the definition used in official statistics to record household consumption. On this issue see section 3.

[6] In the Ninenties, the Italian NHS underwent two main reforms: 1) in 1992-93 Local Health Authorities (Unità Sanitarie Locali) became public enterprises, major hospitals were allowed to become Hospital Enterprises (separated from the LHEs), the central government reduced its responsibility for the financing of health services and Regions were granted more fiscal autonomy to collect resources to finance the total health expenditure; 2) in 1998-2000, with the introduction of fiscal federalism, all residual transfers from the central state to Regions were abolished, each Region received more own tax resources (a share of VAT revenue and of the personal income tax, a new "regional tax on all productive activities"(IRAP)). For an analysis of the reforming process of the National Health system see Bordignon *et al.* (2002).

payments (tickets) are also required for specialist consultations, drugs, ambulatory treatments, certain diagnostic and laboratory tests, and medical appliances. The NHS is characterised by an organizational pluralism. At the central level, the Ministry of Health is responsible for national health planning, general administration, standards setting and, as last resort, financing and paying off debts of Regions. Since the end of the Nineties, Regions have become responsible of health care both on the financing and on the expenditure side. Moreover, they share resources among the Local Health Enterprises (LHEs), appoint the LHEs managers, plan and control their work. Finally, LHEs are responsible for providing health services either directly through public structures or through contracts with private accredited providers[7].

Primary care is provided free of charge by general practitioners (GPs). They are paid according to a capitation fee that applies to the number of people on their list. Within the contract GPs are expected to provide most primary care. Moreover, they should act as gatekeepers for access to secondary services whose provision is refunded by the NHS like diagnostic checks, hospital admissions, specialist visits. People may choose any physician, among those under contract for the LHA they reside in, provided that the physician's list has not reached the maximum of its capacity. The same organization is envisaged for paediatric care provided by paediatricians working under a public contract and paid on a capitation basis.

NHS specialized ambulatory services, including visits and diagnostics and curative activities, are provided either by LHEs or by accredited public and private facilities with which LHEs have agreements and contracts. People are allowed to access NHS specialist care only after approval by their GP, who is responsible for the referral. Once the GP has prescribed the visit or the treatment, the individual is free to choose any provider among those accredited by the NHS, even one outside his LHE. A co-payment is required as an additional source of financing for the provision of specialist ambulatory care and as a way to moderate consumption.

The public health care system coexists with a private market for medical services. For supplying specialist care, private providers are subject to an authorisation based on minimum standard requirements. Visits to private doctors do not require GP referral and expenditures are covered either by out-of-pocket payments by patients or by private health insurance. On average the Italian NHS relies on private providers for approximately the 40% of health services delivered but the public-private mix in the supply of health care varies considerably among Regions and this percentage is generally higher in Southern Italy.

[7] According to the 2003 data of the Ministry of Health, there are in Italy 197 LHEs and 98 Hospital Enterprises.

3. Health Care Data Sources

Empirical studies of health care demand have taken place at the market and at the individual level. The first-generation studies have been based on standard demand theory, sometimes building a model of both supply and demand using macrodata in order to allow for international comparisons.[8] More recently, emphasis has been put on the use of individual level data and on microeconomic analysis and techniques, as microdata become more and more available in health economics. In these studies, the demand of medical services has been measured either by discrete measures, for example the number of visits to a doctor in a given period, or by continuous measures such as medical expenditures. Here we briefly summarize the available data sources for Italian health care consumption both at the aggregate and at the individual level, to identify their characteristics and their limits for the scope of our analysis.

At the aggregate level there are mainly two data sources: a time-series of household consumption for the years 1992-2004 collects data on household consumption for pharmaceutical products, physicians and other professional services, and hospitals. This data is based on the ESA95 definition of '*household final consumption expenditure*' which refers to this sector's *expenditure* on consumption goods and services not to its *acquisition*. Then certain goods and services financed by the government or non-profit institutions but supplied to households as social transfers in kind – such as most health services – are excluded from the household consumption. As for health care items, this data records only co-payments and out-of-pocket payments for private care utilization, therefore these expenditures underestimate the effective level of consumption of health services.

More specifically for health care, a dataset of indicators is available at the national and regional level (database "Health for all") listing average indicators about demographic variables, several illnesses, health resources, and others.

At the microeconomic level, a series of repeated cross-sections of household expenditures "Indagine sui bilanci familiari" (BF) is available for the period 1985–2004 (with a break in the survey design since 1997). Data on expenditures are reported at the household level while demographic characteristics for each family member are available. As for health care, expenditures are recorded along the same ESA95 definition used for the aggregate time-series and detailed in about 12 different items.

Finally, a national survey on "Health conditions and medical services utilization" (CS) is conducted by the Italian National Statistical Institute (ISTAT)

[8] See various chapters in Culyer and Newhouse (2000) for examples of these models.

every 5 years[9]. The survey provides a full account of individual health condition, health care utilization, biometric parameters, socio-economic and other relevant variables. Individuals are also asked about the amount of money they paid out-of-pocket for the last visit among those they had in the last four weeks. The CS survey does not include any information on household income.

In this study we exploit this dataset which presents some useful characteristics for our purposes: i) data are collected at the individual level[10]: health and its care is mainly an individual matter as it depends on personal well-being and perception; ii) the survey contains information on individual health condition and medical services utilization which is fundamental for estimating health care demand and not available from other sources; iii) finally, information on waiting times for medical services is recorded and can be used to estimate the occurrence of rationing on demand (Martin and Smith, 1999; Blundell and Windmeijer, 2000). However this dataset does not allow to evaluate the relationship between income and medical care needs because, as mentioned above, information on either income or total expenditure is not collected. Therefore, a measure of 'purchasing capacity' has been derived performing a statistical matching with data from the BF dataset for the year 2000[11]. The matching procedure is described in Inglese and Oropallo (2004) where the BF is the donor survey while the host survey is the CS, thus the matching is at the household level and the imputed variable is the household total expenditure. This choice does not penalize our analysis because we believe that health expenses are influenced by the family rather than the individual economic conditions.

The integrated dataset allows to estimate the demand for the following items: visits to a general practitioner and to several specialists, diagnostic tests, hospital services, rehabilitation care, pharmaceutical products. In this study, we focus on generic and specialist visits distinguished by provider type (public and private) as a first step to test our model of health services demand.

4. The Model

Health economic considerations suggest that the decision to contact a physician and the decision about the length of treatment are based on different decision-making processes. This implies that for an appropriate specification of a model of health care demand, the contact decision and the frequency decision need to be treated as different stochastic processes. However, they can be driven by the same explanatory variables that may be interpreted differently depending on the stage. This theoretical setting can be interpreted by a two-part model. The more recent applied health literature has often used this modelling approach to explain an integer-valued dependent variable – such as the number of medical visits – although it is equally applicable for continuous outcomes – such as health expenditures --. The two-part model – often referred to as hurdle model – can be interpreted also as a solution to some problems arising with simple count data procedures in the case of health care demand[12].

In fact, the discrete character of the dependent variable calls directly for the application of count data models[13]. The starting point is usually the simple Poisson model, which is characterized by the equi-dispersion property (the mean equals the variance). Unfortunately, many of the variables of interest to health economics show quote the opposite, that is over-dispersion. In other words, data exhibit a higher frequency of zero observations than would be predicted by the simple Poisson model.

One possible explanation for over-dispersion and excess zeros is additional individual heterogeneity beyond differences that can be summarised by the observed explanatory variables. In the Poisson regression model individual differences only enter the model through differences in the covariates. If there are additional unobservable differences across individuals, these could be added as an extra unobservable variable or error term. The effect of adding this further heterogeneity is to spread out the distribution of the count variable, meaning that more observations are shifted to the tails of the distribution so that we would expect to observe more zero values and more high values than would be predicted by the simple Poisson model. The most commonly applied model that allows for additional unobservable heterogeneity is the *negative binomial* or ***negbin** model* which allows for overdispersion by assuming that the individual error term comes from a particular probability distribution (the gamma distribution). The *negbin model* is more flexible and relaxes the equi-dispersion property of the

[9] The last available survey was conducted from september 1999 to august 2000 when a sample of 52.300 households, comprising approximately 140.000 individuals, were interviewed.

[10] The empirical analysis could be performed also at the household level by selecting the appropriate records.

[11] A possible alternative source is the survey conducted by the Bank of Italy as in Proto and Solipaca (2001) and in Atella *et al.* (2004). The reason for our choice lies in the fact that the definition of the survey unit is identical and in that the BF survey could be useful for further developments when going from the analysis of count variables to the expenditures.

[12] We had a previous research experience in the application of hurdle models to explain the consumption of durables (infrequency of purchase) and other items characterized by conscientious abstention from consumption, such as alcohol, meet and tobacco (Bardazzi and Barnabani, 1998). The difference here is that we do not work with a continuous variable (expenditure) but with an integer valued dependent variable and concentrated on a few low values. Moreover, and most important, the information content of zero observations is not the same: where for durables one can assume that a zero expenditure doesn't mean that the consumption is zero but that a household is consuming the services of a durable bought outside the observation period, here zeros divide the population between participants and non participants. Similarities between the two analyses are: the occurrence of many zeros, data is very skewed in non-zero range and is intrinsically heteroskedastic (variance increases with mean).

[13] As a reference for count data models see Cameron and Trivedi (1998).

Poisson model. However, like the Poisson, the *negbin model* assumes that there is a single process underlying all of the observed values of the dependent variable, whether y equals 0 or is greater than 0. In our case, it means that there is only one process behind the decision to contact a doctor and the frequency of visits and that the individual is the only player in this process.

Other recent developments of count data regression have been based on the idea that there is something special about the zero observations and that they are not just a reflection of over-dispersion. This makes a qualitative distinction between participants and non-participants; for example, between those who use health care and those who do not. Along with the modelling approach based upon a combination of the traditional Grossman model and the agency relationship briefly described in the introduction, a way of dealing with this distinction between participants and non-participants is to use a so-called hurdle or two-part specification model. This assumes that the participation decision and the positive values of the count data are generated by two separate probability functions. In some applications, the participation decision is modelled using a standard binary choice model such as the logit or probit. In others, a count data specification such as the Poisson or *negbin* model is used, with a dependent variable that can take values of either 0 or 1. Then a standard count data regression is applied to the subsample of participants, allowing for the fact that the count data is truncated at zero[14].

In the hurdle model, the demand for health services can be specified as follows:

$$I_{ik} = 1(Y_{ik} > 0) = f_{ik}(Z_{ik}, \varepsilon_{1ik}) \tag{1}$$

$$Y_{ik} = f_{2ik}(X_{ik}, \varepsilon_{2ik}) \tag{2}$$

where Y_{ik} is the number of medical visits (k = generic and specialist visits, public and private) of individual i. I_{ik} is a binary index with 1 as indicator of occurrence of the event; X and Z are exogenous sets of variables not necessarily different. Finally there are error terms independently distributed. Note that Y only takes non-negative integer values. Equation (1) describes the initial contact decision while Equation (2) describes the number of visits to the doctor. We are interested in explaining the conditional expectation of Y given the covariates. In the hurdle model, this expectation can be broken down into two terms, the probability of observing a positive outcome (first hurdle) times the conditional expectation of Y given that it is positive (second step). In the first step the probability of crossing a zero threshold is estimated and combined with a truncated count data model on positive counts, explaining the extent of use conditionally to some use.

Hurdle models have the advantages to split estimation into two parts, to allow the same explanatory variables in both parts, and to be numerically well behaved; however, they imply strong prior belief that zeros are from a different process than positives. Besides, the sharp dichotomy between users and non-users may be appealing in modelling data on episodes of medical care but this distinction is tenable only in the case we assume that an individual's visit to a physician corresponds to a single spell of illness during the period covered by the survey. Moreover, with no additional information the first count in the observation period may be misclassified, because it may belong to an illness episode of the preceding period. A longer observation period may reduce the probability of misclassification at the expense of the other specification problem due to multiple illness spells as mentioned above.

5. Data description

Table 1 shows the tabulations respectively for the number of visits to a general practitioner or a paediatrician (GP) and to a specialist (SP) in the four weeks before interview[15]. Zero counts are more than 80% for generic visits and even higher for specialists consultations[16].

Our data shows evidence of overdispersion as the sample variance is almost twice the mean in the case of generic visits and even more for specialist consultations.

The time span covered by the interview (4 weeks) is short enough to be sure that the problem of multiple illness spells is avoided (95 per cent of the population has at most one visit during the period), but it is perhaps to short to assume that an illness spell is well covered by the observation period for the majority of patients so that a problem of misspecification for the second step of the process arises.

A first evidence that the process underlying the contact decision may be different from the second stage process is given in Table 2. For both, the total population and the population of patients, we find the expected relationship between age and the number of medical visits[17]. While the contact decision leads to similar sample means across visits' types, the frequency decision differentiates the conditional frequency of visits across types.

[14] A work by Pohlmeier and Ulrich (1995) proposes and applies this hurdle model to medical visits in Germany. The same model has been applied for Italy by Fabbri and Monfardini (2003) to estimate the determinants of specialist private and public visits.

[15] Visits to a general practitioner and to a paediatrician share some characteristics: they are both mainly provided by the public health care system and are largely free of charge.

[16] This survey data is representative of the population. Sample weights are then used in this work to evaluate the model for the Italian population.

[17] We remind that the generic visits include the paediatric consultations which explains the high participation ratio for the youngest age group.

Table 1. Tabulations of generic and specialist visits

	GP visits			Specialist visits		
count	Freq.	Percent	Cum.	Freq.	Percent	Cum.
0	47.812.781	83,63	83,63	48.772.510	85,31	85,31
1	6.651.514	11,63	95,26	5.703.656	9,98	95,28
2	1.832.525	3,21	98,47	1.679.837	2,94	98,22
3	476.141	0,83	99,30	504.177	0,88	99,10
4	266.628	0,47	99,77	320.597	0,56	99,67
5	57.767	0,10	99,87	74.844	0,13	99,80
6	30.249	0,05	99,92	44.653	0,08	99,87
7	11.081	0,02	99,94	17.564	0,03	99,90
8	22.553	0,04	99,98	31.879	0,06	99,96
9	10.978	0,02	100,00	14.112	0,03	100,00
Total	57.172.217	100,00		57.172.217	100,00	
Mean	0,238			0,229		
Variance	0,432			0,483		

Table 2. Average number of consultations to a G.P. or Specialist by Age Group

AGE GROUPS	GENERIC VISITS			SPECIALIST VISITS		
	mean	conditional mean (*)	participation ratio (**)	mean	Conditional Mean (*)	participation ratio (**)
0–10	0,329	1,407	23,4%	0,110	1,356	8,1%
11–20	0,103	1,244	8,3%	0,191	1,522	12,5%
21–30	0,115	1,257	9,2%	0,208	1,551	13,4%
31–40	0,123	1,251	9,8%	0,219	1,559	14,0%
41–50	0,163	1,339	12,2%	0,238	1,586	15,0%
51–60	0,239	1,454	16,5%	0,259	1,619	16,0%
> 60	0,467	1,630	28,7%	0,302	1,574	19,2%
Total	0,239	1,457	16,4%	0,229	1,559	14,7%

(*) Average number of visits given a contact has taken place; (**) Ratio of patients in age group *j* with at least one consultation to the total number of individuals in this age group.

We measure the demand of health services as the number of visits to a GP and the number of visits to a SP as recorded in the ISTAT survey. Moreover we distinguish each type of visits according to the provider (public or private) as we expect their demand to be different[18]. A full list of the variables used in our model along with their description is presented in Table 3. Explanatory variables can be arranged in several groups. A first set consists of socio-economic variables: besides demographic individual information, we use the imputed variable of total expenditures as a measure of the time opportunity cost rather than to capture an income effect, particularly in the case of generic visits which are mainly covered by the NHS. The same interpretation can be given to the job status. A dummy for holding a private insurance should be relevant in estimating the demand of specialist visits where co-payments are higher and the share covered by the private sector is more significant. Then we have two groups of variables reflecting the individual' short term health status and his health endowments or stocks. Finally, a separate treatment of the contact and the frequency decision, which potentially could be induced by the physician, requires the inclusion of variables reflecting the consumption and leisure preferences of the doctor at the second stage of the estimation process (Pohlmeier and Ulrich, 1995). Unfortunately, the ISTAT survey does not offer much information on the supply side factors of the health care system. Therefore, we use some indicators from the "Health for all" database – such as the physician density – to proxy both the demand response (at the first level this variable may represent an availability effect) and the supplier-induced-response (at the second stage it reflects competition among physicians). As these supply indicators are at the regional level, we indirectly control for geographical location. Finally, we use information on the waiting time to evaluate the relevance of health demand rationing.

Table 3. Description of variables

Dependent variables	Description
1	2
DVISITS (PUB and PRI)	Number of consultations with a GP or a paediatrician in the past 4 weeks (public or private providers)
SVISITS (PUB and PRI)	Number of consultations with a specialist in the past 4 weeks (public or private providers)
Explanatory variables	
- socioeconomic	
MALE	1 if male
AGE	Age in years
LTEXP	ln(monthly family total expenditure)
EDUC	Education in years
EMPLOYEE	1 if wage earner
- insurance	
INSUR	1 if covered by private health insurance
- health status (short term)	
ACTDAYS	Number of days of reduced activity in past four weeks due to illness or injury
OUTWORKDAYS	Number of days off from work in past four weeks due to illness or injury

[18] This distinction has been based upon the assumption that consultations fully charged to the patient are delivered by private providers although a small share of them is performed within public structures (the so-called 'intra-moenia'). The survey collect specific information about the provider only for the last visit in the observation period.

Table 3 (cont.)

1	2
- health status (long term)	
POOR_HEALTH	1 if self-perceived health is poor
DAILYDIFF	1 if the person suffers from a condition that limits activities in daily life
PHYS_LIM	1 if limitation of activity due to chronic illness
SMOKE	1 if smoker or has smoked daily in the past
- supply side	
PHYSDENS	Number (per 10.000 inhabitants) of general practitioners and paediatricians (regional)
DOCDENS	Number (per 10.000 inhabitants) of specialists in public and private institutes (regional)
PUBEXP_GEN	Per-capita public health expenditure for GPs and paediatricians (regional)
PUBEXP_SPEC	Per-capita public health expenditure for outpatients facilities (regional)
- rationing	
WAIT_DVISITS	Waiting days for visits with a GP or a paediatrician
WAIT_SVISITS	Waiting days for visits with a specialist doctor
REFERENCE INDIVIDUAL: female, employed, without private insurance, with no physical limitations or disabilities, no smoking, in good health	

6. Results and comments

In this study we compare a conventional negative binomial model – based upon the hypothesis of a single decision-making process for health services demand – with a hurdle model – built around the assumption of two different processes respectively for the contact and the frequency decision – consisting in a logit specification for the first hurdle and a zero-truncated negative binomial for the second stage.

The negative binomial (**Negbin**) estimates are presented in Table 4 and 5 for the number of generic visits (public and private) and for specialist (public and private) consultations, respectively. We remind that a *negbin* model is aimed to address the problem of overdispersion which cannot be accounted for by the basic count data model[19].

A distinction between generic and specialist visits is given to institutional reasons (NHS specialist visits require a prescription from a GP and a co-payment, while private specialist consultations are without referral and paid either out-of-pocket by the patient or by a private insurance) and this is partly confirmed by the difference in the sign of some variables for the two equations.

[19] The Negbin model addresses the problem by allowing overdispersion over the α parameter. Here we estimate a version of the model where the variance is given by $\mu + \alpha\mu^2$.

Table 4. Demand of generic visits (Negative Binomial Model): Public and Private Providers

Public generic visits			Private generic visits		
	Coef	Std Err		Coef	Std Err
MALE	–0.107***	0.020	MALE	0.046	0.084
AGE	0.009***	0.001	AGE	–0.017***	0.002
LTEXP	–0.129***	0.029	LTEXP	0.230	0.132
EDUC	–0.067***	0.002	EDUC	–0.097***	0.011
EMPLOYEE	0.111***	0.021	EMPLOYEE	–0.105	0.108
INSUR	0.018	0.033	INSUR	0.556***	0.116
ACTDAYS	0.052***	0.002	ACTDAYS	0.049***	0.007
OUTWORKDAYS	0.041***	0.005	OUTWORKDAYS	0.039*	0.018
POOR_HEALTH	0.487***	0.033	POOR_HEALTH	0.864***	0.185
DAILYDIFF	–0.154**	0.053	DAILYDIFF	0.173	0.308
PHYS_LIM	0.304***	0.038	PHYS_LIM	0.265	0.216
SMOKE	–0.124***	0.026	SMOKE	–0.242*	0.121
PHYSDENS	0.086***	0.013	PHYSDENS	0.031	0.051
PUBEXP_GEN	0.003***	0.001	PUBEXP_GEN	0.003	0.003
_cons	–0.659	0.448	_cons	–7.508***	2.034
_alpha	0.629***	0.027	_alpha	3.034***	0.136
N	140011		N	140011	
ll	–3.06e+07		ll	–3.25e+06	

* p<0.05, ** p<0.01, *** p<0.001

Table 5. Demand of specialist visits (Negative Binomial Model): Public and Private Providers

Public specialist visits			Private specialist visits		
	Coef	Std Err		Coef	Std Err
MALE	–0.186***	0.033	MALE	–0.364***	0.029
AGE	0.011***	0.001	AGE	–0.000	0.001
LTEXP	0.015	0.049	LTEXP	0.291***	0.045
EDUC	0.003	0.004	EDUC	0.034***	0.003
EMPLOYEE	0.146***	0.034	EMPLOYEE	0.067*	0.030
INSUR	0.121*	0.053	INSUR	0.406***	0.040
ACTDAYS	0.049***	0.002	ACTDAYS	0.041***	0.002
OUTWORKDAYS	0.037***	0.005	OUTWORKDAYS	0.034***	0.006
POOR_HEALTH	0.684***	0.048	POOR_HEALTH	0.537***	0.055
DAILYDIFF	–0.271**	0.085	DAILYDIFF	–0.189	0.098
PHYS_LIM	0.589***	0.052	PHYS_LIM	0.398***	0.061
SMOKE	–0.033	0.039	SMOKE	0.164***	0.034
DOCDENS	0.033***	0.008	DOCDENS	0.029***	0.007
PUBEXP_SPEC	–0.005***	0.001	PUBEXP_SPEC	–0.006***	0.001
_cons	–3.805***	0.736	_cons	–7.209***	0.695
_alpha	1.610***	0.039	_alpha	1.789***	0.029
N	140011		N	140011	
ll	–1.67e+07		ll	–2.14e+07	

* p<0.05, ** p<0.01, *** p<0.001

As estimated by Pohlmeier and Ulrich (1995) for Germany where the institutional setting is similar, the variables income (total expenditure) and education have different impacts on the two equations. Individuals are more likely to seek care from private specialists and less likely to consult public GPs as income increases. This result may be explained by the opportunity cost to visit a doctor: to seek care in the public sector costs more in terms of waiting-time (moreover to consult a public specialist requires a visit to the GP as well). Education may correlate with medical knowledge, so that higher educated persons tend to favour (private) specialists over general practitioners. Private insurance is not significant in determining visits to a GP while has a positive effect on other consultations where either a co-payment or a full tariff is charged to the patient. This is a common result in applied literature that could be explained in several ways as we will see later. Finally, being a smoker is significant in increasing private specialists visits while a non-smoking behaviour apparently determines a higher number of generic consultations. As for the other demographic characteristics, women appear to seek more medical care than men – mostly due to childbearing – as usually found in empirical studies. Individual age play a significant role in both equations for public visits: the effect is strictly increasing. Instead private generic visits (mostly paediatric) are more likely for young individuals.

It is not surprising that individuals who were ill (with days of reduced activity, out-of-work, in poor-health conditions) require more treatment both from a general doctor and from specialists. Finally, the last set of variables aimed to proxy the accessibility to medical services show the expected signs with the physician (specialist) density increasing the number of generic (specialist) consultations. Per-capita public health expenditure positively affects the number of generic visits, while it has a negative effect on specialists consultations.

Results for the **double hurdle estimates** are shown in Tables 6–7 for public/private generic visits and in Tables 8–9 for public/private specialist visits. A first look at the tables reveals that the first stage model exhibits a better fit than the second one. One reason is the substantial reduction in sample size for the frequency analysis[20]. Another explanation is that while we find in the dataset the most relevant variables to explain the contact decision, it is more difficult to capture the major determinants of multiple visits, such as the competition among doctors, and the preferences for income and leisure of the physicians. Moreover, in our survey the observation period is so short (4 weeks) that more than 98 percent of the individuals did not visit a doctor more than two times (see Table 1). Despite this, there is a number of relevant comments concerning differences between the parameters across the two stages and with the *Negbin* model which does not distinguish between the two parts.

[20] This reduction is particularly severe in the case of private generic visits (Table 7).

Table 6. Demand of Public generic visits (Hurdle Model)

Contact decision			Frequency of treatment	
	Coef	Std Err	Coef	Std Err
MALE	–0.122***	0.022	0.021	0.042
AGE	0.009***	0.001	0.004***	0.001
LTEXP	–0.095**	0.032	–0.296***	0.056
EDUC	–0.069***	0.003	–0.041***	0.005
EMPLOYEE	0.142***	0.022	–0.004	0.045
INSUR	0.056	0.035	–0.207**	0.075
ACTDAYS	0.057***	0.002	0.028***	0.003
OUTWORKDAYS	0.052***	0.007	0.006	0.007
POOR_HEALTH	0.479***	0.040	0.442***	0.051
DAILYDIFF	–0.205**	0.064	–0.052	0.080
PHYS_LIM	0.317***	0.044	0.154*	0.064
SMOKE	–0.131***	0.026	–0.036	0.060
PHYSDENS	0.103***	0.014	–0.022	0.026
PUBEXP_GEN	0.004***	0.001	0.001	0.002
WAIT_DVISITS		0.002	0.007	
_cons	–1.490**	0.493	3.326***	0.872
_alpha		0.432*	0.173	
N	140011		18381	

* p<0.05, ** p<0.01, *** p<0.001

Table 7. Demand of Private generic visits (Hurdle Model)

Contact decision			Frequency of treatment	
	Coef	Std Err	Coef	Std Err
MALE	–0.006	0.076	0.485*	0.240
AGE	–0.018***	0.002	0.007	0.007
LTEXP	0.242	0.125	0.155	0.404
EDUC	–0.093***	0.010	–0.088*	0.041
EMPLOYEE	–0.067	0.095	–0.817*	0.361
INSUR	0.604***	0.110	0.009	0.364
ACTDAYS	0.047***	0.006	0.037*	0.017
OUTWORKDAYS	0.028	0.014	0.015	0.027
POOR_HEALTH	0.660***	0.154	0.847*	0.432
DAILYDIFF	0.013	0.228	–0.671	0.721
PHYS_LIM	0.161	0.182	–0.136	0.502
SMOKE	–0.244*	0.115	–0.055	0.384
PHYSDENS	0.043	0.052	–0.164	0.124
PUBEXP_GEN	0.005	0.003	–0.020	0.014
WAIT_DVISITS			–0.070**	0.025
_cons	–7.990***	1.951	–10.333	6.204
_alpha			10.045***	0.423
N	140011		1125	

* p<0.05, ** p<0.01, *** p<0.001

The regressors mostly exert on the modelled probability of contacting a generic/specialist doctor a similar effect to what is found in the *Negbin* model. However, some variables which are relevant for passing the hurdle are not significant in determining the frequency of the treatment. This is the case of gender and age characteristics for GP consultations; likewise, the last set of variables which was aimed at capturing the effect of supply side factors (physician density and per capita public health expenditure) is relevant in determining the contact but not the frequency of treatment in case of public generic visits. Finally, in the second hurdle we have considered the possibility of a rationing effect on the demand which can be proxied by the waiting time between the request and the effective day of the visit[21]. In case of GP visits – both public and private – this effect is not significant.

More interesting results can be found in the analysis of specialist visits where there is a developed market of private providers[22]. The determinants of the contact decision are similar to those already commented in the *Negbin* model: as we have already noticed there is a positive effect on the propensity to contact a private specialist of being a female, highly educated, with a poor health status. This probability is not influenced by age as old people tend to favour public specialists[23] (see Table 8) but increases with income.

According to our evidence it seems that demographic characteristics, which play a major role in passing the first hurdle, are not significant in determining the frequency of visits which depends mainly on a patient's health status including being a smoker, and on holding a private insurance that is relevant in both stages of demand. In particular, income and education do not affect the frequency behaviour. This is consisting with previous findings for Italy on different data[24]. It is interesting to remark the impact of being privately insured. This can be explained on several grounds: it could be the effect of an adverse selection process making the frequent health services users to look for supplementary coverage.

Another interpretation could be represented by moral hazard where there are incentives by the patient and the physicians for over-treatment. This last explanation has to do with supplier induced demand in a wide sense and could explain our findings, as the frequency equation describes the outcome of the joint

[21] See Martin and Smith (1999), Blundell and Windmeijer (2000).

[22] We remind that while in case of service provided within the NHS there is a role of gatekeeper performed by the GP and co-payments for the patients, in case of private specialists the prescription is not necessary and the service is entirely paid by the patient who may be refunded in case of private insurance.

[23] This result is due to the legislation which exempt from co-payments individuals over 65 (with differences at regional level).

[24] See Fabbri and Monfardini (2003). The same results have been obtained by Pohlmeier and Ulrich (1995) for Germany.

Table 8. Demand of Public specialist visits (Hurdle Model)

Contact decision			Frequency of treatment	
	Coef	Std Err	Coef	Std Err
MALE	–0.170***	0.031	–0.056	0.072
AGE	0.010***	0.001	0.002	0.002
LTEXP	0.031	0.045	–0.202*	0.103
EDUC	0.004	0.003	–0.002	0.009
EMPLOYEE	0.135***	0.032	0.086	0.076
INSUR	0.100*	0.047	0.037	0.125
ACTDAYS	0.046***	0.002	0.022***	0.004
OUTWORKDAYS	0.033***	0.006	0.026***	0.008
POOR_HEALTH	0.633***	0.053	0.439***	0.086
DAILYDIFF	–0.482***	0.082	0.079	0.139
PHYS_LIM	0.541***	0.057	0.272**	0.094
SMOKE	–0.043	0.036	0.127	0.087
DOCDENS	0.031***	0.008	0.016	0.017
PUBEXP_SPEC	–0.004**	0.001	–0.005	0.003
WAIT_SVISITS		–0.001	0.001	
_cons	–4.238***	0.679	–8.330***	1.657
_alpha			10.704***	0.437
N	140011		8781	

* p<0.05, ** p<0.01, *** p<0.001

Table 9. Demand of Private specialist visits (Hurdle Model)

	Contact decision		Frequency of treatment	
	Coef	Std Err	Coef	Std Err
MALE	–0.431***	0.027	0.050	0.057
AGE	–0.000	0.001	–0.003	0.002
LTEXP	0.284***	0.041	0.023	0.099
EDUC	0.036***	0.003	0.003	0.006
EMPLOYEE	0.050	0.028	0.035	0.059
INSUR	0.437***	0.037	0.069	0.079
ACTDAYS	0.041***	0.002	0.009*	0.004
OUTWORKDAYS	0.035***	0.006	0.023*	0.010
POOR_HEALTH	0.490***	0.053	0.242*	0.096
DAILYDIFF	–0.332***	0.085	0.005	0.212
PHYS_LIM	0.423***	0.056	0.111	0.118
SMOKE	0.072*	0.030	0.362***	0.064
DOCDENS	0.036***	0.007	–0.009	0.014
PUBEXP_SPEC	–0.005***	0.001	–0.003	0.003
WAIT_SVISITS		–0.005*	0.002	
_cons	–7.540***	0.626	–9.829***	1.620
_alpha			9.819***	0.343
N	140011		11722	

* p<0.05, ** p<0.01, *** p<0.001

decision of the physician and the patient. Finally, the supply side variables are relevant in the contact but not in the frequency decision as in the case of generic visits. However, the waiting time negatively affects the intensity of treatment thus suggesting that the specialist health care demand can be somewhat rationed.

7. Concluding remarks

In conclusion, there is not a clear supremacy of the hurdle model on the count model (negative binomial). However, some differences in the two step decision-making have been found thus indicating that this approach could give a more valuable insight in the demand of health care. Further developments of this analysis consist firstly in estimating the demand of other health care items, in particular hospital services, which are a very relevant component of health care demand. Then, a major challenge is to connect this analysis – performed at the individual level with count data about medical care utilization – with an Inforum-type cross-section/time-series system of demand, which estimates expenditures at the household level. For the reasons presented in this work this linkage is a necessary step to correctly evaluate and forecast the population needs in terms of health care.

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